

QUANTUM Machine Learning

(qml)^{cq}

Why Quantum Machine Learning?

Cambridge Quantum aims at making near-term quantum computers useful for hard tasks of practical relevance in machine learning and optimization.

Despite advances in classical algorithms and hardware those tasks require large compute resources and cause high energy consumption. Quantum machine learning (QML) comprises a range of flexible techniques for tackling this challenge. On one hand, QML models can perform tasks that go beyond the classically possible. On the other hand, QML allows the workload to be split optimally between quantum and classical processing units in order to make the most of the quantum computers available today.

Better models for prediction and reasoning

Machine learning, in essence, can be broken into three parts: data, models, and training algorithms. A training algorithm learns from data in order to perform and improve on a task. Typical tasks include prediction, classification, decision making, data generation, and anomaly detection.

Augmenting complex models or costly data generation with quantum computing resources could lead to greater accuracy in downstream tasks. The intuition is that quantum computers naturally excel at certain key ingredients that define machine learning – modelling complex probability distributions and generating hard-to-simulate data.

Many traditional machine learning models can be understood as probabilistic models of observable data and unobservable features or variables. For example, a trader may want to base their buy/sell decisions on the state of the equity market: is it bull or bear? While they cannot observe this abstract state directly, they can observe equity returns from traded assets. Based on their domain knowledge they build a probabilistic model that describes how the market state influences equity returns. Given this model and the return data, they can infer and reason about the unobserved market state using statistical methods and machine learning. Performing this inference exactly and quickly becomes intractable for complex models.

Near-term quantum computers are naturally suited for representing such complex probability distributions. Once trained the quantum computer can be used in downstream tasks that rely on sampling complex data. The example of the trader performing inference is one such downstream task.

INPUT (OPTIONAL)



Data sample



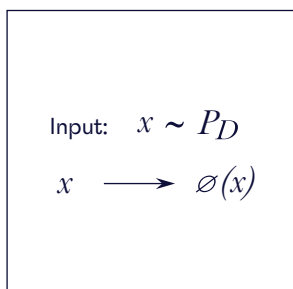
Learnable distribution

OUTPUT

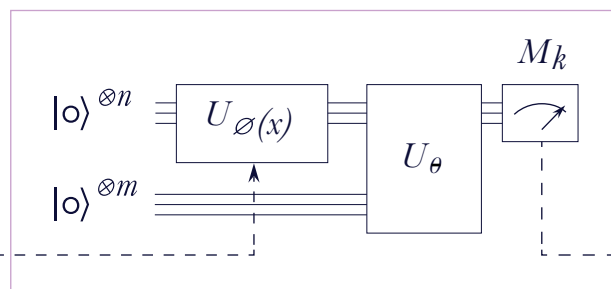


Samples from learned distribution

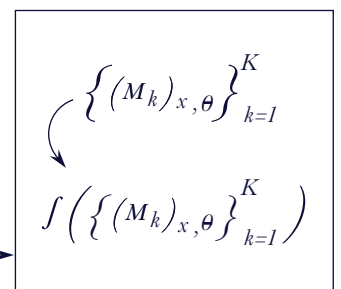
PRE-PROCESSING



PARAMETERIZED QUANTUM CIRCUIT



POST-PROCESSING



Machine Learning

Classical Challenge

Not natively probabilistic as classical computers are deterministic. Resource intensive and data-hungry.

Quantum Improvement

More expressive models and enhanced data generation

Practical Implementations

Cambridge Quantum team are world pioneers in implementing generative models with quantum hardware with many successful public results

