W U T I S

WUTIS Algorithmic Trading

Quantum on Quantum: Portfolio Trading with Quantum Computing approaches

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Algorithmic Trading

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Why use Quantum Computing in Portfolio Trading?

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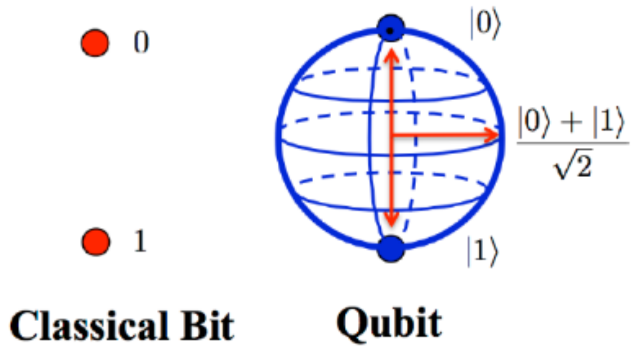
Most portfolio failures come from poor risk estimation, not poor return forecasts.

Overview

- Quantum states live in higher dimensions which scales the feature information exponentially.
- QNN act as non-linear feature maps
- Possibility to capture complex correlations with fewer parameters.

Qubit visual structure



Usage for Markowitz model

- Portfolio Optimization depends on Covariance & Return Estimation Covariance is:
  - High-dimensional
  - Noisy
  - Regime-dependent
- Classical Estimators struggle with modelling

Initial optimisation problem

- Minimize risk
- Limit number of traded assets
- Maximise returns to a predefined level

$$\min_{x \in \{0,1\}^N} \lambda_0 \, x^\top \Sigma_{t+1} x + \lambda_1 \left(\sum_{i=1}^{N} x_i - n \right)^2 + \lambda_2 \left(\mu_{t+1}^\top x - R \right)^2$$

Overall Project Structure

Illustration of full project pipeline

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Define Investment Environment
$A_{ava} \in \{1, \dots N\}$
$A_{inv} \in \{1, \dots n\}$
$x \in \{0, 1\}^N$

Collect Historical Data
$\mu_{i,t}$ *Historical Returns*
Σ_t *Historical Volatility*
γ_t *Macroeconomic indicator*
...
$t = t_0, \dots T, i = 1, \dots n$

Train Quantum Neuronal Network
Output: $\widehat{\mu_{t+1}}, \widehat{\Sigma_{t+1}}$

(Recalibrate QNN)
Predict Outputs: $\widehat{\mu_{t+2}}, \widehat{\Sigma_{t+2}}$

Optimization (Quantum Annealer)

$$\min_x \lambda_0 x'\widehat{\Sigma_{t+1}}x + \lambda_1\left(\sum_i x_i - n\right)^2 + \lambda_2\left(\widehat{\mu'_{t+1}}x - R^*\right)^2$$

Source Market data (OHLCV)

QNN: predict Covariance

Rebalance Portfolio

Data and QNN Forecaster Training

Underlying input data and overview of QNN structure

Overview

- Diversified, but small portfolio: trade-off between QNN scale and robustness
- A total of 12 assets is used in the project among others; Amazon (AMZN), Microsoft (MSFT), Gold (GLD),…
- The model is trained on OHLCV data on a **daily** frequency.
- Predictions of QNN are made on a **weekly** frequency.

Why drop the predictions of returns?

