# Machine Learning

# LABORATORY: LSTM-RNN In Class

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## Objectives:

- Students will implement a Recurrent Neural Network (RNN) from scratch, without using built-in RNN APIs.
- Students will manually implement:
    - o Hidden state updates over a sequence, a simple linear output layer for sentence classification and manual Stochastic Gradient Descent (SGD) updates.
- Students will understand how RNN hidden states summarize past information.
- Students will visualize the loss curve during training and observe model predictions for simple sentences.

## Part 1. Instruction

In this assignment, you will implement a basic Vanilla Recurrent Neural Network (RNN) for simple sequence classification using PyTorch, but without using any high-level RNN modules (no *nn.RNN,* no *optim.SGD* , etc.).

You will manually implement:

- A step-by-step hidden state update based on the RNN equation.
- A manual simple output layer to predict whether a sentence is "good" or "bad".
- Manual parameter updates using basic gradient descent.

The general RNN computation is as follows:

$$s_t = \varphi\left(Ws_{t-1} + Ux_t + b\right)$$

After the final time step, you apply an output layer:

$$logits\ = W_{out}s_T + b_{out}$$

where:

- $W_{out} \in R^{2\times n}$ = output weight matrix
- $b_{out} \in R^{2\times 1}$ = output bias
- The prediction is obtained by applying argmax over the logits.

## Part 2. Code Template

| Step | Procedure |
|---|---|
| 1 | import torch<br>import matplotlib.pyplot as plt<br><br># 1. Vocabulary<br>vocab = { "The": 0, "movie": 1, "is": 2, "good": 3, "bad": 4}<br><br>def word_to_onehot(word):<br>    vec = torch.zeros(len(vocab), 1) |

```
    vec[vocab[word]] = 1.0
    return vec
# 2. Training Samples
train_data = [
    (["The", "movie", "is", "good"], 1),
    (["The", "movie", "is", "bad"], 0)
]
# 3. Define RNN Parameters
n = 2   # hidden size
m = len(vocab)
T = 4   # number of words

torch.manual_seed(42)
```

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```
# Initialize Weights (n x n), (n x m), (n x 1), (2 x n), (2 x 1)
W = None
U = None
b = None

W_out = None
b_out = None

# 4. Training Setup
learning_rate = 0.1
num_epochs = 300
loss_fn = torch.nn.CrossEntropyLoss()

loss_history = []
```

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```
# 5. Training Loop
for epoch in range(num_epochs):
    total_loss = 0.0

    for sentence, label in train_data:
        inputs = [word_to_onehot(word) for word in sentence]
        s_prev = torch.zeros(n, 1)

        for x_t in inputs:
            # TODO: Compute s_t
            s_t = None  # TODO

            s_prev = s_t

        # Output layer
        logits = None  # TODO
        logits = logits.view(1, -1)

        # Loss
        target = torch.tensor([label])
        loss = loss_fn(logits, target)
        total_loss += loss.item()

        # Backward
        loss.backward()
```

```python
        # Manual update (SGD)
        with torch.no_grad():
            # TODO: Update W, U, b, W_out, b_out
            pass

            # Zero gradients after updating
            W.grad.zero_()
            U.grad.zero_()
            b.grad.zero_()
            W_out.grad.zero_()
            b_out.grad.zero_()

    loss_history.append(total_loss)

    if (epoch + 1) % 50 == 0:
        print(f"Epoch [{epoch+1}/{num_epochs}] - Loss: {total_loss:.4f}")
```

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```python
# 6. Plot Loss
plt.plot(loss_history)
plt.xlabel("Epoch")
plt.ylabel("Total Loss")
plt.title("Training Loss Curve")
plt.grid(True)
plt.show()
```

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```python
# 7. Test After Training
print("\n=== Testing ===")
test_sentences = [
    ["The", "movie", "is", "bad"],
    ["The", "movie", "is", "good"]
]

for test_sentence in test_sentences:
    inputs = [word_to_onehot(word) for word in test_sentence]
    s_prev = torch.zeros(n, 1)

    for x_t in inputs:
        #Forward pass again (same as above)
        s_t = None  # TODO
        s_prev = s_t

    logits = None  # TODO
    prediction = torch.argmax(logits)

    print(f"Sentence: {test_sentence} ➔ Prediction: {prediction.item()}")
```

