Quantum Machine learning using Quantum Simulators

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Background

- It is generally recognized that quantum inspired algorithms achieve exponential speed over classical algorithms
- The near-term quantum processors are still unpredictable, in its infancy. cost-prohibitive, and reliability is a concern
- To better understand the effectiveness of these algorithms, quantum system simulation is available to model and develop these algorithms

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Problem and Objective

- What is Quantum Machine Learning and how can we use it for Machine Learning problems?
- Understanding a Quantum system using hybrid quantum-classical systems
- How can we use Quantum Simulators to model a hybrid quantum-classical system for classifier problem?
- An example of a hybrid quantum-classical system
  - Based on Adaptive Filter course, a gradient descent algorithm using quantum circuit was simulated

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Quick introduction

- Quantum Physics, Quantum Mechanics, Quantum Algorithms, we hear this everywhere nowadays
- This has been around from the 1900s
  - Quantized properties
  - Particles of light
  - Waves of matter
- We can look at Quantum Mechanics as the theory that explains the nature of really small things
  - atoms, photons, and individual particles
- For this research, we are focusing more on Quantum Algorithms & Quantum Computing

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Quantum Background

- We begin by looking at qubits and quantum entanglement
- A classical bit can have a value of two states 0 or 1. This can be represented with a transistor switch set to “off” or “on”. Another way to see this is an “arrow” being “up” or “down”.
- When looking at a qubit, we see this having more possibilities
- The state is represented by arrow point to a location on a sphere

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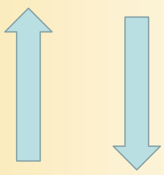
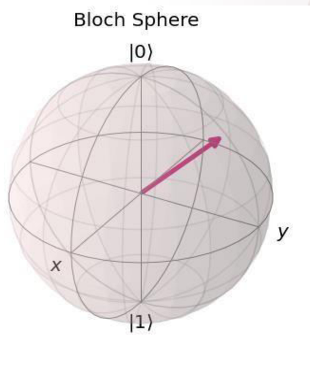
The Transition

Classical bit





Quantum bit

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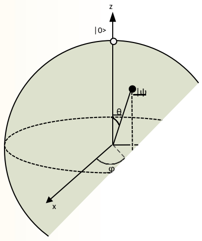
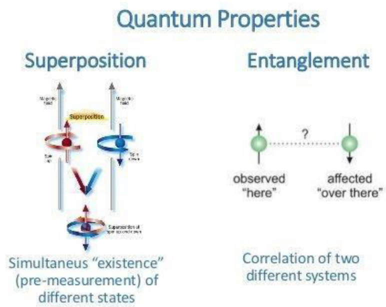
Why a Bloch sphere?

- The qubit, a|0>+b|1>, can be represented as a point on a unit sphere
- Great representation for a single qubit
- Helps understand and build a foundation when building quantum gates



Starting with Quantum Properties

- Two types of quantum properties
  - Superposition
  - Entanglement
- For Quantum Computing, we consider quantum entanglement



Define Quantum Computing

- Idea of Quantum Computing is to have a machine that operates on a quantum state vs a classical one
- Consider a system with N two-level quantum mechanical system
  - This system could perform operations on 2^N numbers at once
  - This may be done in parallel
  - As an example, if N=300, can there be a classical system that stores 300 elements?

Quantum Computing Simplified

- In simplified term, we will look at quantum computing as
  - Prepare entangle state
  - Conditional measurement
  - Output of the computation

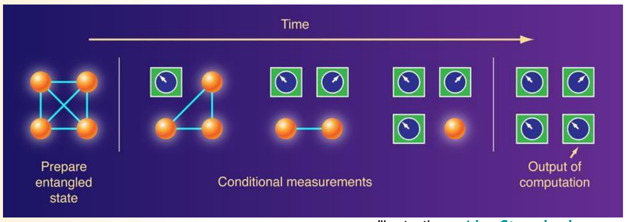
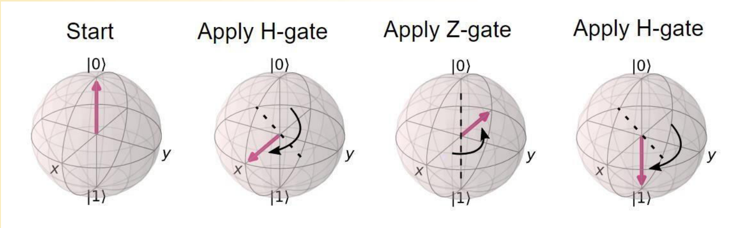


Illustration: Alan Stonebraker

Building a Quantum System Simplified

- Looking at a single qubit, we apply Quantum gates to modify the vector and position



