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ASM 591 AI

Lab 8

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In [1]:
```
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, Dataset
import numpy as np
import matplotlib.pyplot as plt
```

```
/home/tjw/.local/lib/python3.10/site-packages/matplotlib/projections/__init__.py:6
3: UserWarning: Unable to import Axes3D. This may be due to multiple versions of Ma
tplotlib being installed (e.g. as a system package and as a pip package). As a resu
lt, the 3D projection is not available.
  warnings.warn("Unable to import Axes3D. This may be due to multiple versions of "
```

Solved Example 1: Basic RNN for Sequence Classification

Objective

Build a simple RNN to classify sequences based on their cumulative sum. Sequences with a sum above a threshold belong to class 1; otherwise, class 0.

Dataset

- **Input:** Sequences of real numbers.
- **Output:** Binary class label.

In [2]:
```
class SumDataset(Dataset):
    def __init__(self, num_samples=1000, seq_length=10):
        self.num_samples = num_samples
        self.seq_length = seq_length
        self.threshold = 0.0
        np.random.seed(0)
        self.data = np.random.randn(num_samples, seq_length)
        self.labels = (self.data.sum(axis=1) > self.threshold).astype(int)

    def __len__(self):
        return self.num_samples

    def __getitem__(self, idx):
        sequence = torch.tensor(self.data[idx], dtype=torch.float32).unsqueeze(-1)
        label = torch.tensor(self.labels[idx], dtype=torch.long)
        return sequence, label
```

In [3]:
```
class SimpleRNN(nn.Module):
    def __init__(self, input_size=1, hidden_size=16, num_layers=1, num_classes=2):
```

```python
        super(SimpleRNN, self).__init__()
        self.hidden_size = hidden_size
        self.num_layers = num_layers
        self.rnn = nn.RNN(input_size, hidden_size, num_layers, batch_first=True, n
        self.fc = nn.Linear(hidden_size, num_classes)

    def forward(self, x):
        # Initialize hidden state
        h0 = torch.zeros(self.num_layers, x.size(0), self.hidden_size)

        # Forward propagate RNN
        out, _ = self.rnn(x, h0)  # out: [batch, seq_length, hidden_size]

        # Take the output from the last time step
        out = out[:, -1, :]  # [batch, hidden_size]
        out = self.fc(out)
        return out
```

In [4]:

```python
# Hyperparameters
input_size = 1
hidden_size = 16
num_layers = 1
num_classes = 2
num_epochs = 20
batch_size = 32
learning_rate = 0.001

# Dataset and DataLoader
dataset = SumDataset(num_samples=1000, seq_length=10)
train_loader = DataLoader(dataset, batch_size=batch_size, shuffle=True)

# Model, Loss, Optimizer
model = SimpleRNN(input_size, hidden_size, num_layers, num_classes)
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=learning_rate)

# Training Loop
for epoch in range(num_epochs):
    for sequences, labels in train_loader:
        outputs = model(sequences)
        loss = criterion(outputs, labels)

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

    print(f'Epoch [{epoch+1}/{num_epochs}], Loss: {loss.item():.4f}')
```

```
Epoch [1/20], Loss: 0.7510
Epoch [2/20], Loss: 0.5538
Epoch [3/20], Loss: 0.3179
Epoch [4/20], Loss: 0.2257
Epoch [5/20], Loss: 0.2377
Epoch [6/20], Loss: 0.6048
Epoch [7/20], Loss: 0.2674
Epoch [8/20], Loss: 0.0840
Epoch [9/20], Loss: 0.1239
Epoch [10/20], Loss: 0.2784
Epoch [11/20], Loss: 0.4390
Epoch [12/20], Loss: 0.0643
Epoch [13/20], Loss: 0.0522
Epoch [14/20], Loss: 0.0301
Epoch [15/20], Loss: 0.2004
Epoch [16/20], Loss: 0.1011
Epoch [17/20], Loss: 0.3430
Epoch [18/20], Loss: 0.0099
Epoch [19/20], Loss: 0.1442
Epoch [20/20], Loss: 0.0315
```

In [5]:

```
# Evaluation
with torch.no_grad():
    correct = 0
    total = 0
    for sequences, labels in train_loader:
        outputs = model(sequences)
        _, predicted = torch.max(outputs.data, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()
    print(f'Accuracy: {100 * correct / total:.2f}%')
```

```
Accuracy: 97.00%
```

Solved Example 2: LSTM with Hyperparameter Tuning

Objective

Build an LSTM model to perform sentiment analysis on a simple dataset. Highlight how different hyperparameters impact model performance.

Dataset

For simplicity, we'll create a synthetic dataset where sequences of positive numbers represent positive sentiment and sequences of negative numbers represent negative sentiment.

In [6]:

```
class SentimentDataset(Dataset):
    def __init__(self, num_samples=1000, seq_length=15):
        self.num_samples = num_samples
        self.seq_length = seq_length
        np.random.seed(1)
        # Positive samples
        pos_data = np.random.uniform(0.5, 1.5, size=(num_samples//2, seq_length))
```

```python
        # Negative samples
        neg_data = np.random.uniform(-1.5, -0.5, size=(num_samples//2, seq_length)
        self.data = np.vstack((pos_data, neg_data))
        self.labels = np.hstack((np.ones(num_samples//2), np.zeros(num_samples//2)

    def __len__(self):
        return self.num_samples

    def __getitem__(self, idx):
        sequence = torch.tensor(self.data[idx], dtype=torch.float32).unsqueeze(-1)
        label = torch.tensor(self.labels[idx], dtype=torch.long)
        return sequence, label
```

In [7]:
```python
class LSTMModel(nn.Module):
    def __init__(self, input_size=1, hidden_size=32, num_layers=2, num_classes=2,
        super(LSTMModel, self).__init__()
        self.hidden_size = hidden_size
        self.num_layers = num_layers
        self.lstm = nn.LSTM(input_size, hidden_size, num_layers, batch_first=True,
        self.fc = nn.Linear(hidden_size, num_classes)

    def forward(self, x):
        # Initialize hidden and cell states
        h0 = torch.zeros(self.num_layers, x.size(0), self.hidden_size)
        c0 = torch.zeros(self.num_layers, x.size(0), self.hidden_size)

        # Forward propagate LSTM
        out, _ = self.lstm(x, (h0, c0))  # out: [batch, seq_length, hidden_size]

        # Take the output from the last time step
        out = out[:, -1, :]  # [batch, hidden_size]
        out = self.fc(out)
        return out
```

In [8]:
```python
# Hyperparameters to experiment with
hidden_sizes = [16, 32, 64]
num_layers_list = [1, 2]

for hidden_size in hidden_sizes:
    for num_layers in num_layers_list:
        print(f'\nTraining LSTM with hidden_size={hidden_size}, num_layers={num_la

        model = LSTMModel(input_size=1, hidden_size=hidden_size, num_layers=num_la
        criterion = nn.CrossEntropyLoss()
        optimizer = optim.Adam(model.parameters(), lr=0.001)

        # Dataset and DataLoader
        dataset = SentimentDataset(num_samples=1000, seq_length=15)
        train_loader = DataLoader(dataset, batch_size=32, shuffle=True)

        # Training Loop
        num_epochs = 15
        for epoch in range(num_epochs):
            for sequences, labels in train_loader:
                outputs = model(sequences)
```

```
                loss = criterion(outputs, labels)

                optimizer.zero_grad()
                loss.backward()
                optimizer.step()

        # Evaluation
        with torch.no_grad():
            correct = 0
            total = 0
            for sequences, labels in train_loader:
                outputs = model(sequences)
                _, predicted = torch.max(outputs.data, 1)
                total += labels.size(0)
                correct += (predicted == labels).sum().item()
            accuracy = 100 * correct / total
            print(f'Accuracy: {accuracy:.2f}%')
```

```
Training LSTM with hidden_size=16, num_layers=1
/home/tjw/.local/lib/python3.10/site-packages/torch/nn/modules/rnn.py:123: UserWarning: dropout option adds dropout after all but last recurrent layer, so non-zero dropout expects num_layers greater than 1, but got dropout=0.3 and num_layers=1
  warnings.warn(
Accuracy: 100.00%

Training LSTM with hidden_size=16, num_layers=2
Accuracy: 100.00%

Training LSTM with hidden_size=32, num_layers=1
Accuracy: 100.00%

Training LSTM with hidden_size=32, num_layers=2
Accuracy: 100.00%

Training LSTM with hidden_size=64, num_layers=1
Accuracy: 100.00%

Training LSTM with hidden_size=64, num_layers=2
Accuracy: 100.00%
```

Solved Example 3: GRU with Feature Extraction

Objective

Implement a GRU-based model to predict the next value in a time series, highlighting the role of feature extraction.

