Introduction to Quantum Machine Learning and Neural Networks (Part 1)

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What is Quantum Machine Learning?

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What is Quantum Machine Learning?

- Combines quantum computing with machine learning
- Explores whether quantum systems provide new ways to represent and process data
- Seeks potential quantum advantages, such as:
  - More expressive feature representations
  - Efficient computation of certain similarities or structures
- Utilizes superposition and entanglement to represent complex correlations

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How is QML Different from Classical?

Some questions:

- What can we do with classical machine learning?
- What doesn't work?
- What "quantum advantages" exist?
- How can we leverage these advantages?

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Why Not Stick with Classical ML?

- *Incredibly* successful (AI is everywhere!)
- Solves massive scale problems faster than current quantum computers
- Quantum computers are expensive and noisy
- What do we gain?

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Classical Neural Network Overview

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Overview of Classical Neural Nets

- Quick review of main concepts
- Focus on modeling perspective
- Goal: Understand the connection to quantum models

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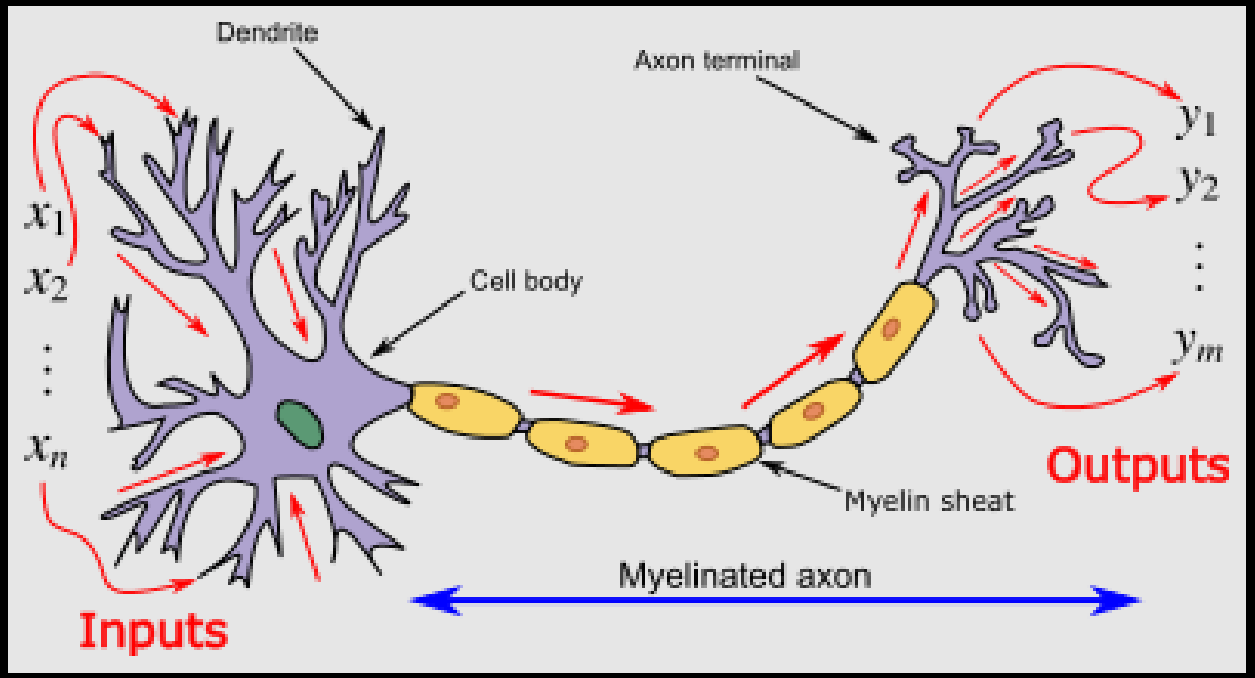
Biological Neurons