## Grading Assignment & Submission (30% Max)

**Implementation:**

1. (5%) Correctly initialize all weights.
2. (5%) Correctly compute the hidden state update and the output layer (logits).
3. (5%) Correctly update all parameters manually using gradients (manual SGD).
4. (5%) The model correctly predicts "good" = 1 and "bad" = 0 in the test sentences.

**Question:**

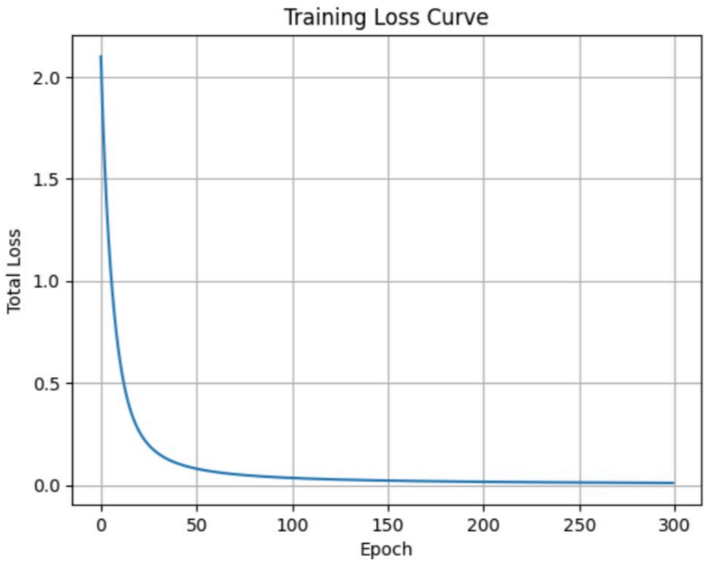
5. (5%) What does the hidden state $s_t$ represent at each time step when processing a sequence of words?
6. (5%) Why are RNNs hard to train?

## Submission :

1. Report: Provide your screenshots of your results in the last pages of this PDF File.
2. Code: Submit your complete Python script in either .py or .ipynb format.
3. Upload both your report and code to the E3 system (**Labs7 In Class Assignment**). Name your files correctly:
    a. Report: StudentID_Lab7_InClass.pdf
    b. Code: StudentID_Lab7_InClass.py or StudentID_Lab7_InClass.ipynb
4. Deadline: 16:20 PM
5. Plagiarism is **strictly prohibited**. Submitting copied work from other students will result in penalties.

## Results and Discussion:

```
Epoch [50/300] - Loss: 0.0816
Epoch [100/300] - Loss: 0.0347
Epoch [150/300] - Loss: 0.0216
Epoch [200/300] - Loss: 0.0156
Epoch [250/300] - Loss: 0.0122
Epoch [300/300] - Loss: 0.0100
```




```
=== Testing ===
Sentence: ['The', 'movie', 'is', 'bad'] -> Prediction: 0
Sentence: ['The', 'movie', 'is', 'good'] -> Prediction: 1
```

5. (5%) What does the hidden state $s_t$ represent at each time step when processing a sequence of words?

at each step, t,

- $S_t = \tanh(W s_{t-1} + U x_t + b)$
  - It is a fixed-size vector that summarize all word up to t
  - It blend the previous memory $S_{t-1}$ with the current input $x_t$
  - At the final step $S_T$ feed into the output layer to predict "good" and "bad"

6. (5%) Why are RNNs hard to train?

- Vanishing gradient: repeated multiplication by W and $\phi'(<1)$ make gradient shrink exponentially, so early input hardly affect the loss.
- Exploding gradient: if those factor exceed 1, gradient blow up, causing instability.
- Sequential dependency: each step depend on the last, limiting parallelization and make optimization sensitive to hyperparameter.