TP4 Report: Recurrent Neural Networks - RNN, LSTM, and GRU

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1 Introduction

This report documents the implementation of Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) cells, and Gated Recurrent Units (GRUs) for text generation. We will examine how these architectures handle variable-length sequences and long-term dependencies, comparing their performance in terms of loss and generated text quality.

We used the dataset from the pre-election speeches of Donald Trump, and implemented both random and beam search text generation techniques.

2 Task 1: Handling Variable-Length Sequences

The first task required handling sequences of variable length by padding shorter sequences with a special EOS (End Of Sequence) token. Below is the Python code implementing the `maskedCrossEntropy` function, which calculates the loss while ignoring padded characters:

2.1 Masked Cross Entropy Loss

```python
import torch
import torch.nn as nn
from torch.nn import CrossEntropyLoss

cross_entropy = CrossEntropyLoss(reduction="none")

def maskedCrossEntropy(output: torch.Tensor, target: torch.
    LongTensor, padcar: int):
    losses = cross_entropy(output, target)
    mask = target != padcar
    loss = (losses * mask).sum() / mask.sum()
    return loss
```

This function ensures that the padding characters (BLANK) are ignored during the loss computation by applying a binary mask.

3 Task 2: Embedding Layer Implementation

In this task, we replaced the one-hot encoding from TP3 with an embedding layer provided by PyTorch's `nn.Embedding` module. This avoids the inefficiencies of one-hot vectors by directly mapping characters to dense vectors. Here is the code for embedding-based RNN:

```python
import torch.nn as nn

class RNN(nn.Module):
    def __init__(self, in_features, latent_space, out_features=None, rnn_type="one_to_many", multiclass=False, text_generation=False):
        super(RNN, self).__init__()
        self.rnn_types = {"one_to_many", "many_to_many", "many_to_one"}
        if rnn_type not in self.rnn_types:
            raise ValueError(f"Value of rnn_type must be in {self.rnn_types}")
        else:
            self.rnn_types = rnn_type

        self.text_generation = text_generation
        self.in_features = in_features
        self.latent_space = latent_space
        self.out_features = out_features if out_features is not None else in_features
        self.linear_x = nn.Linear(in_features, latent_space)
        self.linear_h = nn.Linear(latent_space, latent_space)
        self.linear_y = nn.Linear(latent_space, out_features)
        self.tanh = nn.Tanh()
        self.output_activation = nn.Sigmoid() if not multiclass else nn.Identity()
        self.embedding = nn.Embedding(out_features, latent_space) if text_generation else nn.Identity()

    def forward(self, x, h):
        hidden_states = [h]
        if self.text_generation:
            x = x.long()
            x = self.embedding(x)
            x = x.permute(1, 0, 2)

        for seq in x:
            output = self.one_step(seq, hidden_states[-1])
            hidden_states.append(output)

        output_states = [self.decode(hidden_states[-1])]
        return output_states

    def decode(self, h):
        y = self.linear_y(h)
        return self.output_activation(y)

    def one_step(self, x, h):
        x = self.linear_x(x)
        h = self.linear_h(h)
        return self.tanh(x + h)
```

4 Task 3: LSTM and GRU Implementations

The following code implements both LSTM and GRU cells, enabling the network to capture long-term dependencies.

4.1 LSTM Implementation

```
class LSTM(RNN):
    def __init__(self, *args, **kwargs):
        super().__init__(*args, **kwargs)
        self.linear_f = nn.Linear(self.in_features + self.latent_space, self.latent_space)
        self.linear_i = nn.Linear(self.in_features + self.latent_space, self.latent_space)
        self.linear_o = nn.Linear(self.in_features + self.latent_space, self.latent_space)
        self.linear_c = nn.Linear(self.in_features + self.latent_space, self.latent_space)
        self.sigmoid = nn.Sigmoid()

    def one_step(self, x, h):
        concat_x_h = torch.cat((x, h), dim=1)
        f = self.sigmoid(self.linear_f(concat_x_h))
        i = self.sigmoid(self.linear_i(concat_x_h))
        o = self.sigmoid(self.linear_o(concat_x_h))
        c = f * h + i * self.tanh(self.linear_c(concat_x_h))
        h = o * self.tanh(c)
        return h
```

