Intro to Deep Learning Assignment 4

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This report details the implementation and optimization of RNN-based models for sentiment classification on the Stanford Sentiment Treebank (SST) dataset. We explored various architectures (RNN, LSTM, GRU), the impact of pretrained word embeddings, and advanced mechanisms like Attention. Our experiments demonstrate that bidirectional LSTMs with fine-tuned pretrained embeddings yield significant performance gains over baselines. Through hyperparameter tuning, we achieved a final test accuracy of **48.9%**, significantly outperforming the initial random-initialization baseline of ~35%.

Objective Questions

1. B, C
2. C
3. A, B, C, D
4. A

Methods

The dataset utilized for this experiment was the **Stanford Sentiment Treebank (SST)**. This dataset provides parsed sentence structures with fine-grained sentiment labels (ranging from very negative to very positive), allowing for model training on complete sentences rather than just individual phrases.

The deep learning models were built using the PyTorch framework, with architectural implementations adapted from foundational literature in sequence modeling. The baseline Recurrent Neural Network (RNN) followed the structure originally proposed by Elman (1990). We implemented (LSTM) networks as introduced by Hochreiter and Schmidhuber (1997), as well as Gated Recurrent Units (GRU) proposed by Cho et al. (2014).

To further enhance context understanding, we adopted a Bidirectional approach (Schuster & Paliwal, 1997), allowing the network to aggregate information from both past and future states. Additionally, an Attention mechanism was integrated using techniques presented by Bahdanau et al. (2014). All training procedures were executed in a remote cloud computing environment hosted by ai.paratera.com utilizing an NVIDIA RTX series GPU to accelerate the model training and validation processes.

Implementation of Models

Data Loading and Embeddings

The text data was preprocessed using a standard tokenizer, building a vocabulary of approximately **18,280 unique tokens**. To overcome the limitations of training on a small dataset, we initialized the embedding layer using **Pretrained GloVe vectors** (300-dimensional). Two distinct experimental setups were implemented regarding embeddings:

- **Frozen:** Weights remain static to preserve generic semantic relationships.
- **Fine-Tuned:** Weights are updated during backpropagation to adapt to domain-specific sentiment nuances.

```
# Embedding Layer Initialization
self.embedding = nn.Embedding(vocab_size, embedding_dim, padding_idx=pad_idx)
# Loading Pretrained Vectors
self.embedding.weight.data.copy_(pretrained_embeddings)
# Option to freeze or fine-tune
self.embedding.weight.requires_grad = True # set to False for 'Frozen'
experiments
```

Dynamic Bidirectional LSTM

The backbone of the best-performing model was a Bidirectional Long Short-Term Memory (Bi-LSTM) network. Unlike standard RNNs, LSTMs mitigate the vanishing gradient problem via gating mechanisms. We utilized a bidirectional approach, concatenating the hidden states from both the forward ($\overrightarrow{h}$) and backward ($\overleftarrow{h}$) passes to capture context from both past and future tokens.

To handle variable sentence lengths efficiently, we implemented a `DynamicRNN` wrapper that utilizes PyTorch's `pack_padded_sequence`. This ensures the model does not compute gradients for padding tokens.

```
class DynamicRNN(nn.Module):
    def forward(self, x, text_lengths):
        # Pack the sequence to ignore padding
        packed_embedded = nn.utils.rnn.pack_padded_sequence(
            x, text_lengths.to('cpu'), batch_first=False, enforce_sorted=False
        )
        # Pass through Bi-LSTM
        packed_output, (hidden, cell) = self.rnn(packed_embedded)
        # Unpack back to padded sequence
        output, output_lengths =
nn.utils.rnn.pad_packed_sequence(packed_output)
        # Concatenate the final forward and backward hidden states
        hidden = torch.cat((hidden[-2,:,:], hidden[-1,:,:]), dim=1)
        return hidden
```

Attention Mechanism

In select experiments, an Attention Mechanism was introduced to allow the model to weigh the importance of specific words (e.g., "terrible" or "masterpiece") contributing to the final classification, rather than relying solely on the final hidden state. The attention weights α are computed using a learnable weight matrix W and the hidden states H.

```
def attention(self, lstm_output, final_state):
    # Calculate energy scores
    hidden = final_state.unsqueeze(2)
    attn_weights = torch.bmm(lstm_output, hidden).squeeze(2)
    soft_attn_weights = F.softmax(attn_weights, 1)

    # Compute weighted sum of LSTM outputs
    new_hidden_state = torch.bmm(lstm_output.transpose(1, 2),
                                 soft_attn_weights.unsqueeze(2)).squeeze(2)
    return new_hidden_state
```