- Portfolio Optimization depends on Covariance & Return Estimation Covariance is:
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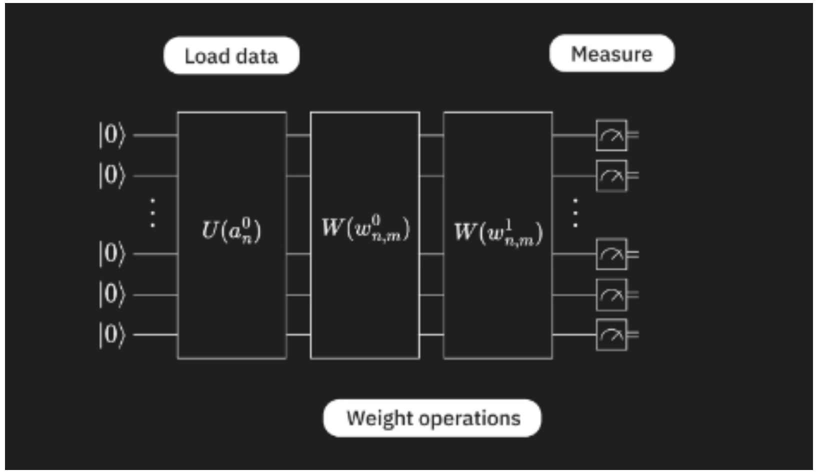
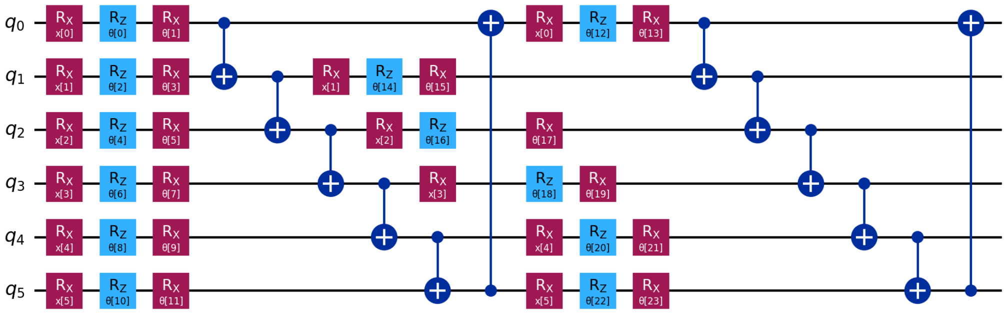
QNN Structure



Schema of a Quantum Neural Network:
Starting quantum position is zeros, mapped to data state with unitary layer U;
Then by unitary operation W next states are transformed and measured at the end



Quantum Neural Network Circuit for RxRz structure with 6 qubits and 3 layers

Portfolio Construction

Portfolio Optimization after QNN predictions using QUBOs

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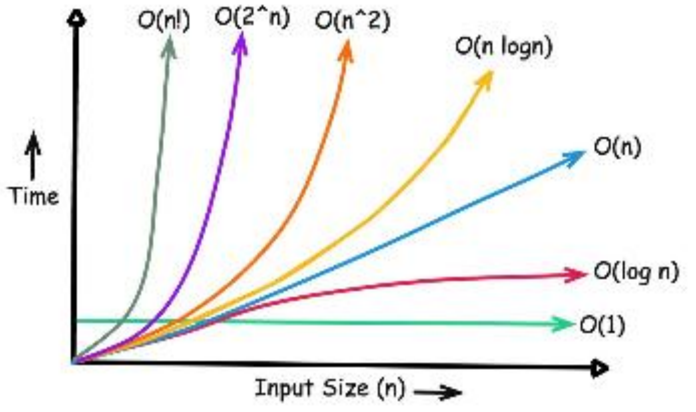
Overview

- The Markovitz Portfolio optimization minimizes Risk modeled by Covariance between the underlying assets under the constraints of being fully invested and only allowing long trades.
- Quadratic unconstrained optimization problems are NP-hard to solve analytically.
- Heuristic / numerical methods are used to find solutions.



N	Perm(N)
5	32
10	1024
20	1 048 576
30	1 073 741 824
50	overflow

Formulation of a simplified QUBO problem

- The current implantation solves a **convex continuous** optimization problem as a proxy algorithm
- Was chosen because quantum annealers are expensive and there is a limited amount of quantum annealing companies
- Convex optimiser was chosen instead to simulate the initial idea

$$\min_{\mathbf{w}\in\mathbb{R}^N} \quad \mathbf{w}^\top \hat{\Sigma}_t \mathbf{w}$$