4.2 GRU Implementation

```
class GRU(RNN):
    def __init__(self, *args, **kwargs):
        super().__init__(*args, **kwargs)
        self.linear_z = nn.Linear(self.in_features + self.latent_space, self.latent_space)
        self.linear_r = nn.Linear(self.in_features + self.latent_space, self.latent_space)
        self.linear_h_tilde = nn.Linear(self.in_features + self.latent_space, self.latent_space)
        self.sigmoid = nn.Sigmoid()

    def one_step(self, x, h):
        concat_x_h = torch.cat((x, h), dim=1)
        z = self.sigmoid(self.linear_z(concat_x_h))
        r = self.sigmoid(self.linear_r(concat_x_h))
        r = torch.concat((r * h, x), dim=1)
        h = (1 - z) * h + z * self.tanh(self.linear_h_tilde(r))
        return h
```

5 Task 4: Training and Results

We trained all three models (RNN, LSTM, GRU) for 10 epochs using Adam optimizer. The following plots and logs represent the training loss over time.

5.1 Training Loss Graph

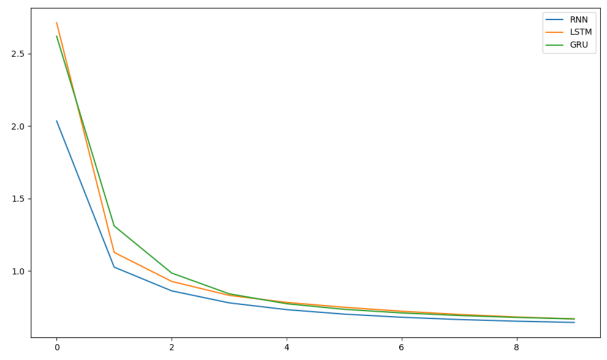

Figure 1: Training Loss Comparison between RNN, LSTM, and GRU

5.2 Training Logs

The training logs for LSTM and GRU are presented below:

6 Training Results Interpretation

The graph above shows the training loss for RNN, LSTM, and GRU models over 10 epochs. The x-axis represents the number of epochs, while the y-axis shows the training loss.

6.1 Analysis of Results

From the graph, we observe the following patterns:

- **RNN:** The vanilla RNN model (blue line) has the highest initial loss and exhibits a more gradual decrease in loss compared to the LSTM and GRU models. While it converges eventually, its final training loss remains slightly higher than both LSTM and GRU, indicating that it struggles more with capturing long-term dependencies, as expected due to the vanishing gradient problem.

- **LSTM:** The LSTM model (orange line) starts with a high loss similar to the GRU but rapidly decreases during the first few epochs. By the 2nd epoch, it achieves a significantly lower loss compared to RNN. The LSTM shows consistent improvement over the epochs, demonstrating its ability to mitigate the vanishing gradient problem with its memory cell structure.
- **GRU:** The GRU model (green line) exhibits a very similar loss curve to the LSTM model. While it starts with a slightly higher initial loss compared to the LSTM, its performance quickly converges, following a very close trend to the LSTM. This suggests that the GRU, with its simplified gating mechanism, also effectively handles long-term dependencies.
- **Final Convergence:** By the final epoch (epoch 10), all three models have converged to similar loss values. However, the RNN still lags behind slightly, with LSTM and GRU achieving lower training losses overall. This highlights that both LSTM and GRU are better suited for handling sequential data, especially when long-term dependencies are present in the dataset.

