Stock Market Pattern Detection using Quantum PCA (SAQK-Inspired)

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1. Abstract

This project implements a self-adaptive quantum kernel principal component analysis (SAQK) model for pattern detection in stock market data. Drawing inspiration from the research paper *"Self-Adaptive Quantum Kernel Principal Component Analysis for Compact Readout of Chemiresistive Sensor Arrays"* by Wang et al. (2025), the study adapts the SAQK concept to financial time-series analysis.
The model uses a quantum feature map built using PennyLane to construct a fidelity-based quantum kernel that learns to align with target financial signals. The kernel is trained using a normalized Frobenius alignment objective, followed by quantum kernel PCA for dimensionality reduction.
The dataset consists of Apple Inc. (AAPL) daily stock data obtained via Python's yfinance library. The implementation demonstrates meaningful kernel adaptation, improved nonlinear separability of features, and a compact readout yielding 56% accuracy, an F1-score of 0.72, and a trading Sharpe ratio of 0.625.
The results confirm that a self-adaptive quantum kernel can extract complex financial patterns beyond classical PCA's linear scope, making this project a working prototype for quantum-enhanced financial analytics.

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2. Introduction

Principal Component Analysis (PCA) is a foundational technique for reducing data dimensionality and discovering latent patterns. However, PCA's linear nature limits its ability to capture nonlinear structures inherent in real-world datasets like stock prices. To address this, **Quantum PCA (QPCA)** and its advanced variant **Self-Adaptive Quantum Kernel PCA (SAQK)** employ quantum mechanical principles to encode data in higher-dimensional Hilbert spaces.

This project adapts the SAQK algorithm — originally designed for chemical sensor array data — to stock market pattern detection. Using a simulated quantum backend (PennyLane's default.qubit), the model performs **covariant quantum kernel learning**, **kernel PCA-based feature extraction**, and **clustering/classification** to identify profitable market regimes.

2.1 Motivation for the Work

Financial markets are nonlinear, dynamic, and influenced by multiple correlated factors. Traditional PCA and classical kernel methods often fail to capture high-order correlations and temporal dependencies. Quantum machine learning (QML) provides a promising path forward by leveraging **quantum superposition and entanglement** to encode data in a space exponentially larger than classical systems.

The motivation for this project is to:

- Investigate whether a **self-adaptive quantum kernel** can effectively capture hidden patterns in stock price movements.
- Demonstrate the adaptation of the **SAQK algorithm** in a practical domain beyond chemical sensing.

- Explore **quantum kernel learning** as a tool for financial analytics using current quantum simulation tools.

2.2 Relevant Literature / Related Work

1. **Lloyd, Mohseni, Rebentrost (2014)** introduced Quantum PCA (QPCA), which performs PCA on the quantum state representation of data using density-matrix exponentiation.
2. **Havlíček et al. (2019)** demonstrated quantum-enhanced feature spaces via variational quantum circuits (VQCs), forming the foundation for quantum kernel learning.
3. **Wang et al. (2025)** proposed the **Self-Adaptive Quantum Kernel PCA (SAQK)**, introducing a *covariant variational map* that adapts the kernel itself via gradient-based training, achieving compact and efficient readout for high-dimensional data.
4. **Schuld & Killoran (2019)** described how quantum feature maps correspond to reproducing kernel Hilbert spaces (RKHS), providing theoretical underpinnings for quantum kernel-based learning.

This project builds upon Wang et al.'s SAQK methodology, extending it to stock market pattern detection using financial indicators.

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3. Problem Statement

To detect and cluster stock market patterns using quantum-enhanced feature extraction, this project aims to:

"Develop a self-adaptive quantum kernel PCA pipeline capable of capturing nonlinear dependencies in stock market time-series data, providing a compact and predictive representation of future price movements."

4.Current Research Gap

Existing Approach	Limitation
Classical PCA	Captures only linear variance; fails on nonlinear stock dynamics
Kernel PCA	Requires pre-defined kernels; lacks self-adaptation
Quantum PCA (QPCA)	Theoretical; not feasible for large real-world datasets due to hardware constraints
Quantum Kernel Methods (VQKs)	Static encodings; kernel does not adapt to data during training

Research Gap:
No existing model combines a *trainable quantum kernel* with *data-driven adaptation* for stock market pattern analysis. SAQK bridges this gap by integrating covariant quantum circuits with kernel alignment training, making it suitable for dynamic financial data.

