EXPERIMENT 6

Poem Generation using RNN Variants: Comparative Analysis Report

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Objective

To investigate the effect of model architecture and input encoding method on the learning capability and convergence behavior for the task of character-level poem generation.

Models and Encoding Methods

- **Models Used:**
  - Vanilla RNN
  - LSTM
  - GRU

- **Encoding Techniques:**
  - One-Hot Encoding (OHE)
  - Embedding Layer (EMB)

Each combination (e.g., RNN-OHE, LSTM-EMB) was trained and monitored for loss over epochs.

Training Curve Analysis

1. RNN with One-Hot Encoding (RNN-OHE)

- **Observation:** Loss curve is noisy and convergence is slow.
- **Inference:** Lacks capacity to learn long-term dependencies; performance limited by sparse input representation.

2. RNN with Embedding (RNN-EMB)

- **Observation:** Training loss is smoother and converges slightly faster.
- **Inference:** Embeddings improve input representation, enabling better learning.

3. LSTM with One-Hot Encoding (LSTM-OHE)

- **Observation:** More stable than RNN-OHE, though convergence is still slower.
- **Inference:** LSTM's gating mechanism helps learn longer dependencies even with sparse input.

4. LSTM with Embedding (LSTM-EMB)

- **Observation:** Fastest convergence with the lowest loss among all models.
- **Inference:** Best combination of architecture and input representation; embeddings enhance LSTM's learning efficiency.

5. GRU with One-Hot Encoding (GRU-OHE)

- **Observation:** Performance is better than RNN-OHE but not as stable as LSTM-OHE.
- **Inference:** GRU is more efficient than RNN in learning sequences, but still affected by input sparsity.

6. GRU with Embedding (GRU-EMB)

- **Observation:** Similar to LSTM-EMB, but with occasional instability in loss.
- **Inference:** Good performance, slightly less stable than LSTM-EMB.

Results

Model	Encoding	Test Loss	Perplexity	Accuracy
RNN	OHE	3.13	22.93	0.1582
RNN	EMB	2.64	14.00	0.2254
LSTM	OHE	2.38	10.77	0.2657
LSTM	EMB	2.09	8.08	0.3056
GRU	OHE	2.43	11.33	0.2619
GRU	EMB	2.15	8.57	0.2946

Conclusion

Model	Encoding	Stability	Convergence Speed	Final Loss (approx.)	Remarks
RNN	OHE	Low	Slow	High	Poor performance
RNN	EMB	Medium	Moderate	Moderate	Improved with embeddings
LSTM	OHE	Medium	Moderate	Moderate	Stable with moderate results
LSTM	EMB	High	Fast	Low	Best overall performance
GRU	OHE	Medium	Moderate	Moderate	Efficient but affected by OHE
GRU	EMB	High	Fast	Low	Near-LSTM performance

