PA1_CS256_colab

April 21, 2024

1 CSE 256: NLP UCSD PA1:

1.1 Text Classification with Logistic Regression and FF Networks(100points).

The goal of this assignment is to get experience developing text classifiers with with linear models and simple feedforward neural networks. You will see the standard pipeline used in many NLP tasks (reading in data, preprocessing, training, and testing).

- Part 1: PyTorch Basics (25 points)
- Part 2: Logistic Regression and Feedforward Neural Networks (60 points)
- Part 3: Exploration (20 points)

Data. You will using a dataset of movie review snippets taken from IMDB.

1.1.1 Due: April 22, 2024 at 10pm

IMPORTANT: After copying this notebook to your Google Drive, paste a link to it below. To get a publicly-accessible link, click the *Share* button at the top right, then click "Get shareable link" and copy the link.

The Link for the ipynb file: https://drive.google.com/file/d/1-FgHp3sdEWjlor–LZ8GhgrZda4F8or5/view?usp=drive_link

The Link for the whole folder : https://drive.google.com/drive/folders/1AmTF_XRjc6Nlu2h0MwV

Notes:

Make sure to save the notebook as you go along.

Submission instructions are located at the bottom of the notebook.

The code should run fairly quickly (a couple of minutes at most even without a GPU), if it takes much longer than that, its likely that you have introduced an error.

1.2 Mount your Google Drive to Colab

Note: TODO: you need to specify your working foldername in this cell below:

[1]:
```
# This mounts your Google Drive to the Colab VM.
from google.colab import drive
```

```
drive.mount('/content/drive')

import warnings
import os
warnings.filterwarnings("ignore")
# TODO: Enter the foldername  in your Drive where you have saved the unzipped
# assignment folder, e.g. 'cse256/assignments/PA1/'
FOLDERNAME = '/CSE256/CSE256_PA1'
assert FOLDERNAME is not None, "[!] Enter the foldername."

current_directory = os.getcwd()

# Construct the absolute path
absolute_path = os.path.join(current_directory)

print(absolute_path)

# This is later used to use the IMDB reviews
%cd /content/drive/My\ Drive/$FOLDERNAME/
!ls
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
/content
/content/drive/My Drive/CSE256/CSE256_PA1
aclImdb  README.txt
```

2 Part 1: PyTorch Basics (25 Points)

We will use PyTorch, a machine learning framework, for the programming assignmets in this course. The first part of this assigment focuses on PyTorch and how it is used for NLP. If you are new to PyTorch, it is highly recommended to go to work through the 60 minute tutorial

##Question 1.1 (2.5 points)

In state-of-the-art NLP, words are represented by low-dimensional vectors, referred to as *embeddings*. When processing sequences such as sentences, movie, reviews, or entire paragraphs, word embeddings are used to compute a vector representation of the sequence, denoted by x. In the cell below, the embeddings for the words in the sequence "Alice talked to" are provided. Your task is to combine these embeddings into a single vector representation x, using element-wise vector addition. This method is a simple way to obtain a sequence representation, namely, it is a *continuous bag-of-words (BoW) representation* of a sequence.

[2]:
```
import torch
#use gpu if available
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(device)
# This scipy_mode=False is used to avoid scientific notation
```

```python
torch.set_printoptions(sci_mode=False)
# Seed the random number generator for reproducibility
torch.manual_seed(0)

input_sequence = 'I like NLP'

# Initialize an embedding matrix
# We have a vocabulary of 5 words, each represented by a 10-dimensional␣
 ↪embedding vector.
embeddings = torch.nn.Embedding(num_embeddings=5, embedding_dim=10)
vocab = {'I': 0, 'like': 1, 'NLP': 2, 'classifiers': 3, '.': 4}

# Convert the word to integer indices. These indices will be used to
# retrieve the corresponding embeddings from the embedding matrix.
# In PyTorch, operations are performed on Tensor objects, so we need to  convert
# the list of indices to a LongTensor.
indices = torch.LongTensor([vocab[w] for w in input_sequence.split()])
input_sequence_embs = embeddings(indices)
print('sequence embedding tensor size: ', input_sequence_embs.size())

# The input_sequence_embs tensor contains the embeddings for each word in the␣
 ↪input sequence.
# The next step is to aggregate these embeddings into a single vector␣
 ↪representation.
# You will use element-wise addition to do this.
# Write the code to add the embeddings element-wise and store the result in the␣
 ↪variable "x".

print(input_sequence_embs)
x = torch.sum(input_sequence_embs, dim=0)

### DO NOT MODIFY THE LINE BELOW
print('input sequence embedding sum (continuous BoW): ', x)
```

```
cpu
sequence embedding tensor size:  torch.Size([3, 10])
tensor([[-1.1258, -1.1524, -0.2506, -0.4339,  0.8487,  0.6920, -0.3160, -2.1152,
          0.3223, -1.2633],
        [ 0.3500,  0.3081,  0.1198,  1.2377,  1.1168, -0.2473, -1.3527, -1.6959,
          0.5667,  0.7935],
        [ 0.5988, -1.5551, -0.3414,  1.8530,  0.7502, -0.5855, -0.1734,  0.1835,
          1.3894,  1.5863]], grad_fn=<EmbeddingBackward0>)
input sequence embedding sum (continuous BoW):  tensor([-0.1770, -2.3993,
-0.4721,  2.6568,  2.7157, -0.1408, -1.8421, -3.6277,
         2.2783,  1.1165], grad_fn=<SumBackward1>)
```

##Question 1.2 (2.5 points) Element-wise addition is not the best way to aggregate individual word embeddings in a sequence into a single vector representation (a process known as *composition*).

State one significant limitation of using element-wise addition as a composition function for word embeddings? —

Write your answer here (2-3 sentences) One significant limitation of using element-wise addition to aggregate individual word embeddings into a single vector representation is that it does not preserve the order of words in the sequence. This means that sequences with the same words in different orders will result in the same aggregated embedding, potentially losing important syntactic and semantic information. Additionally, this method can lead to an issue known as "swamping," where frequent words overly influence the resulting vector, diminishing the contribution of less frequent but potentially more informative words.

##Question 1.3 (5 points) The softmax function is used in nearly all the neural network architectures we will look at in this course. The softmax is computed on an n-dimensional vector $< x_1, x_2, \ldots, x_n >$ as $\mathrm{softmax}(x_i) = \frac{e^{x_i}}{\sum_{1 \leq j \leq n} e^{x_j}}$. Given the sequence representation x we just computed, we can use the softmax function in combination with a linear projection using a matrix W to transform x into a probability distribution p over the next word, expressed as $p = \mathrm{softmax}(Wx)$. Let's look at this in the cell below:

[3]:
```
# Initialize a random matrix W of size 10x5. This will serve as the weight␣
↪matrix
# for the linear projection of the vector x into a 5-dimensional space.
W = torch.rand(10, 5)


# Project the vector x to a 5-dimensional space using the matrix W. This␣
↪projection is achieved through
# matrix multiplication. After the projection, apply the softmax function to␣
↪the result,
# which converts the 5-dimensional projected vector into a probability␣
↪distribution.
# You can find the softmax function in PyTorch's  API (torch.nn.functional.
↪softmax).
# Store the resulting probability distribution in the variable "probs".

projected_x = torch.matmul(W.T, x)
probs = torch.nn.functional.softmax(projected_x, dim=0)


### DO NOT MODIFY THE BELOW LINE!
print('probability distribution', probs)
```

```
probability distribution tensor([0.0718, 0.0998, 0.1331, 0.6762, 0.0191],
grad_fn=<SoftmaxBackward0>)
```

##Question 1.4 (5 points)

In the example so far, we focused on a single sequence ("I like NLP"). However, in practical applications, it's common to process multiple sequences simultaneously. This practice, known as *batching*, allows for more efficient use of GPU parallelism. In batching, each sequence is considered an example within a larger batch

For this question, you will perform redo the previous computation, but with a batch of two sequences instead of just one. The final output of this cell should be a 2x5 matrix, where each row represents a probability distribution for a sequence. **Important: Avoid using loops in your solution, as you will lose points**. The code should be fully vectorized.

[4]:
```python
import torch
import torch.nn.functional as F

# For this example, we replicate our previous sequence indices to create a␣
 ↪simple batch.
# Normally, each example in the batch would be different.
batch_indices = torch.cat(2 * [indices]).reshape((2, 3))
batch_embs = embeddings(batch_indices)
print('Batch embedding tensor size: ', batch_embs.size())

# To process the batch, follow these steps:
# Step 1: Aggregate the embeddings for each example in the batch into a single␣
 ↪representation.
# This is done through element-wise addition. Use torch.sum with the␣
 ↪appropriate 'dim' argument
# to sum across the sequence length (not the batch dimension).
batch_x = torch.sum(batch_embs, dim=1)

# Step 2: Project each aggregated representation into a 5-dimensional space␣
 ↪using the matrix W.
# This involves matrix multiplication, ensuring the resulting batch has the␣
 ↪shape 2x5.
batch_projected_x = torch.matmul(batch_x, W)

# Step 3: Apply the softmax function to the projected representations to obtain␣
 ↪probability distributions.
# Each row in the output matrix should sum to 1, representing a probability␣
 ↪distribution for each batch example.
batch_probs = F.softmax(batch_projected_x, dim=1)

### DO NOT MODIFY THE BELOW LINE
print("Batch probability distributions:", batch_probs)
```

```
Batch embedding tensor size:  torch.Size([2, 3, 10])
Batch probability distributions: tensor([[0.0718, 0.0998, 0.1331, 0.6762,
0.0191],
        [0.0718, 0.0998, 0.1331, 0.6762, 0.0191]], grad_fn=<SoftmaxBackward0>)
```

##Question 1.5 (5 points)

When processing a text sequence, how should the system handle words that are not present in the existing vocabulary? In the current implementation, the presence of such out-of-vocabulary words causes the code to fail, as in the cell below. To address this issue, a simple solution is to use the special token <UNK>, added to the vocabulary to serve as a placeholder for any unknown words.

