GRU Baseline Model

October 30, 2025

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1 Introduction

A preliminary study of 108 experiments was conducted to compare four classical architectures: RNN, LSTM, GRU, and Transformer. This initial analysis concluded that the **Gated Recurrent Unit (GRU)** offered the best balance of high performance and parameter efficiency, identifying it as the strongest candidate for a classical baseline. The objective of this report is to detail a more rigorous, in-depth analysis focused exclusively on the GRU model. This focused study aims to:

1. Confirm the superiority of BERT embeddings over static methods.
2. Determine the maximum performance of the GRU model by extending training to 100 epochs with early stopping.
3. Solidify the final classical baseline to be used for comparison against a future quantum analogue.

2 Experimental Design

This in-depth analysis consisted of 9 experiments, fixing the model architecture (GRU) and optimizer (Adam) to isolate the impact of embedding techniques and datasets.

2.1 Component Choices

- **Datasets:** Three datasets were used: **Yelp**, **IMDb**, and **Amazon** product reviews.
- **Embedding Techniques:** Three methods were evaluated:
  - **Basic (128-dim):** A `torch.nn.Embedding` layer, trained from scratch.
  - **Word2Vec (300-dim):** A pre-trained static embedding model.
  - **BERT (768-dim):** A pre-trained contextual embedding model (`distilbert-base-uncased`).
- **Model Architecture:** Fixed to **Gated-Recurrent-Unit** for all experiments.
- **Optimizer:** Fixed to **Adam** for all experiments.

2.2 Training Methodology

- **Data Split:** 80% training, 10% validation, and 10% test split.
- **Maximum Epochs:** All models were trained for a maximum of **100 epochs**.
- **Early Stopping:** Training was halted if the validation loss did not improve for 5 consecutive epochs.
- **Learning Rate Decay:** The learning rate was reduced if the validation loss did not improve for 2 consecutive epochs.

3 Results

3.1 Key Findings

The results of this focused study are definitive and strongly reinforce the preliminary findings.

1. **BERT Embeddings:** BERT embeddings, when paired with the GRU model, achieved a new peak test accuracy of **94.0%** on the Amazon dataset. This is a significant improvement from the 91.0

2. **Extended Training:** The BERT-based models trained for the **full 100 epochs** without triggering early stopping. This indicates they were still learning and did not overfit, justifying the longer training period.

3. **Static Embeddings:** The basic and word2vec models performed poorly (52.7% accuracy). The early stopping mechanism correctly halted their training in under 10 epochs, confirming they are not competitive and do not benefit from extended training.

3.2 Performance Ranking

Table 1 ranks all 9 experiments, sorted by test accuracy and the test-validation accuracy difference. The results clearly segment into two groups: the high-performing BERT models and the low-performing static models.

Table 1: GRU Models Ranked by Performance & Generalization

Run ID	Test Acc.	Val Acc.	Acc. Diff.	Epochs	Emb. Dim	Params
amazon_gru_bert_adam	0.9400	0.8800	0.0600	100	768	3.5M
yelp_gru_bert_adam	0.8700	0.8800	0.0100	100	768	3.5M
amazon_gru_word2vec_adam	0.8700	0.7400	0.1300	8	300	0.82M
imdb_gru_bert_adam	0.8243	0.9324	0.1081	100	768	3.5M
yelp_gru_basic_adam	0.7700	0.7700	0.0000	7	128	0.75M
yelp_gru_word2vec_adam	0.7500	0.7300	0.0200	8	300	0.82M
amazon_gru_basic_adam	0.7400	0.7500	0.0100	9	128	0.74M
imdb_gru_basic_adam	0.5405	0.4459	0.0946	7	128	0.76M
imdb_gru_word2vec_adam	0.5270	0.5541	0.0270	8	300	0.82M

3.3 Comparative Analysis

The aggregated results from this focused study eliminate all ambiguity about the best approach.

