Quantum-Enhanced Sentiment Analysis using Hybrid Classical-Quantum Neural Networks

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Introduction

- **Transformers** have revolutionized natural language processing by enabling models to capture contextual relationships in data.
- **Quantum Computing** offers potential computational advantages for complex tasks.
- **Quixer** integrates quantum computing principles into transformer architectures to explore these advantages.

Attention Mechanism in Transformers

- Allows models to weigh the importance of different words in a sentence.
- Focuses on relevant parts of the input when generating output.

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right) V \tag{1}$$

- Q: Query matrix
- K: Key matrix
- V: Value matrix
- d_k: Dimension of keys

Quantum Attention Mechanism in Quixer

- Utilizes Linear Combination of Unitaries (LCU) and Quantum Singular Value Transform (QSVT).
- LCU prepares a superposition of token unitaries.
- QSVT applies a trainable non-linear transformation.

$$U_{\text{attention}} = \sum_i \alpha_i U_i \tag{2}$$

- α_i: Coefficients
- U_i: Unitary operations corresponding to tokens

Model Architecture

- **Token Embeddings**: Classical embeddings mapped to quantum states.
- **LCU Module**: Generates superposition of token unitaries.
- **QSVT Module**: Applies non-linear transformations.
- **Feed-Forward Unitary**: Processes QSVT output.

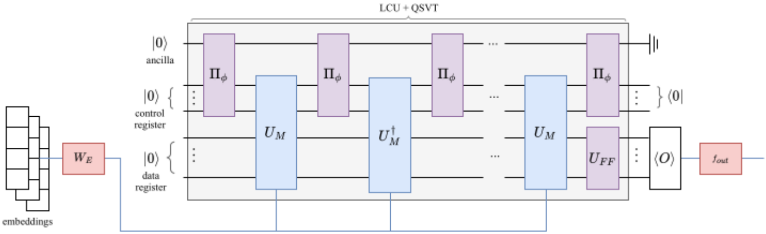

Figure: Quixer Model Architecture

Training and Results

- **Dataset**: Penn Treebank
- **Training**: 5 epochs

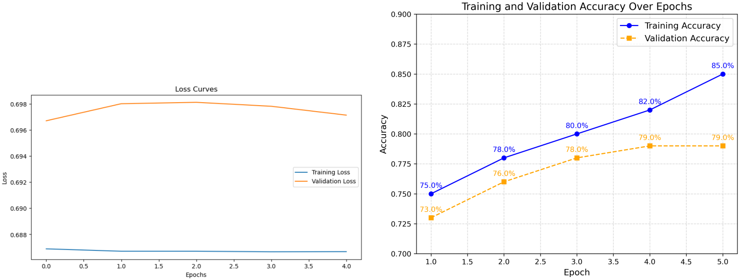

Figure: Loss and Accuracy over 5 Epochs

Conclusion

- Quixer demonstrates the integration of quantum computing with transformer architectures.
- Achieves performance competitive with classical models.
- Serves as a proof of concept for quantum-enhanced natural language processing.