Modify the indexing function to ensure that it checks each word against the known vocabulary and substitutes any out-of-vocabulary words with the <UNK> token. Make sure not to add any new words to the vocabulary except for the <UNK> token. Don't forget to adjust the embedding table.

[5]:
```python
import torch

torch.set_printoptions(sci_mode=False)
# Seed the random number generator for reproducibility
torch.manual_seed(0)

input_sequence = 'I like linear'


# Initialize an embedding matrix
# We have a vocabulary of 5 words, each represented by a 10-dimensional embedding vector.
embeddings = torch.nn.Embedding(num_embeddings=6, embedding_dim=10)
vocab = {'I': 0, 'like': 1, 'NLP': 2, 'classifiers': 3, '.': 4, '<UNK>': 5}


indices = torch.LongTensor([vocab[w] if w in vocab else vocab['<UNK>'] for w in input_sequence.split()]) ### MODIFY THIS INDEXING
input_sequence_embs = embeddings(indices)
print('sequence embedding tensor size: ', input_sequence_embs.size())
```

```
sequence embedding tensor size:  torch.Size([3, 10])
```

---

3 Part 2: Logisitic Regression and Feedforward Neural Networks (60 points)

In this part, you are going to experiment with Logistic Regression and Feedforward Neural Networks. Run the starter code to train a two-layer fully connected neural network on the IMDB Sentiment Classification Dataset. The code provided below generates two plots that display the train accuracy and test accuracy. You will build on code to produce different variants.

[6]:
```python
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import os
import time
import scipy.stats
import copy
import torch
```

```
from torch import nn
import torch.nn.functional as F
from torch.utils.data import Dataset
from torch.utils.data import DataLoader
from sklearn.feature_extraction.text import CountVectorizer

########## Neural network class
#
# Network of two fully connected layers
# with ReLU activation function and Softmax output
###########################################

class NN2(nn.Module):
    def __init__(self, input_size, hidden_size):
        super().__init__()
        self.fc1 = nn.Linear(input_size, hidden_size)  # First fully connected␣
 ↪layer.
        self.fc2 = nn.Linear(hidden_size, 2)  # Second fully connected layer,␣
 ↪outputting two classes.

    # Define the forward pass of the neural network.
    # x: The input tensor.
    def forward(self, x):
        x = F.relu(self.fc1(x))  # Apply ReLU activation function after the␣
 ↪first layer.
        x = self.fc2(x)  # Pass the result to the second layer.
        x = F.softmax(x, dim=1)  # Apply Softmax to obtain output probabilities.
        return x
```

[7]:
```
######### ReviewsDataset class
#
# create a dataset to be used for training and evaluation
#########################
# Function to read reviews from a directory
def read_reviews(directory, num_reviews=1000):
    reviews = []
    for filename in os.listdir(directory)[:num_reviews]:  # Limit the number of␣
 ↪files read
        with open(os.path.join(directory, filename), 'r', encoding='utf-8') as␣
 ↪file:
            reviews.append(file.read())
    return reviews


class ReviewsDataset(Dataset):
    def __init__(self, pos_dir, neg_dir, num_reviews=1000, vectorizer=None,␣
 ↪train=True):
```

```
        self.reviews = read_reviews(pos_dir, num_reviews) +␣
↪read_reviews(neg_dir, num_reviews)
        self.labels = [1] * min(num_reviews, len(os.listdir(pos_dir))) + [0] *␣
↪min(num_reviews, len(os.listdir(neg_dir)))
        if train or vectorizer is None:
            self.vectorizer = CountVectorizer(max_features=512)  # Adjust as␣
↪needed
            self.embeddings = self.vectorizer.fit_transform(self.reviews).
↪toarray()
        else:
            self.vectorizer = vectorizer
            self.embeddings = self.vectorizer.transform(self.reviews).toarray()

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

    def __getitem__(self, idx):
        return self.embeddings[idx], self.labels[idx]
```

[8]:

```
########## train_epoch
#
# function that trains for one epoch (one pass through the training set)
######################

def train_epoch(data_loader, model, loss_fn, optimizer):
    size = len(data_loader.dataset)
    num_batches = len(data_loader)
    model.train()
    train_loss, correct = 0, 0
    for batch, (X, y) in enumerate(data_loader):
        X = X.float()
        # Compute prediction error
        pred = model(X)
        loss = loss_fn(pred, y)
        train_loss += loss.item()
        correct += (pred.argmax(1) == y).type(torch.float).sum().item()

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

    average_train_loss = train_loss / num_batches
    accuracy = correct / size
    return accuracy, average_train_loss
```

```python
########## eval_epoch
#
# function that evaluates a model with a test set
######################
def eval_epoch(data_loader, model, loss_fn, optimizer):
    size = len(data_loader.dataset)
    num_batches = len(data_loader)
    model.eval()
    eval_loss = 0
    correct = 0
    for batch, (X, y) in enumerate(data_loader):
        # Compute prediction error
        X = X.float()
        pred = model(X)
        loss = loss_fn(pred, y)
        eval_loss += loss.item()
        correct += (pred.argmax(1) == y).type(torch.float).sum().item()

    average_eval_loss = eval_loss / num_batches
    accuracy = correct / size
    return accuracy, average_eval_loss



########## experiment
#
# function that trains a neural network with a training set
# and evaluates the neural network with a test set
#####################
def experiment(model):

        # negative log likelihood loss function
        loss_fn = nn.NLLLoss()

        # Adam optimizer
        optimizer = torch.optim.Adam(model.parameters(),lr=0.0001)

        average_train_loss = []
        all_train_accuracy = []
        average_test_loss = []
        all_test_accuracy = []
        for epoch in range(150):
                train_accuracy, train_loss = train_epoch(train_loader, model,␣
 ↪loss_fn, optimizer)
                all_train_accuracy += [train_accuracy]
                test_accuracy, test_loss = eval_epoch(test_loader, model,␣
 ↪loss_fn, optimizer)
```

```
                all_test_accuracy += [test_accuracy]
                if epoch % 10 == 9:
                        print(f'Epoch #{epoch+1}: \t train accuracy␣
 ↪{train_accuracy:.3f}\t train loss {train_loss:.3f}\t test accuracy␣
 ↪{test_accuracy:.3f}\t test loss {test_loss:.3f}')
        return all_train_accuracy, all_test_accuracy
```

[9]:
```
######################
#
# 1) Load data splits: the train and test sets
# 2) Train neural networks
# 3) Plot the results
############################

start_time = time.time()

# Load the dataset
absolute_path = os.path.join(current_directory)
root_dir = 'aclImdb/train'
root_dir_test =  'aclImdb/test'
print(root_dir)

train_dataset = ReviewsDataset(root_dir+'/pos', root_dir+'/neg', train=True)
test_dataset = ReviewsDataset(root_dir_test+'/pos', root_dir_test+'/neg',␣
 ↪vectorizer=train_dataset.vectorizer, train=False)

train_loader = DataLoader(train_dataset, batch_size=16, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=16, shuffle=False)

end_time = time.time()
elapsed_time = end_time - start_time

print(f"Time to load data: {elapsed_time} seconds")
```

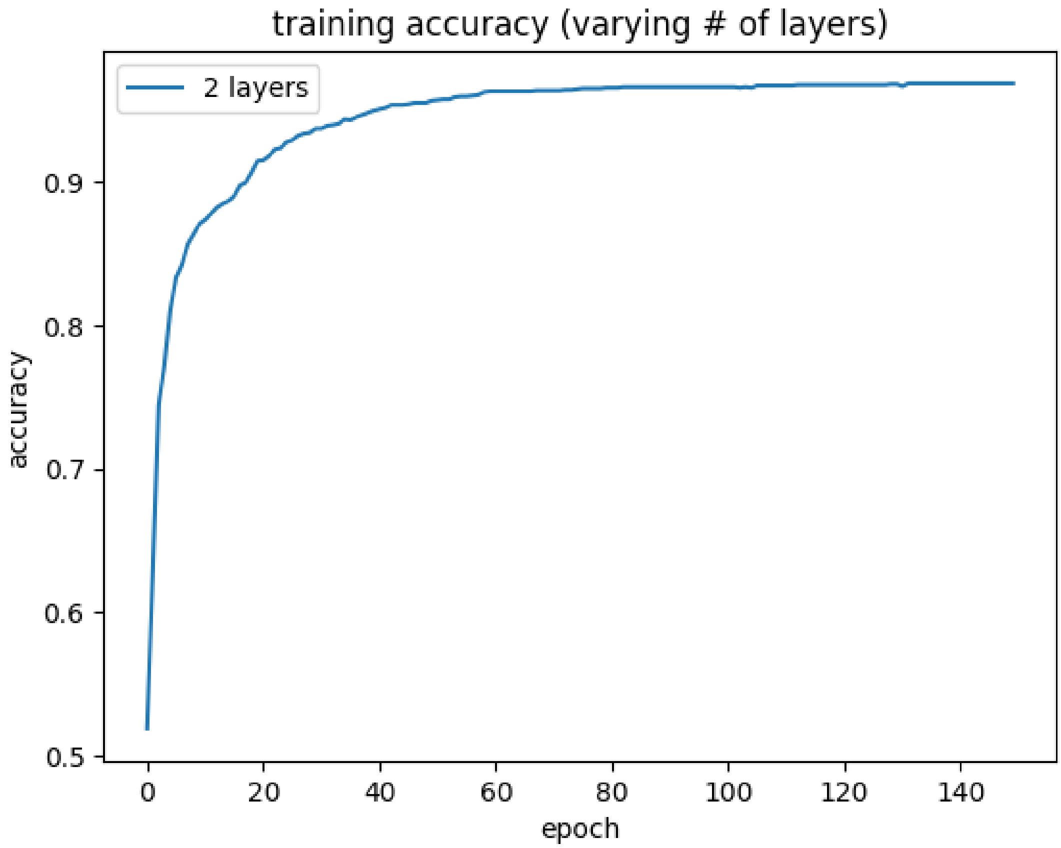
```
aclImdb/train
Time to load data: 148.45341753959656 seconds
```

