Quantum Machine Learning for Finance

Master of Science Thesis Project

November 25, 2025

Background and Motivation

Quantum Computing (QC) and Machine Learning (ML) are two of the most transformative paradigms in modern computational science. Quantum computers operate on qubits, which can exist in superpositions of classical states and can become entangled. These properties allow, in principle, new computational strategies that may outperform classical computers on selected tasks, such as simulation of quantum systems, high-dimensional optimization, and certain data-analysis problems.

Quantum Machine Learning (QML) aims to combine quantum computing with ML techniques to design algorithms that can exploit quantum resources for learning and inference. Typical examples include quantum-enhanced kernel methods (e.g., quantum support vector machines), variational quantum classifiers and regressors (QNNs based on parameterized quantum circuits), and quantum generalizations of generative models such as Boltzmann Machines.

The financial sector provides a rich domain of structured and high-dimensional data, such as time series of asset prices, interest rates, volatility indices, and risk factors. Understanding whether quantum-enhanced models can provide advantages—in accuracy, robustness, sample efficiency, or computational cost—is both scientifically interesting and of potential practical relevance.

In parallel, European quantum infrastructures are maturing. In particular, the EuroHPC Joint Undertaking supports quantum accelerators such as *LUMI-Q* in Finland, which can be accessed through national and European allocations. This creates a realistic opportunity for academic projects to run hybrid quantum–classical workflows on actual quantum hardware, not only on simulators.

Project Scope and Objectives

This thesis will investigate classical and quantum machine learning methods for supervised learning tasks relevant for finance, with a focus on time-series data (e.g., forecasting, classification, anomaly detection). The main methodological components are:

1. **Support Vector Machines (SVM) and Quantum Support Vector Machines (QSVM):**

Classical SVMs will be implemented as a baseline using standard kernels (linear, polynomial, RBF). Quantum kernels will be realized via quantum feature maps and overlap estimation on parameterized quantum circuits, leading to QSVM-type classifiers.

2. **Neural Networks (NN) and Quantum Neural Networks (QNN):**
   Classical deep neural networks (fully connected, and optionally recurrent networks for time series) will be developed as benchmarks. QNNs based on Variational Quantum Circuits (VQCs) will be trained using hybrid quantum–classical optimization loops.

3. **(Optional) Boltzmann Machines (BM) and Quantum Boltzmann Machines (QBM):**
   Time permitting, the thesis will explore classical Boltzmann Machines and their quantum extensions, where a parameterized Hamiltonian defines a quantum generalization of the Boltzmann distribution.

The overarching objectives are:

- To build a robust classical ML pipeline for selected financial datasets.
- To implement corresponding QML models (QSVM, QNN, optionally QBM).
- To execute selected QML algorithms on quantum simulators and on real quantum hardware, including LUMI-Q (Finland) and, where appropriate, IBM Quantum or other accessible devices.
- To systematically compare classical and quantum methods in terms of predictive performance, generalization, resource usage, and sensitivity to noise.

Methodology and Tools

The thesis will rely on a combination of classical and quantum software frameworks:

- **Classical ML:** Python, NumPy, SciPy, Scikit-Learn, and optionally PyTorch or TensorFlow for neural networks.
- **Quantum ML:** Libraries such as PennyLane, Qiskit, or similar frameworks providing:
  - Variational quantum circuits and quantum kernels.
  - Access to backends for both state-vector simulators and noisy hardware.
  - Integration with hardware providers, including LUMI-Q via EuroHPC interfaces when available, and IBM Quantum through cloud APIs.
- **Data:** Publicly available financial time-series data (e.g., equities, indices, interest rates), and/or data provided through NBIM or project partners, subject to access constraints.

Key methodological ingredients include:

- Feature engineering and data preprocessing for financial time series.

- Design of classical baselines (SVM, NN, possibly RNN/LSTM).
- Construction of quantum feature maps and variational ansätze.
- Training and validation protocols (train/validation/test splits, cross-validation).
- Performance metrics (e.g., accuracy, F1-score, MSE, Sharpe-like metrics, calibration).
- Robustness checks under noise, limited data, and hardware imperfections.

Work Plan and Milestones (Spring 2026 – June 2027)

The thesis is planned to start in **spring 2026** and be submitted by **June 2027**. The work is divided into phases with associated milestones.

Phase 1: Foundations and Classical Baselines (Spring 2026)

- Conduct a detailed literature review on:
  - Classical ML in finance (SVMs, NNs, time-series models).
  - Quantum machine learning: QSVMs, QNNs, QBM, and related hybrid algorithms.
- Choose and preprocess one or more financial datasets (classification and regression tasks).
- Implement classical baselines:
  - SVMs (with different kernels).
  - Neural networks (e.g., fully connected, optionally recurrent for time series).
- Define baseline metrics and initial experimental protocols.

Milestone M1 (end of Spring 2026):
Classical pipeline implemented and validated on at least one financial dataset; preliminary results documented.

Phase 2: QML Prototyping on Simulators (Summer – Early Autumn 2026)

- Implement quantum feature maps and QSVM models on simulators.
- Implement simple QNN/VQC architectures for classification and/or regression.
- Explore different data-encoding strategies (angle encoding, amplitude encoding, qubit-efficient encodings).
- Benchmark QML models against classical baselines on small problem instances.

Milestone M2 (early Autumn 2026):
Working QSVM and QNN prototypes on simulators, with initial performance comparison to classical models.

Phase 3: Hardware Experiments (Late 2026 – Early 2027)

- Adapt QML circuits to hardware constraints (depth, connectivity, noise) of LUMI-Q and other available devices.
- Run selected QML models on:
  - LUMI-Q (via EuroHPC or national allocation).
  - IBM Quantum backends (or similar).
- Collect and analyze results under realistic noise conditions.
- Time permitting, implement and test (Q)Boltzmann Machines on simulators or hardware.

Milestone M3 (early Spring 2027):
Demonstrated execution of at least one QML model on LUMI-Q and/or IBM Quantum, with comparative analysis versus simulator runs.

Phase 4: Analysis, Synthesis, and Writing (Spring 2027)

- Perform a systematic comparison between classical and quantum models:
  - Predictive performance and generalization.
  - Resource requirements (number of qubits, circuit depth, training time).
  - Robustness to noise and limited data.
- Discuss implications for the use of QML in finance in the near-term (NISQ) regime.
- Write the thesis, including introduction, methods, results, and discussion.
- Prepare final figures, tables, and appendices (e.g., code snippets).

Milestone M4 (June 2027):
Completed thesis submitted, with all analyses and conclusions finalized.

Expected Outcomes

By the end of the project, the student is expected to have:

- Developed a complete classical ML pipeline for selected financial datasets.
- Implemented and benchmarked QML algorithms (QSVM, QNN, and optionally QBM).
- Executed at least one QML model on real quantum hardware, including LUMI-Q.
- Performed a critical comparison between classical and quantum approaches in terms of performance, feasibility, and future prospects in finance.

Indicative Literature

1. M. Schuld and F. Petruccione, *Supervised Learning with Quantum Computers*, Springer, 2018.

2. C. Conti, *Quantum Machine Learning*, Springer (online).

3. M. Zhao et al., "A Tutorial on Quantum Machine Learning and Quantum Neural Networks", arXiv:2504.16131 (2025).

4. M. Amin et al., "Quantum Boltzmann Machines", *Physical Review X* **8**, 021050 (2018).

5. M. Hjorth-Jensen, *Quantum Computing and Quantum Machine Learning*, lecture notes and codes, `https://github.com/CompPhysics/QuantumComputingMachineLearning`.