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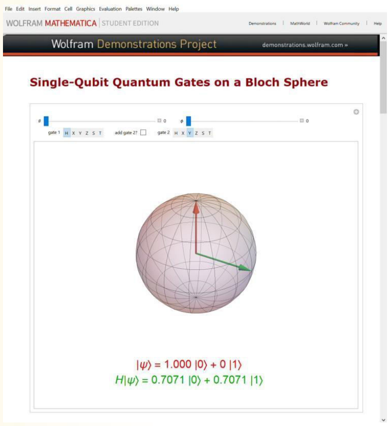
Bloch Sphere Example



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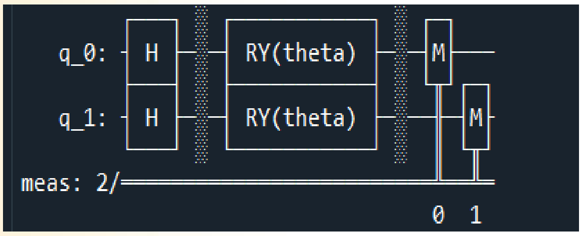
Quantum Circuit

- Quantum gates are ordered in chronological order with the left-most gate as the gate first applied to the qubits
- If we look at the quantum gates, we are applying these through the sequence to build a quantum circuit



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Hybrid Quantum-Classical System

- The idea is letting a quantum simulator work in conjunction with a classical computer
- With the limitation of real quantum computers, we use a hybrid approach to validate our algorithms
- Using a hybrid approach allows for minimal quantum resources
  - inexpensive calculations are performed on a classical computer
  - the difficult part of the computation is accomplished on a quantum simulator

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Building our Quantum system

- In this research we look at building a hybrid quantum neural network
- The process to build the system is
  - Look at QSVM in Qiskit
    - To understand quantum circuits
  - Apply a quantum circuit in the hidden layer of a neural network
  - Try to build a hybrid quantum-classical neural network using gradient descent algorithm
    - This is based on Adaptive Algorithm course from Fall 2020

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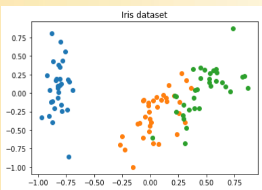
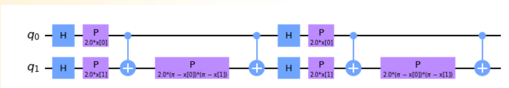
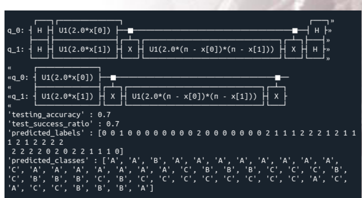
Starting with QSVM

- Using the Qiskit toolkit, we built a classifier using Quantum Support Vector Machines
- This allowed us to quickly build a quantum circuit and run our model
  - Using Iris dataset







Only 70%

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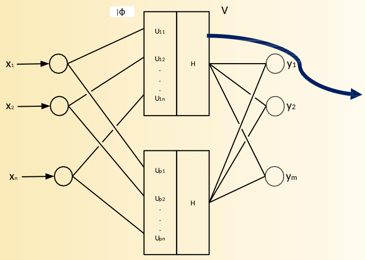
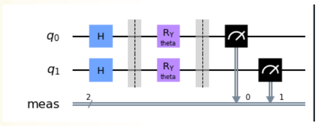
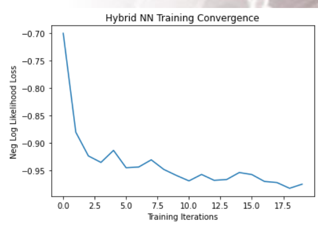
Looking at Neural Network

- Once the modeling and system is understood, we look at a hybrid quantum-classical
- Writing code to build a quantum circuit
- Apply this in the hidden layer of Neural Network



Classical to Quantum to Classical neural network





Results looking good

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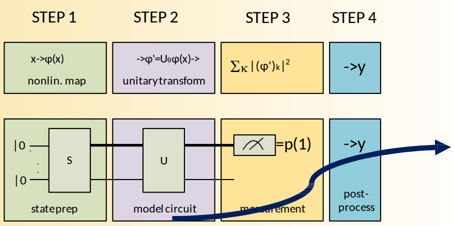
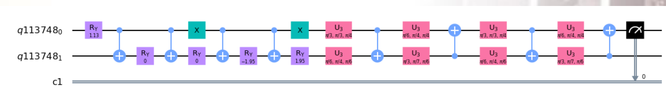
Hybrid Quantum-Classical Neural Network