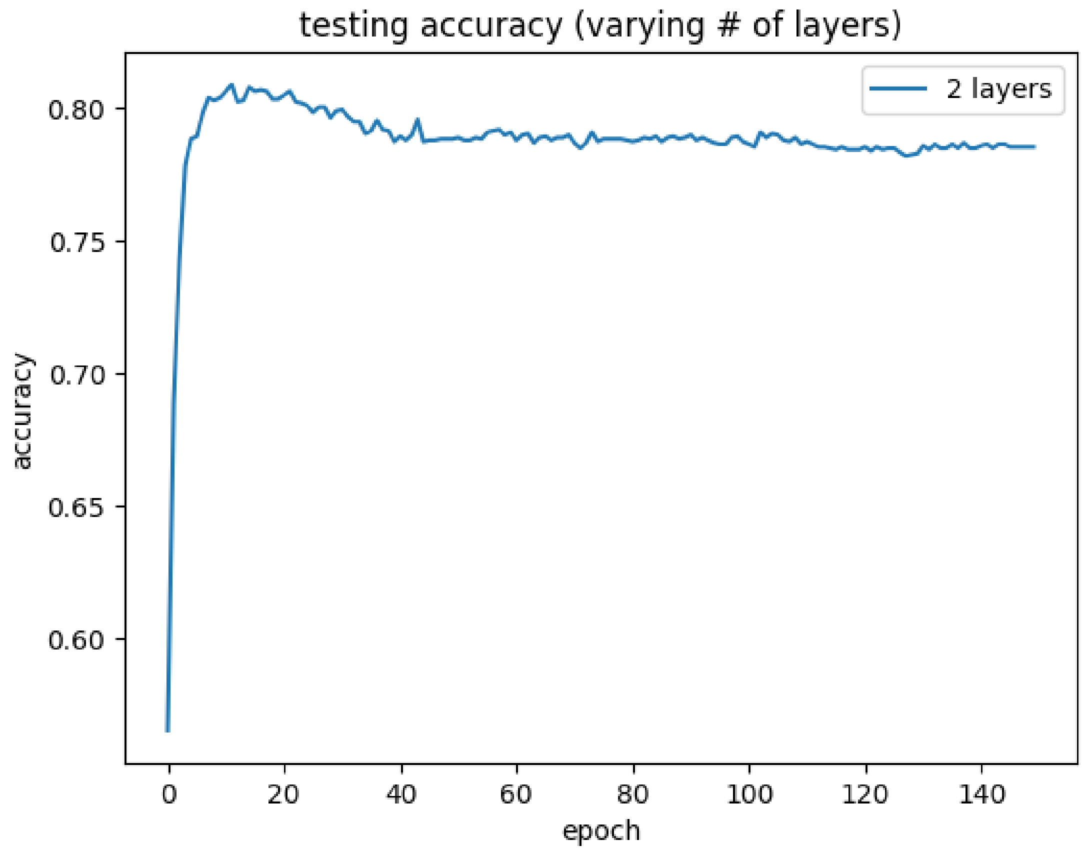
[10]:
```
start_time = time.time()

# train neural networks
print('\n2 layers:')
nn2_train_accuracy, nn2_test_accuracy = experiment(NN2(input_size=512,␣
 ↪hidden_size=100))

# plot training accuracy
plt.plot(nn2_train_accuracy)
plt.title('training accuracy (varying # of layers)')
```

```python
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['2 layers'])
plt.show()

# plot testing accuracy
plt.plot(nn2_test_accuracy)
plt.title('testing accuracy (varying # of layers)')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['2 layers'])
plt.show()


end_time = time.time()
elapsed_time = end_time - start_time

print(f"Time to train, eval model: {elapsed_time} seconds")
```

```
2 layers:
Epoch #10:      train accuracy 0.871    train loss -0.799       test accuracy
0.804     test loss -0.753
Epoch #20:      train accuracy 0.914    train loss -0.870       test accuracy
0.803     test loss -0.782
Epoch #30:      train accuracy 0.937    train loss -0.904       test accuracy
0.799     test loss -0.787
Epoch #40:      train accuracy 0.950    train loss -0.927       test accuracy
0.787     test loss -0.787
Epoch #50:      train accuracy 0.957    train loss -0.942       test accuracy
0.788     test loss -0.787
Epoch #60:      train accuracy 0.963    train loss -0.952       test accuracy
0.791     test loss -0.787
Epoch #70:      train accuracy 0.964    train loss -0.958       test accuracy
0.790     test loss -0.787
Epoch #80:      train accuracy 0.966    train loss -0.962       test accuracy
0.788     test loss -0.787
Epoch #90:      train accuracy 0.966    train loss -0.964       test accuracy
0.789     test loss -0.787
Epoch #100:     train accuracy 0.966    train loss -0.965       test accuracy
0.787     test loss -0.787
Epoch #110:     train accuracy 0.967    train loss -0.966       test accuracy
0.786     test loss -0.786
Epoch #120:     train accuracy 0.968    train loss -0.967       test accuracy
0.784     test loss -0.785
Epoch #130:     train accuracy 0.968    train loss -0.968       test accuracy
0.783     test loss -0.783
Epoch #140:     train accuracy 0.969    train loss -0.968       test accuracy
```

```
0.785     test loss -0.785
Epoch #150:      train accuracy 0.969    train loss -0.968       test accuracy
0.785     test loss -0.784
```






```
Time to train, eval model: 50.90811562538147 seconds
```

3.0.1 TO DO: Impelementation

- Implement and test fully connected networks with 1,2,3, and 4 layers. The starter code above already provides you with an implementation of 2 layers. Each hidden layer should have 100 nodes.
- On the four layer network, modify the code to replace the ReLU activation function with the sigmoid activation function.
- On the four layer network, modify your code to insert a dropout layer with probability 0.5 after each hidden leayer. Tip: see the function nn.dropout().

[11]:
```
class CustomNN(nn.Module):
    def __init__(self, input_size, hidden_size, num_layers=2,␣
 ↪activation='relu', dropout_prob=0.0):
        super().__init__()
        self.activation = activation
        self.num_layers = num_layers
        self.dropout_prob = dropout_prob
        layers = []
```

```
        sizes = [input_size] + [hidden_size] * (num_layers - 1) + [2]

        print(sizes)
        for i in range(num_layers):
            layers.append(nn.Linear(sizes[i], sizes[i+1]))
            if activation == 'relu':
                layers.append(nn.ReLU())
            elif activation == 'sigmoid':
                layers.append(nn.Sigmoid())
            if dropout_prob > 0:
                layers.append(nn.Dropout(dropout_prob))

        self.layers = nn.Sequential(*layers[:-1])  # Exclude the last␣
↪activation or dropout for the output layer

    def forward(self, x):
        for layer in self.layers:
            x = layer(x)
        x = F.softmax(x, dim=1)  # Apply Softmax to obtain output probabilities.
        return x
```

3.1 Question 2.1 Architecture Comparison (20 points)

Generate two plots where the y-axis is the accuracy and the x-axis is the # of epochs. The first plot should include 4 curves that show the training accuracy for 1, 2, 3, and 4 layers. The second plot should include 4 curves that show the testing accuracy for 1, 2, 3, and 4 layers. Use ReLU activation functions without any dropout and 100 nodes per hidden layer. Discuss the results.

[12]:
```
nn1 = CustomNN(input_size=512, hidden_size=100, num_layers=1)
nn2 = CustomNN(input_size=512, hidden_size=100, num_layers=2)
nn3 = CustomNN(input_size=512, hidden_size=100, num_layers=3)
nn4_sigmoid = CustomNN(input_size=512, hidden_size=100, num_layers=4,␣
↪activation='sigmoid', dropout_prob=0.5)
nn4_relu = CustomNN(input_size=512, hidden_size=100, num_layers=4,␣
↪activation='relu')

models = [nn1, nn2, nn3, nn4_sigmoid, nn4_relu]
train_accuracies = []
test_accuracies = []
i = 1

for model in models:
    print(f'Training model with {model.num_layers} layers, {model.activation}␣
↪activation, and dropout probability {model.dropout_prob}')
    i += 1
    train_acc, test_acc = experiment(model)
    train_accuracies.append(train_acc)
```