Industrial Applications

Financial forecasting, synthetic data generation, decision support system

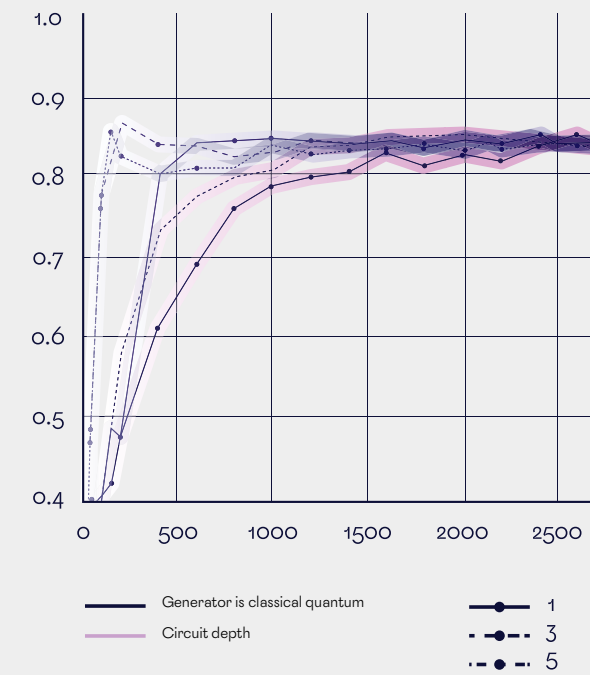
OUR WORK IN QUANTUM MACHINE LEARNING



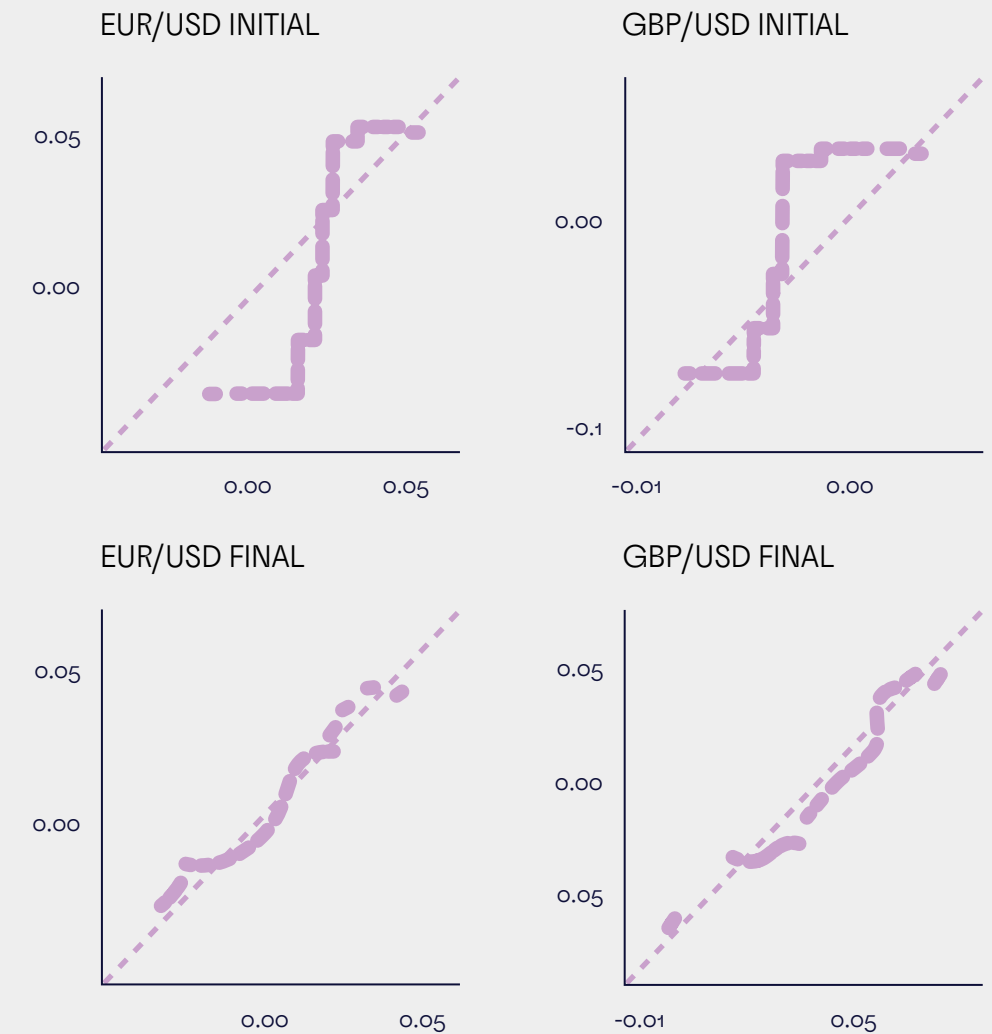
IMAGE RESTORATION AND DATA RECOVERY



ANOMALY DETECTION CREDIT CARD FRAUD DETECTION



MODELLING CORRELATED CURRENCY PAIRS BORN MACHINES



A pragmatic, near-term results-driven approach

Our approach to quantum machine learning is to focus scarce quantum resources on hard subtasks in machine learning algorithms. Consequently, our pioneering research centres around hybrid quantum-classical probabilistic methods for unsupervised learning, generative models, and inference.

A common approach to unsupervised learning is to learn a probabilistic model of data. These models can be trained on unlabelled datasets. Generative modelling is one example of unsupervised learning wherein the model automatically learns the patterns of input data in such a way that it can be used to generate new data samples that would seemingly match the statistical distribution of the original dataset.

Quantum circuit Born machines are an example of generative models and are based on parameterized quantum circuits. They can represent probabilistic models and sample complex probability distributions more efficiently than classical computers for certain tasks or datasets. We can train these Born machines for a diverse range of downstream tasks such as reasoning under uncertainty, data augmentation, and anomaly detection. Generative models can also make machine learning more transparent by incorporating domain expertise.

We implement quantum machine learning methods in a pragmatic and hardware-agnostic way. This allows us to implement small-scale models on today's limited quantum hardware and improve the models as quantum hardware matures.

¹ **Benedetti et al**
<https://arxiv.org/abs/2103.06720>
2021.

Applications of Quantum Machine Learning

Finance	<ul style="list-style-type: none">– Quantum-enhanced variational inference on hidden Markov models for time-series data– Born Machines for foreign exchange spot return modelling– Sampling financial data for Monte Carlo pricing using quantum GANs and Born machines
Pharmaceuticals and Healthcare	<ul style="list-style-type: none">– Meta-heuristics for faster biomarker discovery in drug development based on quantum circuit Born machines– Medical diagnosis with quantum-enhanced inference on Bayesian networks
