Applications of Quantum Computers in Banking

Quantum Computing and near term applications in banking

Dr. Philippe J.S. De Brouwer

all rights reserved by the author
prepared for: University of Wroclaw

April 22, 2025

Table of Contents

Contents

1 Classical Computers

Von Neuman Computers

Logical Gates

The Fastests Supercomputer: EXA FLOPS

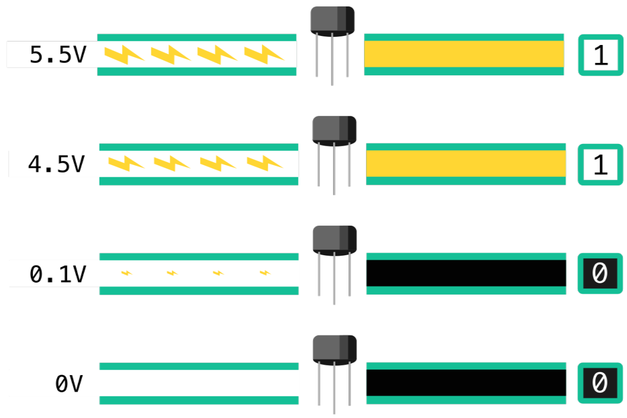


Figure 1: We use transistors to create logical states of 1 and 0.

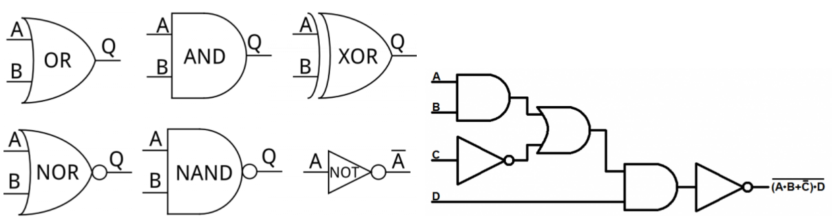


Figure 2: Those transitors are used to create logical gates that are in turn building blocks for logical circuits.

Figure 3: More info wikipedia.org, and top500.org

The Fastest Supercomputer Today: Summit

Details

- Site: DOE/SC/Oak Ridge National Laboratory
- System URL: https://www.olcf.ornl.gov/summit/
- Manufacturer: IBM & NVIDIA
- Cores: 2,414,592
- Processor: IBM POWER9 and NVIDIA Tesla V100 GPUs
- Installation Year: 2018
- Power consumption: Approx. 10 MW
- OS: Customized Linux (RHEL-based)

Performance

- Linpack Performance (Rmax): 148.6 PFLOP/s
- Theoretical Peak (Rpeak): 200 PFLOP/s

Limits of Von Neuman Machines

- **Heat**
  - The main reason why clock speed is not increasing
  - and muliti core archtectures are the solution
- **Quantumn Limitations**
  - Limit the accuracy to which chips can be made with current etching technology
  - Limit the size to which transistor gates can be miniaturised
- **Relativistic Limitations**
  - in a 5 GHz computer maximal processor size is: $4cm = 0.5 * c/5 * 10^9/2$

2 What Are Quantum Computers?

QBits

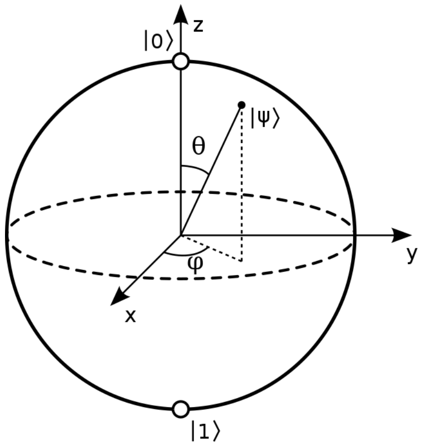


Figure 4: Source: nextplatform.com

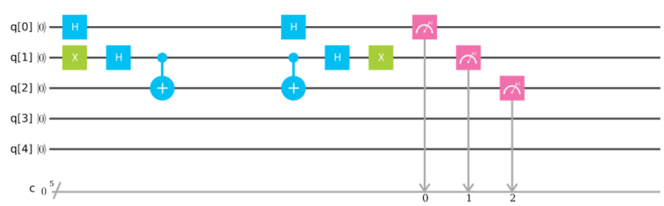


Figure 5: A quantum circuit: quantum gate operations on q-bits. Source: ibm.com

Operations

Aspects of Quantum Computing: Superposition

Superposition is a quantum state that is a combination of 2 mutually exclusive states

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle$$

where α and β are complex numbers representing the probability amplitudes of the qubit being in states $|0\rangle$ and $|1\rangle$, respectively.