In [9]:
```
class SineWaveDataset(Dataset):
    def __init__(self, num_samples=1000, seq_length=50):
        self.num_samples = num_samples
        self.seq_length = seq_length
        self.x = np.linspace(0, 100, num_samples + seq_length)
        self.y = np.sin(self.x) + 0.1 * np.random.randn(len(self.x))
```

```python
    def __len__(self):
        return self.num_samples

    def __getitem__(self, idx):
        sequence = self.y[idx:idx + self.seq_length]
        target = self.y[idx + self.seq_length]
        sequence = torch.tensor(sequence, dtype=torch.float32).unsqueeze(-1)  # [s
        target = torch.tensor(target, dtype=torch.float32)
        return sequence, target
```

In [10]:
```python
class GRUModel(nn.Module):
    def __init__(self, input_size=1, hidden_size=32, num_layers=1, output_size=1,
        super(GRUModel, self).__init__()
        self.conv1 = nn.Conv1d(in_channels=1, out_channels=16, kernel_size=kernel_
        self.relu = nn.ReLU()
        self.gru = nn.GRU(input_size=16, hidden_size=hidden_size, num_layers=num_l
        self.fc = nn.Linear(hidden_size, output_size)

    def forward(self, x):
        # x: [batch, seq_length, 1]
        x = x.permute(0, 2, 1)  # [batch, 1, seq_length]
        x = self.conv1(x)       # [batch, 16, seq_length]
        x = self.relu(x)
        x = x.permute(0, 2, 1)  # [batch, seq_length, 16]
        out, _ = self.gru(x)
        out = out[:, -1, :]     # [batch, hidden_size]
        out = self.fc(out)
        return out
```

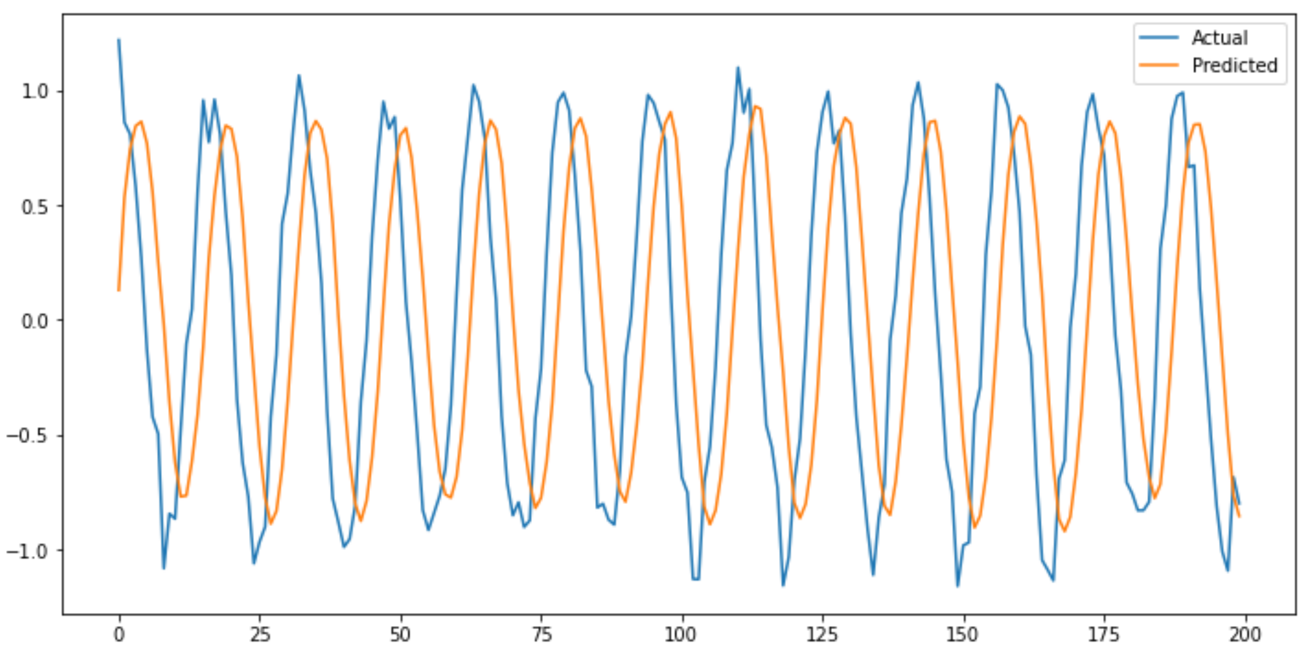
In [11]:
```python
# Hyperparameters
input_size = 1
hidden_size = 32
num_layers = 1
output_size = 1
kernel_size = 3
num_epochs = 30
batch_size = 64
learning_rate = 0.001

# Dataset and DataLoader
dataset = SineWaveDataset(num_samples=1000, seq_length=50)
train_loader = DataLoader(dataset, batch_size=batch_size, shuffle=True)

# Model, Loss, Optimizer
model = GRUModel(input_size, hidden_size, num_layers, output_size, kernel_size)
criterion = nn.MSELoss()
optimizer = optim.Adam(model.parameters(), lr=learning_rate)

# Training Loop
for epoch in range(num_epochs):
    for sequences, targets in train_loader:
        outputs = model(sequences)
        loss = criterion(outputs.squeeze(), targets)

        optimizer.zero_grad()
```

```
        loss.backward()
        optimizer.step()

    if (epoch+1) % 5 == 0:
        print(f'Epoch [{epoch+1}/{num_epochs}], Loss: {loss.item():.4f}')
```

```
Epoch [5/30], Loss: 0.0237
Epoch [10/30], Loss: 0.0144
Epoch [15/30], Loss: 0.0138
Epoch [20/30], Loss: 0.0095
Epoch [25/30], Loss: 0.0097
Epoch [30/30], Loss: 0.0142
```

In [12]:

```
# Evaluation on a new sine wave
model.eval()
with torch.no_grad():
    test_dataset = SineWaveDataset(num_samples=200, seq_length=50)
    test_loader = DataLoader(test_dataset, batch_size=1, shuffle=False)
    predictions = []
    actual = []
    for sequences, targets in test_loader:
        output = model(sequences)
        predictions.append(output.item())
        actual.append(targets.item())

# Plotting
plt.figure(figsize=(12,6))
plt.plot(actual, label='Actual')
plt.plot(predictions, label='Predicted')
plt.legend()
plt.show()
```



Solved Example 4: Combining CNN and LSTM for Text Classification

Objective

Build a text classification model that first uses a Convolutional Neural Network (CNN) for feature extraction from text embeddings, followed by an LSTM to capture sequential dependencies.

In [16]:
```python
import torchtext
from torchtext.datasets import IMDB
from torchtext.data.utils import get_tokenizer
from torchtext.vocab import build_vocab_from_iterator

# Tokenizer and Vocabulary
tokenizer = get_tokenizer('basic_english')
train_iter = IMDB(split='train')

def yield_tokens(data_iter):
    for label, text in data_iter:
        yield tokenizer(text)

vocab = build_vocab_from_iterator(yield_tokens(train_iter), specials=["<unk>"])
vocab.set_default_index(vocab["<unk>"])

# Reload train_iter
train_iter = IMDB(split='train')

# Encoding function
def encode(text):
    return vocab(tokenizer(text))

# Dataset Class
class IMDBDatasetCustom(Dataset):
    def __init__(self, split='train'):
        self.data = list(IMDB(split=split))
        self.labels = [1 if label == 'pos' else 0 for label, _ in self.data]
        self.texts = [encode(text) for _, text in self.data]

    def __len__(self):
        return len(self.labels)

    def __getitem__(self, idx):
        text = self.texts[idx]
        label = self.labels[idx]
        return torch.tensor(text, dtype=torch.long), torch.tensor(label, dtype=tor
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
/tmp/ipykernel_2882423/825108031.py in <module>
      6 # Tokenizer and Vocabulary
      7 tokenizer = get_tokenizer('basic_english')
----> 8 train_iter = IMDB(split='train')
      9 
     10 def yield_tokens(data_iter):

TypeError: IMDB.__init__() missing 3 required positional arguments: 'path', 'text_f
ield', and 'label_field'
```

In [17]:
```python
class CNNLSTMModel(nn.Module):
    def __init__(self, vocab_size, embed_size=128, cnn_out_channels=64, cnn_kernel
                 lstm_hidden_size=128, lstm_num_layers=2, num_classes=2, dropout=0
        super(CNNLSTMModel, self).__init__()
        self.embedding = nn.Embedding(vocab_size, embed_size, padding_idx=0)
        self.conv = nn.Conv1d(in_channels=embed_size, out_channels=cnn_out_channel
```

```
        self.relu = nn.ReLU()
        self.dropout = nn.Dropout(dropout)
        self.lstm = nn.LSTM(input_size=cnn_out_channels, hidden_size=lstm_hidden_s
                            num_layers=lstm_num_layers, batch_first=True, dropout=
        self.fc = nn.Linear(lstm_hidden_size, num_classes)

    def forward(self, x, lengths):
        # x: [batch, seq_length]
        embedded = self.embedding(x)  # [batch, seq_length, embed_size]
        embedded = embedded.permute(0, 2, 1)  # [batch, embed_size, seq_length]
        conv_out = self.conv(embedded)  # [batch, cnn_out_channels, seq_length]
        conv_out = self.relu(conv_out)
        conv_out = conv_out.permute(0, 2, 1)  # [batch, seq_length, cnn_out_channe
        conv_out = self.dropout(conv_out)

        # Pack sequence
        packed_input = nn.utils.rnn.pack_padded_sequence(conv_out, lengths.cpu(),
        packed_output, (hn, cn) = self.lstm(packed_input)
        # Use the last hidden state
        out = self.fc(hn[-1])  # [batch, num_classes]
        return out
```