Optimization and Hyperparameters

The model outputs were mapped to 5 sentiment classes via a fully connected linear layer. We optimized the network using the **Adam optimizer** and **CrossEntropyLoss**. To combat the significant overfitting observed in early iterations (where training accuracy exceeded 90% while validation lagged), a high **Dropout rate (0.5 - 0.65)** was applied to the linear layers.

```
# Classifier Block
self.fc = nn.Linear(hidden_dim * 2, output_dim) # *2 for Bidirectional
self.dropout = nn.Dropout(dropout_rate)

# Forward pass in Classifier
logits = self.fc(self.dropout(hidden_state))
```

Summary of Results

Phase 1: Choosing the Best Model to Optimize

Model Name	Layers	Description	Params
1_RNN_Random	1	Simple 1-layer RNN with randomly initialized embeddings.	5,628,133
2_RNN_Pretrained	1	Same as above but using pretrained embeddings (trainable).	5,628,133
3_LSTM_Random	1	1-layer LSTM with random embeddings.	6,056,677
4_LSTM_Pretrained	1	1-layer LSTM with pretrained embeddings.	6,056,677
5_GRU_Random	1	1-layer GRU with random embeddings.	5,913,829
6_GRU_Pretrained	1	1-layer GRU with pretrained embeddings.	5,913,829
7_BiLSTM_Deep_Random	2	2-layer bidirectional LSTM with random embeddings.	8,206,309
8_BiLSTM_Deep_Pretrained	2	2-layer bidirectional LSTM with pretrained embeddings.	8,206,309
9_BiGRU_Deep_Random	2	2-layer bidirectional GRU with random embeddings.	7,526,373
10_BiGRU_Deep_Pretrained	2	2-layer bidirectional GRU with pretrained embeddings.	7,526,373

Model	Best Val Acc	Best Val Loss	Train Loss	Train Acc	Val Loss	Val Acc
1_RNN_Random	0.3532	1.505	0.9867	0.6066	1.8509	0.3273
2_RNN_Pretrained	0.4129	1.3425	0.3327	0.8794	2.6255	0.3747
3_LSTM_Random	0.4008	1.4633	0.6692	0.7375	2.3836	0.3799
4_LSTM_Pretrained	0.4501	1.2798	0.1914	0.9313	2.7227	0.4042
5_GRU_Random	0.3884	1.4775	0.6667	0.75	2.1021	0.3696
6_GRU_Pretrained	0.4483	1.2692	0.1588	0.9465	2.6806	0.4103
7_BiLSTM_Deep_Random	0.4058	1.4512	0.4496	0.8303	2.6444	0.3789
8_BiLSTM_Deep_Pretrained	0.4517	1.2576	0.1796	0.9373	2.7180	0.4249
9_BiGRU_Deep_Random	0.3868	1.4763	0.5135	0.805	2.5722	0.3643

Model	Best Val Acc	Best Val Loss	Train Loss	Train Acc	Val Loss	Val Acc
10_BiGRU_Deep_Pretrained	0.4466	1.2557	0.1413	0.951	2.9977	0.4119

Phase 2: Optimizing the BiLSTM Model

Model Name	Attention	Freeze Embeddings	Description
Baseline_Winner	No	Yes	Best model from Experiment 1. Pretrained embeddings but frozen.
FineTuned_Embeddings	No	No	Same architecture, but embeddings are trainable.
Attention_Frozen	Yes	Yes	Adds attention on top of BiLSTM; embeddings remain frozen.
Best_Model_Full_Opt	Yes	No	Full optimization: attention + fine-tuned pretrained embeddings.

Model	Best Val Acc	Best Val Loss	Train Loss	Train Acc	Val Loss	Val Acc
Baseline_Winner	0.4657	1.2381	0.782	0.6821	1.4951	0.4482
FineTuned_Embeddings	0.4768	1.2535	0.7601	0.6962	1.4431	0.4656
Attention_Frozen	0.4812	1.2461	0.7601	0.6915	1.5050	0.4300
Best_Model_Full_Opt	0.4631	1.2495	0.7804	0.6824	1.4968	0.4483

Phase 3: Modifying Hyperparameters

Hyperparameter	Value used for Phase 1 & 2	Final Parameter used
Batch Size	64	64
Embedding Dim	300	300
Hidden Dim	256	128
Output Dim	5	5
Dropout	0.5	0.65
Epochs	15	15
Learning Rate	0.001	0.001