Note that if $\alpha > 0$ and $\beta > 0$ then the qubit's state contains both $|0\rangle$ and $|1\rangle$

Superposition is a fundamental principle in quantum mechanics where a quantum system can exist in multiple states simultaneously. For a qubit, this means it can be in a state that is a combination of the basis states $|0\rangle$ and $|1\rangle$.

Examples:

A. **Equal Superposition:** A qubit in an equal superposition of $|0\rangle$ and $|1\rangle$

can be represented as:

$$|\psi\rangle = \frac{1}{\sqrt{2}}|0\rangle + \frac{1}{\sqrt{2}}|1\rangle$$

Here, the qubit has an equal probability of being measured in either state.

B. **Unequal Superposition:** A qubit with different amplitudes might look like:

$$|\psi\rangle = \frac{\sqrt{3}}{2}|0\rangle + \frac{1}{2}|1\rangle$$

In this case, the qubit is more likely to be measured in state $|0\rangle$ than in state $|1\rangle$.

C. **Measurement:** Upon measurement, the qubit collapses to one of the basis states, either $|0\rangle$ or $|1\rangle$, with probabilities given by $|\alpha|^2$ and $|\beta|^2$, respectively.

These examples illustrate how superposition allows qubits to encode and process information in ways that classical bits cannot, enabling the potential for quantum speedup in computations.

Aspects of Quantum Computing: Entanglement

A system of two qubits can be described by the state:

$$\alpha_1|00\rangle + \alpha_2|01\rangle + \alpha_3|10\rangle + \alpha_4|11\rangle$$

where

- $|01\rangle$ indicates the first qubit is in state $|0\rangle$ and the second in state $|1\rangle$.
- The coefficients satisfy the normalization condition: $\sum_{i=1}^{4} |\alpha_i|^2 = 1$.

If the state cannot be expressed as a tensor product of individual qubit states, the qubits are entangled. This implies that the measurement outcomes of one qubit are correlated with those of the other, regardless of the distance separating them.

Examples

- The state $\frac{\sqrt{2}}{2}|11\rangle + \frac{\sqrt{2}}{2}|10\rangle$ is separable (not entangled).
- The state $\frac{\sqrt{2}}{2}|01\rangle + \frac{\sqrt{2}}{2}|10\rangle$ is entangled.

Consider the two-qubit state:

$$|\psi\rangle = \frac{1}{\sqrt{2}}\left(|11\rangle + |10\rangle\right)$$

This state can be factored as:

$$|\psi\rangle = |1\rangle \otimes \left(\frac{1}{\sqrt{2}}(|1\rangle + |0\rangle)\right)$$

Here, $|1\rangle$ and $\frac{1}{\sqrt{2}}(|1\rangle + |0\rangle)$ are individual qubit states, indicating that $|\psi\rangle$ is separable and not entangled.

In contrast, consider the state:

$$|\phi\rangle = \frac{1}{\sqrt{2}}(|01\rangle + |10\rangle)$$

Attempting to express $|\phi\rangle$ as a tensor product:

$$|\phi\rangle = (a|0\rangle + b|1\rangle) \otimes (c|0\rangle + d|1\rangle)$$

Expanding and equating coefficients, we find no solution for a, b, c, and d that satisfies the equation, confirming that $|\phi\rangle$ is entangled.

Quantum Interference

Quantum interference is a phenomenon where quantum amplitudes (probability waves) combine, leading to constructive or destructive interference. This concept is fundamental to understanding the behavior of quantum systems.

- **Constructive Interference**: Occurs when amplitudes add up, increasing the probability of a particular outcome.

- **Destructive Interference**: Occurs when amplitudes cancel each other out, reducing the probability of a particular outcome.

A classic example is the double-slit experiment, where particles like electrons or photons pass through two slits and create an interference pattern on a screen. The pattern is a result of the wave-like nature of particles interfering with themselves.