Neural networks are inspired by the structure of biological neurons



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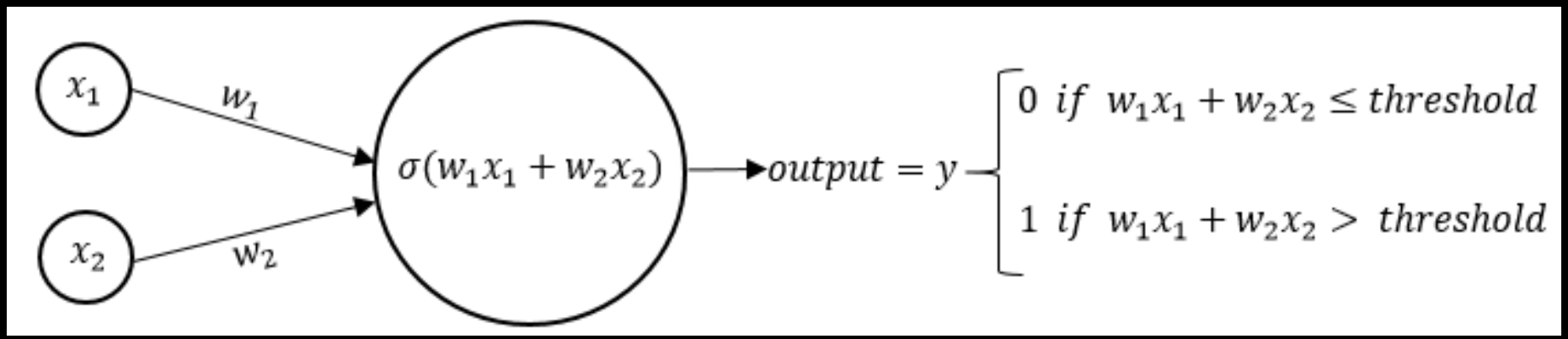
Classical Neuron (Perceptron)