Energy	<ul style="list-style-type: none">– Crude oil flow classification with quantum support vector machines– Inference-based risk assessment of wind turbines– Generative modelling for renewable energy scenario generation
Materials and Chemistry	<ul style="list-style-type: none">– Molecular discovery with quantum-enhanced generative models

Some of our collaborations

PHARMACEUTICAL

JSR Life Science / CrownBio

Novel biomarker discovery

Cambridge Quantum's quantum machine learning algorithms enable more accurate biomarker discovery for cancer drug development.

FINANCE

Large investment firm

Pricing for risk management

Sampling financial data for Monte Carlo pricing using quantum generative adversarial networks and Born machines.

WHY GET STARTED WITH QML TODAY?

Work towards quantum advantage for your intractable machine learning problems

Accelerate R&D efforts and showcase leading capabilities

Develop pathway for easy scalability as hardware matures

Educate your workforce in quantum computing methodologies

CONTACT US

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Cambridge Quantum

We set out our vision to positively transform the world using the power of quantum computing back in 2014. Today, we are recognised as one of the foremost quantum computing companies, delivering science-led, enterprise-driven solutions to tackle hard problems across a diverse range of industries.

Cambridge Quantum designs, engineers and deploys algorithms and enterprise application libraries, translating cutting-edge research into industry leading technologies through a product-centric focus. TKET, our hardware-agnostic software development platform, and other technologies are currently utilised by an expansive and ever-growing user base.

The team at Cambridge Quantum has been developing the theoretical foundations of quantum computing for over 25 years, forging ahead with breakthroughs in the fields of quantum chemistry, quantum artificial intelligence, quantum cybersecurity and quantum algorithms.

At present, we have the deepest roster of researchers, developers and engineers, working to democratise quantum computation and realise the benefits for the greatest possible number of people.

FOR MORE INFORMATION

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