In [18]:

```
# Collate Function with Padding
from torch.nn.utils.rnn import pad_sequence

def collate_batch(batch):
    texts, labels = zip(*batch)
    lengths = [len(text) for text in texts]
    texts_padded = pad_sequence(texts, batch_first=True, padding_value=0)
    return texts_padded, torch.tensor(labels, dtype=torch.long), torch.tensor(leng
```

In [19]:

```
# Hyperparameters
vocab_size = len(vocab)
embed_size = 128
cnn_out_channels = 64
cnn_kernel_size = 5
lstm_hidden_size = 128
lstm_num_layers = 2
num_classes = 2
dropout = 0.5
num_epochs = 5
batch_size = 64
learning_rate = 0.001

# Dataset and DataLoader
train_dataset = IMDBDatasetCustom(split='train')
train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True, coll

# Model, Loss, Optimizer
model = CNNLSTMModel(vocab_size, embed_size, cnn_out_channels, cnn_kernel_size,
                    lstm_hidden_size, lstm_num_layers, num_classes, dropout)
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=learning_rate)

# Training Loop
```

```
for epoch in range(num_epochs):
    model.train()
    total_loss = 0
    for texts, labels, lengths in train_loader:
        outputs = model(texts, lengths)
        loss = criterion(outputs, labels)

        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        total_loss += loss.item()
    avg_loss = total_loss / len(train_loader)
    print(f'Epoch [{epoch+1}/{num_epochs}], Loss: {avg_loss:.4f}')
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
/tmp/ipykernel_2882423/1712956551.py in <module>
      1 # Hyperparameters
----> 2 vocab_size = len(vocab)
      3 embed_size = 128
      4 cnn_out_channels = 64
      5 cnn_kernel_size = 5

NameError: name 'vocab' is not defined
```

In [20]:

```
# Evaluation on test set
test_dataset = IMDBDatasetCustom(split='test')
test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False, colla

model.eval()
with torch.no_grad():
    correct = 0
    total = 0
    for texts, labels, lengths in test_loader:
        outputs = model(texts, lengths)
        _, predicted = torch.max(outputs.data, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()
    print(f'Test Accuracy: {100 * correct / total:.2f}%')
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
/tmp/ipykernel_2882423/177577601.py in <module>
      1 # Evaluation on test set
----> 2 test_dataset = IMDBDatasetCustom(split='test')
      3 test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=Fals
e, collate_fn=collate_batch)
      4 
      5 model.eval()

NameError: name 'IMDBDatasetCustom' is not defined
```

Problem Set

Problem 1: Building a Bidirectional RNN for Sequence Labeling

Task: Implement a bidirectional RNN using PyTorch to perform part-of-speech tagging on a synthetic dataset. Compare its performance with a unidirectional RNN.

Requirements:

- Create a synthetic dataset where each word is associated with a POS tag.
- Implement both unidirectional and bidirectional RNN models.
- Evaluate and compare their accuracies.

In [35]:
```
DEP = [
    "pnv", # preposition, noun, verb
    "pnvn", # + noun
    "pnvan", # + adjective, noun
    "panv", # preposition, adjective, noun
    "panvan", # + adjective, noun
    "vpn", # verb, prep, noun
    "vpan", # + adjective, noun
    "pan" # prep, adjective, noun
]
IND = [
    "nv", # noun, verb
    "anv", # adjective, noun, verb
    "nvpn", # noun, verb, prep, noun
    "nvpan", # + adjective, noun
    "anvpan", # adjective +
    "anvpn", # adjective + nvpn
]

TYPES = {0: "simple", 1: "compound", 2: "complex", 3: "compound-complex"}
CODES = {
    "a": 1, # adjective
    "c": 2, # conjunction
    "n": 3, # noun
    "p": 4, # preposition
    "v": 5, # verb
    0: "-"  # padding
}


class PosDataset(Dataset):
    def __init__(self, num_samples=1000, max_words=20):
        self.num_samples = num_samples
        self.seq_length = max_words
        np.random.seed(1)

        self.data = []
        self.labels = []
        # Build sentences one phrase at a time
        for _ in range(num_samples):
            label = ""
```

```
            t = np.random.randint(0, 4)
            if TYPES[t] == "simple":
                label += np.random.choice(IND)
            elif TYPES[t] == "compound":
                label += np.random.choice(IND)
                label += "c" # conjunction
                label += np.random.choice(IND)
            elif TYPES[t] == "complex":
                if np.random.randint(0, 2) == 0:    # DI
                    label += np.random.choice(DEP)
                    label += np.random.choice(IND)
                else:                               # ID
                    label += np.random.choice(IND)
                    label += np.random.choice(DEP)
            else: # compound-complex
                t = np.random.randint(0,3)
                if t == 0: # DII
                    label += np.random.choice(DEP)
                    label += np.random.choice(IND)
                    label += "c"
                    label += np.random.choice(IND)
                elif t == 1: # IDI
                    label += np.random.choice(IND)
                    label += np.random.choice(DEP)
                    label += "c"
                    label += np.random.choice(IND)
                elif t == 2: # IID
                    label += np.random.choice(IND)
                    label += "c"
                    label += np.random.choice(IND)
                    label += np.random.choice(DEP)

            # Encode sentences as numbers
            data = [CODES[word] + np.random.uniform(-0.5, 0.5) for word in label]
            outl = [CODES[word] for word in label]

            # Pad every sentence to same length
            while len(data) < max_words:
                data.append(0)
                outl.append(0)

            # Save encoded sequences to dataset
            self.data.append(data)
            self.labels.append(outl)


    def __len__(self):
        return self.num_samples

    def __getitem__(self, idx):
        sequence = torch.tensor(self.data[idx], dtype=torch.float32).unsqueeze(-1)
        label = torch.tensor(self.labels[idx], dtype=torch.float32)
        return sequence, label
```

In [45]:

```
class UniRNN(nn.Module):
    def __init__(self, input_size=1, hidden_size=16, num_layers=1, num_classes=2):
```

```python
        super(UniRNN, self).__init__()
        self.hidden_size = hidden_size
        self.num_layers = num_layers
        self.rnn = nn.RNN(input_size, hidden_size, num_layers, batch_first=True,
                          nonlinearity='relu', bidirectional=False)
        self.fc = nn.Linear(hidden_size, num_classes)

    def forward(self, x):
        # Initialize hidden state
        h0 = torch.zeros(self.num_layers, x.size(0), self.hidden_size)

        # Forward propagate RNN
        out, _ = self.rnn(x, h0)  # out: [batch, seq_length, hidden_size]

        # Take the output from the last time step
        out = out[:, -1, :]  # [batch, hidden_size]
        out = self.fc(out)
        return out

class BiRNN(nn.Module):
    def __init__(self, input_size=1, hidden_size=16, num_layers=1, num_classes=2):
        super(BiRNN, self).__init__()
        self.hidden_size = hidden_size
        self.num_layers = num_layers
        self.rnn = nn.RNN(input_size, hidden_size, num_layers, batch_first=True,
                          nonlinearity='relu', bidirectional=True)
        self.fc = nn.Linear(2*hidden_size, num_classes)

    def forward(self, x):
        # Initialize hidden state
        h0 = torch.zeros(2*self.num_layers, x.size(0), self.hidden_size)

        # Forward propagate RNN
        out, _ = self.rnn(x, h0)  # out: [batch, seq_length, hidden_size]

        # Take the output from the last time step
        out = out[:, -1, :]  # [batch, hidden_size]
        out = self.fc(out)
        return out
```

In [66]:

```python
# Hyperparameters
input_size = 1
hidden_size = 16
num_layers = 1
num_classes = 20
num_epochs = 20
batch_size = 32
learning_rate = 0.001

# Dataset and DataLoader
dataset = PosDataset()
train_loader = DataLoader(dataset, batch_size=batch_size, shuffle=True)

# Model, Loss, Optimizer
unimodel = UniRNN(input_size, hidden_size, num_layers, num_classes)
bimodel = BiRNN(input_size, hidden_size, num_layers, num_classes)
```

