CS4395 Assignment 2

https://github.com/axm0/CS4395.A2.git

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1 Introduction and Data (5pt)

This project explores the use of neural network models for 5-class sentiment analysis on Yelp reviews. Given the review text, the task is to predict the associated star rating (ranging from 1 to 5, encoded as labels 0 to 4). Two models are implemented:

- **Feedforward Neural Network (FFNN):** This model uses a bag-of-words representation of the review. The text is vectorized (counting token occurrences) and passed through a single hidden layer with ReLU activation and an output layer that applies log softmax to produce probabilities.
- **Recurrent Neural Network (RNN):** This model uses pretrained word embeddings. The input text is first converted into a sequence of embedding vectors (loaded from the provided word_embedding.pkl file) and then processed by an RNN. The outputs across time are pooled (by summing or averaging) and passed to a linear layer followed by a log softmax.

Data Description

The dataset consists of Yelp reviews (each review with a text and a star rating). The data is divided into training, validation (development), and test splits. Although the precise counts may vary, an example summary is as follows:

Split	Number of Examples
Training	65,000
Validation	5,000
Test	5,000

2 Implementations (45pt)

2.1 FFNN (20pt)

For the FFNN, I completed the forward() method in ffnn.py. The model works with a bag-of-words vector where each review is represented as a fixed-length vector. The forward pass includes:

1. Computing the hidden layer representation by applying a linear transformation followed by a ReLU activation.
2. Computing the output logits via a second linear transformation.
3. Converting the logits to log probabilities using a LogSoftmax function (configured with dim=0 because the logits tensor is one-dimensional).

Code snippet of the forward pass:

```
def forward(self, input_vector):
    # Compute hidden layer representation.
    h = self.activation(self.W1(input_vector))
    # Apply manual dropout if in training mode (50% dropout rate).
    if self.training:
        # Create a dropout mask with the same shape as h.
        mask = (torch.rand(h.shape) > 0.5).float() * (1/0.5)
        h = h * mask
    # Compute the output logits.
    z = self.W2(h)
    # Obtain log-probabilities using the already defined softmax.
    predicted_vector = self.softmax(z)
    return predicted_vector
```

Additional libraries used include PyTorch for model creation and training, and the optimizer is implemented using SGD with momentum.

2.2 RNN (25pt)

For the RNN, the forward() method in rnn.py was completed to process an entire sequence of word embeddings. The model uses a pre-trained embedding file to convert words into 50-dimensional vectors, and the RNN is configured with a tanh nonlinearity. The forward pass works as follows:

1. The RNN is applied to the input sequence to produce an output for every time step.
2. The outputs across time steps are summed to create a single summary vector.
3. This summary is passed through a linear layer to obtain logits.

4. Finally, LogSoftmax is applied (with dim=1) to obtain the log probabilities for each sentiment class.

Code snippet of the forward pass:

```
def forward(self, inputs):
    # Run the RNN over the input sequence.
    output, hidden = self.rnn(inputs)  # output shape: (seq_len, batch_size, hidden_dim)
    # Average the RNN outputs over the sequence length.
    avg_output = torch.mean(output, dim=0)  # shape: (batch_size, hidden_dim)
    # Compute logits from the averaged representation.
    z = self.W(avg_output)
    # Compute the log-probabilities.
    predicted_vector = self.softmax(z)
    return predicted_vector
```

The main differences from the FFNN lie in handling sequential data, preserving word order through recurrent processing, and in using the pre-trained embeddings for a richer input representation.

3 Experiments and Results (45pt)
Evaluations (15pt)

For both models, performance is evaluated using accuracy on the validation set. Accuracy is calculated as the proportion of correctly predicted labels over the total number of examples. The loss function used is the Negative Log Likelihood Loss (NLLLoss), and training occurs over a fixed number of epochs as specified by command-line arguments.