- We tried to build some circuits by adding gradient descent algorithm
  - Attempt to realize this using a quantum circuit
- For hybrid quantum-classical system, we keep the state preparation classical space





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Looking at the design

- The State Preparation is used to apply various strategies to encode the input vectors into n-qubits
- The Model Circuit maps the vector to another vector $\varphi' = U_\theta \varphi(x)$ by a unitary operation U_θ. In this, the unitary U can be decomposed into

$$U = U_L \ldots U_\ell \ldots U_1$$

where each U_ℓ is a single qubit or two-qubit quantum gate

- The measurement and post-processing steps are ways to look and inspect the quantum bit and transforms

Quantum Circuit Design

- We run the gradient descent algorithm to determine the weights needed to optimize the training
- We start with a standard least-squares objective to evaluate the cost of a parameter configuration θ and the bias b
- Being with a training set $D = \{(x^1, y^1), \ldots, (x^M, y^M)\}$
- We can look at the cost as

$$C(\theta, b, D) = \frac{1}{2}\sum_{m=1}^{M} |\pi(x^m; \theta, b) - y^m|^2$$

where π is the continuous output of the model: $\pi(x; \theta, b) = p(q_0 = 1, x, \theta) + b$.

$$(q_0 = 1, x, \theta) = \sum_{k=2^{n-1}+1}^{2^n} |(U_\theta \varphi(x))_k|^2$$

where this is the probability of state 1 after the execution of the quantum circuit $U_\theta \varphi(x)$.

Quantum Circuit Design

- We run through similar gradient descent updates with each step size μ. We can now define as

$$\mu^{(t)} = \mu^{(t-1)} - \eta \frac{\partial C(\theta, b, D)}{\partial \theta}$$

•bias is

$$b^{(t)} = b^{(t-1)} - \eta \frac{\partial C(\theta, b, D)}{\partial b}$$

- The learning rate η may be adapted during the training as needed to decrease the convergence time.

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Model Algorithms

- Training set $D = \{(x^1, y^1), \ldots, (x^M, y^M)\}$
- Cost $C(\theta, b, D) = \frac{1}{2} \sum_{m=1}^{M} |\pi(x^m; \theta, b) - y^m|^2$
  - $\pi(x; \theta, b) = p(q_0 = 1, x, \theta) + b$
  - $(q_0 = 1, x, \theta) = \sum_{k=2^{n-1}+1}^{2^n} |(U_\theta \varphi(x)))|_k^2$
- Grad $\mu^{(t)} = \mu^{(t-1)} - \eta \frac{\partial C(\theta, b, D)}{\partial \theta}$
- Bias $b^{(t)} = b^{(t-1)} - \eta \frac{\partial C(\theta, b, D)}{\partial b}$
- Where we have learning rate η

```
def gradients(params, angles, label, bias=0):
    grads = np.zeros_like(params)
    imag = imaginary(params, params, angles)
    for i in range(params.shape[0]):
        for j in range(params.shape[1]):
            params_bis = np.copy(params)

            params_bis[i,j,0]+=np.pi
            grads[i,j,0] = -0.5 * real(params, params_bis, angles)
            params_bis[i,j,0]-=np.pi

            params_bis[i,j,1]+=np.pi
            grads[i,j,1] = 0.5 * (imaginary(params, params_bis, angles) - imag)
            params_bis[i,j,1]-=np.pi

            params_bis[i,j,2]+=np.pi
            grads[i,j,2] = 0.5 * (imaginary(params, params_bis, angles) - imag)
            params_bis[i,j,2]-=np.pi
    p = execute_circuit(params, angles, bias=bias)
    grad_bias = (p - label) / (p * (1 - p))
    grads *= grad_bias
    return grads, grad_bias
```

Quantum circuit

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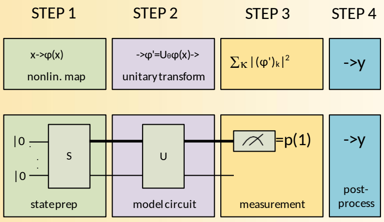
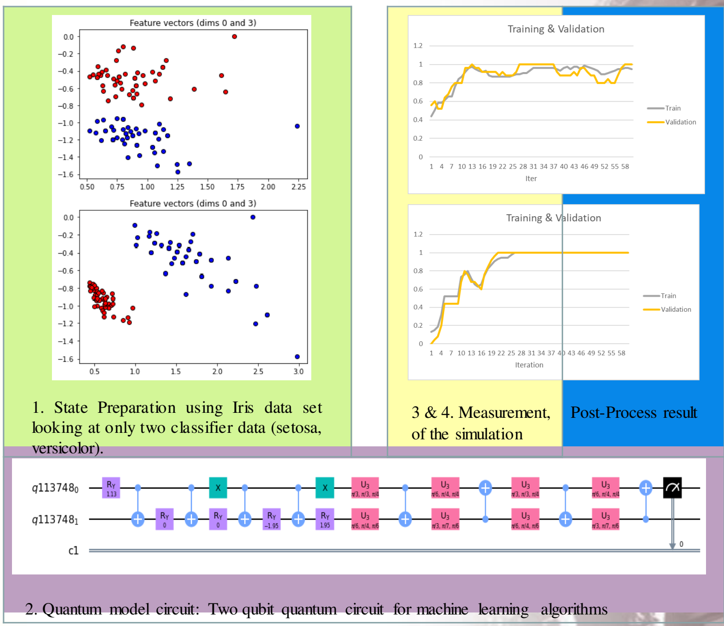
Mapping the Steps