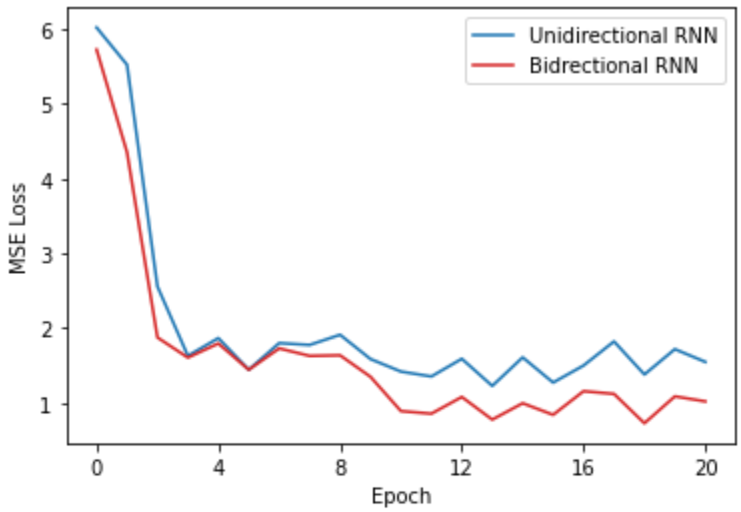
```python
criterion = nn.functional.mse_loss
optimizer1 = optim.Adam(unimodel.parameters(), lr=learning_rate)
optimizer2 = optim.Adam(bimodel.parameters(), lr=learning_rate)

# Log data for later
losses1 = []
losses2 = []

# Training Loop
for epoch in range(num_epochs+1):
    for sequences, labels in train_loader:
        # Train unidirectional model
        output1 = unimodel(sequences)
        loss1 = criterion(output1, labels)
        optimizer1.zero_grad()
        loss1.backward()
        optimizer1.step()

        # Train bidirectional model
        output2 = bimodel(sequences)
        loss2 = criterion(output2, labels)
        optimizer2.zero_grad()
        loss2.backward()
        optimizer2.step()

    losses1.append(loss1.item())
    losses2.append(loss2.item())
    print(f'Epoch [{epoch}/{num_epochs}], Loss: {loss1.item():.04f} & {loss2.item(
```

```
Epoch [0/20], Loss: 6.0240 & 5.7290
Epoch [1/20], Loss: 5.5259 & 4.3549
Epoch [2/20], Loss: 2.5586 & 1.8759
Epoch [3/20], Loss: 1.6301 & 1.6065
Epoch [4/20], Loss: 1.8674 & 1.7954
Epoch [5/20], Loss: 1.4447 & 1.4442
Epoch [6/20], Loss: 1.8008 & 1.7296
Epoch [7/20], Loss: 1.7762 & 1.6295
Epoch [8/20], Loss: 1.9124 & 1.6375
Epoch [9/20], Loss: 1.5874 & 1.3499
Epoch [10/20], Loss: 1.4197 & 0.8907
Epoch [11/20], Loss: 1.3542 & 0.8563
Epoch [12/20], Loss: 1.5907 & 1.0799
Epoch [13/20], Loss: 1.2280 & 0.7768
Epoch [14/20], Loss: 1.6095 & 0.9962
Epoch [15/20], Loss: 1.2726 & 0.8408
Epoch [16/20], Loss: 1.5008 & 1.1573
Epoch [17/20], Loss: 1.8228 & 1.1210
Epoch [18/20], Loss: 1.3807 & 0.7283
Epoch [19/20], Loss: 1.7197 & 1.0878
Epoch [20/20], Loss: 1.5491 & 1.0205
```

In [67]:

```python
plt.plot(losses1, color="tab:blue", label="Unidirectional RNN")
plt.plot(losses2, color="tab:red", label="Bidrectional RNN")
plt.legend()

plt.ylabel("MSE Loss")
```

```
plt.xticks(range(0, num_epochs+1, num_epochs // 5), range(0, num_epochs+1, num_epo
plt.xlabel("Epoch")

plt.show()
```



In [68]:
```
# The Bidirectional RNN converges to more accurate answers
# faster than the Unidirectional RNN does.
```

Problem 2: Exploring Hyperparameter Effects on LSTM Performance

Task: Using the SentimentDataset from Solved Example 2, train multiple LSTM models with varying hyperparameters (e.g., hidden size, number of layers, dropout). Analyze how these hyperparameters affect the model's ability to generalize.

Requirements:

- Experiment with at least three different hidden sizes and two different numbers of layers.
- Plot training and validation accuracies for each configuration.
- Provide insights on the optimal hyperparameter settings based on your observations.

In [89]:
```
num_epochs = 8
learning_rate = 0.0001
accuracies = {}

for hidden_size in [2, 3, 4, 5]:
    for num_layers in [2, 4]:
        # Prepare model + dataset
        print(f'Training LSTM with {hidden_size=} & {num_layers=}')
        model = LSTMModel(1,hidden_size, num_layers)
        criterion = nn.CrossEntropyLoss()
        optimizer = optim.Adam(model.parameters(), lr=learning_rate)
        dataset = SentimentDataset(num_samples=5000)
        train_loader = DataLoader(dataset, batch_size=32, shuffle=True)

        accuracies[(hidden_size, num_layers)] = {}
```

```
        # Training
        for epoch in range(num_epochs):
            correct = 0
            total = 0
            for sequences, labels in train_loader:
                outputs = model(sequences)
                loss = criterion(outputs, labels)

                _, predicted = torch.max(outputs.data, 1)
                total += labels.size(0)
                correct += (predicted == labels).sum().item()

                optimizer.zero_grad()
                loss.backward()
                optimizer.step()
            accuracy = 100 * correct / total
            print(f"\r[{epoch+1}/{num_epochs}] Training " +
                  f"{(hidden_size, num_layers)}... " +
                  f"({accuracy:.2f}% accurate)", end="")

        accuracies[(hidden_size, num_layers)]["training"] = accuracy

        # Testing
        with torch.no_grad():
            correct = 0
            total = 0
            for sequences, labels in train_loader:
                outputs = model(sequences)
                _, predicted = torch.max(outputs.data, 1)
                total += labels.size(0)
                correct += (predicted == labels).sum().item()
            accuracy = 100 * correct / total
            print(f'\n {(hidden_size, num_layers)} Testing Accuracy: {accuracy:.2f

        accuracies[(hidden_size, num_layers)]["testing"] = accuracy
```

```
Training LSTM with hidden_size=2 & num_layers=2
[8/8] Training (2, 2)... (50.00% accurate)
 (2, 2) Testing Accuracy: 50.00%
Training LSTM with hidden_size=2 & num_layers=4
[8/8] Training (2, 4)... (50.00% accurate)
 (2, 4) Testing Accuracy: 50.00%
Training LSTM with hidden_size=3 & num_layers=2
[8/8] Training (3, 2)... (87.94% accurate)
 (3, 2) Testing Accuracy: 88.42%
Training LSTM with hidden_size=3 & num_layers=4
[8/8] Training (3, 4)... (50.00% accurate)
 (3, 4) Testing Accuracy: 50.64%
Training LSTM with hidden_size=4 & num_layers=2
[8/8] Training (4, 2)... (50.00% accurate)
 (4, 2) Testing Accuracy: 50.00%
Training LSTM with hidden_size=4 & num_layers=4
[8/8] Training (4, 4)... (99.86% accurate)
 (4, 4) Testing Accuracy: 99.98%
Training LSTM with hidden_size=5 & num_layers=2
[8/8] Training (5, 2)... (100.00% accurate)
 (5, 2) Testing Accuracy: 100.00%
Training LSTM with hidden_size=5 & num_layers=4
[8/8] Training (5, 4)... (99.98% accurate)
 (5, 4) Testing Accuracy: 100.00%
```

In [90]:

```python
y = [0]
train_bars = []
test_bars = []
for key in accuracies:
    train_bars.append(accuracies[key]["training"])
    test_bars.append(accuracies[key]["testing"])
    y.append(y[-1]+1)
y.pop()
print(f"{train_bars=}")
print(f"{test_bars=}")
```

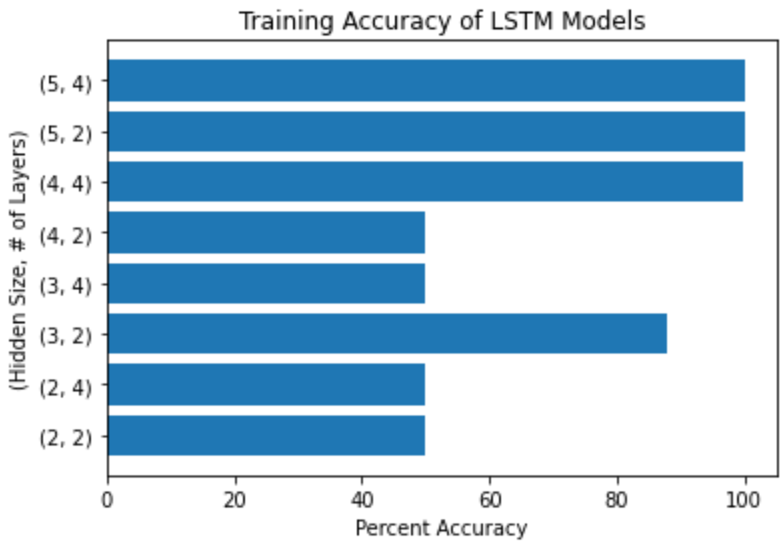
```
train_bars=[50.0, 50.0, 87.94, 50.0, 50.0, 99.86, 100.0, 99.98]
test_bars=[50.0, 50.0, 88.42, 50.64, 50.0, 99.98, 100.0, 100.0]
```

In [91]:

```python
plt.barh(y, train_bars)
plt.yticks(y, list(accuracies.keys()))
plt.ylabel("(Hidden Size, # of Layers)")
plt.xlabel("Percent Accuracy")
plt.title("Training Accuracy of LSTM Models")
```

