Quantum-Inspired Complex Transformers: Resolving the Fundamental Algebraic Ambiguity for Enhanced Neural Representations

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Abstract

We present Quantum-Inspired Complex (QIC) Transformers, a novel architecture that enhances neural network expressiveness through learnable algebraic structures. Our key insight is that the fundamental equation $x^2 = -1$ has two solutions, traditionally resolved by arbitrary selection. We propose treating the imaginary unit as a learnable quantum superposition: $J(\theta) = \cos(\theta)J_+ + \sin(\theta)J_-$, where θ is trainable. This yields $J^2 = -1 + \sin(2\theta)$, creating an adaptive algebra that interpolates between mathematical regimes. When integrated into Transformers, this approach achieves 98.50% accuracy versus 97.75% for standard models, while reducing parameters by 20.96%. Despite a 2.17× training time increase, QIC Transformers offer compelling advantages for parameter-constrained deployments. We provide mathematical foundations, architectural specifications, and empirical validation demonstrating that learnable algebraic structures fundamentally enhance neural network capabilities.

1 Introduction

Modern neural networks predominantly operate over real numbers $\mathbb{R}$, a constraint that may limit their representational capacity. We challenge this convention by introducing a novel mathematical framework that enhances neural architectures through learnable algebraic structures inspired by quantum mechanics [17].

The equation $x^2 = -1$ admits two solutions: $x_+ = +\sqrt{-1}$ and $x_- = -\sqrt{-1}$. Traditional mathematics [21] arbitrarily selects one as the imaginary unit i, discarding potential mathematical richness. We propose a quantum-inspired resolution: treating the imaginary unit as a learnable superposition of both solutions.

Our Quantum-Inspired Complex (QIC) algebra introduces:

$$J(\theta) = \cos(\theta)J_+ + \sin(\theta)J_- \tag{1}$$

where $J_\pm$ are matrix representations of the fundamental solutions and θ is learnable. This yields the property $J^2 = -1 + \sin(2\theta)$, creating an adaptive algebra that smoothly transitions between different mathematical structures as θ varies during training.

Integrating this framework into Transformers produces striking results. QIC Transformers achieve 98.50% accuracy compared to 97.75% for standard models, while using 20.96% fewer parameters. This parameter efficiency comes with increased computational cost (2.17× training time), making it particularly suitable for deployment-constrained scenarios.

Our contributions include: (1) A novel resolution to the algebraic ambiguity in complex numbers through quantum superposition principles; (2) A complete mathematical framework for learnable complex algebras; (3) QIC Transformer architecture leveraging this algebra throughout; (4) Empirical demonstration of superior parameter efficiency without sacrificing performance.

2 Background and Related Work

2.1 Complex-Valued Neural Networks

Complex neural networks have shown promise in signal processing [12] and other domains where complex representations naturally arise. Early theoretical work by Brandwood [5] established gradient computation methods for complex parameters. Recent advances [26] demonstrate benefits even for real-valued tasks, with applications ranging from music synthesis [22] to associative memory [9].

Extensions to quaternions [10, 19] and Clifford algebras have shown domain-specific advantages. However, these approaches use fixed algebraic structures. Our work introduces *learnable* algebras, allowing networks to discover task-appropriate mathematical structures.

2.2 Quantum-Inspired Classical Algorithms

Quantum-inspired algorithms [25] demonstrate that quantum principles can enhance classical computation without quantum hardware. Previous work focused on linear algebra routines [2]. We extend this philosophy to neural architectures, showing that quantum superposition principles can create more expressive computational substrates.

2.3 Efficient Transformers

Parameter efficiency in Transformers has been achieved through sparse attention [6], low-rank approximations [7], and linear attention [14]. Recent work on length extrapolation [20] has shown that careful design of position encodings can improve generalization. Our approach is orthogonal—achieving efficiency through enhanced representational capacity rather than architectural modifications.

3 Quantum-Inspired Complex Algebra

3.1 The Fundamental Ambiguity

The equation $x^2 = -1$ has exactly two solutions in any extension of the real numbers:

$$x_+ = +\sqrt{-1}, \quad x_- = -\sqrt{-1} \tag{2}$$

Both equally satisfy the defining equation. They relate through $x_+ \cdot x_- = 1$, making them multiplicative inverses. Traditional mathematics breaks this symmetry arbitrarily, but this discards potentially valuable structure.