Recommendation

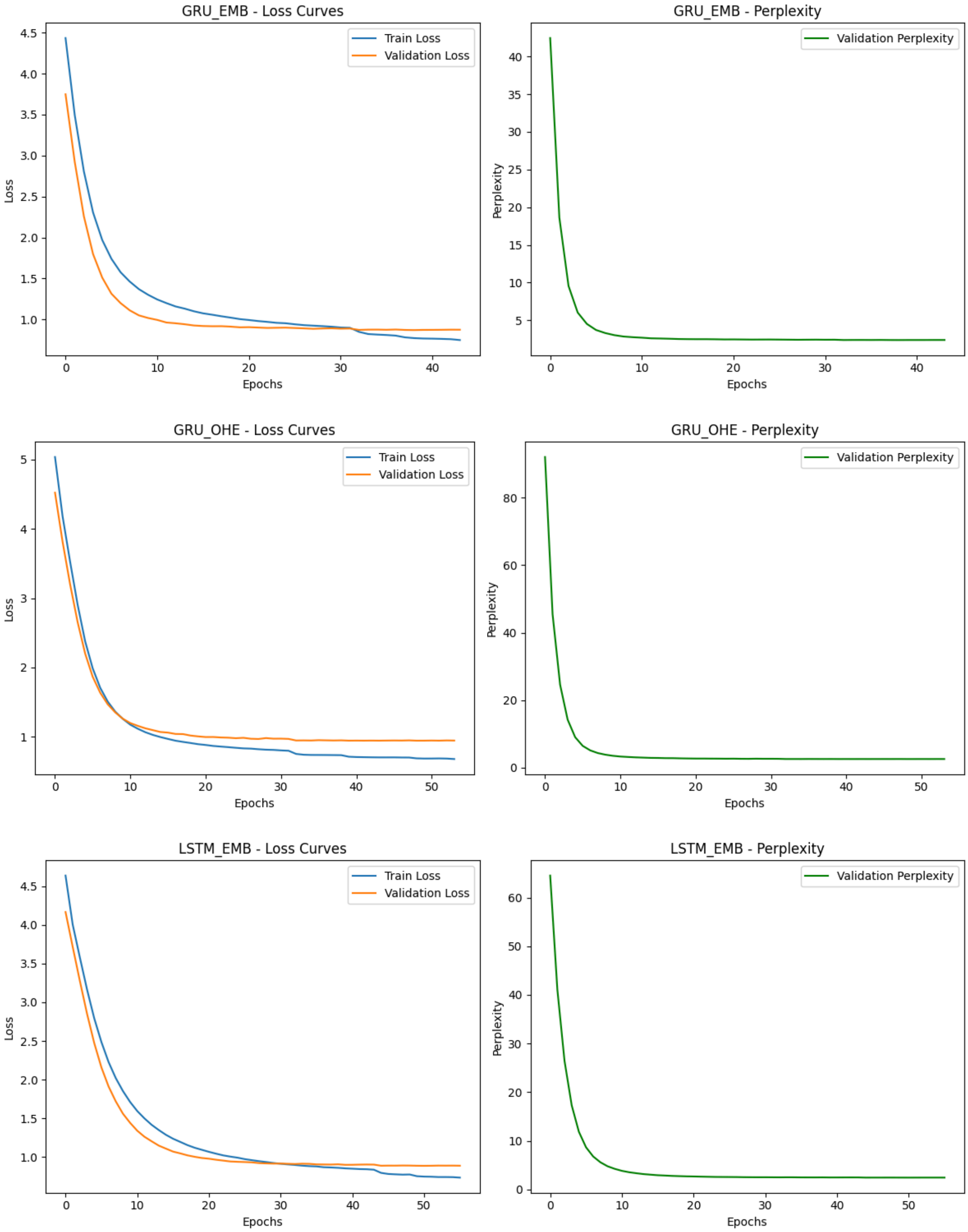
For optimal poem generation performance:

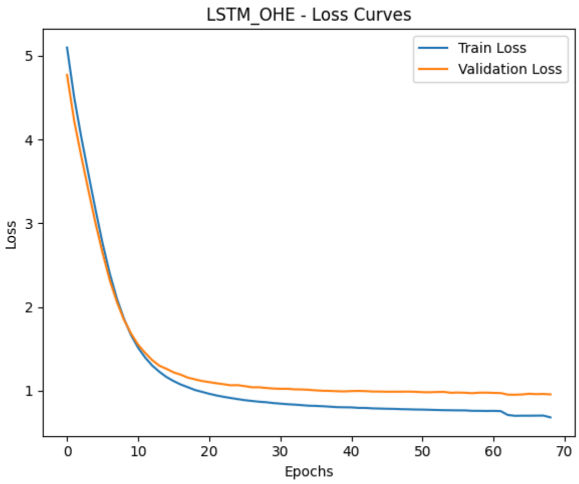
- **Use LSTM or GRU** architectures.
- **Prefer Embedding** over One-Hot Encoding.

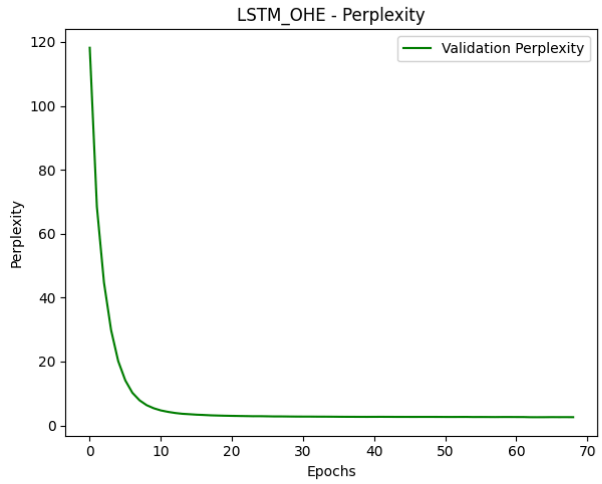
LSTM-EMB offers the best trade-off between stability, speed, and final model accuracy.

