# Quantum Feature Encoding and Dimensionality Reduction

Adequate Module10

## Project Report

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June 2025

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# 1. Abstract

Quantum computing introduces novel paradigms for processing classical data through quantum feature encoding and dimensionality reduction techniques. This report consolidates insights and experiments from four core modules: Quantum Data Encoding, Quantum State Tomography, Quantum Principal Component Analysis (QPCA), and Quantum Machine Learning (QML). We explore how classical data can be effectively transformed and compressed into quantum states, enabling enhanced feature extraction, noise mitigation, and model generalization in hybrid quantum-classical workflows. The work highlights practical implementations of variational quantum circuits, quantum kernels, and transfer learning techniques, offering a comprehensive perspective on emerging quantum algorithms for machine learning. Challenges, results, and future directions are discussed, laying the foundation for scalable quantum-enhanced data analytics.

# 2. Introduction

Advancements in quantum computing promise transformative improvements for data processing tasks traditionally dominated by classical algorithms. Central to this promise is the ability to encode classical data into quantum states, allowing quantum algorithms to operate in exponentially large Hilbert spaces. Quantum Feature Encoding serves as the bridge between classical inputs and quantum processing units, enabling hybrid quantum-classical machine learning pipelines that leverage both paradigms' strengths.

Dimensionality reduction remains a crucial preprocessing step to manage the complexity and noise inherent in high-dimensional quantum data. Quantum Principal Component Analysis (QPCA) and hybrid quantum-classical autoencoders are key techniques investigated for extracting essential features and reducing resource requirements. Furthermore, quantum machine learning methodologies utilizing variational circuits and transfer learning offer promising paths for practical implementations and enhanced generalization.

This report synthesizes knowledge and experimental outcomes from four modules that collectively address quantum feature encoding and dimensionality reduction, thereby contributing to the broader objective of scalable quantum data analytics.

# 3. Quantum Data Encoding

Quantum data encoding is the initial and pivotal step in preparing classical data for quantum processing. It involves mapping classical numeric features onto quantum states via parameterized quantum gates, most commonly using angle encoding techniques where features modulate rotation angles on qubits.

Our investigations demonstrate angle encoding with rotations about different axes (e.g., Ry and Rz) to prepare distinguishable quantum states corresponding to input data vectors. This mapping not only serves as a data preprocessing stage but also sets the stage for subsequent quantum operations such as quantum principal component analysis and variational circuits.

Experimentation on simulators shows the utility of encoding classical samples and visualizing their quantum states on Bloch spheres, providing intuitive insights into the quantum representation of classical features.

# 4. Quantum State Tomography

Quantum State Tomography (QST) allows reconstructing an unknown quantum state by aggregating measurement data from various bases. This reconstructed state provides a classical representation of the quantum information for analysis and visualization.

In the project, we implemented QST using measurement calibration and error mitigation techniques to ensure high-fidelity reconstructions. The resulting data, originally quantum in origin, was converted into classical feature vectors amenable to classical statistical tools.

Furthermore, classical Principal Component Analysis (PCA) was applied to these measurement results, facilitating dimensionality reduction and visualization of dominant quantum features. This hybrid approach, combining quantum measurements with classical data analysis, bridges experimental quantum data and classical machine learning models.

# 5. Quantum Principal Component Analysis (QPCA)

QPCA offers a quantum-native approach to dimensionality reduction by leveraging quantum algorithms to identify principal components efficiently in high-dimensional quantum states.

Our work details the theoretical foundations of QPCA and implements variational quantum autoencoders (VQAE) as hybrid models capable of compressing quantum-encoded data. These autoencoders utilize parameterized quantum circuits as encoders, with classical neural networks acting as decoders, enabling end-to-end optimization of quantum feature compression.

Results confirm that VQAEs can effectively learn compact representations of quantum data, improving classical post-processing efficiency and aiding in noise reduction. This module

underscores the potential of QPCA and hybrid quantum-classical frameworks as scalable solutions for high-dimensional quantum data analytics.

# 6. Quantum Machine Learning for Feature Encoding and Dimensionality Reduction

The final module extends feature encoding into the realm of quantum machine learning by integrating advanced quantum circuit designs and classical optimization techniques.

Key techniques explored include:

- Quantum Data Reuploading: Encoding classical data multiple times within variational circuits to enhance expressivity without requiring more qubits.
- Variational Embeddings: Trainable quantum circuits that adapt encoding parameters during training, dynamically optimizing feature extraction.
- Quantum Transfer Learning: Reusing pretrained quantum feature maps combined with trainable ansatz circuits to reduce training time and improve generalization on new tasks.

These approaches were implemented with Qiskit's TwoLayerQNN and TorchConnector frameworks, demonstrating effective hybrid quantum-classical model training and inference. Experimental training loops and loss visualizations highlight the potential and current challenges of quantum-enhanced machine learning pipelines.

# 7. Additional Activities

To enhance the learning experience, each notebook in this project is accompanied by coding activities that reinforce the theoretical concepts discussed. These activities include practical implementations, followed by code-based solutions to facilitate self-evaluation and deeper understanding. Additionally, an extra notebook has been developed containing a comprehensive module assessment quiz composed of multiple-choice questions. This quiz allows students to test their grasp of the material covered across all notebooks, with a complete answer key provided at the end for immediate feedback.

# 8. Challenges and Issues

While the project showcases promising advances, several challenges remain:

- **Hardware limitations**: Current quantum devices have limited qubit counts and noisy operations, restricting scalability.
- **Error mitigation**: Despite progress in measurement error mitigation, quantum noise remains a significant hurdle.

- **Complexity of training**: Variational circuit optimization requires careful parameter tuning and is computationally intensive.
- **Data preparation**: Encoding large and complex classical datasets efficiently into quantum states demands further research.
- **Interpretability**: Understanding and interpreting quantum-encoded features within classical ML frameworks is still evolving.

Addressing these challenges is vital for the practical deployment of quantum-enhanced data analytics.

# 9. Conclusions and Next Steps

This comprehensive study validates the feasibility and advantages of quantum feature encoding and dimensionality reduction for machine learning. By combining classical data encoding, quantum state reconstruction, quantum principal component analysis, and hybrid quantum-classical learning, we pave the way for more efficient and powerful ML pipelines.

Future directions include:

- Extending experiments to real quantum hardware to assess noise impact.
- Exploring more sophisticated quantum feature maps and embedding strategies.
- Developing quantum-native dimensionality reduction algorithms beyond VQAEs.
- Integrating quantum ML models into broader data analytics ecosystems.

These efforts will further unlock quantum computing's potential in practical data science.

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