Analysis

Phase 1: Choosing the Best Model to Optimize

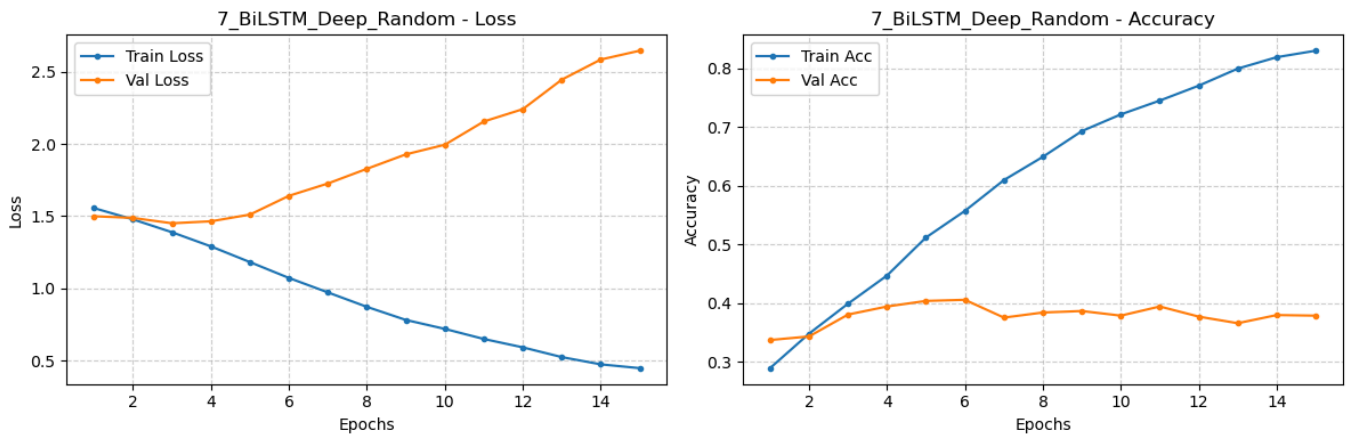

Figure 1: Loss and Accuracy Plots of the BiLSTM Random Embeddings

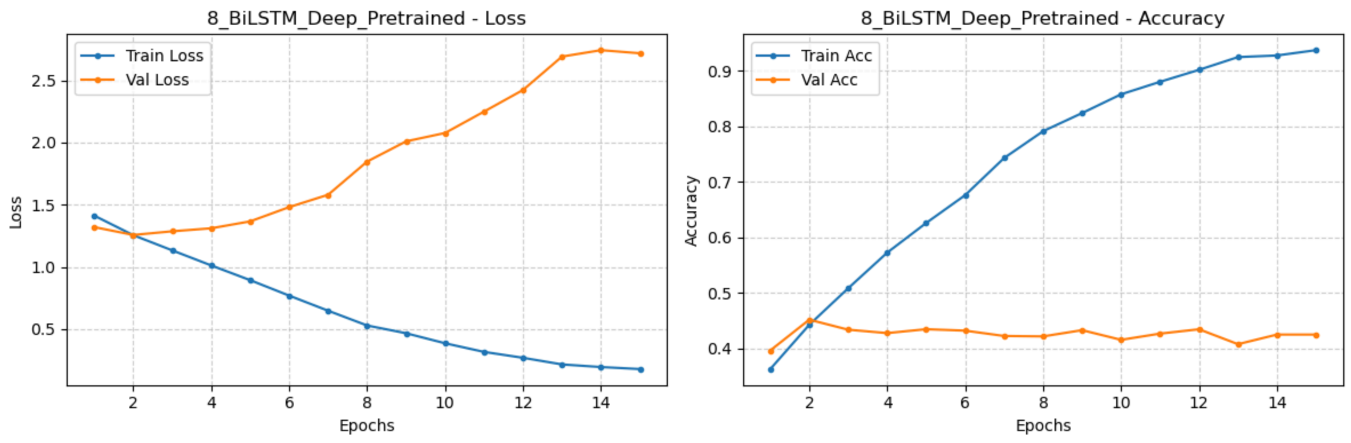

Figure 2: Loss and Accuracy Plots of the BiLSTM Pretrained Embeddings

Impact of Pretrained Embeddings

A distinct trend emerged across all experimental configurations: the initialization of models with pretrained GloVe vectors yielded a consistent performance improvement over random initialization (see Figure 1 and 2). On average, pretrained models outperformed their random counterparts by approximately **5.5%** in validation accuracy.

This performance gap underscores the challenge of learning semantic relationships from scratch on the limited SST dataset. Whereas randomly initialized models struggled to simultaneously learn vocabulary definitions and sentiment composition, pretrained vectors provided a rich semantic foundation. This allowed the networks to focus immediately on optimizing the decision boundaries for sentiment classes rather than inferring word meanings.