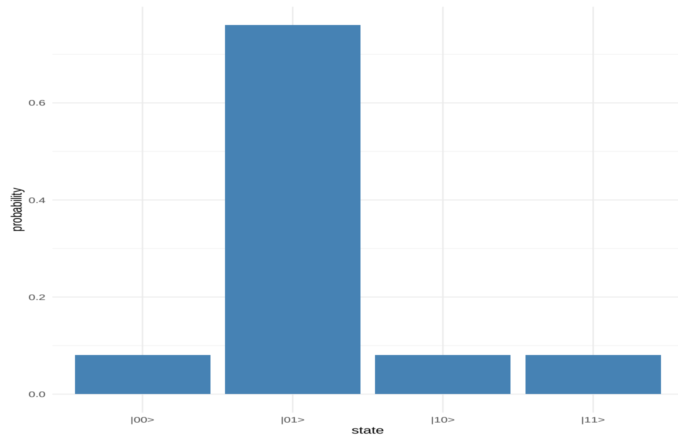
Mathematically, if a quantum state can be represented as:

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle$$

then the probability of observing the system in state $|0\rangle$ or $|1\rangle$ is given by $|\alpha|^2$ and $|\beta|^2$, respectively. Interference effects are observed when these probabilities are influenced by the phase relationship between α and β.

Aspects of Quantum Computing: Interference

Increase the probability of getting the correct answer (and reducing the probability of the wrong answer).



The Qubit

$\boxed{\text{Quantum World}} + \boxed{\text{Superposition}} + \boxed{\text{Qu. Interference}} = \boxed{\text{Qubit}}$

$\boxed{\text{Qubit}} + \boxed{\text{Entanglement}} + \boxed{\text{Gates}} = \boxed{\text{Quantum Processor}}$

The Concept of Quantum Computing

- Physicists measure Expectation Values of Quantum Systems or Observables:
  - Expectation Values of Quantum Observables are:
    - The average outcome of a measurement repeated many times or
    - The average outcome of a measurement performed on many copies of a system over a region of the Multiverse.
  - A Boolean Observable: A Quantum Observable whose spectrum contains two values and which can be either or both values simultaneously.
    - Sharp (Same Value for all observers in all Universes)
    - Non-Sharp (Superposition)
  - A QuBit: A physical system, each of whose non-trivial observables are Boolean.

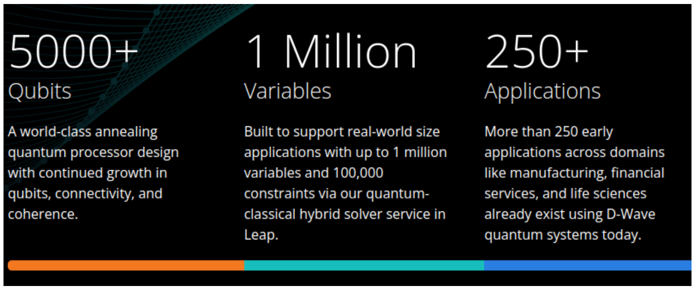


Figure 6: State of the art with D-Wave. Source: dwavesys.com

Aspects of Quantum Computing: Exponential Power

- qubit → 2 quantum states dimensions: $\alpha\ |0\rangle + \beta\ |1\rangle$
- 2 qubits → 4 states: $\alpha_1\ |00\rangle + \alpha_2\ |01\rangle + \alpha_3\ |10\rangle + \alpha_4\ |11\rangle$
- 3 qubits → 8 quantum state dimensions
- 6 qubits → 64 quantum state dimensions (card deck)
- 10 qubits → 1024 quantum state dimensions (810 listed companies on WSE)
- 20 qubits → 1.048576×10^6 quantum state dimensions (ca. number of all possible liquid investments)
- 60 qubits → 1.1529215×10^{18} states (ca. 10^{19} grains of sand on earth)
- 175 qubits → 4.7890486×10^{52} states (ca. 10^{50} atoms on earth)
- 275 qubits → 6.0708403×10^{82} quantum states (ca. 10^{82} atoms in the visible universe)

3 Existing Quantum Computers

D-Wave

Banking application with D-Wave and Multiverse Computing

IBM

Figure 7: A paper about portfolio optimisation with the D-Wave computers. Source: arxiv.org