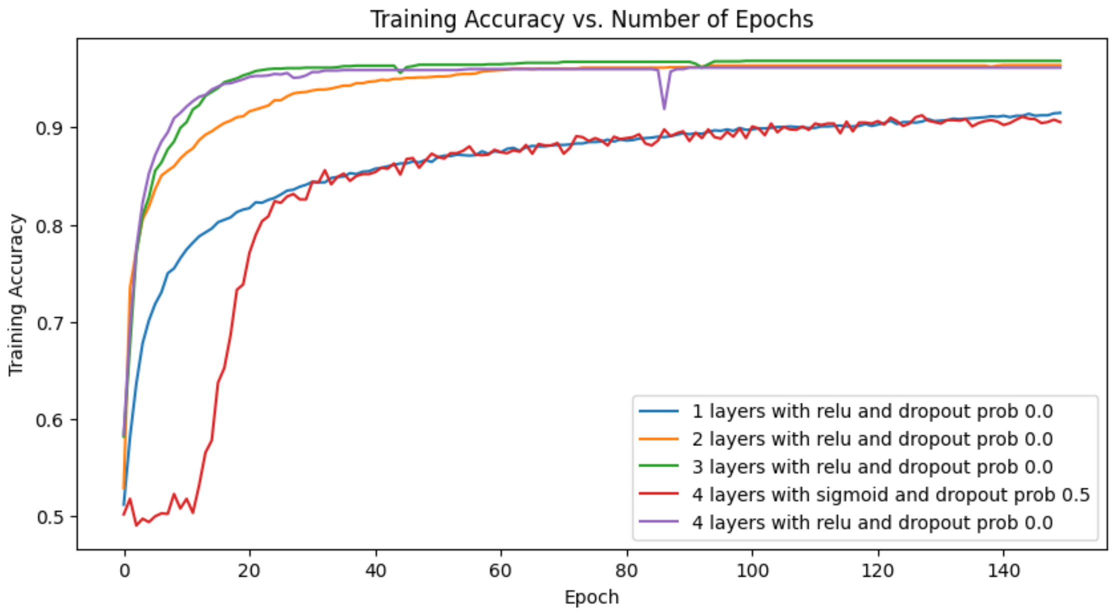
```
    test_accuracies.append(test_acc)

# Plot training accuracies
plt.figure(figsize=(10, 5))
for model, acc in zip(models, train_accuracies):
    label = f'{model.num_layers} layers with {model.activation} and dropout␣
 ↪prob {model.dropout_prob}'
    plt.plot(acc, label=label)
plt.title('Training Accuracy vs. Number of Epochs')
plt.xlabel('Epoch')
plt.ylabel('Training Accuracy')
plt.legend()
plt.show()

# Plot testing accuracies
plt.figure(figsize=(10, 5))
for model, acc in zip(models, test_accuracies):
    label = f'{model.num_layers} layers with {model.activation} and dropout␣
 ↪prob {model.dropout_prob}'
    plt.plot(acc, label=label)
plt.title('Testing Accuracy vs. Number of Epochs')
plt.xlabel('Epoch')
plt.ylabel('Testing Accuracy')
plt.legend()
plt.show()
```

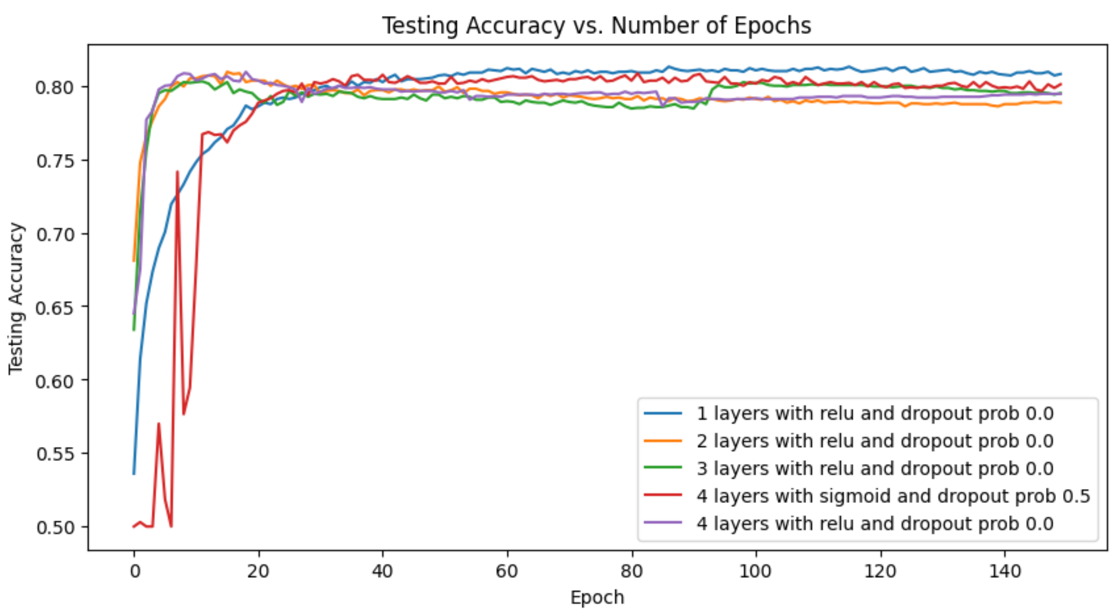
```
[512, 2]
[512, 100, 2]
[512, 100, 100, 2]
[512, 100, 100, 100, 2]
[512, 100, 100, 100, 2]
Training model with 1 layers, relu activation, and dropout probability 0.0
Epoch #10:      train accuracy 0.765    train loss -0.645       test accuracy
0.742    test loss -0.630
Epoch #20:      train accuracy 0.816    train loss -0.707       test accuracy
0.784    test loss -0.677
Epoch #30:      train accuracy 0.841    train loss -0.743       test accuracy
0.797    test loss -0.705
Epoch #40:      train accuracy 0.855    train loss -0.768       test accuracy
0.804    test loss -0.723
Epoch #50:      train accuracy 0.865    train loss -0.786       test accuracy
0.807    test loss -0.736
Epoch #60:      train accuracy 0.875    train loss -0.800       test accuracy
0.810    test loss -0.745
Epoch #70:      train accuracy 0.882    train loss -0.811       test accuracy
0.809    test loss -0.753
Epoch #80:      train accuracy 0.887    train loss -0.821       test accuracy
```

```
0.809     test loss -0.758
Epoch #90:        train accuracy 0.894    train loss -0.829       test accuracy
0.810     test loss -0.762
Epoch #100:       train accuracy 0.897    train loss -0.836       test accuracy
0.812     test loss -0.766
Epoch #110:       train accuracy 0.899    train loss -0.842       test accuracy
0.811     test loss -0.769
Epoch #120:       train accuracy 0.901    train loss -0.847       test accuracy
0.810     test loss -0.771
Epoch #130:       train accuracy 0.906    train loss -0.852       test accuracy
0.810     test loss -0.773
Epoch #140:       train accuracy 0.911    train loss -0.857       test accuracy
0.808     test loss -0.775
Epoch #150:       train accuracy 0.915    train loss -0.861       test accuracy
0.808     test loss -0.776
Training model with 2 layers, relu activation, and dropout probability 0.0
Epoch #10:        train accuracy 0.868    train loss -0.805       test accuracy
0.805     test loss -0.755
Epoch #20:        train accuracy 0.911    train loss -0.871       test accuracy
0.803     test loss -0.782
Epoch #30:        train accuracy 0.936    train loss -0.903       test accuracy
0.800     test loss -0.785
Epoch #40:        train accuracy 0.947    train loss -0.923       test accuracy
0.797     test loss -0.788
Epoch #50:        train accuracy 0.952    train loss -0.936       test accuracy
0.799     test loss -0.789
Epoch #60:        train accuracy 0.959    train loss -0.947       test accuracy
0.795     test loss -0.789
Epoch #70:        train accuracy 0.961    train loss -0.953       test accuracy
0.792     test loss -0.788
Epoch #80:        train accuracy 0.962    train loss -0.957       test accuracy
0.791     test loss -0.789
Epoch #90:        train accuracy 0.962    train loss -0.959       test accuracy
0.789     test loss -0.788
Epoch #100:       train accuracy 0.964    train loss -0.962       test accuracy
0.792     test loss -0.788
Epoch #110:       train accuracy 0.964    train loss -0.963       test accuracy
0.789     test loss -0.787
Epoch #120:       train accuracy 0.964    train loss -0.963       test accuracy
0.788     test loss -0.787
Epoch #130:       train accuracy 0.964    train loss -0.963       test accuracy
0.788     test loss -0.787
Epoch #140:       train accuracy 0.964    train loss -0.962       test accuracy
0.786     test loss -0.786
Epoch #150:       train accuracy 0.964    train loss -0.964       test accuracy
0.788     test loss -0.787
Training model with 3 layers, relu activation, and dropout probability 0.0
Epoch #10:        train accuracy 0.899    train loss -0.867       test accuracy
```

```
0.802    test loss -0.784
Epoch #20:      train accuracy 0.954    train loss -0.941       test accuracy
0.795    test loss -0.789
Epoch #30:      train accuracy 0.962    train loss -0.958       test accuracy
0.794    test loss -0.789
Epoch #40:      train accuracy 0.964    train loss -0.962       test accuracy
0.791    test loss -0.791
Epoch #50:      train accuracy 0.965    train loss -0.964       test accuracy
0.794    test loss -0.792
Epoch #60:      train accuracy 0.965    train loss -0.965       test accuracy
0.789    test loss -0.789
Epoch #70:      train accuracy 0.967    train loss -0.966       test accuracy
0.790    test loss -0.790
Epoch #80:      train accuracy 0.968    train loss -0.967       test accuracy
0.786    test loss -0.788
Epoch #90:      train accuracy 0.968    train loss -0.967       test accuracy
0.785    test loss -0.787
Epoch #100:     train accuracy 0.969    train loss -0.968       test accuracy
0.801    test loss -0.797
Epoch #110:     train accuracy 0.969    train loss -0.968       test accuracy
0.801    test loss -0.796
Epoch #120:     train accuracy 0.969    train loss -0.968       test accuracy
0.799    test loss -0.794
Epoch #130:     train accuracy 0.969    train loss -0.968       test accuracy
0.799    test loss -0.793
Epoch #140:     train accuracy 0.969    train loss -0.968       test accuracy
0.796    test loss -0.792
Epoch #150:     train accuracy 0.969    train loss -0.968       test accuracy
0.795    test loss -0.791
Training model with 4 layers, sigmoid activation, and dropout probability 0.5
Epoch #10:      train accuracy 0.508    train loss -0.501       test accuracy
0.595    test loss -0.501
Epoch #20:      train accuracy 0.739    train loss -0.542       test accuracy
0.781    test loss -0.550
Epoch #30:      train accuracy 0.826    train loss -0.635       test accuracy
0.802    test loss -0.625
Epoch #40:      train accuracy 0.852    train loss -0.655       test accuracy
0.803    test loss -0.635
Epoch #50:      train accuracy 0.873    train loss -0.665       test accuracy
0.801    test loss -0.638
Epoch #60:      train accuracy 0.877    train loss -0.670       test accuracy
0.805    test loss -0.640
Epoch #70:      train accuracy 0.884    train loss -0.673       test accuracy
0.803    test loss -0.640
Epoch #80:      train accuracy 0.888    train loss -0.677       test accuracy
0.807    test loss -0.640
Epoch #90:      train accuracy 0.896    train loss -0.680       test accuracy
0.803    test loss -0.640
```

```
Epoch #100:      train accuracy 0.889   train loss -0.679      test accuracy
0.802    test loss -0.640
Epoch #110:      train accuracy 0.897   train loss -0.682      test accuracy
0.803    test loss -0.640
Epoch #120:      train accuracy 0.904   train loss -0.684      test accuracy
0.802    test loss -0.639
Epoch #130:      train accuracy 0.905   train loss -0.687      test accuracy
0.800    test loss -0.639
Epoch #140:      train accuracy 0.906   train loss -0.686      test accuracy
0.798    test loss -0.639
Epoch #150:      train accuracy 0.905   train loss -0.686      test accuracy
0.801    test loss -0.639
Training model with 4 layers, relu activation, and dropout probability 0.0
Epoch #10:       train accuracy 0.915   train loss -0.895      test accuracy
0.808    test loss -0.797
Epoch #20:       train accuracy 0.950   train loss -0.947      test accuracy
0.804    test loss -0.800
Epoch #30:       train accuracy 0.954   train loss -0.950      test accuracy
0.794    test loss -0.792
Epoch #40:       train accuracy 0.959   train loss -0.959      test accuracy
0.798    test loss -0.795
Epoch #50:       train accuracy 0.959   train loss -0.959      test accuracy
0.795    test loss -0.795
Epoch #60:       train accuracy 0.960   train loss -0.960      test accuracy
0.792    test loss -0.793
Epoch #70:       train accuracy 0.960   train loss -0.960      test accuracy
0.794    test loss -0.794
Epoch #80:       train accuracy 0.960   train loss -0.960      test accuracy
0.796    test loss -0.794
Epoch #90:       train accuracy 0.960   train loss -0.960      test accuracy
0.789    test loss -0.790
Epoch #100:      train accuracy 0.962   train loss -0.961      test accuracy
0.791    test loss -0.791
Epoch #110:      train accuracy 0.962   train loss -0.961      test accuracy
0.792    test loss -0.791
Epoch #120:      train accuracy 0.962   train loss -0.961      test accuracy
0.792    test loss -0.792
Epoch #130:      train accuracy 0.962   train loss -0.961      test accuracy
0.792    test loss -0.792
Epoch #140:      train accuracy 0.962   train loss -0.961      test accuracy
0.793    test loss -0.793
Epoch #150:      train accuracy 0.962   train loss -0.961      test accuracy
0.794    test loss -0.793
```