A simple perceptron



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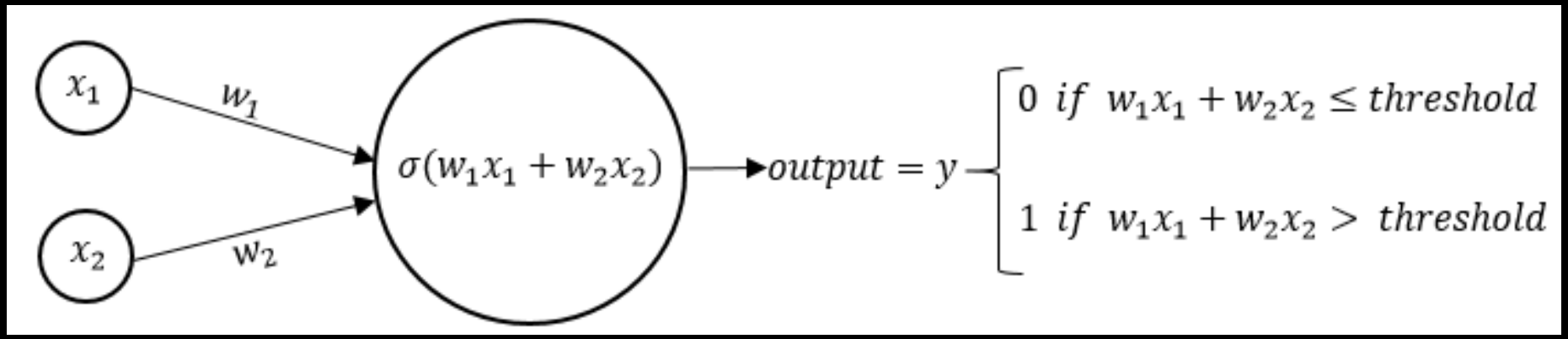
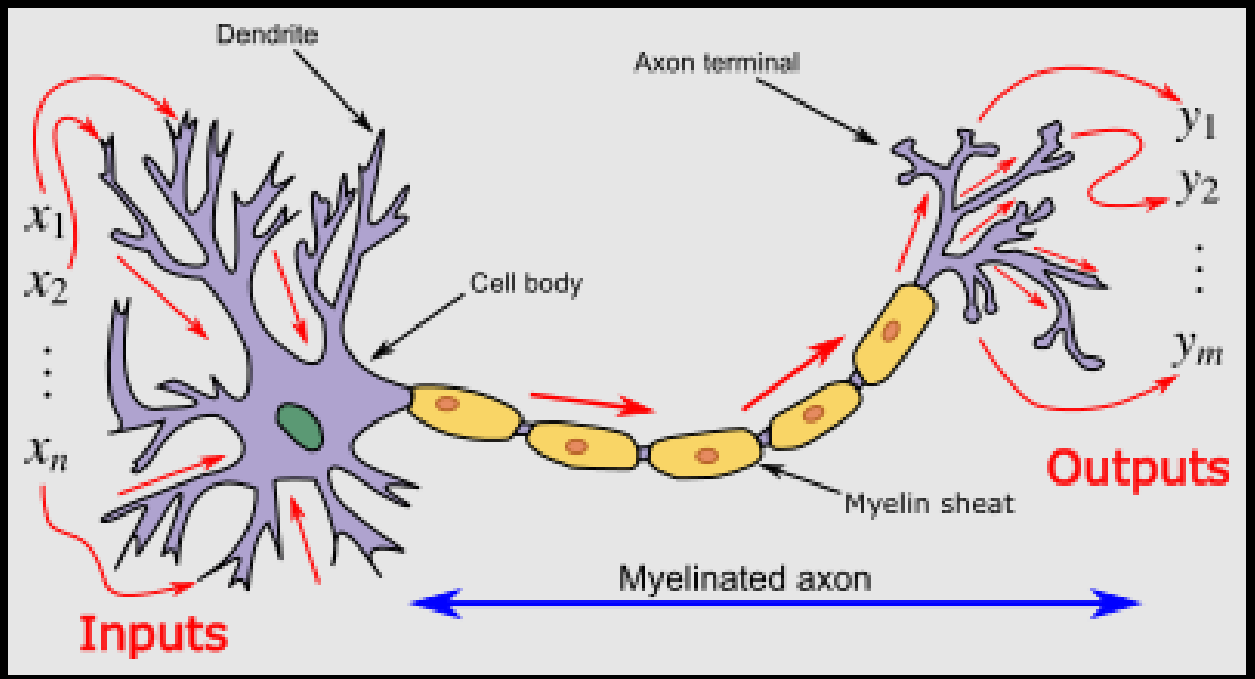
Classical Neuron (Perceptron)





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Neural Networks as Models

- A neural network is a parametrized function

$$y = f(x; W)$$

- Maps inputs x to outputs y
- Parameters (weights) W are learned from data

Function Idea is Key

Think about neural networks as a function with many parameters; this is the best way to connect them to quantum models