Table 2: Average Performance by Embedding Technique

Embedding	Avg. Test Acc.	Avg. Val Acc.	Avg. Epochs Trained
BERT	**87.81%**	**89.75%**	**100.0**
Word2Vec	71.57%	67.47%	8.0
Basic	68.35%	65.53%	7.7

Table 3: Average Performance by Dataset

Dataset	Avg. Test Acc.	Avg. Val Acc.	Avg. Epochs Trained
Amazon	85.00%	79.00%	39.0
Yelp	79.67%	79.33%	38.3
IMDb	63.06%	64.41%	38.3

3.4 Visual Analysis

The provided visualizations clearly illustrate these conclusions.

Figure 1: Comparision by Embedding and Dataset type.

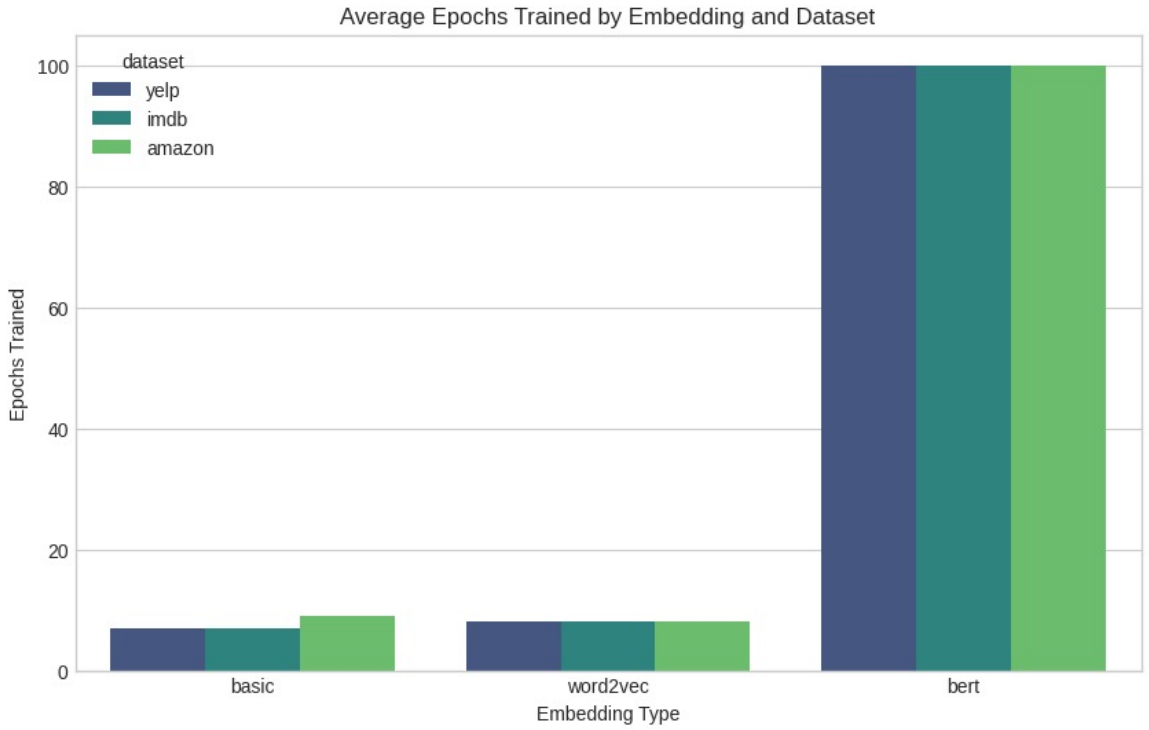

Figure 2: BERT models trained for the full 100 epochs, while static models stopped in under 10.

4 Conclusion

This in-depth study, combined with the findings from the preliminary 108 experiments, provide a definitive answer. The recommended classical baseline model is the GRU architecture paired with BERT embeddings and an Adam optimizer.

This combination is justified by:

- **Performance:** It produced the highest, most consistent test accuracies, peaking at **94.0%**.
- **Training Stability:** It benefits from extended training without overfitting, demonstrating its robustness.
- **Efficiency:** As established through the preliminary experiments, the GRU architecture is significantly more parameter efficient than LSTM and Transformer models, making it an ideal and elegant baseline for comparison against a future quantum analogue.