# Quantum Neural Networks (QNNs)

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# Topics of interest


1. Introduction
2. Classical Neural Networks (ANNs)
3. ANNs Limitations
4. Quantum Neural Networks (QNNs)
5. QNNs Simulation
6. QNNs Limitations
7. Conclusion
8. References

# Introduction (1)

Some interesting **quotes**.

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> *To create an artificial being has been the dream of man... since the birth of science. Not merely the beginning of the modern age... when our for-bearers astonished the world with the first thinking machines - Primitive monsters that could play chess.*
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*Science is a differential equation.*
*Religion is a boundary condition.*
*— Alan Turing. . .*

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4. What kind of unexpected **failures** might occur in a world built upon AI?

# Introduction (3)

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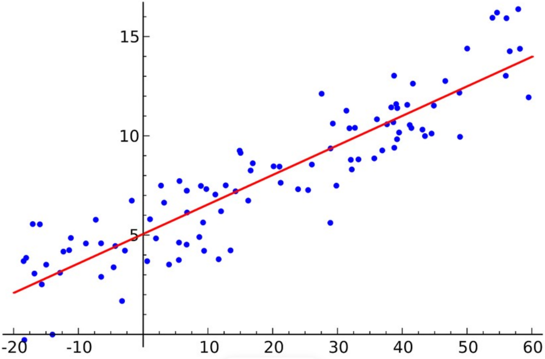


Figure: Regression Line for a given **data** set.

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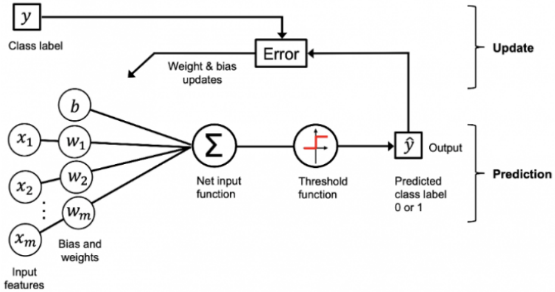


Figure: Perceptron

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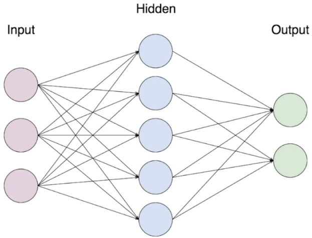


Figure: Feedforward ANN

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## Definition (Cost Function)

$$J(\theta) = \frac{1}{m} \cdot \sum_{i=1}^{m} \left\{ -y^{(i)} \cdot \log \left[ h_\theta \left( x^{(i)} \right) \right] - (1 - y^{(i)}) \cdot \log \left[ 1 - h_\theta \left( x^{(i)} \right) \right] \right\}$$

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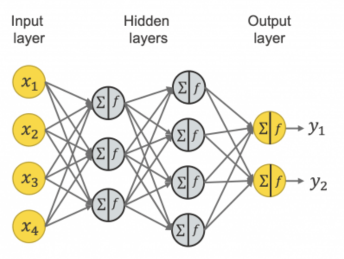


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**Backpropagation** refers to the method of calculating the gradient of neural network parameters.
The algorithm stores any intermediate variables (partial derivatives) required while calculating the gradient with respect to some parameters.

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3. $\theta$ it is a **vector**, $\theta \in \mathbb{R}^{s_2 \cdot (s_1+1) + s_3 \cdot (s_2+1)}$, and it stores the elements from $\Theta^{(1)}$ and $\Theta^{(2)}$.