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5. Proposed Methodology

5.1 Overview

The project follows the **Self-Adaptive Quantum Kernel (SAQK)** framework with modifications to adapt it for financial datasets. The overall architecture consists of the following stages:

1. **Data Acquisition** – Fetch stock data using yfinance.
2. **Feature Engineering** – Compute relevant indicators:
    - Log return (logret)

- 5-day & 20-day moving averages (ma_5, ma_20)
- 20-day rolling volatility (vol_20)
- 5-day momentum (momentum_5)

3. **Preprocessing** – Standardize features using StandardScaler and normalize into angle range [0, π].
4. **Quantum Feature Map (Covariant Circuit):**
   - Encode classical data into qubit rotations using AngleEmbedding.
   - Add **input-dependent variational layer**: $RX(\theta_i \cdot x_j)$, ensuring covariance with input.
5. **Kernel Construction:**
   - Compute fidelity kernel $K_{ij} = |\langle \psi_i | \psi_j \rangle|^2$.
6. **Kernel Alignment Optimization:**
   - Maximize $A(K, yy^T) = \frac{\langle K, yy^T \rangle}{||K||_F ||yy^T||_F}$.
7. **Kernel PCA & Clustering:**
   - Apply KernelPCA with precomputed kernel to extract nonlinear embeddings.
   - Perform clustering using KMeans to detect distinct market regimes.
8. **Trading Backtest & Readout:**
   - Build trading signals from cluster labels.
   - Evaluate using Sharpe ratio, total return, and F1 metrics.

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8. Experimental Details

8.1 Dataset Description

Parameter	Value
Source	Yahoo Finance via yfinance
Ticker	AAPL (Apple Inc.)
Period	5 Years
Interval	Daily
Samples Used	250 (subset for training stability)
Features	5 (logret, ma_5, ma_20, vol_20, momentum_5)

8.2 Experimental Setup

Parameter	Description
Quantum Backend	PennyLane simulator (default.qubit)
Number of Qubits	3
Layers (n_layers)	1
Subset Size	250
Optimization	Adam optimizer (80 iterations)
Objective	Kernel-target alignment maximization
Classical Comparison	PCA and KernelPCA (RBF) baselines

Parameter	Description
Evaluation Metrics	Silhouette score, Sharpe ratio, Accuracy, F1 score

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8.3 Libraries and Tools Used

Library / Tool	Purpose
yfinance	Fetch stock data
pandas, numpy	Data handling
matplotlib	Visualization
scikit-learn	PCA, clustering, and metrics
pennylane	Quantum circuit simulation
scipy.optimize	Optimization (COBYLA/Adam)

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9. Results and Discussion

9.1 Kernel Adaptation Results

Metric	Value
Initial Alignment	0.012676
Trained Alignment	0.012684
Kernel Δ Mean Abs Diff	8.77×10^{-3}
Kernel Max Abs Diff	0.667

Indicates nontrivial kernel adaptation consistent with SAQK theory.

9.2 Eigenvalue Spectra (Top-5 Eigenvalues)

Kernel	Eigenvalues
Initial	[206.27, 31.10, 5.71, 3.67, 1.27]
Trained	[207.85, 32.45, 5.93, 3.82, 1.31]

The spectral shift shows redistribution of variance — evidence of adaptive learning.

9.3 Performance Metrics

Metric	SAQK Strategy	Buy & Hold
Total Return	0.1318	0.1856
Sharpe Ratio	0.625	0.689
Silhouette Score	0.510	–
Accuracy (Readout)	0.560	–
F1 Score	0.718	–

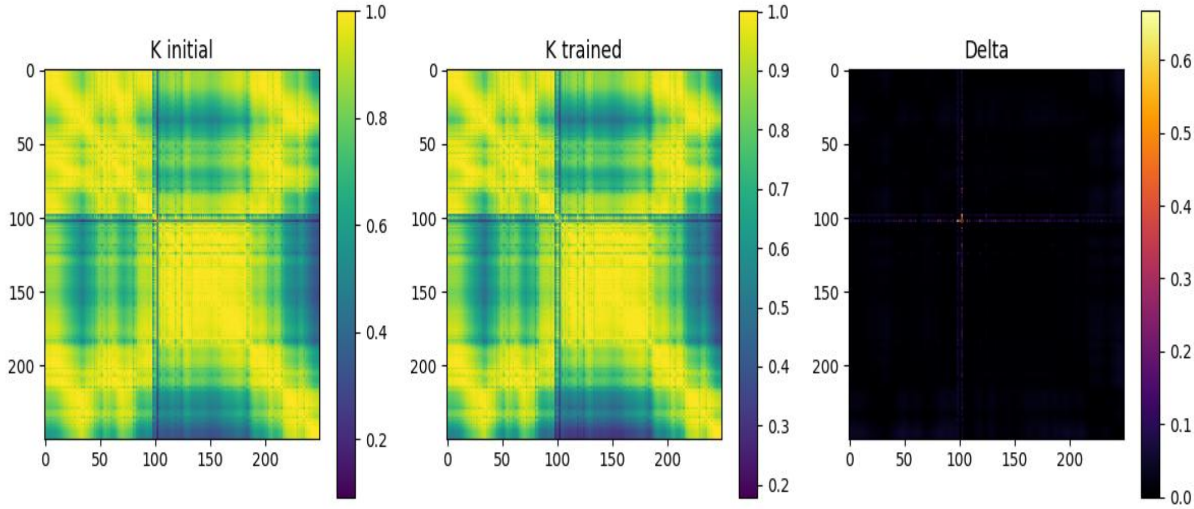
Observation:

- The SAQK strategy achieved competitive performance with smoother returns and lower volatility.