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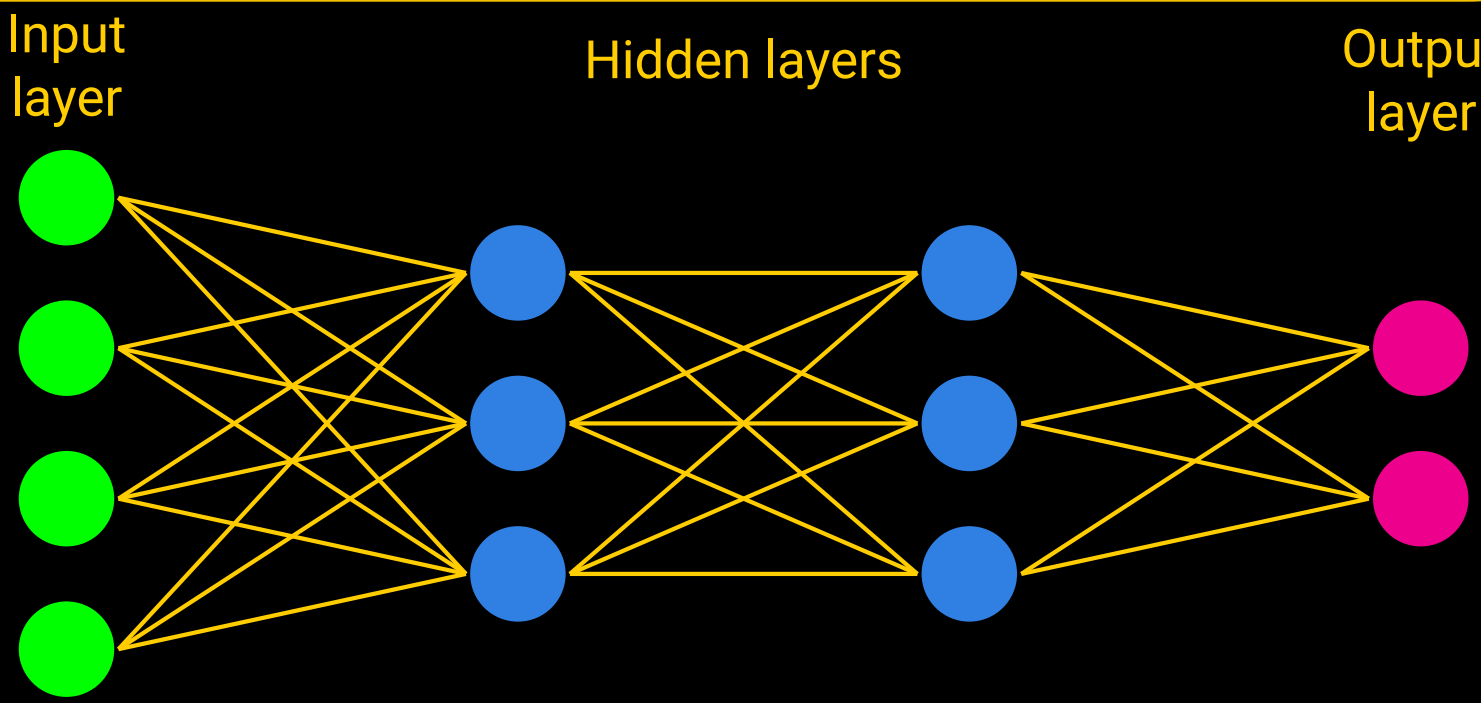
Multi-layer Perceptron



- Composed of layers
  - Affine transformations in each layer
  - Nonlinear activation functions
- $f_\ell(x) = \sigma_\ell\left(W_\ell\, x + b_\ell\right)$
- $f(x, W) = f_L \circ f_{L-1} \circ \ldots \circ f_1(x)$

Depth increases expressivity

"Learning" is Optimization

- Define a cost function

$$C(f(x, W), y)$$

- Adjust parameters of f to minimize C
- Possible optimization schemes:
  - Stochastic Gradient Descent
  - Gauss-Newton Method
  - Levenberg-Marquardt

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Hypothesis Classes

- A neural network defines a hypothesis class
- Its architecture determines:
  - What functions are possible
  - What patterns can be learned
- Training selects one function in this class

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Quick Check-in

If we fix the structure of the network but change the encoding, are we using the same model?

No!

The encoding changes the representation of the inputs and hence changes the *hypothesis class*.

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What Shapes the Hypothesis Class?

- A model does not represent all possible functions
- The set of possible functions is determined by design choices

Key Components

- **Data encoding:** how inputs are mapped into the model
- **Model structure:** layers, connectivity, or circuit architecture
- **Output rule:** how predictions are extracted

Main Idea

These choices define what patterns can be represented and learned

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What are the Limitations?

Classical machine learning faces the following challenges:

- Choosing effective representations
- Capturing complex correlations
- Balancing expressivity and trainability
- Optimization can be difficult

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Can We Do Better?

- Can we build different kinds of models?
- Can we represent data in new ways?
- Can we capture information structure that is difficult classically?