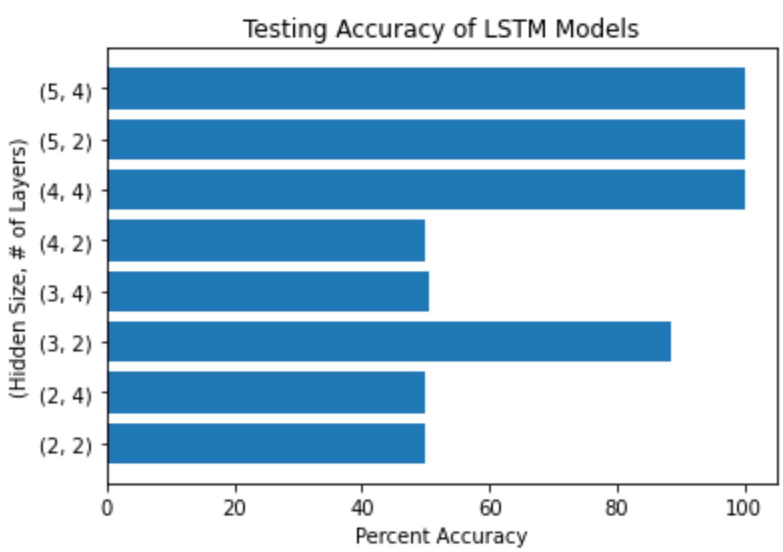
Out[91]:

```
Text(0.5, 1.0, 'Training Accuracy of LSTM Models')
```



In [93]:
```
plt.barh(y, test_bars)
plt.yticks(y, list(accuracies.keys()))
plt.ylabel("(Hidden Size, # of Layers)")
plt.xlabel("Percent Accuracy")
plt.title("Testing Accuracy of LSTM Models")
```

Out[93]:
```
Text(0.5, 1.0, 'Testing Accuracy of LSTM Models')
```



In [ ]:
```
# Based on the results shown above, the accuracy seems to scale more with hidden
# size than number of layers, but both are important. The smallest model that
# still has excellent performance is 4 hidden layers with 4 nodes each.
```

Problem 3: GRU for Multivariate Time Series Forecasting

Task: Apply a GRU model to a multivariate time series dataset (e.g., predicting stock prices using multiple indicators). Highlight the importance of feature extraction in handling multiple input features.

Requirements:

- Choose a real-world multivariate time series dataset.
- Preprocess the data and create appropriate input sequences.
- Implement a GRU model to predict the next value of one of the series.
- Discuss how feature extraction (e.g., normalization, dimensionality reduction) impacts model performance.

In [149…

```python
from sklearn.datasets import fetch_openml

bike_demand = fetch_openml(
    "Kaggle_bike_sharing_demand_challange", version=1, as_frame=True, parser="pand
)

bike_demand.data
```

Out[149…

	time	season	holiday	workingday	weather	temp	atemp	humidity	windspeed	dayOf
0	00:00:00	1	0	0	1	9.84	14.395	81	0.000	zat
1	01:00:00	1	0	0	1	9.02	13.635	80	0.000	zat
2	02:00:00	1	0	0	1	9.02	13.635	80	0.000	zat
3	03:00:00	1	0	0	1	9.84	14.395	75	0.000	zat
4	04:00:00	1	0	0	1	9.84	14.395	75	0.000	zat
...	...	...	...	...	...	...	...	...	...	
10881	19:00:00	4	0	1	1	15.58	19.695	50	260.027	v
10882	20:00:00	4	0	1	1	14.76	17.425	57	150.013	v
10883	21:00:00	4	0	1	1	13.94	15.910	61	150.013	v
10884	22:00:00	4	0	1	1	13.94	17.425	61	60.032	v
10885	23:00:00	4	0	1	1	13.12	16.665	66	89.981	v

10886 rows × 10 columns

In [189…

```python
# Int: Targets
print(type(bike_demand.target[0]))
print(f"{bike_demand.target.min()} - {bike_demand.target.max()}")
```

```
<class 'numpy.int64'>
1 - 977
```

In [148…

```python
# Int: Hour of day
print(type(bike_demand.data["time"][0]))
print(bike_demand.data["time"].unique().tolist())
```

```
<class 'str'>
['00:00:00', '01:00:00', '02:00:00', '03:00:00', '04:00:00', '05:00:00', '06:00:00'
, '07:00:00', '08:00:00', '09:00:00', '10:00:00', '11:00:00', '12:00:00', '13:00:00
', '14:00:00', '15:00:00', '16:00:00', '17:00:00', '18:00:00', '19:00:00', '20:00:0
0', '21:00:00', '22:00:00', '23:00:00']
```

In [152…
```
# Int: Season of year (spring, summer, fall, winter)
print(type(bike_demand.data["season"][0]))
print(bike_demand.data["season"].unique().tolist())
```

```
<class 'str'>
['1', '2', '3', '4']
```

In [154…
```
# Bool: If day is holiday or not
print(type(bike_demand.data["holiday"][0]))
print(bike_demand.data["holiday"].unique().tolist())
```

```
<class 'str'>
['0', '1']
```

In [155…
```
# Bool: If day is not a weekend or holiday
print(type(bike_demand.data["workingday"][0]))
print(bike_demand.data["workingday"].unique().tolist())
```

```
<class 'str'>
['0', '1']
```

In [156…
```
# Int: Hourly weather (clear, mist/fog, rain/snow, heavy rain/hail)
print(type(bike_demand.data["weather"][0]))
print(bike_demand.data["weather"].unique().tolist())
```

```
<class 'str'>
['1', '2', '3', '4']
```

In [160…
```
# Float: Temp in C
print(type(bike_demand.data["temp"][0]))
print(f'{bike_demand.data["temp"].min():0.2f} - {bike_demand.data["temp"].max():0.
```

```
<class 'numpy.float64'>
0.82 - 41.00
```

In [161…
```
# Float: Apparent temp in C
print(type(bike_demand.data["atemp"][0]))
print(f'{bike_demand.data["atemp"].min():0.2f} - {bike_demand.data["atemp"].max():
```

```
<class 'numpy.float64'>
0.76 - 45.45
```

In [166…
```
# Int: Humidity
print(type(bike_demand.data["humidity"][0]))
print(f'{bike_demand.data["humidity"].min()} - {bike_demand.data["humidity"].max()
```

```
<class 'numpy.int64'>
0 - 100
```

In [165…
```
# Float: Wind speed (no units given)
print(type(bike_demand.data["windspeed"][0]))
print(f'{bike_demand.data["windspeed"].min():0.2f} - {bike_demand.data["windspeed"
```

```
<class 'numpy.float64'>
0.00 - 569.97
```

In [172…
```
# Int: Day of week
translate = {
    "zondag": 0,    # sunday
```

```
    "maandag": 1,   # monday
    "dinsdag": 2,   # tuesday
    "woensdag": 3,  # wednesday
    "donderdag": 4, # thursday
    "vrijdag": 5,   # friday
    "zaterdag": 6   # saturday
}
print(" | ".join([str(translate[day]) for day in bike_demand.data["dayOfWeek"].uni
```

```
6 | 0 | 1 | 2 | 4 | 5 | 3
```

In [181…

```
bike_data = torch.zeros(bike_demand.data.shape, dtype=torch.float)

for i in range(bike_demand.data.shape[0]):
    bike_data[i,0] = int(bike_demand.data["time"][i][:2])
    bike_data[i,1] = int(bike_demand.data["season"][i])
    bike_data[i,2] = int(bike_demand.data["holiday"][i])
    bike_data[i,3] = int(bike_demand.data["workingday"][i])
    bike_data[i,4] = int(bike_demand.data["weather"][i])
    bike_data[i,5] = bike_demand.data["temp"][i]
    bike_data[i,6] = bike_demand.data["atemp"][i]
    bike_data[i,7] = bike_demand.data["humidity"][i]
    bike_data[i,8] = bike_demand.data["windspeed"][i]
    bike_data[i,9] = translate[bike_demand.data["dayOfWeek"][i]]

bike_data
```

Out[181…

```
tensor([[  0.0000,   1.0000,   0.0000,  ...,  81.0000,   0.0000,   6.0000],
        [  1.0000,   1.0000,   0.0000,  ...,  80.0000,   0.0000,   6.0000],
        [  2.0000,   1.0000,   0.0000,  ...,  80.0000,   0.0000,   6.0000],
        ...,
        [ 21.0000,   4.0000,   0.0000,  ...,  61.0000, 150.0130,   5.0000],
        [ 22.0000,   4.0000,   0.0000,  ...,  61.0000,  60.0320,   5.0000],
        [ 23.0000,   4.0000,   0.0000,  ...,  66.0000,  89.9810,   5.0000]])
```

In [196…

```
bike_target = torch.tensor(bike_demand.target)
bike_target
```

Out[196…

```
tensor([ 16,  40,  32,  ..., 168, 129,  88])
```

In [402…

```
# Simple 1-D normalization class
class CustomScaler():
    def fit_transform(self, tensor):
        self.offset = torch.mean(tensor, dtype=torch.float)
        self.var = torch.var(tensor)
        return (tensor - self.offset) / self.var

    def inverse_transform(self, tensor):
        return (self.var * tensor) + self.offset
```