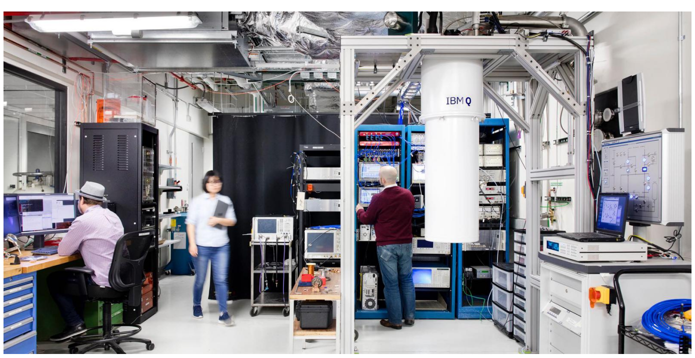


Figure 8: A quantum computer today. Source: ibm.com

Leading Companies in Quantum Computing

- – **IBM**:
  - **Strategy**: Superconducting qubits and cloud-based quantum computing services.
  - **Strengths**: Strong research foundation, extensive quantum hardware development, and the IBM Q Experience platform.
  - **Challenges**: Scalability of qubits and maintaining coherence times.
- – **Microsoft**:
  - **Strategy**: Topological qubits and the Quantum Development Kit (QDK) for software.
  - **Strengths**: Innovative qubit technology, integration with Azure cloud services.
  - **Challenges**: Topological qubits are still in the experimental phase.
- – **Google**:
  - **Strategy**: Research in superconducting qubits and quantum supremacy experiments.
  - **Strengths**: Strong AI and quantum research teams, achievements in quantum supremacy.
  - **Challenges**: Transitioning from experimental success to practical applications.
- – **Amazon**:
  - **Strategy**: Providing cloud-based quantum computing services through Amazon Braket.
  - **Strengths**: Leveraging AWS infrastructure, partnerships with various quantum hardware providers.
  - **Challenges**: Dependence on third-party hardware, integration with classical systems.
- – **IonQ**:
  - **Strategy**: Focus on trapped ion technology for quantum computing.
  - **Strengths**: High-fidelity qubits, partnerships with major tech companies.

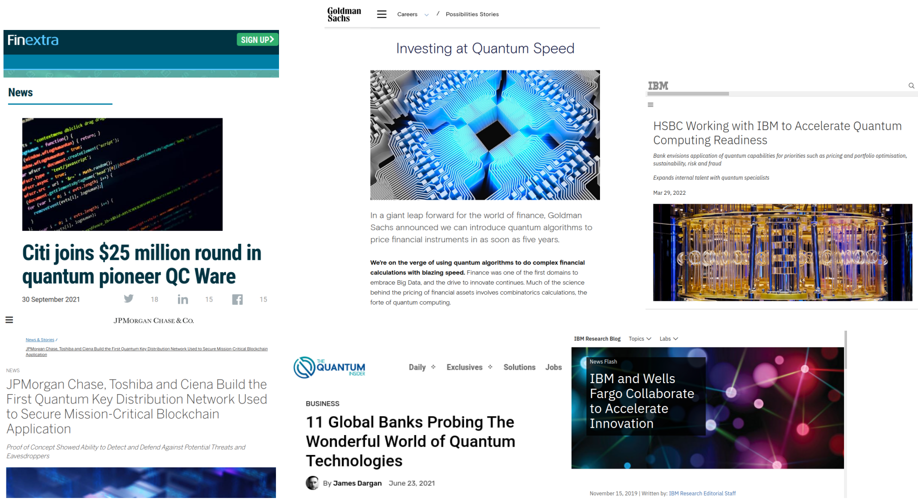


Figure 9: Sources: finextra.com, goldmansachs.com, ibm.com, and thequantuminsider.com

  – **Challenges**: Scaling up the number of qubits while maintaining performance.

- – **Rigetti Computing**:
  – **Strategy**: Developing superconducting qubits and quantum cloud services.
  – **Strengths**: Focus on practical applications, integration with classical computing.
  – **Challenges**: Competing with larger tech companies in the quantum space.