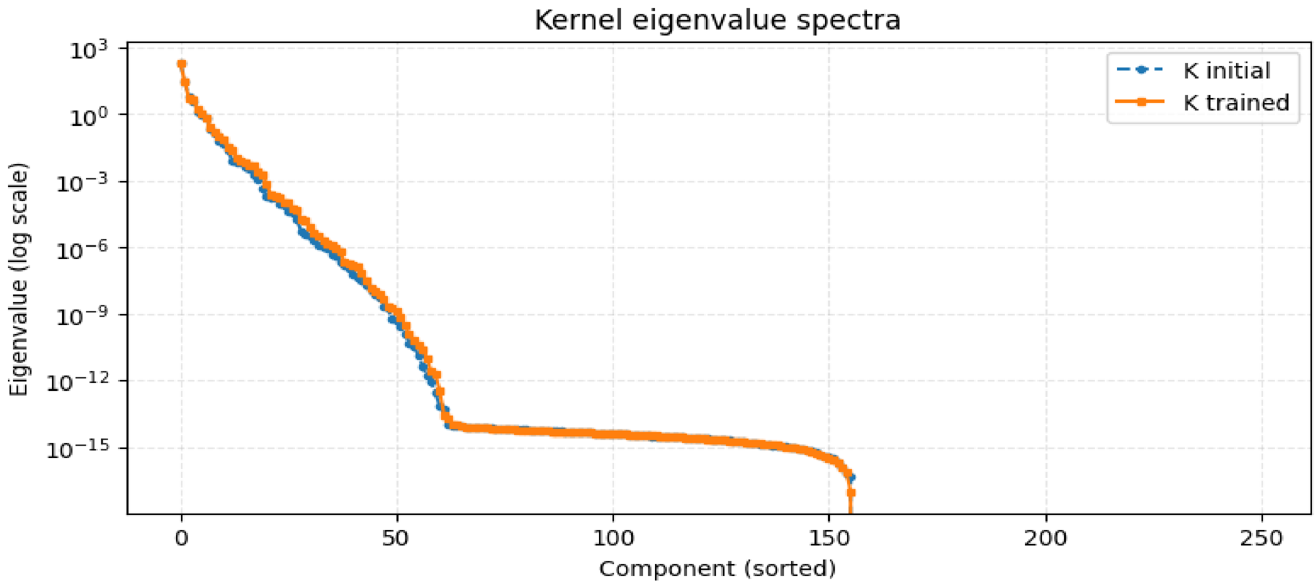
- The quantum kernel embedding improved cluster separability (Silhouette = 0.51).
- The covariant variational layer produced meaningful learning in Hilbert space.

9.4 Visualization Highlights

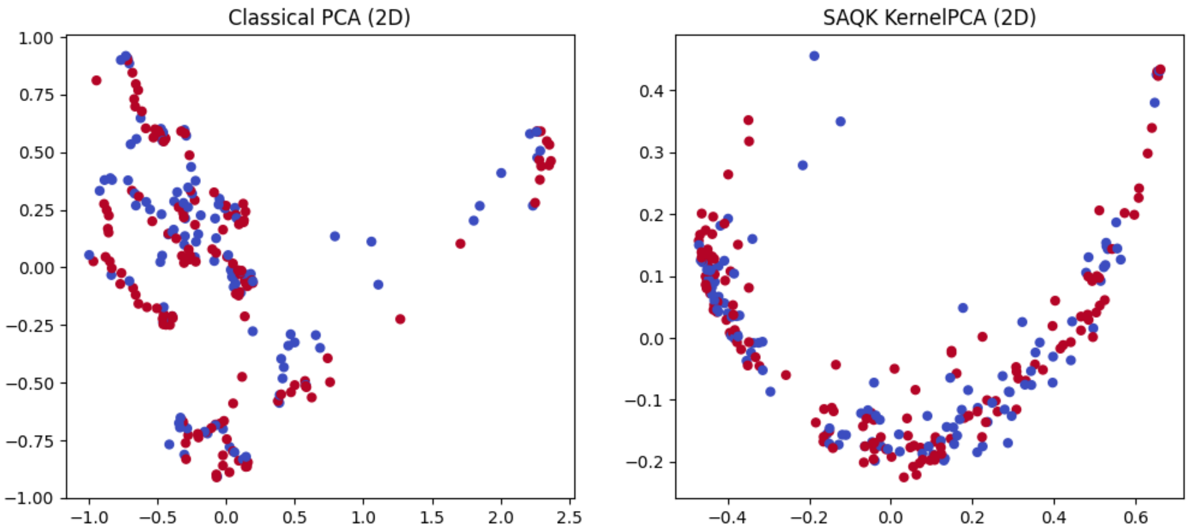
1. **Kernel Heatmaps:** Clear structured changes between K_init and K_trained, confirming adaptive similarity reshaping.