Analysis and discussion here (< 5 sentences) : From the training accuracy graph, we observe that networks with more layers tend to reach higher accuracy faster. All configurations plateau around the same accuracy, with the 3-layer network slightly outperforming others. Notably, the 4-layer network with a sigmoid activation function and 0.5 dropout probability starts lower but reaches a comparable final accuracy, suggesting that dropout helps prevent overfitting and allows the network to generalize better, despite initial underperformance.

The testing accuracy graph shows that the networks with ReLU activation without dropout generalize similarly, regardless of the number of layers. The 4-layer network with sigmoid and dropout appears to have the least overfitting due to a smaller gap between training and testing accuracy. Despite fluctuations during initial epochs, all networks stabilize, with no clear overfitting indicated by the close alignment of training and testing curves.

3.2 Question 2.2 Activation functions (20 points)

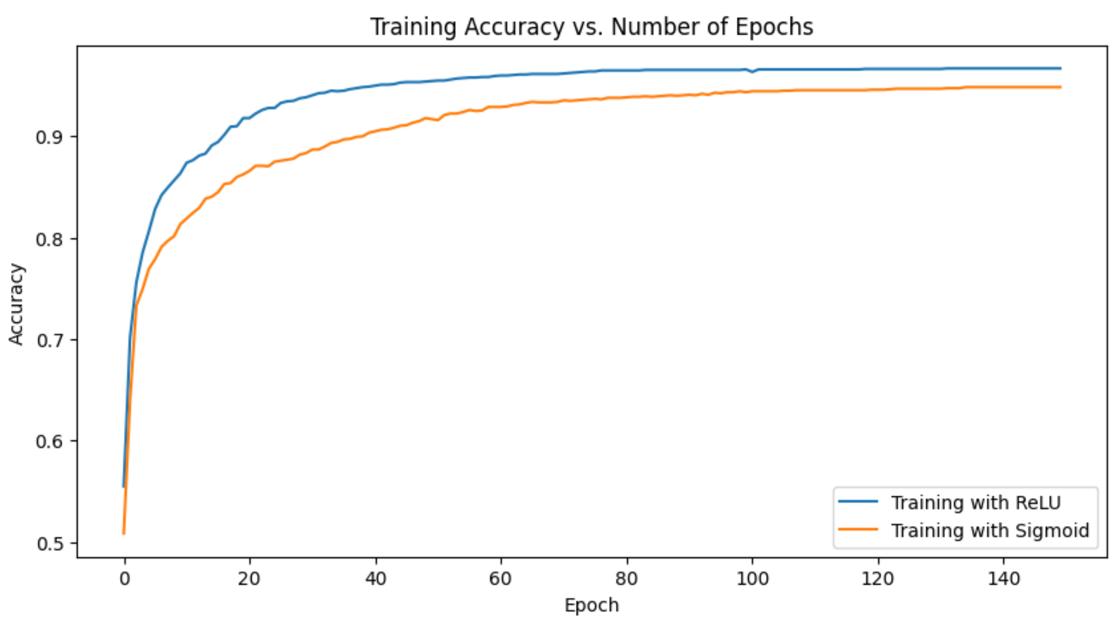
Generate two plots where the y-axis is the accuracy and the x-axis is the # of epochs. The first plot should include 2 curves that show the training accuracy when using the ReLU versus sigmoid activation functions. The second plot should include 2 curves that show the testing accuracy when using the ReLU versus sigmoid activation functions. Use 2 layers and 100 nodes per hidden layer without any dropout. Discuss the results.

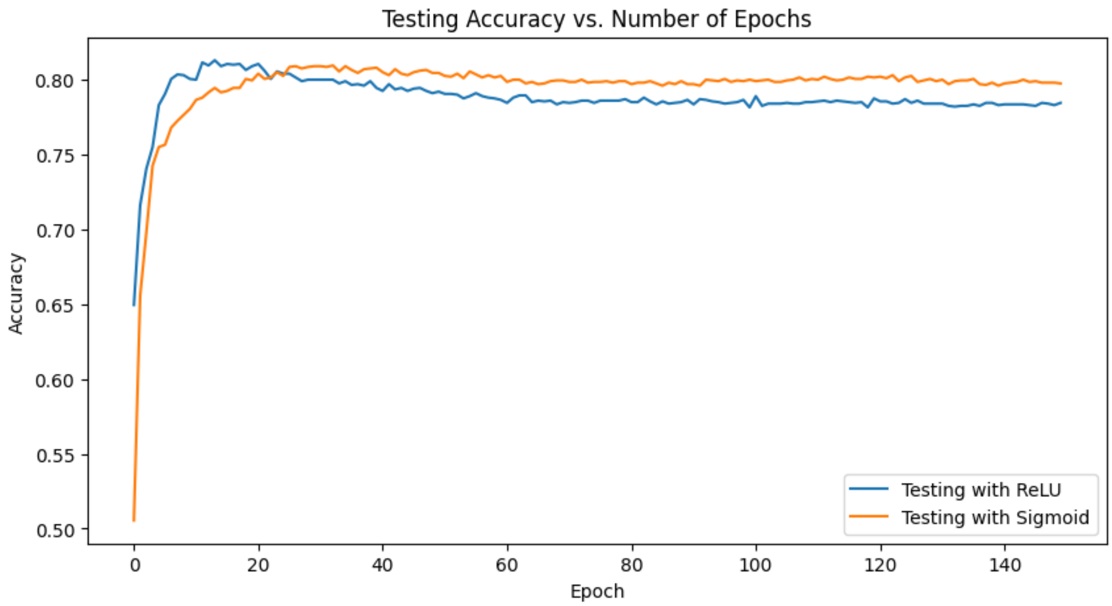
[13]:
```python
# Setting up models with different activations
relu_model = CustomNN(input_size=512, hidden_size=100, num_layers=2,␣
 ↪activation='relu')
sigmoid_model = CustomNN(input_size=512, hidden_size=100, num_layers=2,␣
 ↪activation='sigmoid')

train_relu, test_relu = experiment(relu_model)
train_sigmoid, test_sigmoid = experiment(sigmoid_model)

#print the shape of the train_relu and test_relu
print(np.shape(train_relu))

# Extract accuracies from the nested lists for ReLU
relu_train_accuracies = [np.mean(epoch_acc) for epoch_acc in zip(train_relu)]
relu_test_accuracies = [np.mean(epoch_acc) for epoch_acc in zip(test_relu)]

sigmoid_train_accuracies = [np.mean(epoch_acc) for epoch_acc in␣
 ↪zip(train_sigmoid)]
sigmoid_test_accuracies = [np.mean(epoch_acc) for epoch_acc in␣
 ↪zip(test_sigmoid)]

# Plot training accuracies
plt.figure(figsize=(10, 5))
plt.plot(relu_train_accuracies, label='Training with ReLU')
plt.plot(sigmoid_train_accuracies, label='Training with Sigmoid')
plt.title('Training Accuracy vs. Number of Epochs')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.show()

# Plot testing accuracies
plt.figure(figsize=(10, 5))
```

```
plt.plot(relu_test_accuracies, label='Testing with ReLU')
plt.plot(sigmoid_test_accuracies, label='Testing with Sigmoid')
plt.title('Testing Accuracy vs. Number of Epochs')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```