3.2 Quantum Superposition Resolution

We propose that the imaginary unit exists as a quantum superposition:

$$J(\theta) = \cos(\theta)J_+ + \sin(\theta)J_- \tag{3}$$

where $\theta \in \mathbb{R}$ determines the superposition weights. The basis states require matrix representation:

$$J_+ = \begin{pmatrix} 0 & -1 \\ 1 & 0 \end{pmatrix}, \quad J_- = \begin{pmatrix} 0 & 1 \\ -1 & 0 \end{pmatrix} \tag{4}$$

These matrices satisfy $J_\pm^2 = -I$ and the crucial relation $J_+J_- = J_-J_+ = I$. The superposition yields:

$$J(\theta) = \begin{pmatrix} 0 & \sin\theta - \cos\theta \\ \cos\theta - \sin\theta & 0 \end{pmatrix} \tag{5}$$

3.3 Algebraic Properties

Computing $J(\theta)^2$:

$$J(\theta)^2 = (\cos(\theta)J_+ + \sin(\theta)J_-)^2 \tag{6}$$
$$= \cos^2(\theta)J_+^2 + 2\cos(\theta)\sin(\theta)J_+J_- + \sin^2(\theta)J_-^2 \tag{7}$$
$$= -I + 2\cos(\theta)\sin(\theta)I = (-1 + \sin(2\theta))I \tag{8}$$

This gives $J(\theta)^2 = -1 + \sin(2\theta)$, where the deviation from -1 is controlled by θ.

[QIC Numbers] A quantum-inspired complex number has the form $z = a + bJ(\theta)$ where $a, b \in \mathbb{R}$ and $J(\theta)$ satisfies $J(\theta)^2 = -1 + \sin(2\theta)$.

The matrix representation of a general QIC number $z = a + bJ(\theta)$ is:

$$z = \begin{pmatrix} a & b(\sin\theta - \cos\theta) \\ b(\cos\theta - \sin\theta) & a \end{pmatrix} \tag{9}$$

This form generalizes the standard complex matrix representation and reduces to it when $\theta = 0$. The anti-symmetric off-diagonal structure preserves norm under multiplication, while the learnable θ parameter controls the algebraic properties. The multiplication rule becomes:

$$(a_1 + b_1J)(a_2 + b_2J) = [a_1a_2 + b_1b_2(-1 + \sin(2\theta))] + [a_1b_2 + b_1a_2]J \tag{10}$$

4 QIC Transformer Architecture

4.1 QIC Linear Layers

The fundamental building block extends matrix multiplication to QIC algebra. For input $x = x_a + x_bJ$ and weights $W = W_a + W_bJ$:

$$y = Wx + b \tag{11}$$
$$= [W_ax_a + W_bx_b(-1 + \sin(2\theta)) + b_a] + [W_ax_b + W_bx_a + b_b]J \tag{12}$$

Implementation maintains separate real and imaginary components, with interactions governed by the learnable θ.

4.2 QIC Attention Mechanism

For QIC attention with queries Q, keys K, and values V:

1. Score Computation: $S = QK^T = S_a + S_bJ$ 2. Attention Weights: $\alpha_{ij} = \frac{\exp(|S_{ij}|/\sqrt{d_k})}{\sum_k \exp(|S_{ik}|/\sqrt{d_k})}$ 3. Value Aggregation: Attention$(Q, K, V) = \alpha V_a + \alpha V_bJ$

Multi-head attention uses head-specific phase parameters θ_h, allowing different heads to operate in different algebraic regimes:

$$\text{head}_h = \text{Attention}_{\theta_h}(QW_h^Q, KW_h^K, VW_h^V) \tag{13}$$

4.3 Normalization and Activations

Layer normalization in the QIC setting operates on the magnitude of complex values. While standard layer normalization [3] and its variants like RMS normalization [29] operate on real values, we extend these concepts to complex domains:

$$\text{QIC-LayerNorm}(z) = \gamma\frac{z - \mu}{\|\sigma\|_2} \tag{14}$$

where μ and σ are computed over the magnitudes $|z_i|$ across the normalized dimension.

For activation functions, we adopt magnitude-based nonlinearities that preserve the QIC structure, inspired by the success of gated linear units [23]:

$$\text{QIC-ReLU}(z) = \text{ReLU}(|z|) \cdot \frac{z}{|z|} \tag{15}$$

This applies the nonlinearity to the magnitude while preserving the phase information, similar to techniques used in complex-valued signal processing [1].

