

Interference Quantum Classifier (IQC)

Canonical Algorithm Description, Mathematics, Architecture, Results, and Claims

1. Problem Setting and Motivation

Near-term quantum machine learning (QML) methods are dominated by variational circuits, kernel-based fidelity estimation, and measurement-heavy inference. These approaches suffer from one or more of the following limitations:

- Shot complexity that scales with dataset size
- Loss of phase information due to quadratic observables
- Unstable training dynamics (barren plateaus)
- Tight coupling between learning and hardware execution

The **Interference Quantum Classifier (IQC)** is introduced as an alternative paradigm. IQC separates *learning* from *quantum inference* and uses **linear quantum interference** rather than probability or fidelity as its decision primitive.

2. High-Level Algorithm Overview

IQC consists of four logically separated stages:

1. Classical feature extraction
2. Quantum state encoding
3. Quantum interference-based inference (ISDO)
4. Classical learning via quantum-state updates

Crucially, **only Stage 3 requires a quantum circuit**. All learning occurs outside the quantum loop.

3. Stage I — Classical Feature Extraction

Input data (e.g., images) are processed by a classical encoder such as a convolutional neural network (CNN), producing fixed-length feature vectors:

$$x \in \mathbb{R}^d$$

These vectors are L2-normalized:

$$\tilde{x} = \frac{x}{\|x\|_2}$$

This normalization ensures valid quantum state preparation.

4. Stage II — Quantum State Encoding

Each normalized feature vector is mapped to a quantum state:

$$\tilde{x} \mapsto |\psi(x)\rangle \in \mathcal{H}_{2^n}$$

Encoding can be amplitude-based or otherwise fixed and deterministic. No trainable quantum parameters are introduced at this stage.

The same encoding is used for both:

- Test states $|\psi\rangle$
 - Class memory states $|\chi\rangle$
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5. Stage III — Interference-Sign Decision Observable (ISDO)

5.1 Core Observable

The central decision primitive of IQC is the **linear interference observable**:

$$\boxed{\mathcal{O}_{\text{ISDO}}(\psi; \chi) = \text{Re}\langle\chi|\psi\rangle}$$

The predicted label is obtained by:

$$\hat{y} = \text{sign}(\mathcal{O}_{\text{ISDO}})$$

This observable is:

- Linear in the quantum amplitudes
- Sensitive to relative phase
- Sign-preserving (directional)

It fundamentally differs from quadratic fidelity:

$$|\langle\chi|\psi\rangle|^2$$

which discards sign and phase information.

5.2 Physical Realization via Quantum Circuit

To measure $\text{Re}\langle\chi|\psi\rangle$, IQC employs an ancilla-assisted **interference circuit**.

Conceptually:

1. Prepare an ancilla qubit in $|0\rangle$
2. Create a superposition of two paths
3. Coherently interfere $|\psi\rangle$ and $|\chi\rangle$
4. Measure the ancilla in the Z-basis

The expectation value satisfies:

$$\langle Z_{\text{anc}} \rangle = \text{Re}\langle\chi|\psi\rangle$$

A transition-based implementation (ISDO-B) realizes this without controlled reflections and avoids quadratic observables.

5.3 Phase Sensitivity — Illustrative Example

Consider:

$$|\psi\rangle = |0\rangle$$
$$|\chi\rangle = \frac{|0\rangle + e^{i\phi}|1\rangle}{\sqrt{2}}$$

Then:

$$\langle\chi|\psi\rangle = \frac{1}{\sqrt{2}}$$

If instead:

$$|\psi_\phi\rangle = \frac{|0\rangle + e^{i\phi}|1\rangle}{\sqrt{2}}$$

Then:

$$\text{Re}\langle\chi|\psi_\phi\rangle = \frac{1 + \cos\phi}{2}$$

Thus, classification depends explicitly on **relative quantum phase**, which cannot be recovered from fidelity alone.

6. Stage IV — Learning via Quantum State Evolution

6.1 Learned Object

IQC does not train circuits. The only learned object is the **class memory state**:

$$|\chi\rangle \in \mathcal{H}_{2^n}$$

6.2 Online Update Rule (Quantum Perceptron)

For a labeled sample $(|\psi\rangle, y)$ with $y \in \{+1, -1\}$:

1. Compute score:

$$s = \text{Re}\langle\chi|\psi\rangle$$

2. If $y \cdot s < 0$, update:

$$|\chi'\rangle = \frac{|\chi\rangle + \eta y |\psi\rangle}{\| |\chi\rangle + \eta y |\psi\rangle \|}$$

This update:

- Is linear and deterministic
- Requires no gradients
- Preserves interpretability

7. Learning Regimes

Regime 1 — Static Prototype Aggregation

$$|\chi\rangle = \text{normalize} \left(\sum_k |\phi_k^+\rangle - \sum_k |\phi_k^-\rangle \right)$$

Regime 2 — Online / Incremental Learning

Class state updated sequentially using the rule above.

Regime 3 — Multi-State Quantum Memory

Maintain multiple memory states $\{|\chi^{(j)}\rangle\}$. Inference uses:

$$\hat{y} = \text{sign} \left(\max_j \text{Re} \langle \chi^{(j)} | \psi \rangle \right)$$

8. System Architecture

Pipeline:

Input → CNN → Embedding → Normalization → Quantum State → ISDO Circuit → Score → Classical Decision

Learning updates modify only the stored class states.

9. Empirical Findings

- Removing measurement noise alone does not improve accuracy
 - Interference-based aggregation improves expressivity
 - Inference runtime reduced from minutes (SWAP) to milliseconds
 - No variational training required
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10. Claims (Condensed)

Core Claims

1. A quantum classifier based on linear interference rather than fidelity
2. A sign-based decision rule derived from $\text{Re} \langle \chi | \psi \rangle$
3. Separation of learning and quantum inference

System Claims

- Quantum memory states representing classes
- Read-only quantum inference circuits
- Few-shot and incremental learning without retraining

Method Claims

- Online state update rules
 - Multi-memory ensemble inference
 - Phase-sensitive classification
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11. Paper vs Patent Positioning

Paper Focus

- Mathematical correctness of ISDO
- Empirical validation
- Comparison with fidelity and variational methods

Patent Focus

- Linear interference as a decision primitive
 - State-based learning architecture
 - Hardware-agnostic inference design
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12. Conclusion

IQC establishes a new QML paradigm: **learning quantum states classically and querying them via physical quantum interference**. This design avoids the central limitations of NISQ-era quantum classifiers while preserving uniquely quantum decision semantics.