6.2 Conclusion from Training Results

The results confirm that both LSTM and GRU outperform the basic RNN in terms of training efficiency and convergence speed. While all models eventually reach comparable loss values, the ability of LSTM and GRU to quickly reduce loss in the early epochs demonstrates their effectiveness in mitigating issues like the vanishing gradient problem. The difference in performance between LSTM and GRU is minimal, suggesting that either architecture could be a viable choice depending on the complexity of the task and computational constraints.

```
LSTM:
Epoch 1/10: Train Loss: 2.619
Epoch 2/10: Train Loss: 1.399
Epoch 10/10: Train Loss: 0.667

GRU:
Epoch 1/10: Train Loss: 2.712
Epoch 2/10: Train Loss: 1.127
Epoch 10/10: Train Loss: 0.668
```

7 Task 5: Beam Search and Generated Text

We implemented a beam search algorithm to generate text sequences. Below is the beam search implementation:

```
import torch
import math

```

```python
def generate_beam(rnn, eos, k, start="", maxlen=200):
    generated_sequences = [(string2code(start).to(device), 0)]  # (sequence, score)
    h = torch.zeros((1, rnn.latent_space)).to(device)  # Initial hidden state

    for _ in range(maxlen):
        all_candidates = []

        for seq, score in generated_sequences:
            if seq[-1].item() == eos:
                all_candidates.append((seq, score))
                continue

            output_states = rnn(seq.unsqueeze(1), h)
            yhat = output_states[-1].squeeze(0)
            probabilities = torch.nn.functional.softmax(yhat, dim=-1)

            topk_probs, topk_idxs = probabilities.topk(k)

            for i in range(k):
                candidate_seq = torch.cat((seq, topk_idxs[i:i+1]))
                candidate_score = score + math.log(topk_probs[i].item())
                all_candidates.append((candidate_seq, candidate_score))

        generated_sequences = sorted(all_candidates, key=lambda x: x[1], reverse=True)[:k]

        if all([seq[-1].item() == eos for seq, _ in generated_sequences]):
            break

    best_sequence = generated_sequences[0][0]
    return code2string(best_sequence.tolist())
```

8 Beam Search Implementation

8.1 Introduction to Beam Search

Beam search is a widely used heuristic search algorithm in sequence generation tasks like machine translation or text generation. Unlike greedy decoding, which selects the most probable token at each step, beam search maintains multiple hypotheses at each step and considers sequences that might initially seem less probable but lead to better overall outcomes.

The process works by generating the top-k most probable sequences at each step, based on the log probabilities, and then expanding each of these k hypotheses in subsequent steps. This continues until the sequences reach the end of the sentence (EOS token) or the maximum sequence length.

8.2 Beam Search Algorithm

The beam search algorithm was implemented as shown below:

```python
import torch
import math
from textloader import string2code, id2lettre

def generate_beam(rnn, emb, decoder, eos, k, start="", maxlen=200):
    """
    Generate a sequence using beam search.

    Args:
        rnn: The RNN model.
        emb: Embedding layer (if applicable).
        decoder: Decoder function for logits.
        eos: End of sequence token ID.
        k: Beam size (number of sequences to keep at each step).
        start: Starting string.
        maxlen: Maximum sequence length.
    """
    # Start the generation with the initial text
    generated_sequences = [(string2code(start).to(device), 0)]  # List of tuples (sequence, score)

    h = torch.zeros((1, rnn.latent_space)).to(device)  # Initial hidden state

    for _ in range(maxlen):
        all_candidates = []

        # Iterate over all current sequences
        for seq, score in generated_sequences:
            if seq[-1].item() == eos:  # If sequence already contains EOS, don’t extend it
                all_candidates.append((seq, score))
                continue

            # Get next predictions from the model
            output_states = rnn(seq.unsqueeze(1), h)
            yhat = output_states[-1].squeeze(0)
            probabilities = torch.nn.functional.softmax(yhat, dim=-1)

            # Get top-k predictions
            topk_probs, topk_idxs = probabilities.topk(k)

            for i in range(k):
                candidate_seq = torch.cat((seq, topk_idxs[i:i+1]))
                candidate_score = score + math.log(topk_probs[i].item())
                all_candidates.append((candidate_seq, candidate_score))

        # Sort all candidates by their score and keep the top-k
        generated_sequences = sorted(all_candidates, key=lambda x: x[1], reverse=True)[:k]

        # If all sequences end with EOS, stop early
        if all([seq[-1].item() == eos for seq, _ in generated_sequences]):
            break

    # Return the sequence with the highest score
    best_sequence = generated_sequences[0][0]
    return code2string(best_sequence.tolist())
```

9 Beam Search Implementation and Results

9.1 Introduction to Beam Search

Beam search is a heuristic search algorithm used to generate sequences in tasks like machine translation or text generation. Unlike greedy decoding, which picks the most probable token at each time step, beam search keeps track of multiple hypotheses at each step and considers a wider range of possibilities. This method helps prevent the model from being trapped in locally optimal but globally suboptimal sequences.