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Neural Networks $\rightarrow$ Quantum

Classical	Quantum
Parameters W	Gate parameters
Network layers	Circuit layers
Activation functions	Measurement
Features $\phi(x)$	Quantum states $\|\psi(x)\rangle$

Classical machine learning:

$$x \rightarrow \phi(x) \rightarrow f(x)$$

Quantum machine learning:

$$x \rightarrow |\psi(x)\rangle \rightarrow \text{measurement}$$

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Moving Toward Quantum ML

- Replace classical representations with quantum states
- Replace layers with quantum circuits
- Replace outputs with measurements

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Machine Learning, but Quantum

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Quantum Machine Learning Pipeline

What does a QML model actually do?

- Encode classical data into quantum states
- Apply a parameterized quantum circuit
- Measure outcomes to produce predictions

Starting Point

Encoding is the first step in defining the model

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Encoding Quantum Data

- How do we represent classical data in a quantum system?
- Any QML process's first step is data encoding
- Model performance strongly influenced by encoding
- Encoding is one of the key choices defining the hypothesis class

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From Data to Quantum States

We need to map

$$x \rightarrow |\psi(x)\rangle$$

where x is a classical vector and $|\psi(x)\rangle$ is a quantum state and require the encoding to have the following properties:

- Efficient to compute
- Preserve the structure in the data
- Compatible with the model

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Encoding as a Feature Map

- Classical ML: choose features $\phi(x)$
- QML: choose quantum state $|\psi(x)\rangle$
- Choices determine:
  - What patterns are visible
  - What it means to be “similar”
  - What can be learned

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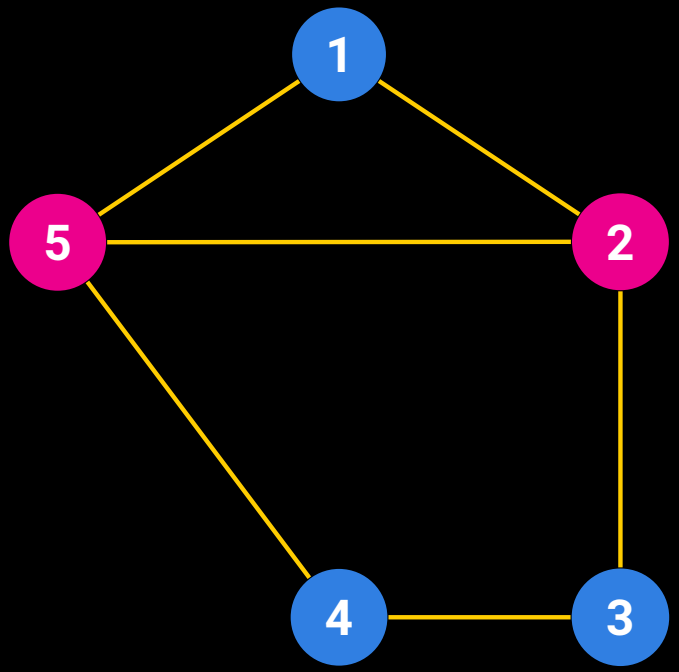
Why Feature Maps Matter



- In $\mathbb{R}^2$, this isn't linearly separable
- In a higher-dimensional space, it might be
- Next section preview: MaxCut

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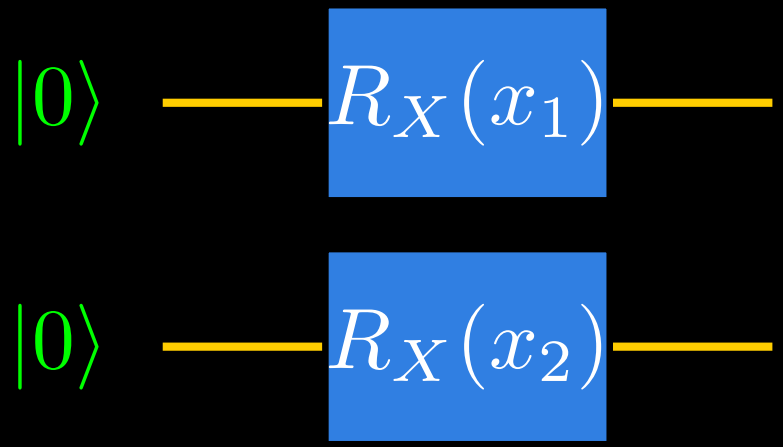
Example: Encoding Data