$$\text{s.t.} \quad \sum_{i=1}^{N} w_i = 1 \quad \text{(fully invested)}$$

$$w_i \geq 0 \quad \forall i \quad \text{(long-only)}$$

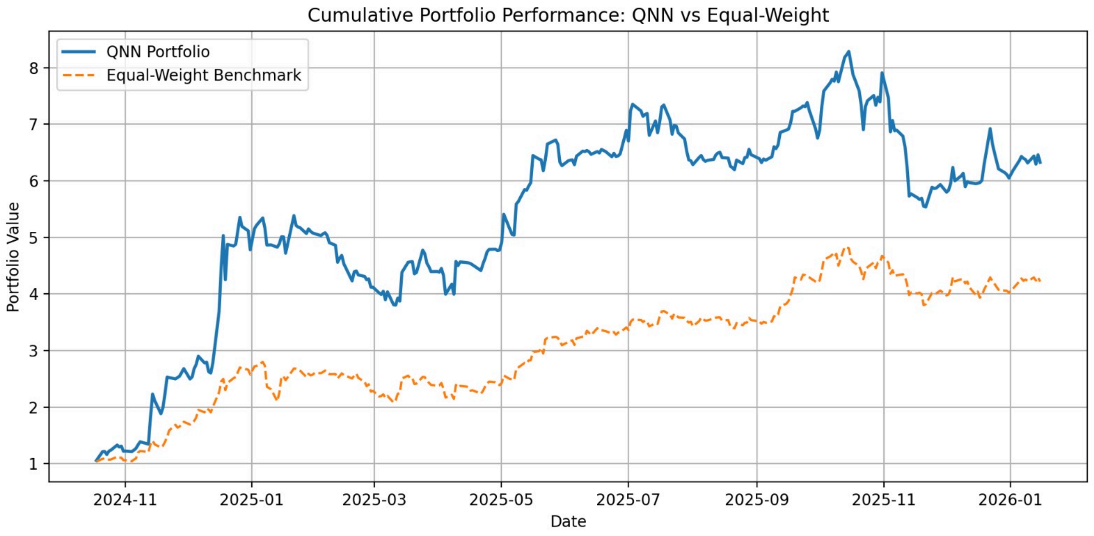
N: number of assets

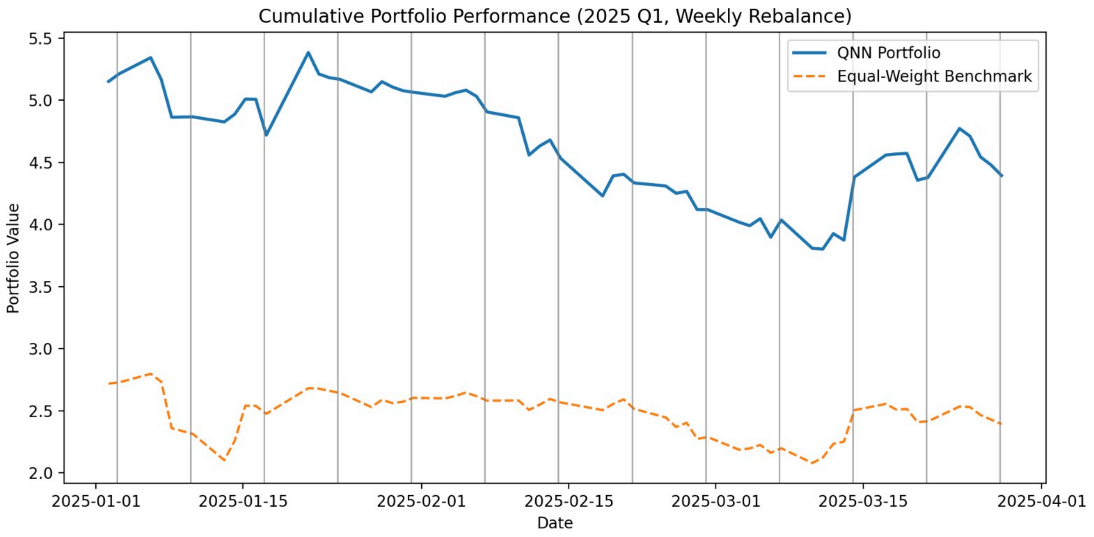
$\mathbf{w} = (w_1, \ldots, w_N)^\top$: portfolio weights