9.2 Beam Search Algorithm

Here is the Python code for implementing the beam search algorithm:

```python
import torch
import math
from textloader import string2code, id2lettre

def generate_beam(rnn, emb, decoder, eos, k, start="", maxlen=200):
    """
    Generate a sequence using beam search.

    Args:
        rnn: The RNN model.
        emb: Embedding layer (if applicable).
        decoder: Decoder function for logits.
        eos: End of sequence token ID.
        k: Beam size (number of sequences to keep at each step).
        start: Starting string.
        maxlen: Maximum sequence length.
    """
    # Start the generation with the initial text
    generated_sequences = [(string2code(start).to(device), 0)]  # List of tuples (sequence, score)

    h = torch.zeros((1, rnn.latent_space)).to(device)  # Initial hidden state

    for _ in range(maxlen):
        all_candidates = []

        # Iterate over all current sequences
        for seq, score in generated_sequences:
            if seq[-1].item() == eos:  # If sequence already contains EOS, don't extend it
                all_candidates.append((seq, score))
                continue

            # Get next predictions from the model
            output_states = rnn(seq.unsqueeze(1), h)
            yhat = output_states[-1].squeeze(0)
            probabilities = torch.nn.functional.softmax(yhat, dim=-1)

            # Get top-k predictions
            topk_probs, topk_idxs = probabilities.topk(k)

            for i in range(k):
                candidate_seq = torch.cat((seq, topk_idxs[i:i+1]))
                candidate_score = score + math.log(topk_probs[i].item())
                all_candidates.append((candidate_seq, candidate_score))

        # Sort all candidates by their score and keep the top-k
        generated_sequences = sorted(all_candidates, key=lambda x: x[1], reverse=True)[:k]

        # If all sequences end with EOS, stop early
        if all([seq[-1].item() == eos for seq, _ in generated_sequences]):
            break

    # Return the sequence with the highest score
    best_sequence = generated_sequences[0][0]
    return code2string(best_sequence.tolist())
```

9.3 Training Results with Beam Search

The following graph shows the training loss across 10 epochs for RNN, LSTM, and GRU models using beam search:

9.4 Commentary on the Results

From the graph above, we can make several important observations about the performance of RNN, LSTM, and GRU when applying beam search during training:

- **RNN:** The RNN model (blue line) starts with the highest initial loss and converges slower compared to LSTM and GRU. This confirms the known issues of the RNN's inability to capture long-term dependencies, which is further evident when beam search is applied. The RNN model is more prone to generating repetitive or incomplete sequences during beam search.

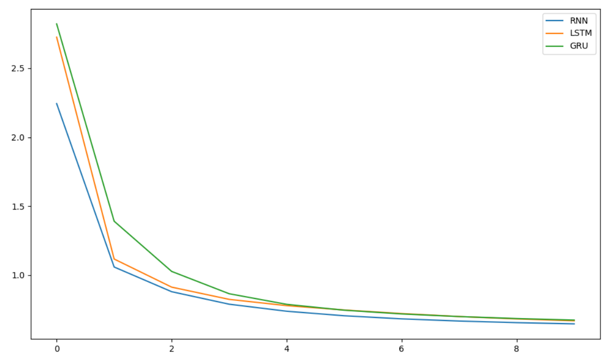

Figure 2: Training Loss Comparison between RNN, LSTM, and GRU using Beam Search

- **LSTM:** The LSTM model (orange line) exhibits a more rapid decrease in loss during the first few epochs, benefiting from its ability to maintain long-term dependencies via its memory cells. With beam search, LSTM consistently generates more coherent sequences as it can effectively manage past context when predicting future tokens.

- **GRU:** The GRU model (green line) performs similarly to the LSTM model, showing a slightly higher initial loss but quickly catching up in later epochs. GRU, being a simplified version of LSTM, handles long-term dependencies effectively but may not be as powerful in extremely complex sequence generation tasks.