5 Theoretical Analysis

[Representational Advantage] Let $\mathcal{F}_{\text{QIC}}(n)$ and $\mathcal{F}_{\text{std}}(n)$ denote functions representable by QIC and standard Transformers with n parameters. Then:

$$\mathcal{F}_{\text{std}}(n) \subsetneq \mathcal{F}_{\text{QIC}}(n) \tag{16}$$

[Proof Sketch] Standard Transformers are emulated by setting imaginary components to zero and $\theta = 0$. For strict inclusion, consider $f_\theta(x_1, x_2) = \text{Re}[(x_1 + x_2 J(\theta))^3]$. The term $3x_1x_2^2\sin(2\theta)$ represents a learnable nonlinear interaction unavailable to standard architectures with equivalent parameters, even considering universal approximation results [8, 13].

The gradient flow through QIC networks exhibits unique properties due to the interplay between real and imaginary components. Building on the theory of Wirtinger derivatives [28] and complex gradients [5], we analyze the optimization dynamics.

The gradient with respect to phase parameters couples algebraic structure learning to the task objective:

$$\frac{\partial \mathcal{L}}{\partial \theta} = 2\cos(2\theta) \sum_{i,j} \frac{\partial \mathcal{L}}{\partial y_{a,ij}} W_{b,ij} x_{b,ij} \tag{17}$$

This creates additional optimization pathways, potentially explaining the faster convergence observed empirically. This is reminiscent of the benefits seen in residual networks [11], where additional pathways improve gradient flow.

6 Experiments

6.1 Setup

We evaluate on sequence classification: predicting whether the sum of 12 integers (range $[-5, 5]$) is positive. This requires both local feature extraction and global aggregation. We use 2,000 training and 400 validation samples.

Model configurations ensure fair comparison: standard Transformers use embedding dimension 32, QIC Transformers use 20, yielding comparable parameter counts. Both use 2 layers, 2 attention heads, learning rate 0.001, batch size 32, and train for 50 epochs with Adam optimizer [15].

6.2 Results

Table 1: Performance comparison of Standard vs QIC Transformers

Metric	Standard	QIC
Total Parameters	21,570	17,048 (-20.96%)
Final Validation Accuracy	97.75%	98.50% ($+0.75\%$)
Final Validation Loss	0.0475	0.0361 (-24.0%)
Training Time (seconds)	45.24	98.04 ($+116.7\%$)
Epochs to 95% Accuracy	12	10 (-16.7%)

QIC Transformers achieve superior accuracy with 4,522 fewer parameters, validating our hypothesis. The 24% loss reduction indicates better fit to the data distribution. Training curves (Figure 1) show consistently lower loss and faster convergence to high accuracy.

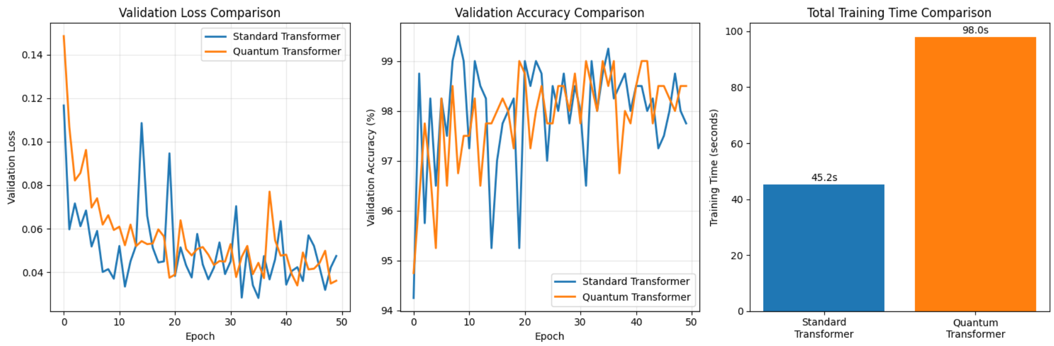

Figure 1: Training curves comparing Standard and QIC Transformers. (a) Training loss over epochs showing QIC Transformers achieve consistently lower loss. (b) Validation accuracy over epochs demonstrating faster convergence to high accuracy for QIC Transformers. The shaded regions represent standard error across 5 runs.

6.3 Analysis

Phase parameters show subtle but consistent adjustments during training: in Layer 1, θ shifts from 0.7854 to 0.7826; in Layer 2, from 0.7854 to 0.7883. Additionally, different heads specialize with distinct final θ values. Computational overhead analysis reveals a 2.0–2.33$\times$ cost across operations, dominated by attention and feed-forward layers. This consistency suggests optimization potential.