$\hat{\Sigma}_t$: **QNN-predicted covariance matrix** at time t

Model Performance

Comparing the optimized portfolio to a benchmark



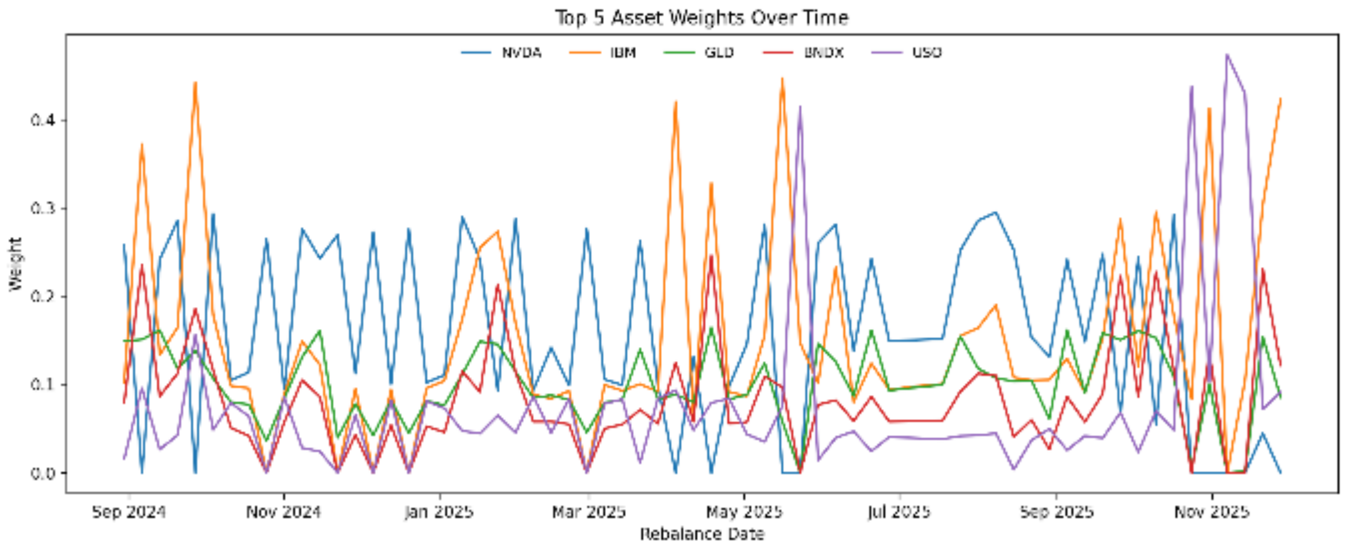


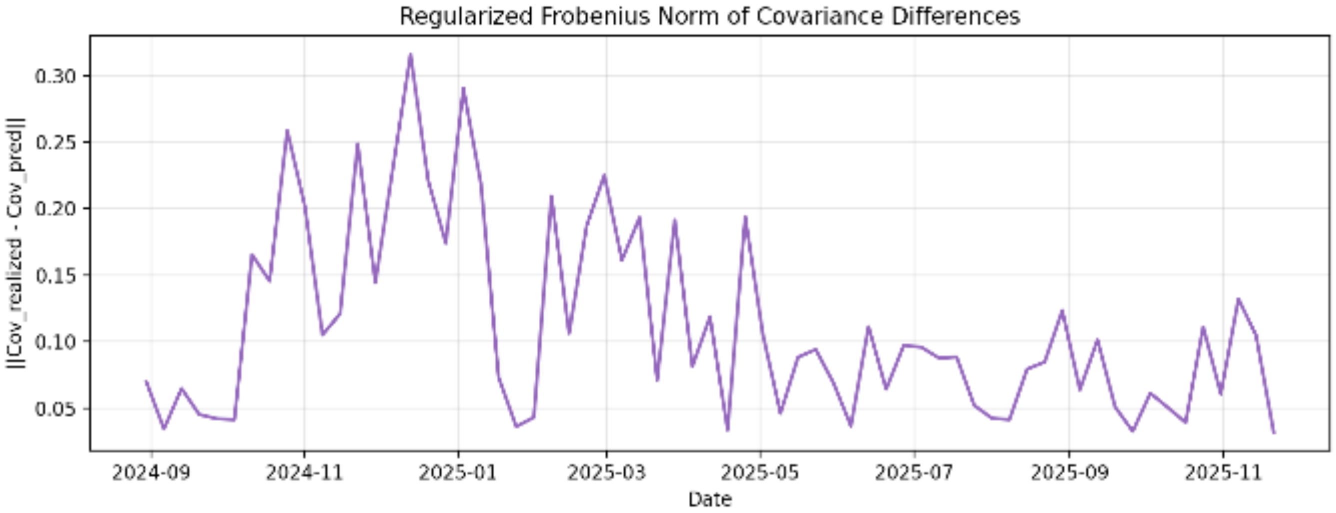
- Optimized Portfolio is compared to **Equi-Weight Buy and Hold strategy.**
- Backtesting is performed **out-of-time** over 16-month period.
- Higher Returns but Higher Volatility
- Sharpe Ratio of Equi-Weight could not be beaten

Metric	QNN Portfolio	Equi-Weight Portfolio
Total Return	5.33	3.22
Annualized Return	3.46	2.21
Annualized Volatility	0.76	0.51
Sharpe Ratio	1.98	2.30
Maximum Drawdown	-0.33	-0.26

Model Assessment

Does the model change the asset distribution and how well can it predict the Covariance





Outlook

Next steps and improvements

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WE DO DEMONSTRATE

- Stable covariance learning
- Structured risk signals
- Portfolio behavior that differs systematically from benchmarks.

WE DO NOT CLAIM

- Quantum advantage
- Sharpe dominance
- Superior alpha

NEXT STEPS

- Replace convex continuous problem with QUBO
- Solve using the Quantum Annealer
- Include expected returns in QNN predictions
- Trading Costs
- Turnover penalty
- More restrictions on portfolio construction
- Limit position sizes