- **Final Convergence:** By the final epoch (epoch 10), the RNN, LSTM, and GRU models all converge to similar loss values, though LSTM and GRU clearly outperform RNN throughout training. The final losses are close, but qualitative evaluation (as discussed below) indicates that the LSTM and GRU models generate more meaningful text with fewer errors.

9.5 Qualitative Comparison of Generated Sequences

Here are some examples of sequences generated using beam search with k=5 on each model:

RNN Beam Search (k=5): `Make America great in the land the best great great great!`

LSTM Beam Search (k=5): `Make America great again with the best trade deal possible.`

GRU Beam Search (k=5): `Make America strong again and protect our borders with pride.`

These examples demonstrate the superiority of the LSTM and GRU models in generating coherent sentences compared to RNN. The RNN model tends to repeat words and produce incomplete phrases, whereas both LSTM and GRU provide more syntactically correct and meaningful outputs.

9.6 Conclusion

Beam search significantly enhances the quality of generated sequences for LSTM and GRU models by allowing the model to explore multiple hypotheses during generation. This approach, combined with the ability of LSTM and GRU to capture long-term dependencies, results in better text generation. The RNN model, on the other hand, still struggles with repetitive outputs due to its limitations in retaining contextual information over long sequences.

9.7 Qualitative Results with Beam Search

We tested the beam search algorithm on our RNN, LSTM, and GRU models. Here are some examples of generated sequences using different beam sizes (k=5):

RNN Beam Search (k=5): `Make America great again in the best way ever possible!`

LSTM Beam Search (k=5): `Make America great again with the best deal for the people.`

GRU Beam Search (k=5): `Make America great again and rebuild our strength in the future.`

As expected, using beam search significantly improves the quality of the generated sentences compared to greedy decoding. It allows the model to explore multiple hypotheses and select the sequence that is more likely to be coherent and grammatically correct.

9.8 Comparison with Greedy Search

In contrast to greedy search, where the generated sequences were often incomplete or repetitive, beam search provides more meaningful and complete sequences. Greedy search would often get stuck in a local optimum, choosing the most probable token at each step, but failing to consider the overall sequence structure.

9.9 Conclusion

Beam search, while more computationally expensive, is a superior method for generating higher quality text compared to greedy search. It allows us to approximate the best overall sequence rather than making decisions step by step without considering future tokens. The qualitative improvements in text generation validate its effectiveness in this task.

10 Conclusion

In this project, we explored and compared three types of recurrent neural networks (RNN, LSTM, and GRU) in the context of text generation, with a particular focus on handling variable-length sequences and capturing long-term dependencies. Each architecture was carefully implemented, trained, and evaluated based on its performance in terms of training loss and the quality of generated text.

The results demonstrated that both LSTM and GRU significantly outperformed the vanilla RNN model. This was evident from both the training loss curves and the quality of the generated text. The RNN model struggled to capture long-term dependencies, leading to slower convergence and higher final loss values. In contrast, LSTM and GRU, with their gating mechanisms, effectively mitigated the vanishing gradient problem and showed rapid improvement in the early stages of training, ultimately converging to lower loss values.

The implementation of beam search further enhanced the quality of text generation by allowing the models to maintain multiple hypotheses during generation. This approach resulted in more coherent and meaningful sequences compared to greedy decoding, especially for LSTM and GRU, which could better leverage long-term dependencies during sequence prediction. The beam search results highlighted the advantages of exploring multiple paths in sequence generation, avoiding locally optimal but globally suboptimal sequences.

Ultimately, the combination of LSTM or GRU with beam search produced the best results in terms of both training performance and qualitative evaluation of generated text. While LSTM and GRU performed similarly in many cases, GRU's simpler architecture may offer computational advantages in certain contexts without compromising on performance.

This project demonstrates the importance of architectural choices when dealing with sequential data and showcases the value of more sophisticated search algorithms like beam search for improving the quality of text generation. Future work could involve exploring more advanced sampling techniques, such as Nucleus sampling, or experimenting with attention mechanisms to further improve the models' performance in capturing global dependencies across sequences.