```
[512, 100, 2]
[512, 100, 2]
Epoch #10:      train accuracy 0.864    train loss -0.802       test accuracy
0.800   test loss -0.752
Epoch #20:      train accuracy 0.918    train loss -0.872       test accuracy
0.809   test loss -0.782
Epoch #30:      train accuracy 0.939    train loss -0.906       test accuracy
0.800   test loss -0.786
Epoch #40:      train accuracy 0.949    train loss -0.927       test accuracy
0.794   test loss -0.787
Epoch #50:      train accuracy 0.955    train loss -0.941       test accuracy
0.792   test loss -0.787
Epoch #60:      train accuracy 0.960    train loss -0.950       test accuracy
0.786   test loss -0.785
Epoch #70:      train accuracy 0.962    train loss -0.956       test accuracy
0.785   test loss -0.784
Epoch #80:      train accuracy 0.965    train loss -0.961       test accuracy
0.787   test loss -0.783
Epoch #90:      train accuracy 0.966    train loss -0.963       test accuracy
0.786   test loss -0.784
Epoch #100:     train accuracy 0.966    train loss -0.964       test accuracy
0.781   test loss -0.784
Epoch #110:     train accuracy 0.966    train loss -0.965       test accuracy
0.785   test loss -0.784
Epoch #120:     train accuracy 0.967    train loss -0.966       test accuracy
0.787   test loss -0.784
Epoch #130:     train accuracy 0.967    train loss -0.966       test accuracy
0.784   test loss -0.783
Epoch #140:     train accuracy 0.967    train loss -0.967       test accuracy
0.783   test loss -0.783
Epoch #150:     train accuracy 0.967    train loss -0.967       test accuracy
0.784   test loss -0.784
Epoch #10:      train accuracy 0.814    train loss -0.693       test accuracy
0.780   test loss -0.672
Epoch #20:      train accuracy 0.863    train loss -0.794       test accuracy
0.799   test loss -0.745
Epoch #30:      train accuracy 0.883    train loss -0.837       test accuracy
0.809   test loss -0.771
Epoch #40:      train accuracy 0.903    train loss -0.863       test accuracy
0.808   test loss -0.782
```

```
Epoch #50:      train accuracy 0.917    train loss -0.881       test accuracy
0.804     test loss -0.787
Epoch #60:      train accuracy 0.929    train loss -0.895       test accuracy
0.802     test loss -0.789
Epoch #70:      train accuracy 0.934    train loss -0.906       test accuracy
0.799     test loss -0.790
Epoch #80:      train accuracy 0.938    train loss -0.914       test accuracy
0.799     test loss -0.791
Epoch #90:      train accuracy 0.941    train loss -0.921       test accuracy
0.797     test loss -0.791
Epoch #100:     train accuracy 0.944    train loss -0.927       test accuracy
0.800     test loss -0.792
Epoch #110:     train accuracy 0.946    train loss -0.932       test accuracy
0.800     test loss -0.793
Epoch #120:     train accuracy 0.946    train loss -0.936       test accuracy
0.801     test loss -0.793
Epoch #130:     train accuracy 0.947    train loss -0.939       test accuracy
0.799     test loss -0.792
Epoch #140:     train accuracy 0.949    train loss -0.942       test accuracy
0.796     test loss -0.792
Epoch #150:     train accuracy 0.949    train loss -0.943       test accuracy
0.797     test loss -0.793
(150,)
```





Analysis and discussion here (< 5 sentences) : In the training accuracy graph, the model using ReLU activation converges faster and achieves a slightly higher final accuracy than the model using Sigmoid activation. This is consistent with the well-known advantage of ReLU in accelerating the convergence of stochastic gradient descent compared to the Sigmoid function due to its non-saturating nature.

The testing accuracy graph reveals that both models generalize similarly to new data, with ReLU having a marginal edge. The Sigmoid model's performance is a bit more volatile, which could be due to the vanishing gradient problem, making it more sensitive to the choice of initial weights and learning rate.

3.3 Question 2.3 Dropout comparison (15 points)

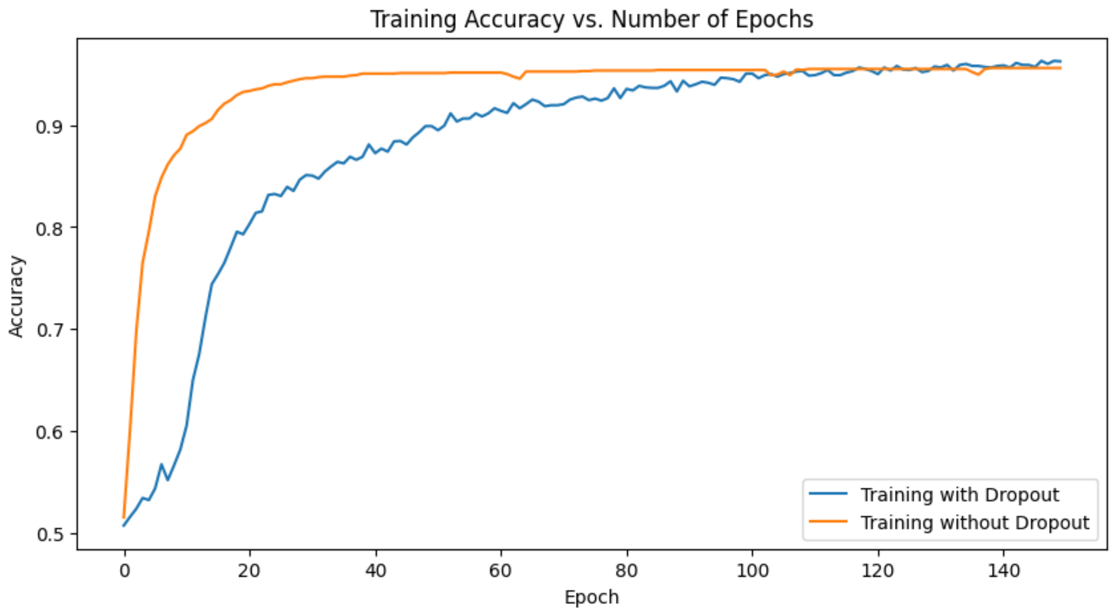
Generate two plots where the y-axis is the accuracy and the x-axis is the # of epochs. The first plot should include 2 curves that show the training accuracy with and without dropout (with probability 0.5) after each hidden layer. The second plot should include 2 curves that show the testing accuracy with and without dropout (with probability 0.5) after each hidden layer. Use 4 layers and 36 nodes per hidden layer with ReLU activation functions. Discuss the results.

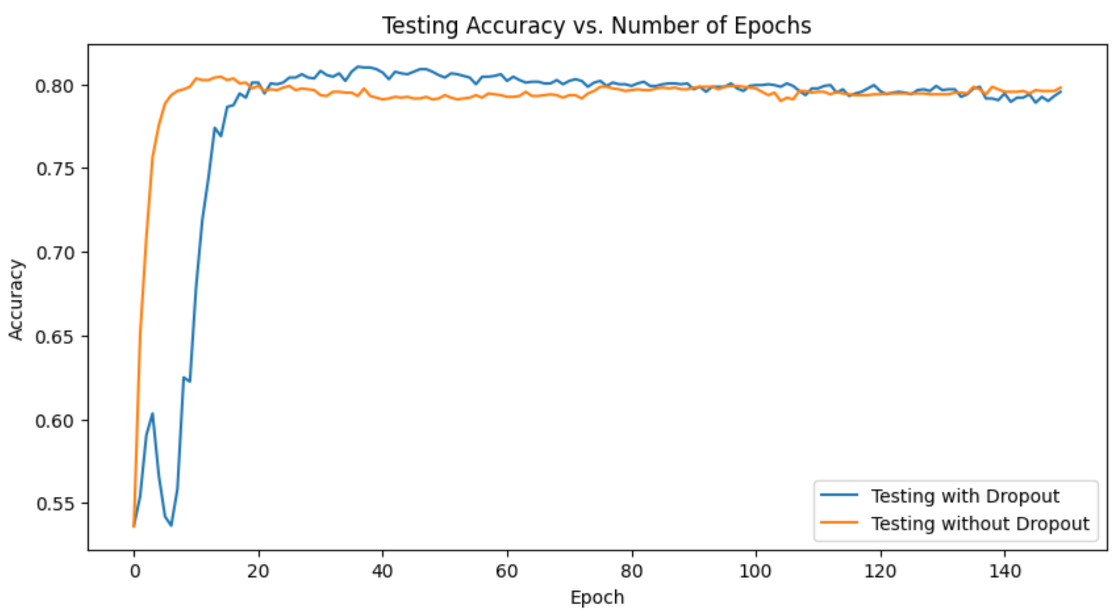
[14]:
```
model_withdropout = CustomNN(input_size=512, hidden_size=36, num_layers=4,␣
  ↪activation='relu', dropout_prob=0.5)
model_withoutdropout = CustomNN(input_size=512, hidden_size=36, num_layers=4,␣
  ↪activation='relu', dropout_prob=0)

train_dropout, test_dropout = experiment(model_withdropout)
train_nodropout, test_nodropout = experiment(model_withoutdropout)
```

```python
dropout_train_accuracies = [np.mean(epoch_acc) for epoch_acc in␣
 ↪zip(train_dropout)]
dropout_test_accuracies = [np.mean(epoch_acc) for epoch_acc in␣
 ↪zip(test_dropout)]

nodropout_train_accuracies = [np.mean(epoch_acc) for epoch_acc in␣
 ↪zip(train_nodropout)]
nodropout_test_accuracies = [np.mean(epoch_acc) for epoch_acc in␣
 ↪zip(test_nodropout)]