1. State Preparation using Iris data set looking at only two classifier data (setosa, versicolor).

3 & 4. Measurement, of the simulation

Post-Process result

2. Quantum model circuit: Two qubit quantum circuit for machine learning algorithms

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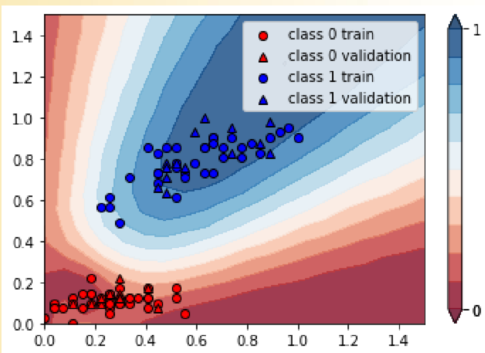
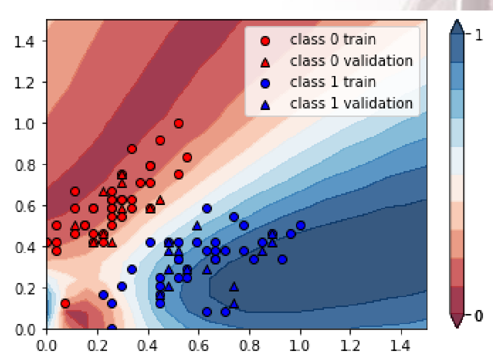
Results





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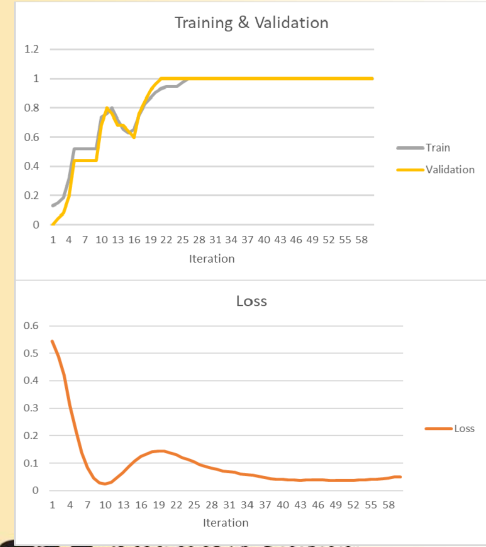
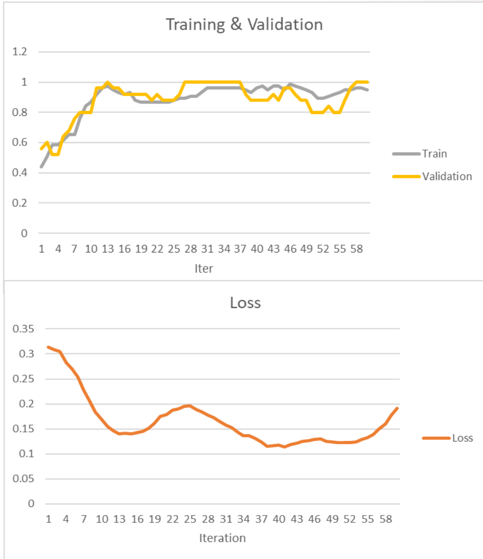
Training Results





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Conclusion

- We have developed a quantum machine learning design that are both Quantum inspired and implementable using quantum simulators
- To build the QNN, the building block of this is the unitary model circuit with few trainable parameters that assumes amplitude encoding of the data vectors
- This allows the use of systematically entangling properties of quantum circuits
- Another key area is the state preparation, though not shown in the results, the preparation of the data took some significant time
- After state preparation, the prediction of the model is computed by applying only a small number of one- and two-qubit gates quantum gates
- This allows for a simpler testing and use on a quantum simulator

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