4 Quantum Computing Achievements in Banking

Examples of banks's efforts

Some Real Results

- JPMC and IBM calculated prices for differnt options (European, path dependent, etc.) by Quantum Amplitude Estimation (similar to Monte-Carlo simulations)
- Goldman Sachs had a similar PoC in 2021 using QC Ware and IonQ

- JPMorgan used Honeywell's quantum computer for mathematical operations that involve Fibonacci numbers
- Caixa Bank runs a hybrid framework of quantum and classical computing to improve credit risk scoring (PoC)

5 Quantum Computing Potential

Use cases in banking

- **Optimization**:
  - portfolio optimization
  - collateral optimization
  - stress testing
  - transaction settlement
  - asset pricing
  - ATM replenishment
- Machine Learning
  - fraud detection
  - credit scoring
  - synthetic data and data augmentation
- **Simulations**:
  - random number generator
  - Monte Carlo, LPDE simulations, etc.
  - asset valuation
  - ES and VaR calculations
- **Encryption**:
  - quantum key encryption
  - quantum currency
  - quantum blockchain

Resulting Advantages

quadratic to exponential speedup

- better risk management
- lower costs
- greener computing
- better forecasting
- more suitable investments
- etc.

Boston Consulting Group estimates a value of \$42B to \$67B for financial institutions

5.1 Stochastic Modelling

5.1.1 Quantum Methods for Monte Carlo-based pricing and risk analysis

Monte Carlo Integration

QMCI

- Numerical integration by random sampling
- Applicable to high-dimensional problems
- Convergence proportional to $\frac{1}{\sqrt{N}}$

In Finance

- **Option pricing**
- **Risk assessment**
- **Portfolio optimization**
- **Interest rate modeling**
- **Credit risk analysis**
- **Stochastic volatility models**
- **Capital allocation**

Quantum

- **Potential** Quadratic speedup — requires $O(\sigma/\varepsilon)$ samples (down from $O(\sigma^2/\varepsilon^2)$)
- **Challenges** Error correction, implementation, and hardware reliance
- **Realistic?** – high potential

Scalable and shallow quantum circuits encoding probability distributions informed by asymptotic entanglement analysis

Vladyslav Bohun[1], Illia Lukin[1,2], Mykola Luhanko[1,3], Georgios Korpas[4,5,6], Philippe J.S. De Brouwer[7], Mykola Maksymenko[1], and Maciej Koch-Janusz[1,8]

QUANTUM MONTE CARLO INTEGRATION FOR SIMULATION-BASED OPTIMISATION

JINGJING CUI [2], PHILIPPE J.S. DE BROUWER [3], STEVEN HERBERT [1], PHILIP INTALLURA [4], CAHIT KARGI [1], GEORGIOS KORPAS [5,6,7], ALEXANDRE KRAJENBRINK [2], WILLIAM SHOOSMITH [4], IFAN WILLIAMS [1], BAN ZHENG [8]

Figure 10: Papers published in 2024 about QMCI.

Progress for QMCI

5.1.2 Quantum Methods for Differential-Equation-Based Pricing and Risk Analysis

PDE-Based Pricing & Quantum Methods

PDE Methods

- Transform SDEs $\rightarrow$ parabolic PDEs (e.g., Black-Scholes)
- Finite-difference methods (FDM) dominate
- Curse of dimensionality persists

In Finance

- **Black-Scholes**
- **American options**
- **Feynman-Kac PDEs**
- **Stochastic volatility**
- **Trinomial trees**

Quantum

- **QLSAs** Solve FDM systems with $\mathcal{O}(\log N)$ scaling
- **Hamiltonian simulation** PDEs as Schrödinger-like equations

- **Variational quantum simulation** Encode PDEs into parametrized circuits
- **Challenges** State prep, error correction, sampling overhead
- **Outlook** Hybrid workflows for high-dimensional PDEs

5.2 Optimizations

5.2.1 Quantum Methods for Continuous Optimization

Continuous Optimization

Basics

- Real-valued variables (convex/non-convex)
- Classical workhorses: IPMs, MMW, gradient descent
- Non-convex: Heuristics dominate

In Finance

- **Portfolio optimization**
- **Cash-flow management**
- **Arbitrage detection**
- **Utility maximization**

