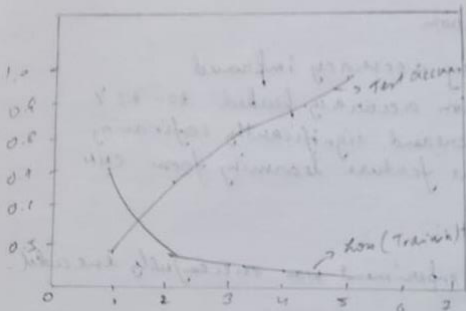


Output : Epoch 1: Loss: 0.6832 Accuracy: 0.4921
 Epoch 2: Loss: 0.0424 Accuracy: 0.8921
 Epoch 3: Loss: 0.0019 Accuracy: 0.7842
 Epoch 4: Loss: 0.0011 Accuracy: 0.8492
 Epoch 5: Loss: 0.0009 Accuracy: 0.9531



30-9-23

Lab 9 Build a Recurrent Neural Network

AIM:

To design, implement and evaluate a RNN model for sequential data, such as text, and analyze its performance.

Pseudo code:

- Load the dataset
- Preprocess data
 - convert sequences into input-output pairs
- Define RNN model:
 - RNN layer + dense output layer with activation
- Compile Model
- Select optimizer
- Train Model
 - Fit data into RNN for given a batch size
- Monitor validation Loss.
- Evaluate Model:
 - Test data
- Visualize result:
 - Plot accuracy and loss curves
 - Conclude observation and results

Observation

- The training accuracy increases with epochs, while the loss decreases.
- Overfitting can occur if too many epochs are used without regularization (dropout)
- RNN captures seq. dependencies better than feedforward networks

- LSTM variants perform more effectively on long sequences due to vanishing gradient mitigation.
- Validation performance depends on dataset complexity and preprocessing quality.

Result:

RNN was successfully built and trained on sequential data. "Successfully implemented".

30/9/23

```
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Commands + Code + Text ▶ Run all

[1] 1 import torch
    2 import torch.nn as nn
    3 import torch.optim as optim
    4 import matplotlib.pyplot as plt
    ✓ 5s

[2] 1 data = torch.tensor([
    2     [0, 1, 2],
    3     [1, 2, 3],
    4     [2, 3, 4]], dtype=torch.float32)
    targets = torch.tensor([
    5     [3], [4], [5]], dtype=torch.float32)
    ✓ 0s

[3] 1 data = data.view(3, 1, 3)
    ✓ 0s

[4] 1 class SimpleRNN(nn.Module):
    2     def __init__(self, input_size, hidden_size, output_size):
    3         super(SimpleRNN, self).__init__()
    4         self.rnn = nn.RNN(input_size, hidden_size, batch_first=True)
    5         self.fc = nn.Linear(hidden_size, output_size)
    6
    7     def forward(self, x):
    8         out, _ = self.rnn(x)
    9         out = self.fc(out[:, -1, :])
    10        return out
    ✓ 0s

[5] 1 input_size = 3
    2 hidden_size = 5
    3 output_size = 1
    4 learning_rate = 0.01
    5 epochs = 200
    ✓ 0s

[6] 1 model = SimpleRNN(input_size, hidden_size, output_size)
    2 criterion = nn.MSELoss()
    3 optimizer = optim.Adam(model.parameters(), lr=learning_rate)
    ✓ 6s

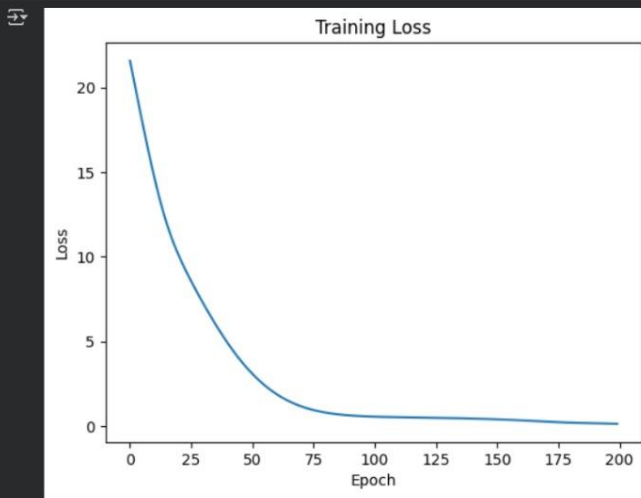
[7] 1 losses = []
    2 for epoch in range(epochs):
    3     optimizer.zero_grad()
    4     output = model(data)
    5     loss = criterion(output, targets)
    6     loss.backward()
    7     optimizer.step()
    8
    9     losses.append(loss.item())
    10    if (epoch+1) % 20 == 0:
    11        print(f'Epoch [{epoch+1}/{epochs}], Loss: {loss.item():.4f}')
    ✓ 0s

Epoch [20/200], Loss: 10.3701
Epoch [40/200], Loss: 5.0838
Epoch [60/200], Loss: 1.9604
Epoch [80/200], Loss: 0.8091
Epoch [100/200], Loss: 0.5502
Epoch [120/200], Loss: 0.4939
Epoch [140/200], Loss: 0.4378
Epoch [160/200], Loss: 0.3354
Epoch [180/200], Loss: 0.1930
Epoch [200/200], Loss: 0.1241

[8] 1 plt.plot(losses)
    2 plt.xlabel('Epoch')
    3 plt.ylabel('Loss')
    ✓ 0s
```

[8]
✓ Os

```
1 plt.plot(losses)
2 plt.xlabel('Epoch')
3 plt.ylabel('Loss')
4 plt.title('Training Loss')
5 plt.show()
```



[9]
✓ Os

```
1 test_input = torch.tensor([[3, 4, 5]], dtype=torch.float32).view(1, 1, 3)
2 pred = model(test_input)
3 print("Prediction for input [3,4,5]:", pred.item())
```

Prediction for input [3,4,5]: 4.472318649291992