Quantum Machine Learning: A Comprehensive Review of Integrating AI with Quantum Computing Advancements

CSSE 313 Cutting Edge Research Presentation

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Motivation

- Explosive growth of ML model sizes (e.g., GPT-scale networks with *trillions* of parameters) demands unprecedented compute and energy.
- Moore's Law and Dennard scaling are slowing — transistor miniaturization no longer yields proportional performance gains.
- GPU/TPU architectures are reaching thermal and power-efficiency ceilings.
- Data movement—not arithmetic—is the dominant energy and latency bottleneck.

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Motivation

- Quantum computing promises to unlock a **fundamentally different computational paradigm**—processing information via **superposition**, **entanglement**, and **interference**.
- We will explore whether this promise is real, where it fits in AI, and what's holding it back.

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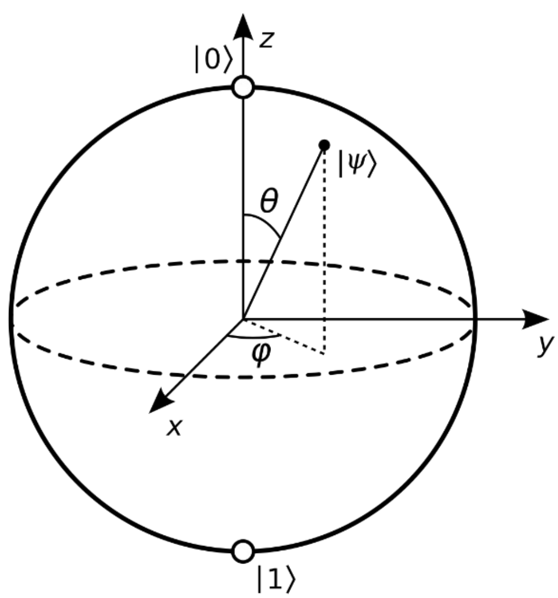
Qubits

- Store information a *quantum state*
- Visualize a qubit's information with Bloch Sphere:
  - Point on the sphere's surface
  - Value "collapses" to either pole (0 or 1) when observed
  - Proximity to poles → Probability of collapsing to that value
  - Infinitely many states between 0 and 1



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Entanglement

- When two or more qubits interact, they can become **entangled** — their states become interdependent.
- The system can no longer be described as individual qubits; only the **combined state:**
  - $\begin{bmatrix} Probability\ 0 \\ Probability\ 1 \end{bmatrix}$ Becomes $\begin{bmatrix} Probability\ 0,0 \\ Probability\ 0,1 \\ Probability\ 1,0 \\ Probability\ 1,1 \end{bmatrix}$
  - Measurement of one qubit **instantly determines** the outcome of the other, regardless of physical distance.

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Misconceptions

- Quantum Computers are **NOT** general purpose supercomputers
- They are very specialized at completing specific tasks

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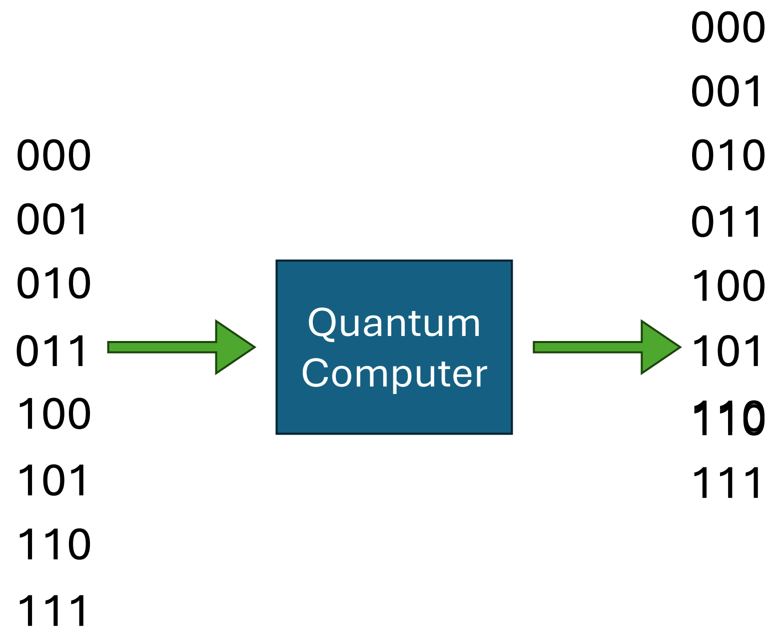
Demo



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- Quantum computers really do a huge amount of parallel computation with the same cost as a single classical computation, extracting the information in a meaningful way requires clever algorithms that are highly specific to the context/problem they are designed to solve