Quantum

- **QBLAS** Speed up IPMs/MMW via $\mathcal{O}(\sqrt{mn})$ linear algebra
- **MMW** Quantum $\tilde{\mathcal{O}}(s\sqrt{m}\gamma^4)$ vs. classical $\tilde{\mathcal{O}}(mns\gamma^4)$
- **Non-convex** Variational circuits for landscapes
- **Challenges** Conditioning, sampling noise, NISQ coherence
- **Outlook** Hybrid workflows for high-dimension IPMs

5.2.2 Quantum Methods for Discrete Optimization

Discrete Optimization

Basics

- Solutions from discrete sets (e.g., integers)
- Classical methods: B&B, SA, LP relaxations
- NP-hard: Heuristics dominate for scalability

In Finance

- **Portfolio optimization**
- **Crash detection**
- **Index tracking**
- **Transaction cost optimization**

Quantum

- **QWS** Quadratic speedup for B&B tree search
- **Quantum heuristics** QAOA, VQE, VQS for landscapes
- **Quantum annealing** Tunneling for global minima
- **Challenges** Parameter tuning, NISQ noise, sampling costs
- **Outlook** Hybrid quantum-classical workflows near-term

5.2.3 Quantum Methods for Dynamic Programming

Dynamic Programming

Basics

- Sequential decision-making
- Bellman principle: Optimal substructure
- Curse of dimensionality

In Finance

- **American options**
- **CMO structuring**

- **Real options valuation**
- **Optimal stopping**

Quantum

- **Quantum DP** Reduce state-space exploration
- **Algorithms** Quantum value/policy iteration
- **Applications** High-dim CMOs, real options
- **Challenges** State preparation, NISQ coherence
- **Outlook** Hybrid quantum-classical DP

5.3 Quantum Methods for Machine Learning

Quantum Machine Learning

Basics

- Classical ML: Pattern recognition, optimization
- Key techniques: Neural nets, kernels, anomaly detection
- Data-driven decision-making

In Finance

- **Portfolio optimization**
- **Anomaly detection**
- **News sentiment analysis**
- **Algorithmic trading**

Quantum

- **QBLAS** Accelerate linear algebra (e.g., PCA, SVM)
- **Quantum-native** QNNs, kernels, Born machines
- **Challenges** Data loading, NISQ noise, dequantization
- **Outlook** Hybrid models for finance-specific tasks

5.3.1 Quantum Methods for Regression

Regression Techniques

Basics

- Fits functions to numeric data
- Least-squares: Minimize $\|\mathbf{y} - X\beta\|^2$
- GP Regression: Bayesian non-parametric

In Finance

- **Asset pricing**
- **Volatility forecasting**
- **Risk modeling**
- **Economic indicators**

Quantum

- **QLSA** Speed up least-squares via $\mathcal{O}(\log N)$ scaling
- **Quantum GPR** Sparse kernel matrices with QBLAS
- **QNNs** Variational circuits for non-linear fits
- **Challenges** Data encoding, NISQ noise, rank limits
- **Outlook** Hybrid quantum-classical regression

5.3.2 Quantum Methods for Classification

Classification

Basics

- Assign labels to data points
- Classical methods: SVM, neural nets, k-NN
- Critical for pattern recognition

In Finance

- **Fraud detection**
- **Credit scoring**

(c) Philippe De Brouwer

- **Risk tiering**
- **Sentiment analysis**

Quantum

- **QLSA** Speed up SVM training via $\mathcal{O}(\log N)$ scaling
- **Quantum kernels** High-dim feature maps for separability
- **QNNs** Variational circuits for non-linear decision boundaries
- **Quantum k-NN** Grover-like search for nearest neighbors
- **Challenges** Data encoding, NISQ noise, dequantization
- **Outlook** Hybrid quantum-classical classifiers for finance

5.3.3 Quantum Methods for Supervised Machine Learning

Quantum Machine Learning: Supervised Learning

Basics

- Classical ML: Pattern recognition, optimization
- Key enablers: Rich datasets, algorithmic advances
- Techniques: Classification, regression, clustering

In Finance

- **Fraud detection**
- **Portfolio optimization**
- **News sentiment analysis**
- **Credit scoring**

Quantum

- **QBLAS** Accelerate linear algebra (e.g., PCA, SVM)
- **Quantum-native** QNNs, Born machines, kernels
- **Challenges** Data encoding, NISQ noise, dequantization
- **Outlook** Hybrid models for finance tasks