# Plot training accuracies
plt.figure(figsize=(10, 5))
plt.plot(dropout_train_accuracies, label='Training with Dropout')
plt.plot(nodropout_train_accuracies, label='Training without Dropout')
plt.title('Training Accuracy vs. Number of Epochs')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.show()

# Plot testing accuracies
plt.figure(figsize=(10, 5))
plt.plot(dropout_test_accuracies, label='Testing with Dropout')
plt.plot(nodropout_test_accuracies, label='Testing without Dropout')
plt.title('Testing Accuracy vs. Number of Epochs')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```

```
[512, 36, 36, 36, 2]
[512, 36, 36, 36, 2]
Epoch #10:       train accuracy 0.582    train loss -0.537       test accuracy
0.623     test loss -0.547
Epoch #20:       train accuracy 0.793    train loss -0.723       test accuracy
0.801     test loss -0.747
Epoch #30:       train accuracy 0.851    train loss -0.820       test accuracy
0.803     test loss -0.792
Epoch #40:       train accuracy 0.881    train loss -0.863       test accuracy
0.809     test loss -0.803
Epoch #50:       train accuracy 0.899    train loss -0.884       test accuracy
0.805     test loss -0.804
Epoch #60:       train accuracy 0.916    train loss -0.904       test accuracy
0.806     test loss -0.803
Epoch #70:       train accuracy 0.919    train loss -0.912       test accuracy
0.800     test loss -0.801
Epoch #80:       train accuracy 0.926    train loss -0.923       test accuracy
```

```
0.800     test loss -0.800
Epoch #90:       train accuracy 0.944    train loss -0.938       test accuracy
0.800     test loss -0.800
Epoch #100:      train accuracy 0.951    train loss -0.946       test accuracy
0.799     test loss -0.797
Epoch #110:      train accuracy 0.949    train loss -0.946       test accuracy
0.797     test loss -0.796
Epoch #120:      train accuracy 0.953    train loss -0.951       test accuracy
0.799     test loss -0.799
Epoch #130:      train accuracy 0.958    train loss -0.955       test accuracy
0.799     test loss -0.798
Epoch #140:      train accuracy 0.958    train loss -0.955       test accuracy
0.790     test loss -0.792
Epoch #150:      train accuracy 0.963    train loss -0.961       test accuracy
0.795     test loss -0.795
Epoch #10:       train accuracy 0.877    train loss -0.844       test accuracy
0.798     test loss -0.778
Epoch #20:       train accuracy 0.932    train loss -0.916       test accuracy
0.797     test loss -0.792
Epoch #30:       train accuracy 0.946    train loss -0.941       test accuracy
0.796     test loss -0.792
Epoch #40:       train accuracy 0.951    train loss -0.948       test accuracy
0.792     test loss -0.793
Epoch #50:       train accuracy 0.951    train loss -0.950       test accuracy
0.791     test loss -0.793
Epoch #60:       train accuracy 0.952    train loss -0.951       test accuracy
0.793     test loss -0.794
Epoch #70:       train accuracy 0.953    train loss -0.952       test accuracy
0.792     test loss -0.794
Epoch #80:       train accuracy 0.954    train loss -0.953       test accuracy
0.796     test loss -0.796
Epoch #90:       train accuracy 0.954    train loss -0.954       test accuracy
0.797     test loss -0.797
Epoch #100:      train accuracy 0.954    train loss -0.954       test accuracy
0.798     test loss -0.796
Epoch #110:      train accuracy 0.955    train loss -0.955       test accuracy
0.795     test loss -0.796
Epoch #120:      train accuracy 0.955    train loss -0.955       test accuracy
0.794     test loss -0.795
Epoch #130:      train accuracy 0.955    train loss -0.955       test accuracy
0.794     test loss -0.795
Epoch #140:      train accuracy 0.956    train loss -0.956       test accuracy
0.797     test loss -0.798
Epoch #150:      train accuracy 0.956    train loss -0.956       test accuracy
0.798     test loss -0.798
```





Analysis and discussion here (< 5 sentences) : In the training accuracy plot, the model without dropout converges to a higher accuracy more quickly compared to the model with dropout. This is a common consequence of dropout, as it is a form of regularization that prevents overfitting by randomly "dropping" a subset of features during each training epoch.

However, when we observe the testing accuracy, both models achieve similar accuracy, with the dropout model showing slightly more stability in its performance over epochs. This stability is indicative of better generalization to unseen data, a desired effect of using dropout. The model without dropout exhibits minor fluctuations, suggesting it may have overfit the training data slightly, although not severely.

3.4 Question 2.4 (5 points)

Now that you have trained a Neural Network classifier, you may find that your testing accuracy is much lower than the training accuracy. In what ways can we decrease this gap? Pick all that apply.

1. Train on a larger dataset.
2. Add more hidden units.
3. Increase the regularization strength.
4. None of the above.

Answer here : 1 and 3

Explanation (< 5 sentences) here: : Train on a larger dataset: Increasing the amount of training data can help the model learn more generalizable patterns rather than memorizing the specifics of a smaller dataset. This is often effective in reducing overfitting. Increase the regularization strength: Regularization techniques (such as L1, L2 regularization, or dropout) add constraints to the network that discourage complex models. This is done by penalizing the loss function for large weights or by randomly dropping units during training, which helps to prevent the model from fitting too closely to the training data.

4 Part 3: Exploration (20 points)

4.1 Question 3.1 Explore (20 points)

There are other aspects to optimizing neural network performance. Explore two here, and discuss your findings. You may also try different neural architures here, other than feedforward networks.

4.1.1 Add a learning rate scheduler

[15]:
```
import torch
import torch.nn as nn
from torch.optim.lr_scheduler import StepLR

def experiment_with_scheduler(model, train_loader, test_loader, epochs=150,␣
↪learning_rate=0.0001, log_interval=10, step_size=30, gamma=0.1):

    # Loss and optimizer
    loss_fn = nn.NLLLoss()
    optimizer = torch.optim.Adam(model.parameters(), lr=learning_rate)

    # Initialize scheduler
    scheduler = StepLR(optimizer, step_size=step_size, gamma=gamma)
```

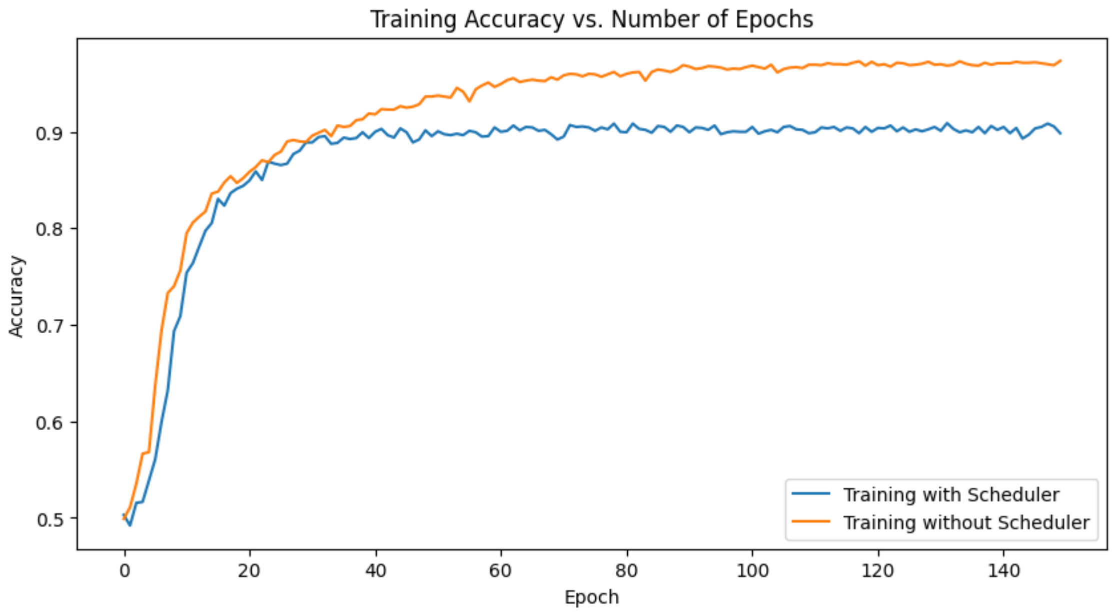
```
    # Metrics
    all_train_accuracy = []
    all_test_accuracy = []

    for epoch in range(epochs):
        train_accuracy, train_loss = train_epoch(train_loader, model, loss_fn,␣
 ↪optimizer)
        test_accuracy, test_loss = eval_epoch(test_loader, model, loss_fn,␣
 ↪optimizer)

        all_train_accuracy.append(train_accuracy)
        all_test_accuracy.append(test_accuracy)

        # Update learning rate
        scheduler.step()

        if epoch % log_interval == log_interval - 1:
            print(f'Epoch #{epoch + 1}: train accuracy {train_accuracy:.3f},␣
 ↪train loss {train_loss:.3f}, test accuracy {test_accuracy:.3f}, test loss␣
 ↪{test_loss:.3f}')

    return all_train_accuracy, all_test_accuracy
```