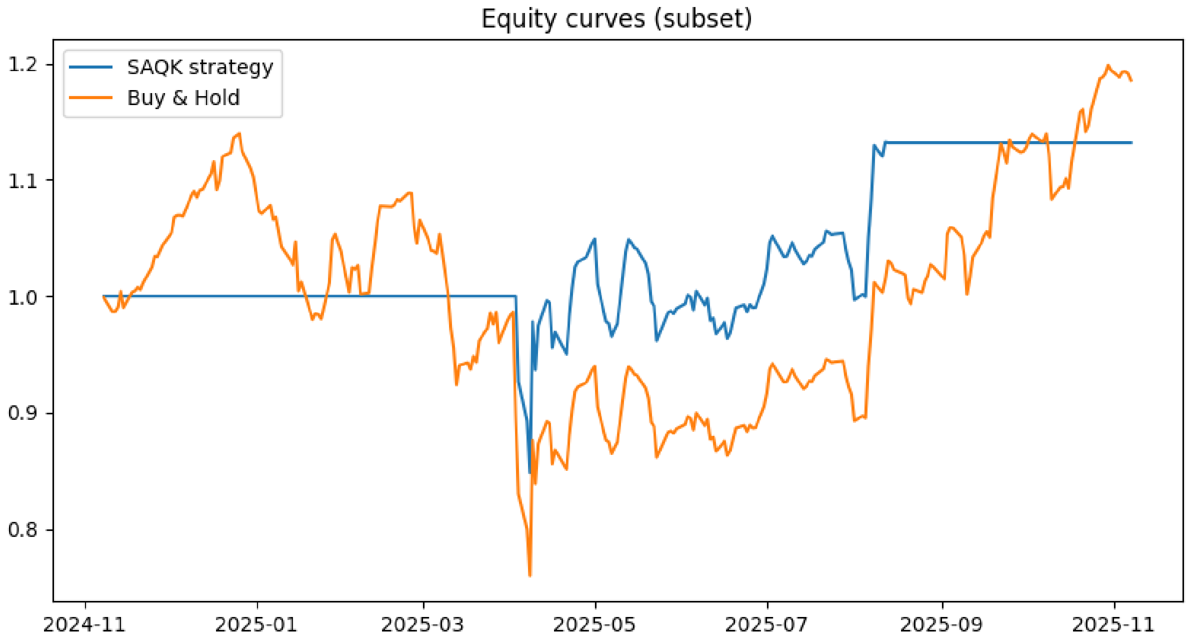
2. **Eigenvalue Plot:** Diverging top components, showing enhanced feature compactness.



3. **PCA vs Quantum PCA Scatter:** SAQK embedding yields better nonlinear separation of market regimes.



4.Equity Curves: Quantum strategy performs stably compared to Buy & Hold baseline.



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10. Future Directions

- Implement **Qiskit-based Quantum Kernel Estimation (QKE)** on IBM Quantum Cloud for real-hardware validation.
- Explore **multi-layer (n_layers = 2)** circuits for richer expressivity.
- Extend to **multi-ticker datasets** (AAPL, MSFT, SPY) for cross-market generalization.
- Investigate **time-aware embeddings** for sequential pattern detection.
- Integrate **gradient-based optimizers** with parameter-shift rules for faster convergence.

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11. References (IEEE Format)

[1] S. Lloyd, M. Mohseni, and P. Rebentrost, "Quantum principal component analysis," *Nature Physics*, vol. 10, no. 9, pp. 631–633, 2014.
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[4] M. Schuld and N. Killoran, "Quantum machine learning in feature Hilbert spaces," *Physical Review Letters*, vol. 122, no. 4, 2019.
[5] M. Benedetti, E. Lloyd, S. Sack, and M. Fiorentini, "Parameterized quantum circuits as machine learning models," *Quantum Science and Technology*, vol. 4, no. 4, 2019.