Comparative Analysis Report

Quantum RNN vs Quantum LSTM for Sentiment Analysis

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1. Introduction

In this report, we conduct a comprehensive comparative study of various quantum neural network (QNN) architectures applied to sentiment analysis. The objective is to evaluate the learning capability and generalization performance of different configurations of Quantum Recurrent Neural Networks (Q-RNNs) and a Quantum Long Short-Term Memory network (Q-LSTM). The models are evaluated on a preprocessed Amazon review dataset containing 1000 labeled reviews (balanced between positive and negative), with each review represented by a GloVe embedding.

Previously, we used only 100 training samples and the model overfit quickly. This time, we used the entire training dataset and present the improved results. In this version, we explore enhanced encoding strategies, QNode repetition which achieve improved performance.

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2. Model Architectures

2.1 Quantum RNN Variants

We implemented several Q-RNN variants, each exploring different encoding schemes, repetition strategies, and input dimensionalities. These are outlined below:

Variant	Encoding Type	GloVe Dim	Qubits	QNode Repeats	Notes
Q-RNN v1	Simple Angle	5	6	1	Basic model with minimal configuration
Q-RNN v2	Simple Angle	5	6	2	Repetition to enhance expressivity
Q-RNN v3a	Dense Angle	15	4	1	Dense angle encoding
Q-RNN v3b	Dense Angle	15	4	3	Repetition improves depth
Q-RNN v4	Amplitude	32	6	1	Full-dimension amplitude encoding
Q-RNN v5	Amp + Dense Angle	32	8	1	Hybrid encoding

2.2 Quantum LSTM

The Quantum LSTM integrates quantum gates into the four major LSTM components (input, forget, output, and candidate). Each gate is represented as a separate QNode and processes 32-dimensional GloVe input using amplitude + angle encoding over 8 qubits.

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3. Quantum Node and Model Architecture Overview

Each model consists of a quantum node (QNode) and a PyTorch class for sequential processing. The differences in QNode structure and model class for each architecture are summarized below:

- **Q-RNN v1 & v2 (Simple Angle):**
  - Uses 5-dimensional input.
  - QNode encodes each input element with RY and hidden state with RY on separate wires.
  - CNOT gates create entanglement.
  - Q-RNN v2 repeats the QNode twice.
- **Q-RNN v3a & v3b (Dense Angle):**
  - Input: 15-dimensional (dense packed angle encoding).
  - RY and RZ gates encode subsets of input on 3 wires, hidden on 4th.
  - Uses parameterized trainable gates and entanglement.
  - Q-RNN v3b repeats the QNode 3 times.
- **Q-RNN v4 (Amplitude):**
  - Full 32-dimensional input normalized and encoded via amplitude encoding.
  - 6 qubits used; hidden state applied via a separate RY gate.
- **Q-RNN v5 (Amp + Dense Angle):**
  - Amplitude encoding followed by dense angle encoding using both RY and RZ.
  - Most expressive hybrid encoding strategy over 8 qubits.
- **Quantum LSTM:**
  - 32-dimensional GloVe input processed by four separate QNodes.
  - Each QNode handles one LSTM gate and uses hybrid encoding.
  - LSTM equations combine QNode outputs to update states.

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4. Training Performance

Model	GloVe Dim	QNode Repeats	Final Train Accuracy
Q-RNN v1	5	1	50.00%
Q-RNN v2	5	2	50.00%
Q-RNN v3a	15	1	51.62%
Q-RNN v3b	15	3	53.50%
Q-RNN v4	32	1	52.88%

Model	GloVe Dim	QNode Repeats	Final Train Accuracy
Q-RNN v5	32	1	52.00%
Quantum LSTM	32	1	52.88%

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5. Test Performance

Model	GloVe Dim	Test Accuracy	Notes
Q-RNN v1	5	46.50%	Poor generalization
Q-RNN v2	5	46.50%	Similar to v1 despite repetition
Q-RNN v3a	15	53.50%	Moderate gain from dense encoding
Q-RNN v3b	15	53.50%	Best among dense variants
Q-RNN v4	32	53.50%	Full amp encoding yields balanced output
Q-RNN v5	32	52.00%	Slight drop with hybrid encoding
Quantum LSTM	32	53.50%	Best generalization with hybrid gates

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6. Model Behavior Diagnostics

- Early Q-RNNs (v1–v2) showed minimal logit diversity, often predicting constant outputs.
- Intermediate models (v3a–v4) showed improved class separation and higher variance in probability distribution.
- Q-RNN v5 and Q-LSTM had the best confidence scores with meaningful variability.

Most models improved prediction diversity with QNode repetition and encoding complexity, suggesting stronger learning potential.

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7. Conclusion

This updated study demonstrates that training quantum models on the full dataset significantly improves generalization. Key findings include:

- Dense angle and Amplitude encoding is a competitive option requiring fewer qubits.
- Hybrid encoding (Amplitude + Angle) offers a balance of global and local expressivity.
- Quantum LSTM, despite complexity, achieves a similar performance to that of the QRNN variants.

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