In [403…

```
# Create datasets
from torch.utils.data import Dataset, DataLoader
from random import sample

class BikeSet(Dataset):
    def __init__(self, data, targets, ids):
```

```python
        self.X = torch.zeros(size=(len(ids), data.shape[1]), dtype=torch.float)
        self.y = torch.zeros(len(ids))

        for i in range(len(ids)):
            self.X[i,:] = data[ids[i],:]
            self.y[i] = targets[ids[i]]

    def __len__(self):
        return len(self.y)

    def __getitem__(self, idx):
        return self.X[idx, :], self.y[idx]

class BikeSetNorm(Dataset):
    def __init__(self, data, targets, ids):
        self.X = torch.zeros(size=(len(ids), data.shape[1]), dtype=torch.float)
        self.y = torch.zeros(len(ids))

        for i in range(len(ids)):
            self.X[i,:] = data[ids[i],:]
            self.y[i] = targets[ids[i]]

        # Normalize each column of dataset
        self.scalers = []
        for j in range(self.X.shape[1]):
            self.scalers.append(CustomScaler())
            self.X[:,j] = self.scalers[j].fit_transform(self.X[:,j].float())

        # Normalize targets too
        self.scalers.append(CustomScaler())
        self.y = self.scalers[-1].fit_transform(self.y.float())

    def __len__(self):
        return len(self.y)

    def __getitem__(self, idx):
        return self.X[idx, :], self.y[idx]
```

In [404…

```python
# Prepare data loaders
N = len(bike_target)
testN = int(0.2*N)
test_ids = sample(range(N), testN)
train_ids = [i for i in range(N) if i not in test_ids]

# Create datasets
train_set3 = BikeSet(
    data = bike_data,
    targets = bike_target,
    ids = train_ids
)
test_set3 = BikeSet(
    data = bike_data,
    targets = bike_target,
    ids = test_ids
)
```

```python
# Create data loaders
train_data3 = DataLoader(
    dataset = train_set3,
    batch_size = 20,
    shuffle = True
)
test_data3 = DataLoader(
    dataset = test_set3,
    batch_size = 50,
    shuffle = True
)
```

In [405…

```python
# Create NORMALIZED datasets
train_set3n = BikeSetNorm(
    data = bike_data,
    targets = bike_target,
    ids = train_ids
)
test_set3n = BikeSetNorm(
    data = bike_data,
    targets = bike_target,
    ids = test_ids
)

# Create NORMALIZED data loaders
train_data3n = DataLoader(
    dataset = train_set3n,
    batch_size = 20,
    shuffle = True
)
test_data3n = DataLoader(
    dataset = test_set3n,
    batch_size = 50,
    shuffle = True
)
```

In [406…

```python
# Create training function
def train(epoch, model, device, optimizer, data, loss_function):
    # Prepare model
    model.to(device)
    model.train()

    for batch_idx, (X, y) in enumerate(data):
        # Load data into `device`
        X = X.to(device)
        y = y.to(device)
        optimizer.zero_grad()

        # Calculate and record output & loss
        output = model(X).reshape(-1)
        loss = loss_function(output, y)
        loss.backward()
        optimizer.step()

        # Periodically report on training progress
```

```
        print(f"\rEpoch {epoch}: Training {batch_idx * len(X)}/{len(data.dataset)}
              f"(Loss: {loss.item():02.4})", end=" "*10)
    print(f"\rEpoch {epoch}: Trained {len(data.dataset)}/{len(data.dataset)} " +
              f"(Loss: {loss.item():02.4})" + " "*10)
```

In [407…

```
# Create testing function
def test(epoch, model, device, data, loss_function):
    # Prepare model and data
    model.to(device)
    model.eval()
    test_loss = []
    map = []

    with torch.no_grad():
        for batch_idx, (X, y) in enumerate(data):
            # Load data into `device`
            X = X.to(device)
            y = y.to(device)

            # Calculate and record output & loss
            output = model(X).reshape(-1)
            test_loss.append(loss_function(output, y).item())
            map.append(torch.mean(torch.abs((output - y) / y)) * 100)

            # Periodically report on testing progress
            print(f"\rEpoch {epoch}: Testing {batch_idx*len(X)}/{len(data.dataset)
        print(f"\rEpoch {epoch}: Testing {len(data.dataset)}/{len(data.dataset)}")

    # Report results
    test_loss = torch.mean(torch.tensor(test_loss))
    accuracy = torch.mean(torch.tensor(map))
    print(f"Test Result, epoch {epoch}: Avg loss {test_loss:04.4}, MAPE {accuracy:

    return accuracy
```

In [408…

```
# Create NN
import torch.nn as nn
import torch.nn.functional as F

class Problem3Net(nn.Module):
    def __init__(self) -> None:
        super().__init__()
        self.hsize = 24
        hlayers = 10
        self.nn1 = nn.GRU(10, self.hsize, hlayers, batch_first=True)
        self.nn2 = nn.Linear(self.hsize, 1)

    def forward(self, x):
        x, _ = self.nn1(x)
        x = F.relu(x)
        x = self.nn2(x)
        return x
```

In [1]:

```
# Enable GPU acceleration
import torch
```

```python
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
print(device)
```

```
cuda
```