5.3.4 Quantum Methods for Clustering

Clustering

Basics

- Unsupervised grouping of data
- Classical workhorse: Lloyd's algorithm
- Curse of dimensionality

In Finance

- **Portfolio diversification**
- **Market segmentation**
- **Anomaly detection**
- **Index construction**

Quantum

- **q-means** $\mathcal{O}\left(\frac{M\sqrt{k}\log k}{\epsilon}\right)$ vs. classical $\mathcal{O}(kMN)$
- **QEM** Quantum expectation-maximization for GMMs
- **Spectral clustering** QAOA for graph partitioning
- **Challenges** NISQ noise, data encoding, hybrid workflows
- **Outlook** Quantum annealing for high-D finance datasets

5.3.5 Quantum Methods for Generative Learning

Generative Learning

Basics

- Models probability distributions
- Generates synthetic data samples **Goal:** Learn underlying data patterns (e.g., stock returns, transaction histories).

In Finance

- **Derivative pricing** Model complex payoff distributions (e.g., path-dependent options).
- **Risk assessment** Generate stress-test scenarios for tail-risk analysis.

- **Anomaly detection** Synthesize normal transactions to identify outliers.

Quantum

- **QCBM** Quantum Circuit Born Machine Encodes distributions via parametrized quantum states.
- **QGANs** Quantum Generative Adversarial Networks Quantum generator/discriminator for complex financial data.
- **Boltzmann Machines** Quantum sampling for training Leverage quantum annealing for efficient Gibbs sampling.
- **Challenges** NISQ noise, training stability NISQ = Noisy Intermediate-Scale Quantum; barren plateaus in gradients.
- **Outlook** Hybrid workflows for synthetic financial data Near-term focus: Portfolio stress-testing & pricing exotic derivatives.

5.3.6 Quantum Methods for Feature Extraction

Feature Extraction

Basics

- Preprocess data
- Reduce dimensions **Goal:** Remove noise/redundancy while preserving critical information.
- Retain interpretability **Tools:** PCA, autoencoders, manifold learning.

In Finance

- **Risk factor modeling** Identify latent market drivers (e.g., Fama-French factors).
- **Algorithmic trading signals** Compress high-frequency data into actionable features.
- **Credit scoring** Extract default predictors from client histories.

Quantum

- **qPCA** Exponential speedup for covariance diagonalization Quantum Principal Component Analysis via density matrix exponentiation.
- **TDA** Quantum speedups for persistent homology Topological Data Analysis (TDA) for detecting market regime shifts.

- **Quantum annealing** Feature selection via QUBO QUBO = Quadratic Unconstrained Binary Optimization; e.g., sparse portfolio features.
- **Challenges** NISQ noise, hybrid workflow integration NISQ = Noisy Intermediate-Scale Quantum; limited qubit coherence.
- **Outlook** Quantum-enhanced factor models Near-term focus: Hybrid quantum-classical risk factor extraction.

5.3.7 Quantum Methods for Reinforcement Learning

Reinforcement Learning

Basics

- Agent learns via trial-and-error
- Maximizes cumulative rewards **Core loop:** State → action → reward → policy update.

In Finance

- **Algorithmic trading** Optimal execution, market-making strategies.
- **Portfolio optimization** Dynamic asset allocation under uncertainty.
- **Risk hedging** Derivative pricing and hedging in incomplete markets.

Quantum

- **Grover-based RL** Amplify high-reward actions Quadratic speedup in action-space exploration.
- **Policy gradients** QMCI for gradient estimation Quantum Monte Carlo Integration for policy updates.
- **QNNs** Quantum policies for high-dim state spaces Quantum Neural Networks for parametrized policies.
- **Challenges** NISQ noise, reward function design NISQ = Noisy Intermediate-Scale Quantum; sparse rewards in finance.
- **Outlook** Hybrid RL for trading/hedging Near-term focus: Quantum-enhanced market simulators.

5.3.8 Dequantized Algorithms

Dequantized Methods

Basics

- Classical algorithms inspired by quantum **Dequantization:** Mimic quantum-inspired speedups classically (e.g., recommendation systems).
- Pros: Dimension efficiency
- Cons: Poor error scaling

In Finance

- **High-dimensional problems** Portfolio optimization, covariance matrix estimation.
- **Low-precision tasks** Risk modeling, market regime clustering.
- **Inspires classical heuristics** E.g., randomized numerical linear algebra.