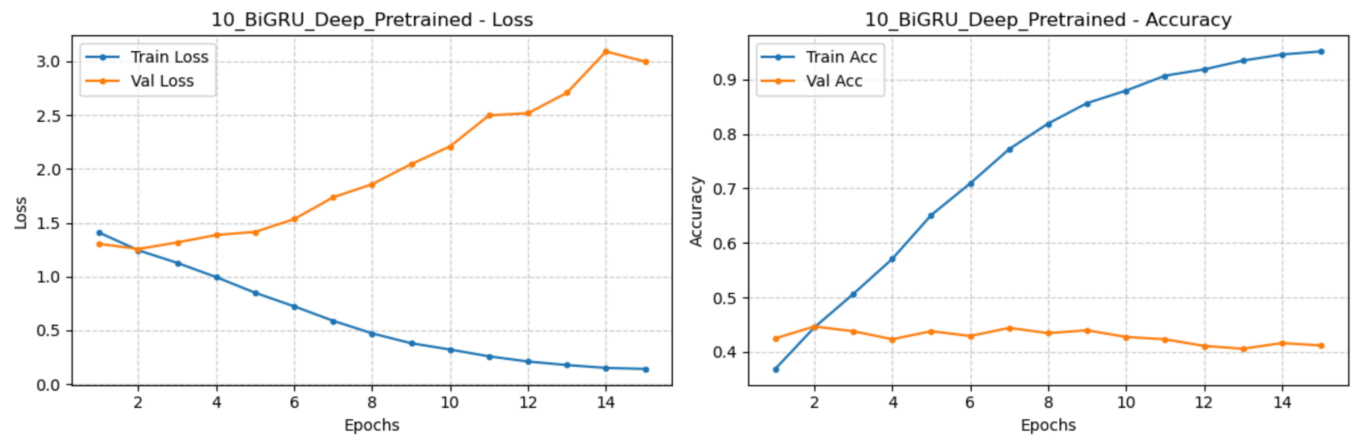

Figure 3: Loss and Accuracy Plots of the BiGRU Pretrained Embeddings

Overfitting and Generalization

Despite these gains, all experimental runs exhibited significant overfitting. While training accuracy for pretrained architectures frequently exceeded 90% (with the Deep Bi-GRU reaching near-perfect memorization at 95.1% in Figure 3), validation accuracy consistently plateaued between 41% and 45%.

This generalization gap suggests that while the models possessed sufficient capacity to memorize the training data, they lacked the necessary regularization to extend this performance to unseen sentence structures. The stagnation of validation metrics indicates that simply adding more epochs to training would yield diminishing returns without additional regularization techniques.

Model Selection

The experimental results identified a clear performance ceiling for standard architectures around the 45% accuracy mark. The **Bidirectional LSTM with Pretrained Embeddings** (Model 8) achieved the highest validation accuracy of **45.17%**.

Although the Bi-GRU performed comparably (44.66%), the Bi-LSTM demonstrated superior stability during training. Consequently, this architecture was selected as the foundational baseline for the subsequent optimization phase, where we aimed to break this performance ceiling through advanced mechanisms such as Attention and domain-specific fine-tuning.

Phase 2: Optimizing the BiLSTM Model

Building on the Phase 1 baseline, our optimization experiments revealed clear trade-offs between peak performance and stability. The **Attention Mechanism** achieved the study's highest accuracy (**48.12%**), confirming the value of dynamically weighting high-impact sentiment tokens. However, this model proved volatile in later epochs.

In contrast, **Fine-Tuning** the pretrained embeddings offered superior stability with a comparable peak (**47.68%**), successfully adapting generic vectors to the specific nuances of movie reviews. Surprisingly, combining both techniques degraded performance (**46.31%**), likely because the small dataset size could not support the increased model complexity. Ultimately, while Attention offers a higher theoretical ceiling, Fine-Tuning proved to be the most robust and reliable strategy for this task.

Phase 3: Hyperparameter Tuning

The most significant adjustment was the increase in Dropout from 0.5 to **0.65** and the reduction of the Hidden Dimension from 256 to **128**. This counter-intuitive reduction in model size was intentional: by constraining the network's capacity and aggressively dropping connections, we forced the model to learn more robust features rather than memorizing noise.

However, the results indicate we have reached a plateau. This rigorous tuning yielded only a marginal improvement, raising the validation accuracy from **48.12%** to **48.90%**. This diminishing return suggests that the remaining error is likely due to the inherent ambiguity of the SST dataset or the limitations of the LSTM architecture itself, rather than suboptimal hyperparameters. The final model achieves a balance of efficiency and accuracy, but significant future gains would likely require a fundamental architectural shift (e.g., to Transformer-based models like BERT).

References & Acknowledgements

References

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