In [411…

```python
# Train models on either dataset or normalized dataset
MAX_EPOCHS = 20
p3net = Problem3Net()
optimizer = torch.optim.Adam(p3net.parameters(), lr=0.01)
p3netNORM = Problem3Net()
optimNORM = torch.optim.Adam(p3netNORM.parameters(), lr=0.01)

for epoch in range(1, MAX_EPOCHS+1):
    # Non-normalized data
    print("-"*10 + "  UNSCALED  " + "-"*10)
    train(
        epoch = epoch,
        model = p3net,
        device = device,
        optimizer = optimizer,
        data = train_data3,
        loss_function = F.mse_loss
    )
    test(
        epoch = epoch,
        model = p3net,
        device = device,
        data = test_data3,
        loss_function = F.mse_loss
    )

    # Normalized data
    print("-"*10 + " NORMALIZED " + "-"*10)
    train(
        epoch = epoch,
        model = p3netNORM,
        device = device,
        optimizer = optimNORM,
        data = train_data3n,
        loss_function = F.mse_loss
    )
    test(
        epoch = epoch,
        model = p3netNORM,
        device = device,
        data = test_data3n,
        loss_function = F.mse_loss
    )
    print("="*52)
```

```
----------  UNSCALED  ----------
Epoch 1: Trained 8709/8709 (Loss: 4.726e+04)
Epoch 1: Testing 2177/2177...
Test Result, epoch 1: Avg loss 5.687e+04, MAPE 154.7%
---------- NORMALIZED ----------
Epoch 1: Trained 8709/8709 (Loss: 1.621e-05)
Epoch 1: Testing 2177/2177...
Test Result, epoch 1: Avg loss 3.626e-05, MAPE 429.4%
====================================================
----------  UNSCALED  ----------
Epoch 2: Trained 8709/8709 (Loss: 6.563e+03)
Epoch 2: Testing 2177/2177...
Test Result, epoch 2: Avg loss 4.843e+04, MAPE 250.6%
---------- NORMALIZED ----------
Epoch 2: Trained 8709/8709 (Loss: 3.863e-05)
Epoch 2: Testing 2177/2177...
Test Result, epoch 2: Avg loss 3.584e-05, MAPE 391.3%
====================================================
----------  UNSCALED  ----------
Epoch 3: Trained 8709/8709 (Loss: 4.725e+04)
Epoch 3: Testing 2177/2177...
Test Result, epoch 3: Avg loss 4.22e+04, MAPE 342.7%
---------- NORMALIZED ----------
Epoch 3: Trained 8709/8709 (Loss: 3.566e-05)
Epoch 3: Testing 2177/2177...
Test Result, epoch 3: Avg loss 3.098e-05, MAPE 152.5%
====================================================
----------  UNSCALED  ----------
Epoch 4: Trained 8709/8709 (Loss: 1.949e+04)
Epoch 4: Testing 2177/2177...
Test Result, epoch 4: Avg loss 3.834e+04, MAPE 420.6%
---------- NORMALIZED ----------
Epoch 4: Trained 8709/8709 (Loss: 1.762e-05)
Epoch 4: Testing 2177/2177...
Test Result, epoch 4: Avg loss 3.172e-05, MAPE 209.5%
====================================================
----------  UNSCALED  ----------
Epoch 5: Trained 8709/8709 (Loss: 7.705e+04)
Epoch 5: Testing 2177/2177...
Test Result, epoch 5: Avg loss 3.546e+04, MAPE 498.2%
---------- NORMALIZED ----------
Epoch 5: Trained 8709/8709 (Loss: 4.563e-05)
Epoch 5: Testing 2177/2177...
Test Result, epoch 5: Avg loss 4.015e-05, MAPE 532.7%
====================================================
----------  UNSCALED  ----------
Epoch 6: Trained 8709/8709 (Loss: 1.851e+04)
Epoch 6: Testing 2177/2177...
Test Result, epoch 6: Avg loss 3.397e+04, MAPE 575.8%
---------- NORMALIZED ----------
Epoch 6: Trained 8709/8709 (Loss: 1.678e-05)
Epoch 6: Testing 2177/2177...
Test Result, epoch 6: Avg loss 3.912e-05, MAPE 502.3%
====================================================
----------  UNSCALED  ----------
Epoch 7: Trained 8709/8709 (Loss: 1.538e+04)
```

```
Epoch 7: Testing 2177/2177...
Test Result, epoch 7: Avg loss 3.31e+04, MAPE 613.7%
---------- NORMALIZED ----------
Epoch 7: Trained 8709/8709 (Loss: 5.798e-06)
Epoch 7: Testing 2177/2177...
Test Result, epoch 7: Avg loss 4.402e-05, MAPE 570.1%
====================================================
----------  UNSCALED  ----------
Epoch 8: Trained 8709/8709 (Loss: 2.123e+04)
Epoch 8: Testing 2177/2177...
Test Result, epoch 8: Avg loss 3.258e+04, MAPE 650.3%
---------- NORMALIZED ----------
Epoch 8: Trained 8709/8709 (Loss: 2.875e-05)
Epoch 8: Testing 2177/2177...
Test Result, epoch 8: Avg loss 3.26e-05, MAPE 250.8%
====================================================
----------  UNSCALED  ----------
Epoch 9: Trained 8709/8709 (Loss: 1.576e+04)
Epoch 9: Testing 2177/2177...
Test Result, epoch 9: Avg loss 3.259e+04, MAPE 679.3%
---------- NORMALIZED ----------
Epoch 9: Trained 8709/8709 (Loss: 6.577e-05)
Epoch 9: Testing 2177/2177...
Test Result, epoch 9: Avg loss 7.882e-05, MAPE 1.12e+03%
====================================================
----------  UNSCALED  ----------
Epoch 10: Trained 8709/8709 (Loss: 1.923e+04)
Epoch 10: Testing 2177/2177...
Test Result, epoch 10: Avg loss 3.226e+04, MAPE 695.7%
---------- NORMALIZED ----------
Epoch 10: Trained 8709/8709 (Loss: 7.578e-05)
Epoch 10: Testing 2177/2177...
Test Result, epoch 10: Avg loss 3.162e-05, MAPE 208.7%
====================================================
----------  UNSCALED  ----------
Epoch 11: Trained 8709/8709 (Loss: 2.223e+04)
Epoch 11: Testing 2177/2177...
Test Result, epoch 11: Avg loss 3.251e+04, MAPE 709.4%
---------- NORMALIZED ----------
Epoch 11: Trained 8709/8709 (Loss: 2.832e-05)
Epoch 11: Testing 2177/2177...
Test Result, epoch 11: Avg loss 3.423e-05, MAPE 346.0%
====================================================
----------  UNSCALED  ----------
Epoch 12: Trained 8709/8709 (Loss: 1.855e+04)
Epoch 12: Testing 2177/2177...
Test Result, epoch 12: Avg loss 3.231e+04, MAPE 712.3%
---------- NORMALIZED ----------
Epoch 12: Trained 8709/8709 (Loss: 2.173e-05)
Epoch 12: Testing 2177/2177...
Test Result, epoch 12: Avg loss 3.516e-05, MAPE 382.5%
====================================================
----------  UNSCALED  ----------
Epoch 13: Trained 8709/8709 (Loss: 2.594e+04)
Epoch 13: Testing 2177/2177...
Test Result, epoch 13: Avg loss 3.248e+04, MAPE 717.8%
```

```
---------- NORMALIZED ----------
Epoch 13: Trained 8709/8709 (Loss: 3.2e-05)
Epoch 13: Testing 2177/2177...
Test Result, epoch 13: Avg loss 3.108e-05, MAPE 156.4%
====================================================
----------  UNSCALED  ----------
Epoch 14: Trained 8709/8709 (Loss: 5.11e+04)
Epoch 14: Testing 2177/2177...
Test Result, epoch 14: Avg loss 3.241e+04, MAPE 714.6%
---------- NORMALIZED ----------
Epoch 14: Trained 8709/8709 (Loss: 2.335e-05)
Epoch 14: Testing 2177/2177...
Test Result, epoch 14: Avg loss 3.809e-05, MAPE 441.4%
====================================================
----------  UNSCALED  ----------
Epoch 15: Trained 8709/8709 (Loss: 1.496e+04)
Epoch 15: Testing 2177/2177...
Test Result, epoch 15: Avg loss 3.239e+04, MAPE 715.9%
---------- NORMALIZED ----------
Epoch 15: Trained 8709/8709 (Loss: 8.55e-05)
Epoch 15: Testing 2177/2177...
Test Result, epoch 15: Avg loss 3.397e-05, MAPE 310.6%
====================================================
----------  UNSCALED  ----------
Epoch 16: Trained 8709/8709 (Loss: 2.287e+04)
Epoch 16: Testing 2177/2177...
Test Result, epoch 16: Avg loss 3.228e+04, MAPE 717.1%
---------- NORMALIZED ----------
Epoch 16: Trained 8709/8709 (Loss: 2.334e-05)
Epoch 16: Testing 2177/2177...
Test Result, epoch 16: Avg loss 3.269e-05, MAPE 277.2%
====================================================
----------  UNSCALED  ----------
Epoch 17: Trained 8709/8709 (Loss: 1.526e+04)
Epoch 17: Testing 2177/2177...
Test Result, epoch 17: Avg loss 3.243e+04, MAPE 730.6%
---------- NORMALIZED ----------
Epoch 17: Trained 8709/8709 (Loss: 3.674e-05)
Epoch 17: Testing 2177/2177...
Test Result, epoch 17: Avg loss 3.248e-05, MAPE 266.3%
====================================================
----------  UNSCALED  ----------
Epoch 18: Trained 8709/8709 (Loss: 4.733e+04)
Epoch 18: Testing 2177/2177...
Test Result, epoch 18: Avg loss 3.232e+04, MAPE 714.9%
---------- NORMALIZED ----------
Epoch 18: Trained 8709/8709 (Loss: 9.717e-05)
Epoch 18: Testing 2177/2177...
Test Result, epoch 18: Avg loss 3.395e-05, MAPE 338.3%
====================================================
----------  UNSCALED  ----------
Epoch 19: Trained 8709/8709 (Loss: 3.873e+04)
Epoch 19: Testing 2177/2177...
Test Result, epoch 19: Avg loss 3.226e+04, MAPE 724.6%
---------- NORMALIZED ----------
Epoch 19: Trained 8709/8709 (Loss: 1.08e-05)
```

```
Epoch 19: Testing 2177/2177...
Test Result, epoch 19: Avg loss 3.112e-05, MAPE 166.1%
====================================================
----------  UNSCALED  ----------
Epoch 20: Trained 8709/8709 (Loss: 4.079e+04)
Epoch 20: Testing 2177/2177...
Test Result, epoch 20: Avg loss 3.229e+04, MAPE 725.2%
---------- NORMALIZED ----------
Epoch 20: Trained 8709/8709 (Loss: 5.009e-05)
Epoch 20: Testing 2177/2177...
Test Result, epoch 20: Avg loss 3.105e-05, MAPE 131.2%
====================================================
```

In [412…

```
# Models trained on normalized data seem to converge better and faster than
# models trained on unscaled data.
```

Problem 4: Integrating CNN and LSTM for Video Classification

Task: Design a model that uses a Convolutional Neural Network (CNN) to extract spatial features from video frames and an LSTM to capture temporal dynamics for video classification.

Requirements:

- Use a dataset of short video clips with classification labels (e.g., action recognition).
- Implement a CNN (e.g., pre-trained ResNet) to extract features from each frame.
- Feed the sequence of extracted features into an LSTM for classification.
- Train and evaluate the model, ensuring that the CNN is properly integrated before the LSTM.

In [2]:

```
# dataset downloaded from https://www.di.ens.fr/~laptev/actions/hollywood2/
import os, torch

path_sets = "/home/tjw/Downloads/Hollywood2/ClipSets"
path_vids = "/home/tjw/Downloads/Hollywood2/AVIClips"

clipset_files = sorted([file for file in os.listdir(path_sets) if
                        ("autotrain" not in file) and ("actions" not in file)])

file_lists = {"train": {}, "test": {}}

for file in clipset_files:
    action, _ = file.split("_")
    if "train" in file:
        file_lists["train"][action] = os.path.join(path_sets, file)
    elif "test" in file:
        file_lists["test"][action] = os.path.join(path_sets, file)

file_lists
```