Impact & Outlook

- **Tang's algorithms** Challenge quantum speedup claims E.g., quantum PCA/Recommendation Systems vs. classical sampling-based methods.
- **Areas affected** PCA, clustering, SDPs SDPs = Semidefinite Programs; PCA = Principal Component Analysis.
- **Challenges** Limited to low-rank/sparse data Struggle with noisy, high-rank financial datasets.
- **Outlook** Hybrid quantum-classical workflows Leverage dequantization insights for NISQ-era practicality.

5.4 Encryption

Encryption

Basics

- Secures data via cryptographic protocols
- Symmetric (AES) vs. asymmetric (RSA) **Symmetric:** Shared key (e.g., AES-256). **Asymmetric:** Public/private key pairs (e.g., RSA, ECC).
- Critical for confidentiality, integrity

In Finance

- **Securing transactions** Encrypt payment gateways, SWIFT messages, blockchain ledgers.
- **Data privacy compliance** GDPR, PCI-DSS, SOX regulatory requirements.
- **Secure communication** TLS/SSL for client-bank interactions, API security.

Quantum

- **Threat:** Shor's algorithm breaks RSA/ECC Quantum computers factor large integers efficiently, compromising asymmetric encryption.
- **Post-quantum crypto** Lattice-based, hash-based schemes NIST-standardized algorithms (e.g., CRYSTALS-Kyber, SPHINCS+).
- **QKD** Quantum Key Distribution (BB84 protocol) Unhackable key exchange via quantum entanglement; used in high-frequency trading networks.
- **Challenges** Standardization, legacy system upgrades Migration from RSA/ECC to post-quantum algorithms.
- **Outlook** Hybrid encryption systems Combine classical + quantum-resistant crypto during transition.

6 Conclusion

Quantum Finance: Key Takeaways

Transformative Potential

- **Breaking Boundaries**: Solve intractable problems (e.g., high-dim portfolio optimization, real-time risk simulations).
- **Precision & Speed**: Quadratic speedups for Monte Carlo, PDEs, and machine learning.
- **Green Compute**: Energy-efficient solutions for data-heavy tasks.

Challenges Ahead

- NISQ-era hardware limits practical scaling.
- Hybrid classical-quantum workflows critical for near-term impact.
- Urgent need for post-quantum cryptography.

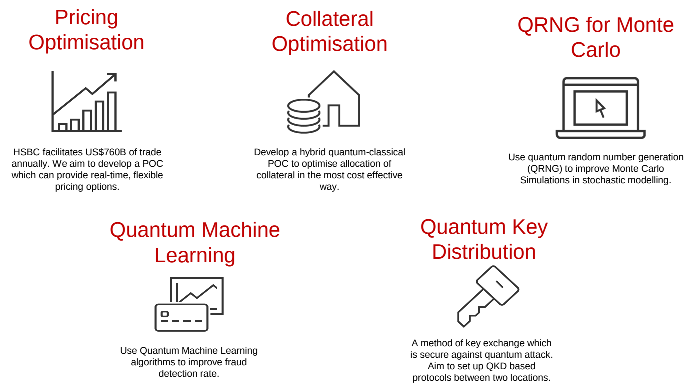


Figure 11: Quantum initiatives at HSBC (2023)

HSBC's Quantum Proofs of Concept

The Road Ahead

2025–2030: Hybrid algorithms for niche finance tasks **2030+**: Fault-tolerant quantum advantage
Beyond: Quantum-native financial ecosystems

- **Act Now**: Upskill teams, pilot use cases, engage with regulators.
- **Think Beyond Speed**: Reimagine workflows for quantum-native logic.

Further Reading

- McKinsey Report *How Quantum Computing Could Change Financial Services* (2020)
- IBM E-book *The Quantum Decade* (2021)
- MIT Book *Quantum Computing: A Gentle Introduction* (Rieffel & Polak)
- Springer Book *Quantum Computing for the Quantum Curious* (Hughes et al.)
- E-Books Directory Open-access quantum computing books
- Q&A Forum Quantum Computing StackExchange
- Classiq Insights Technical blog for quantum algorithm design

Stay updated: quantumcomputingreport.com