- Suppose $x = (x_1, x_2)$
- Angle encoding:

$$x \to R_X(x_1)\,|0\rangle \otimes R_X(x_2)\,|0\rangle$$



- After encoding:
  - Data represented as a quantum state
  - Each feature x_j controls a rotation
  - Model operates on this state, not x directly

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What Makes a "Good" Encoding?

- Efficient state preparation
- Captures structure of data
- Scales well with dimension of input
- Compatible with hardware limitations

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Basis Encoding

- Encode data as computational basis states
- Examples:
  - $x = (1, 0, 1) \rightarrow |101\rangle$
  - $6 = 4 + 2 + 0 = 1 \cdot 2^2 + 1 \cdot 2^1 + 0 \cdot 2^0 = 110_2 = |110\rangle$
- Typically one qubit per feature

Pros

- Simple
- Implementation is straightforward

Cons

- Poor for continuous data
- No natural notion of similarity

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Angle Encoding

- Encode features as rotation angles
- Example:
  - $x \rightarrow \bigotimes_i R_Y(x_i) \left|0\right\rangle$

Pros

- Natural for continuous data
- Efficient and hardware friendly
- Effective with shallow circuits

Cons

- Needs one rotation per feature
- Limited expressivity without entangling layers
- Capturing global correlations requires deep circuits

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Amplitude Encoding

- Encode features as state amplitudes
- Example:
  - $x \rightarrow \sum_i \frac{x_i}{\|x\|} |i\rangle$

Pros

- Most compact
- Full vector stored as single state

Cons

- State preparation is expensive
- Difficult to implement in practice

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Comparing Encoding Strategies

Considerations:

- Qubit cost vs gate complexity
- Modeling local vs global structure
- Practical vs theoretical usefulness

Summary:

- Basis – simple yet limited
- Angle – practical and flexible
- Amplitude – powerful but costly

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Defining Similarity

- Machine learning tasks rely on “similarity” between inputs
- In QML, similarity is computed directly from quantum states via the quantum kernel

$$K(x, x') = |\langle \psi(x) | \psi(x') \rangle|^2$$

- Choosing an encoding determines
  - Geometry of feature space
  - Which points are close together

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Quick Check-in

What does it mean if $K(x, x') \approx 1$?

What if $K(x, x') \approx 0$?

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Encoding is a Bottleneck

- State preparation is not free
- Cost often scales with input size
- Encoding can dominate total runtime

Main Point

Efficient algorithms require efficient encoding

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The Data Access Problem

- Many quantum algorithms assume efficient access to data
- Real data is typically classical
- Loading data into quantum states can cost $O(n)$
- This cost can offset gains from quantum processing

Impact

Any potential speedup must include the cost of data loading

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Quantum Data Encoding

Key Takeaways:

- Encoding is part of the model, not just pre-processing
- Data encoding = quantum feature map
- Shapes what the model can learn
- Tradeoff between expressivity and efficiency
- Central to both:
  - Variational models
  - Quantum kernel methods

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XOR Example

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XOR

Classic Machine Learning Example

- Requires a non-linear separator
- Not solvable by a (single-layer) perceptron

Input	Output
0 & 0	0
0 & 1	1
1 & 0	1
1 & 1	0

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Session 1 Summary

- Quantum machine learning explores new ways to represent data
- Models are defined by a hypothesis class
- In QML, encoding plays a central role
- Encoding defines:
  - The feature space
  - Similarity between inputs
  - What can be learned
- Efficient data encoding is crucial for any advantage

Up Next

How quantum circuits act as models (parameterized quantum circuits) and how we train them

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Any Questions?

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Thank you!

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