Out[2]:
```
{'train': {'AnswerPhone': '/home/tjw/Downloads/Hollywood2/ClipSets/AnswerPhone_tr
ain.txt',
  'DriveCar': '/home/tjw/Downloads/Hollywood2/ClipSets/DriveCar_train.txt',
  'Eat': '/home/tjw/Downloads/Hollywood2/ClipSets/Eat_train.txt',
  'FightPerson': '/home/tjw/Downloads/Hollywood2/ClipSets/FightPerson_train.txt',
  'GetOutCar': '/home/tjw/Downloads/Hollywood2/ClipSets/GetOutCar_train.txt',
  'HandShake': '/home/tjw/Downloads/Hollywood2/ClipSets/HandShake_train.txt',
  'HugPerson': '/home/tjw/Downloads/Hollywood2/ClipSets/HugPerson_train.txt',
  'Kiss': '/home/tjw/Downloads/Hollywood2/ClipSets/Kiss_train.txt',
  'Run': '/home/tjw/Downloads/Hollywood2/ClipSets/Run_train.txt',
  'SitDown': '/home/tjw/Downloads/Hollywood2/ClipSets/SitDown_train.txt',
  'SitUp': '/home/tjw/Downloads/Hollywood2/ClipSets/SitUp_train.txt',
  'StandUp': '/home/tjw/Downloads/Hollywood2/ClipSets/StandUp_train.txt'},
 'test': {'AnswerPhone': '/home/tjw/Downloads/Hollywood2/ClipSets/AnswerPhone_tes
t.txt',
  'DriveCar': '/home/tjw/Downloads/Hollywood2/ClipSets/DriveCar_test.txt',
  'Eat': '/home/tjw/Downloads/Hollywood2/ClipSets/Eat_test.txt',
  'FightPerson': '/home/tjw/Downloads/Hollywood2/ClipSets/FightPerson_test.txt',
  'GetOutCar': '/home/tjw/Downloads/Hollywood2/ClipSets/GetOutCar_test.txt',
  'HandShake': '/home/tjw/Downloads/Hollywood2/ClipSets/HandShake_test.txt',
  'HugPerson': '/home/tjw/Downloads/Hollywood2/ClipSets/HugPerson_test.txt',
  'Kiss': '/home/tjw/Downloads/Hollywood2/ClipSets/Kiss_test.txt',
  'Run': '/home/tjw/Downloads/Hollywood2/ClipSets/Run_test.txt',
  'SitDown': '/home/tjw/Downloads/Hollywood2/ClipSets/SitDown_test.txt',
  'SitUp': '/home/tjw/Downloads/Hollywood2/ClipSets/SitUp_test.txt',
  'StandUp': '/home/tjw/Downloads/Hollywood2/ClipSets/StandUp_test.txt'}}
```

In [3]:
```python
def read_clipset(filepath):
    output = {}
    with open(filepath) as file:
        for line in file.readlines():
            clip, num = line.rstrip().split("  ")
            output[clip] = 1 if num == "1" else 0

    return output

test = read_clipset(file_lists["train"]["Eat"])
for i in range(10): print(f"{list(test.keys())[i]}: {test[list(test.keys())[i]]}")
```

```
actioncliptrain00001: 0
actioncliptrain00002: 0
actioncliptrain00003: 0
actioncliptrain00004: 1
actioncliptrain00005: 0
actioncliptrain00006: 0
actioncliptrain00007: 0
actioncliptrain00008: 0
actioncliptrain00009: 0
actioncliptrain00010: 0
```

In [4]:
```python
# Create dataset
from torch.utils.data import Dataset, DataLoader

class VideoSet(Dataset):
    def __init__(self, clipsets, video_folder):
        self.actions = list(clipsets.keys())
```

```python
        self.n_actions = len(self.actions)
        file_values = {}

        # Parse provided documentation
        first = True
        for action in self.actions:
            file_values[action] = read_clipset(clipsets[action])
            if first:
                self.files = list(file_values[action].keys())
                self.n_videos = len(self.files)
                first = False
            elif len(file_values[action]) != self.n_videos:
                print(f"ERROR! {action} has {len(file_values[action])} videos," +
                      f"but previously only found {self.n_videos} per action!")
                raise IndexError

        print(f"Loaded dataset with {self.n_actions} labeled actions")

        # Get targets and save to tensor
        self.y = torch.zeros(size=(self.n_videos, self.n_actions))
        for i in range(len(self.files)):
            for j in range(len(self.actions)):
                video = self.files[i]
                action = self.actions[j]
                self.y[i,j] = file_values[action][video]

        # Get videos and save filepaths to list
        self.X = []
        for file in self.files:
            self.X.append(os.path.join(video_folder, file + ".avi"))


    def __len__(self):
        return self.n_videos

    def __getitem__(self, idx):
        return self.X[idx], self.y[idx, :]
```

In [5]:

```python
# Create data loaders
train_set = VideoSet(file_lists["train"], path_vids)
test_set = VideoSet(file_lists["test"], path_vids)

train_data = DataLoader(
    dataset = train_set,
    batch_size = 1,
    shuffle = True
)
test_data = DataLoader(
    dataset = test_set,
    batch_size = 1,
    shuffle = True
)
```

```
Loaded dataset with 12 labeled actions
Loaded dataset with 12 labeled actions
```

In [6]:

```
import cv2, time
from threading import Thread
from queue import Queue

class FileVideoStream:
    # queue up frames in the background for faster playback
    # adapted from https://pyimagesearch.com/2017/02/06/faster-video-file-fps-with
    def __init__(self, path, queueSize=60):
        self.stream = cv2.VideoCapture(path)
        self.stopped = False
        self.Q = Queue(maxsize=queueSize)

    def more(self): return self.Q.qsize() > 0
    def read(self): return self.Q.get()
    def stop(self): self.stopped = True

    def update(self):
        while True:
            if self.stopped: return
            if not self.Q.full():
                (grabbed,frame) = self.stream.read()
                if not grabbed:
                    self.stop()
                    return
                self.Q.put(frame)

    def start(self):
        t = Thread(target=self.update, args=())
        t.daemon = True
        t.start()
        time.sleep(1.0) # give the queue a second to fill a bit
        return self
```

In [7]:

```
# Create NN
import torch.nn as nn
import torch.nn.functional as F

class Problem4Net(nn.Module):
    def __init__(self):
        super().__init__()
        # Convolutional layers to learn spatial features
        self.conv1 = nn.Conv2d(3, 10, kernel_size=3, padding=1)
        self.conv2 = nn.Conv2d(10, 3, kernel_size=3, padding=3, dilation=2)
        self.conv3 = nn.Conv2d(3, 1, kernel_size=5, padding=2)

        # LSTM network to learn temporal features
        self.rnn1 = nn.LSTM(input_size=1024,
                            hidden_size=64, num_layers=5,
                            bidirectional=True, batch_first=True)

        # And a few FC layers to tie it all together
        self.fc1 = nn.Linear(640, 64)
        self.fc2 = nn.Linear(64, 12)

    def forward(self, x):         # input [B x  3 x 256 x 256]
```

```
        x = F.relu(self.conv1(x)) # shape [B x 10 x 256 x 256]
        x = F.avg_pool2d(x, 2)    # shape [B x 10 x 128 x 128]
        x = F.relu(self.conv2(x)) # shape [B x  3 x 128 x 128]
        x = F.max_pool2d(x, 4)    # shape [B x  3 x  32 x  32]
        x = F.relu(self.conv3(x)) # shape [B x  1 x  32 x  32]
        x = x.reshape(-1, 1024)   # shape [B x 1024]

        _, (x, _) = self.rnn1(x)  # shape [B x 10 x 64]
        x = F.relu(x.reshape(-1, 640))
        x = F.relu(self.fc1(x))       # shape [B x 64]
        x = F.sigmoid(self.fc2(x))    # shape [B x 12]
        return x
```

In [12]:

```
# Create training function
def train(epoch, model, device, optimizer, data, loss_function):
    # Prepare model
    model.to(device)
    model.train()

    for batch_idx, (X, y) in enumerate(data): # batch_size should be 1 ********
        # Load targets into `device`
        y = y.to(device).reshape(-1)
        optimizer.zero_grad()

        # Open video file
        video = FileVideoStream(X[0]).start()
        N = video.stream.get(cv2.CAP_PROP_FRAME_COUNT)
        while video.more():
            # Get frame from queue
            frame = video.read()
            frame = cv2.resize(frame, (256,256)) # make all frames same size
            frame = torch.tensor(frame, device=device, dtype=torch.float)
            frame = frame.permute(2, 0, 1) # put into [C x W x H]

            # Calculate and record output & loss
            output = model(frame).reshape(-1)
            loss = loss_function(output, y)
            loss.backward()
            optimizer.step()
            print(f"\rFrame {video.stream.get(cv2.CAP_PROP_POS_FRAMES):.0f}/{N:.0f

        # Periodically report on training progress
        print(f"\nEpoch {epoch}: Training {batch_idx}/{len(data.dataset)} " +
              f"(Loss: {loss.item():02.4})", end=" "*10)
    print(f"\rEpoch {epoch}: Trained {len(data.dataset)}/{len(data.dataset)} " +
              f"(Loss: {loss.item():02.4})" + " "*10)
```

In [ ]:

```
MAX_EPOCHS = 10
p4net = Problem4Net()
optimizer = torch.optim.Adam(p4net.parameters())

for epoch in range(1, MAX_EPOCHS+1):
    train(
        epoch = epoch,
```

```python
        model = p4net,
        device = device,
        optimizer = optimizer,
        data = train_data,
        loss_function = F.binary_cross_entropy
    )
```

```
Frame 878/878
Frame 777/777
Frame 147/147
Frame 111/111
Frame 552/552
Frame 294/294
Frame 221/221
Frame 311/311
Frame 76/76
```