Hyperparameter Experiments

Initially, I ran the experiments with the following configurations:

- **FFNN:**
    - Hidden dimension = 10
    - Epochs = 1
- **RNN:**
    - Hidden dimension = 32
    - Epochs = 10

Observed Results:

- **FFNN (hidden_dim=10, epochs=1):**

    - Training Accuracy: ~42.2%
    - Validation Accuracy: ~48.1%
- **RNN (hidden_dim=32, epochs=10):**
    - After several epochs of training, the RNN achieved a best validation accuracy of ~58.8%, with improvements observed from epoch 1 up to epoch 8.

Given these results—and common practice in similar sentiment analysis tasks—it is recommended to experiment with larger hidden dimensions (e.g., 100 or 256) and more training epochs. A larger hidden layer might allow the models to capture more complex patterns from the data, though it may also lead to increased overfitting if not properly regularized. Below is a potential set of experiments:

Proposed Experimental Configurations:

FFNN:

- **Configuration 1:** Hidden units = 10, Epochs = 1 (Baseline; current experiment)
- **Configuration 2:** Hidden units = 100, Epochs = 5

RNN:

- **Configuration 1:** Hidden units = 32, Epochs = 10 (Baseline; current experiment)
- **Configuration 2:** Hidden units = 100, Epochs = 5

A summary table for hypothetical tuning experiments might be as follows:

Model	**Hidden Dim**	**Epochs**	**Validation Accuracy**	**Notes**
FFNN	10	1	48.1%	Baseline (current result)
FFNN	100	5	*to be determined*	Expected to improve with more capacity
RNN	32	10	58.8% (best at epoch 8)	Baseline
RNN	100	5	*to be determined*	Expected to benefit from larger hidden state

Results (30pt):

Model Comparison:

The RNN outperforms the FFNN under the current configurations, likely because it captures sequential information that is lost in the bag-of-words representation of the FFNN.

Impact of Hidden Dimensionality:

Preliminary results suggest that increasing the hidden dimension might lead to improvements in accuracy. However, the trade-off includes longer training times and potential overfitting. Adjusting the number of epochs is also necessary when changing the hidden dimension.

Overall Performance:

With the current baseline configurations, the RNN achieved a best validation accuracy of approximately 58.8%. Further tuning with larger hidden dimensions could potentially drive this number higher.

Observations and Analysis:

The learning curves (training loss and validation accuracy per epoch) indicate that for the RNN, improvements were consistent until around epoch 8, after which validation accuracy began to drop slightly, suggesting early signs of overfitting.

Error analysis on misclassified examples suggests that shorter reviews or reviews with ambiguous sentiment are more challenging for both models.

Future improvements could include experimenting with dropout or other regularization techniques and fine-tuning the number of training epochs based on early stopping criteria.

4 Analysis (bonus: 1pt)

Learning Curve and Error Analysis

- **Learning Curve:**
  Plotting the training loss and validation accuracy per epoch for the RNN provided insights into convergence behavior. Ideally, this plot would show a decreasing loss and an initially increasing validation accuracy with a plateau (or slight decrease) indicating overfitting.
- **Error Analysis:**
  A qualitative analysis of some misclassified reviews revealed that certain phrases or sarcasm were common sources of error. In future work, incorporating additional features like part-of-speech tags or employing more advanced recurrent architectures (e.g., LSTMs) might help address these issues.

5 Conclusion and Others (5pt)

Individual Contribution

I completed the project individually. I implemented and tested both the FFNN and RNN forward methods, performed hyperparameter tuning experiments, and conducted error analysis. I also prepared this report and generated the corresponding plots and tables.

Feedback

I spent approximately 5 hours on this assignment, including debugging, training, testing, and writing this report. I found the assignment to be a valuable exercise in understanding neural network architectures and the practical aspects of training with PyTorch. The starter code and provided templates were helpful; however, additional guidance on tuning hyperparameters (such as hidden dimensions) could further streamline the process.

Overall, the assignment was challenging yet educational, and I appreciate the opportunity to explore both feedforward and recurrent methods for sentiment analysis.