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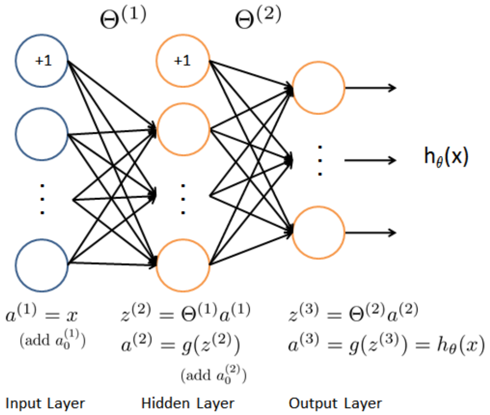


Figure: A Neural Network Architecture

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2. **Classification**, including pattern and sequence recognition, novelty detection and sequential decision making.
3. Data **processing**, including filtering, clustering, blind signal separation and compression.

# ANNs Limitations

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Arguments for Dewdney's position are that to implement large and effective software neural networks, much processing and storage resources need to be committed.

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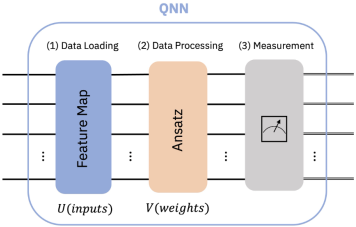


Figure: Quantum Neural Network

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Ideas to imitate the **perceptron** activation function with a quantum mechanical formalism reach from special measurements to postulating non-linear quantum operators.

A direct implementation of the **activation function** using the circuit-based model of quantum computation has recently been proposed by Schuld, Sinayskiy and Petruccione based on the **quantum phase estimation algorithm**.

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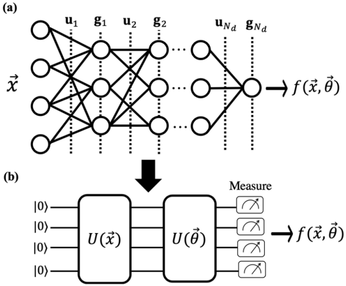


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# Quantum Neural Networks (4)

For a quantum neural network, the cost function is determined by measuring the fidelity of the outcome state $\rho^{\text{out}}$ with the desired outcome state $\phi^{\text{out}}$, seen in Equation 2 below.
In this case, the Unitary operators are adjusted after each iteration, and the cost function is optimized when C = 1.

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$$C = \frac{1}{N}\sum_{x}^{N}\langle\phi^{\text{out}}|\rho^{\text{out}}|\phi^{\text{out}}\rangle$$

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However, in a quantum neural network, where each perceptron is a qubit, this would violate the **no-cloning** theorem.

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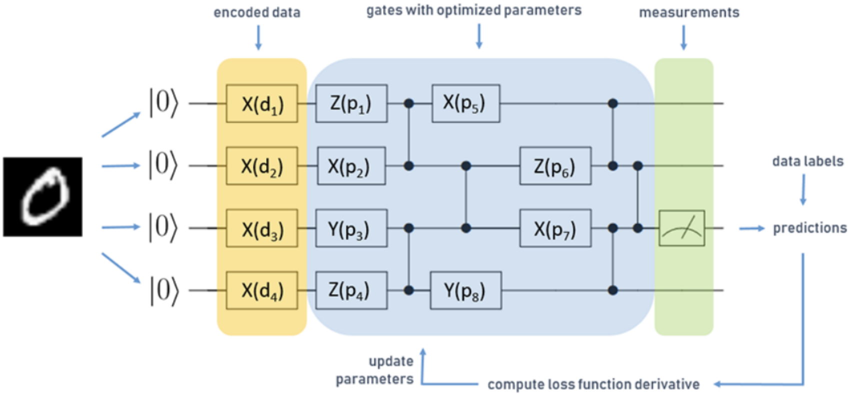


Figure:

# QNNs Simulation (1)

We can test what we have learned using a Qiskit Jupyter Notebook.

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2. Another limitation of QNNs is their lack of robustness.
3. QNNs are limited in their ability to generalize.

# Conclusion

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A new **WORLD** will be DAWNING...

# References

1. Qiskit: Machine Learning
2. Wikipedia: Quantum Computing
3. Deep Neural Networks
4. The Power of QNNs

# The End