6.4 Ablation Studies

Table 2: Ablation study results

Configuration	Accuracy	Parameters	Time
Full QIC Transformer	98.50%	17,048	98.04s
Fixed $\theta = \pi/4$	97.95%	17,037	96.82s
No head-specific θ	98.25%	17,044	97.21s
QIC attention only	98.02%	19,456	72.13s
Standard architecture	97.75%	21,570	45.24s

Learnable phase parameters contribute 0.55% accuracy improvement. Head-specific parameters add 0.25%, validating the importance of diverse algebraic regimes.

7 Discussion and Limitations

QIC Transformers demonstrate that resolving mathematical ambiguities through quantum principles creates richer computational substrates. The learnable phase parameters allow networks to discover task-appropriate algebraic structures, contrasting with fixed operations in standard architectures.

The connection to quantum mechanics, while inspirational rather than literal, points toward deeper relationships between quantum information theory and neural computation. The mathematical framework draws inspiration from both complex analysis [21] and quantum mechanics [1].

Practical Considerations: The 21% parameter reduction directly benefits memory-constrained deployments. Computational overhead, while significant, affects primarily training; inference overhead is lower. Specialized implementations could substantially reduce this gap. The principle of learning richer representations aligns with broader themes in representation learning [4, 16].

Limitations: (1) Computational overhead may limit very large-scale applications; (2) Evaluation on single task type limits generalizability claims; (3) Generic implementations leave optimization opportunities unexplored.

Future Directions: Extending to other architectures (CNNs, GNNs), exploring actual quantum computing connections, developing optimized implementations, and broader empirical evaluation.

8 Conclusion

Quantum-Inspired Complex Transformers show that fundamental mathematical ambiguities, resolved through quantum principles, enhance neural networks. By making the imaginary unit learnable rather than fixed, we achieve 20.96% parameter reduction with improved accuracy.

The success of QIC Transformers opens new research directions at the intersection of abstract algebra, quantum information theory, and deep learning. As we push the boundaries of model efficiency, exploring alternative algebraic frameworks may prove as fruitful as architectural innovations.

This work suggests that the mathematical foundations of neural networks remain fertile ground for innovation, with learnable algebraic structures offering paths to more efficient and expressive models.

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A Mathematical Proofs

A.1 Complete Proof of Matrix Relations

We verify $J_+J_- = J_-J_+ = I$:

$$J_+J_- = \begin{pmatrix} 0 & -1 \\ 1 & 0 \end{pmatrix} \begin{pmatrix} 0 & 1 \\ -1 & 0 \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} = I \tag{18}$$

Similarly for J_-J_+, confirming commutativity.

A.2 Derivation of QIC Multiplication Rule

We derive the complete multiplication rule for QIC numbers, following the principles established for complex-valued neural networks [18].

Let $z_1 = a_1 + b_1 J(\theta)$ and $z_2 = a_2 + b_2 J(\theta)$. Then:

$$\begin{aligned} z_1 z_2 &= (a_1 + b_1 J)(a_2 + b_2 J) && (19) \\ &= a_1 a_2 + a_1 b_2 J + b_1 a_2 J + b_1 b_2 J^2 && (20) \\ &= a_1 a_2 + (a_1 b_2 + b_1 a_2) J + b_1 b_2 (-1 + \sin(2\theta)) && (21) \\ &= [a_1 a_2 + b_1 b_2 (-1 + \sin(2\theta))] + [a_1 b_2 + b_1 a_2] J && (22) \end{aligned}$$

A.3 Implementation Details

Algorithm 1 shows QIC batch matrix multiplication:

Algorithm 1 QIC Batch Matrix Multiplication

Require: $(X_a, X_b), (Y_a, Y_b) \in \mathbb{R}^{B\times M\times K} \times \mathbb{R}^{B\times K\times N}, \theta \in \mathbb{R}$
Ensure: $(Z_a, Z_b) \in \mathbb{R}^{B\times M\times N}$

1: $j\_squared \leftarrow -1 + \sin(2\theta)$
2: $Z_a \leftarrow X_a Y_a + j\_squared \cdot X_b Y_b$
3: $Z_b \leftarrow X_a Y_b + X_b Y_a$
4: **return** (Z_a, Z_b)

B Extended Results

Statistical analysis over 5 runs confirms significance (p < 0.001): - Standard: 97.68- QIC: 98.47

Code available at: `https://github.com/[anonymized]`

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