- Not many practical quantum algorithms exist for most problems
  - In some cases, algorithms exist but are not found yet
  - In some cases, there is no algorithm to find (Quantum can't solve this class of problem)
  - We never know which case a given problem falls into

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Functional Example

- Shor’s Algorithm developed in the 90s
- Successfully uses quantum principles to factorize big numbers
- Reliant on mathematical patterns in the process of finding prime factors, such that the entangled output data can be collapsed into useful information
- (Demo at end if there is time and interest)

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Quantum Computing and AI

- Sounds promising, though no true end-to-end quantum algorithm yet exists.
- Hybrid approaches seem to be the more realistic first step:
  - VQE (Variational Quantum Eigensolver) – minimizes quantum system energies.
  - QAOA (Quantum Approximate Optimization Algorithm) – solves discrete optimization tasks.
  - Quantum Neural Networks (QNNs) – quantum layers trained with classical feedback loops.

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Challenges

- Data encoding: Loading classical data into quantum states can take exponential time, voiding the speedup of quantum computation
- Barren Plateaus: Learning gradients grow flat as quantum circuits grow, halting learning
- Measurement: Extracting results collapses quantum states, algorithms to preserve useful information are required.

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Cool theory

- Quantum Kernel Theory:
  - Quantum feature spaces can represent data in exponentially large dimensions *implicitly*.
  - This could make complex patterns separable with fewer training examples.
- Quantum Linear Algebra (HHL Algorithm):
  - Solves linear systems exponentially faster *if data is already in quantum form*.
  - Could one day accelerate regression, optimization, or backpropagation steps.

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Hardware Challenges

- **Decoherence:** Qubits lose quantum information in microseconds due to interaction with the environment.
- **Noise and Crosstalk:** Each gate operation introduces small errors that compound quickly with circuit depth.
- **Scalability:** Adding qubits increases the difficulty of maintaining isolation, synchronization, and error correction exponentially.
- **Cryogenic requirements:** Most qubits must operate near **absolute zero** to maintain stability.
- **Error correction overhead:** Reliable logical qubits may require **thousands of physical qubits each**, vastly increasing hardware demands.

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Conclusion

- **Quantum computing** offers a fundamentally new way to process information — leveraging superposition, entanglement, and interference.
- **End-to-end quantum ML algorithms** do **not yet exist** — most approaches are *hybrid*, combining quantum circuits with classical optimization.
- **Software challenges** like data encoding, barren plateaus, and measurement noise remain major barriers to scalable training.

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Shor's Algorithm

- Algorithm begins with an arbitrary guess g
- Raising g to some power P will result in some multiple m of N, plus one:

$$g^P = m*N+1$$

- If P is known, Euclid's algorithm can be used to determine the factors of N:

$$(g^{\frac{p}{2}} + 1)*\left(g^{\frac{p}{2}} - 1\right) = m * N$$

- For any arbitrary guess for P, x, the result will be m*N plus some remainder, y:

$$g^x = m*N+y$$

- Adding multiples of P to x results in no change to this remainder :

$$g^{x+nP} = m*N+y$$

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Shor's Algorithm

- N = 15, g = 2

$$g^p = m * N + 1$$

- Clearly, p = 4

$$2^4 = 15 + 1$$

- As such, for arbitrary guess p = 6:

- $2^6 = 4 * 15 + 4$ | $2^{10} = 68 * 15 + 4$ | $2^{14} = 1092 * 15 + 4$

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Shor's Algorithm

$2^{6} = 4 * 15 + 4$
$2^{7} = 8 * 15 + 8$
$2^{8} = 17 * 15 + 1$
$2^{9} = 34 * 15 + 2$
$2^{10} = 68 * 15 + 4$
$2^{11} = 136 * 15 + 8$
$2^{12} = 273 * 15 + 1$
$2^{13} = 546 * 15 + 2$
$2^{14} = 1092 * 15 + 4$
$2^{15} = 2184 * 15 + 8$

$|6, 4\rangle$
$|7, 8\rangle$
$|8, 1\rangle$
$|9, 2\rangle$
$|10, 4\rangle$
$|11, 8\rangle$
$|12, 1\rangle$
$|13, 2\rangle$
$|14, 4\rangle$
$|15, 8\rangle$

$$\begin{bmatrix} Probability\ 6 \\ Probability\ 7 \\ Probability\ 8 \\ Probability\ 9 \\ \vdots \\ Probability\ 4 \\ Probability\ 8 \\ Probability\ 1 \\ Probability\ 2 \end{bmatrix} \quad \begin{bmatrix} 0.0 \\ \\ 0.0 \\ 0.0 \\ \vdots \\ 0.0 \\ 1.0 \\ 0.0 \\ 0.0 \end{bmatrix}$$

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