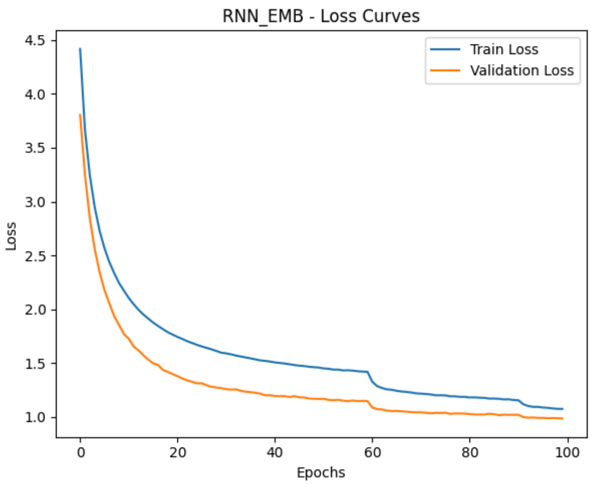
Appendix

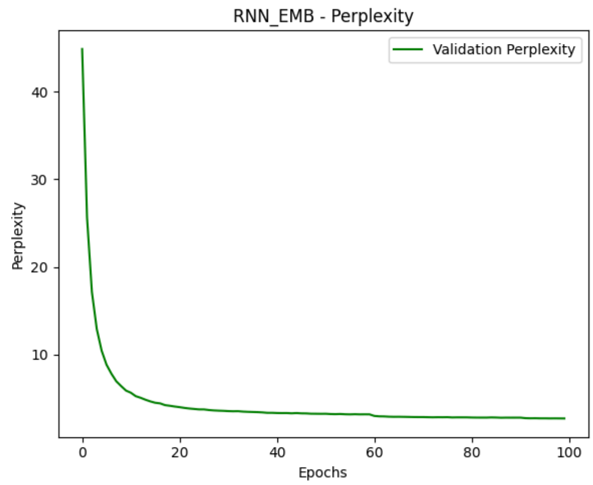
- Training Curves:

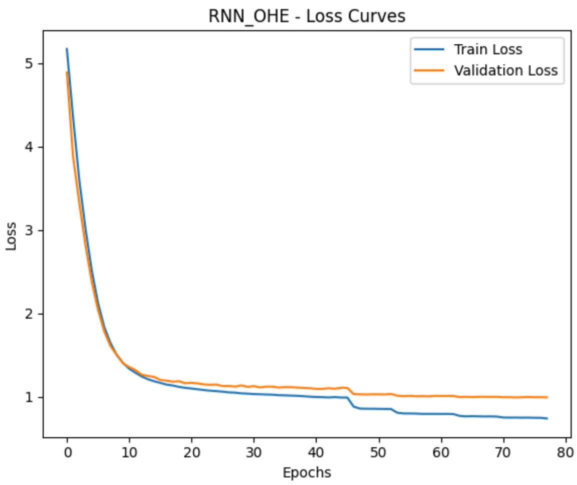



LSTM_OHE - Loss Curves
Train Loss
Validation Loss
Loss
Epochs


LSTM_OHE - Perplexity
Validation Perplexity
Perplexity
Epochs


RNN_EMB - Loss Curves
Train Loss
Validation Loss
Loss
Epochs


RNN_EMB - Perplexity
Validation Perplexity
Perplexity
Epochs


RNN_OHE - Loss Curves
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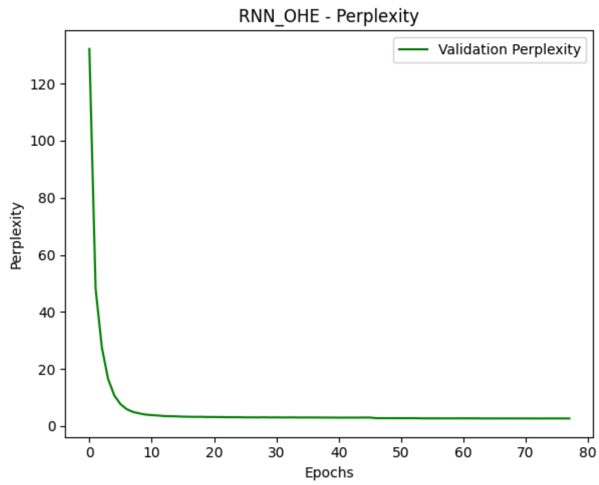
RNN_OHE - Perplexity
Validation Perplexity
Perplexity
Epochs