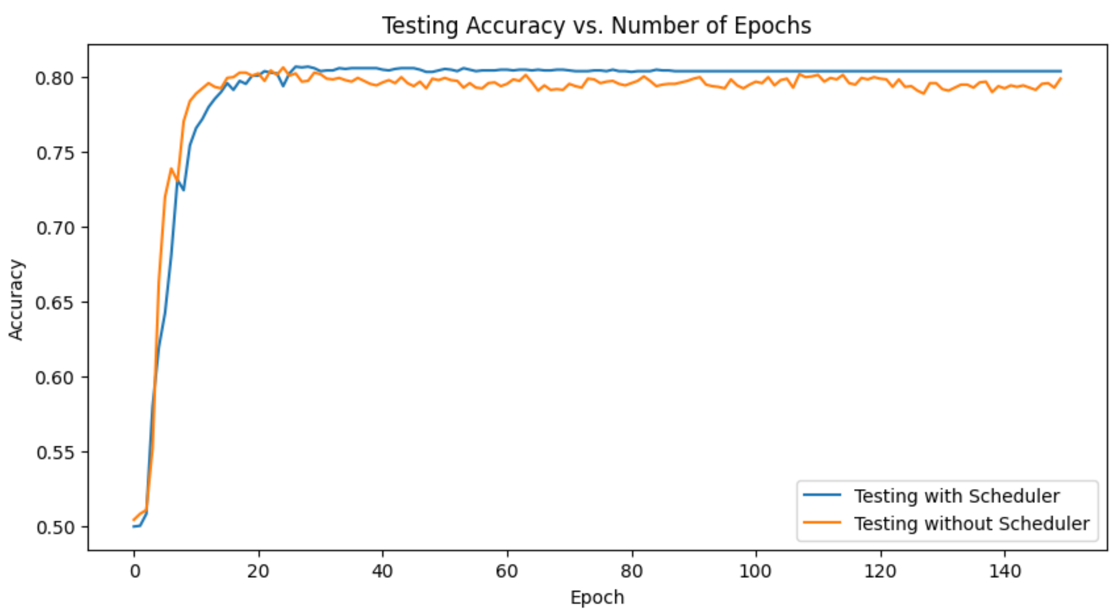
[16]:
```
model_with_scheduler = CustomNN(input_size=512, hidden_size=100, num_layers=4,␣
 ↪activation='relu', dropout_prob=0.5)
model_without_scheduler = CustomNN(input_size=512, hidden_size=100,␣
 ↪num_layers=4, activation='relu', dropout_prob=0.5)

train_scheduler, test_scheduler =␣
 ↪experiment_with_scheduler(model_with_scheduler, train_loader, test_loader)
train_noscheduler, test_noscheduler = experiment(model_without_scheduler)

scheduler_train_accuracies = [np.mean(epoch_acc) for epoch_acc in␣
 ↪zip(train_scheduler)]
scheduler_test_accuracies = [np.mean(epoch_acc) for epoch_acc in␣
 ↪zip(test_scheduler)]

noscheduler_train_accuracies = [np.mean(epoch_acc) for epoch_acc in␣
 ↪zip(train_noscheduler)]
noscheduler_test_accuracies = [np.mean(epoch_acc) for epoch_acc in␣
 ↪zip(test_noscheduler)]


# Plot training accuracies
plt.figure(figsize=(10, 5))
plt.plot(scheduler_train_accuracies, label='Training with Scheduler')
```

```
plt.plot(noscheduler_train_accuracies, label='Training without Scheduler')
plt.title('Training Accuracy vs. Number of Epochs')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.show()

# Plot testing accuracies
plt.figure(figsize=(10, 5))
plt.plot(scheduler_test_accuracies, label='Testing with Scheduler')
plt.plot(noscheduler_test_accuracies, label='Testing without Scheduler')
plt.title('Testing Accuracy vs. Number of Epochs')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```

```
[512, 100, 100, 100, 2]
[512, 100, 100, 100, 2]
Epoch #10: train accuracy 0.709, train loss -0.622, test accuracy 0.754, test
loss -0.672
Epoch #20: train accuracy 0.844, train loss -0.822, test accuracy 0.801, test
loss -0.791
Epoch #30: train accuracy 0.889, train loss -0.875, test accuracy 0.806, test
loss -0.802
Epoch #40: train accuracy 0.893, train loss -0.883, test accuracy 0.806, test
loss -0.803
Epoch #50: train accuracy 0.895, train loss -0.885, test accuracy 0.804, test
loss -0.803
Epoch #60: train accuracy 0.904, train loss -0.894, test accuracy 0.805, test
loss -0.803
Epoch #70: train accuracy 0.892, train loss -0.885, test accuracy 0.805, test
loss -0.803
Epoch #80: train accuracy 0.900, train loss -0.889, test accuracy 0.804, test
loss -0.803
Epoch #90: train accuracy 0.905, train loss -0.894, test accuracy 0.804, test
loss -0.804
Epoch #100: train accuracy 0.900, train loss -0.890, test accuracy 0.804, test
loss -0.804
Epoch #110: train accuracy 0.898, train loss -0.889, test accuracy 0.804, test
loss -0.804
Epoch #120: train accuracy 0.900, train loss -0.889, test accuracy 0.804, test
loss -0.804
Epoch #130: train accuracy 0.905, train loss -0.894, test accuracy 0.804, test
loss -0.804
Epoch #140: train accuracy 0.902, train loss -0.894, test accuracy 0.804, test
loss -0.804
Epoch #150: train accuracy 0.898, train loss -0.891, test accuracy 0.804, test
```

```
loss -0.804
Epoch #10:      train accuracy 0.756    train loss -0.711       test accuracy
0.784    test loss -0.739
Epoch #20:      train accuracy 0.852    train loss -0.840       test accuracy
0.801    test loss -0.794
Epoch #30:      train accuracy 0.889    train loss -0.878       test accuracy
0.803    test loss -0.802
Epoch #40:      train accuracy 0.919    train loss -0.911       test accuracy
0.794    test loss -0.795
Epoch #50:      train accuracy 0.936    train loss -0.931       test accuracy
0.798    test loss -0.798
Epoch #60:      train accuracy 0.947    train loss -0.943       test accuracy
0.794    test loss -0.794
Epoch #70:      train accuracy 0.954    train loss -0.952       test accuracy
0.791    test loss -0.793
Epoch #80:      train accuracy 0.958    train loss -0.955       test accuracy
0.794    test loss -0.795
Epoch #90:      train accuracy 0.969    train loss -0.967       test accuracy
0.797    test loss -0.797
Epoch #100:     train accuracy 0.967    train loss -0.966       test accuracy
0.795    test loss -0.795
Epoch #110:     train accuracy 0.970    train loss -0.968       test accuracy
0.800    test loss -0.799
Epoch #120:     train accuracy 0.973    train loss -0.971       test accuracy
0.800    test loss -0.800
Epoch #130:     train accuracy 0.970    train loss -0.969       test accuracy
0.796    test loss -0.795
Epoch #140:     train accuracy 0.971    train loss -0.970       test accuracy
0.794    test loss -0.793
Epoch #150:     train accuracy 0.974    train loss -0.973       test accuracy
0.799    test loss -0.796
```





Analysis and discussion here ($<$ 15 sentences) : In the experiment, a learning rate scheduler was applied to a neural network during training, and its performance was compared against an identical network trained without a scheduler. The scheduler's purpose is to adjust the learning rate at certain intervals, which theoretically helps the model to converge more effectively by taking larger steps when far from the optimum and smaller steps when closer.

The training accuracy plot indicates that the scheduler may contribute to a faster initial increase in accuracy. This suggests that the learning rate adjustments are helping the network to avoid early plateaus or local minima that can trap the optimization process when using a constant learning rate.

For testing accuracy, both models display similar performance throughout training, indicating that the learning rate scheduler does not have a significant detrimental effect on the network's ability to generalize. In fact, there are points where the model with the scheduler appears to have a smoother accuracy curve, which might imply enhanced stability in learning due to the adjusted learning rate steps.

The periodic drops in training accuracy for the model with the scheduler correspond to the points at which the learning rate is reduced. These drops are followed by recovery, demonstrating the model's ability to refine its parameters in response to the new learning rate, which may lead to better generalization in some cases.

4.1.2 Add a L2 regularization

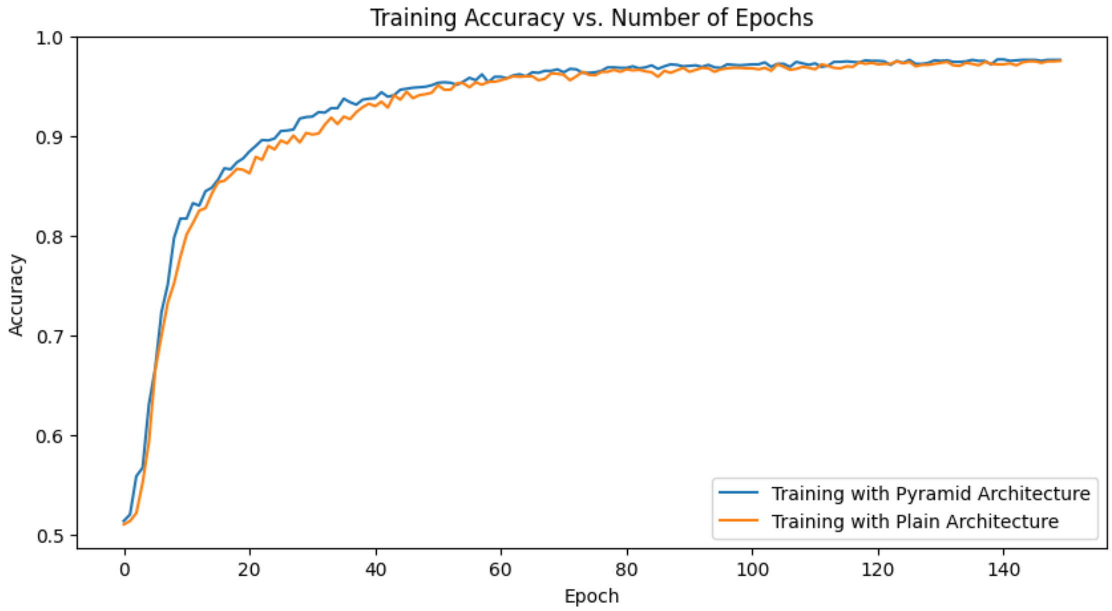
[17]:
```
### Add a batch normalization layer
class NN_pyramid(nn.Module):
    def __init__(self, num_layers, activation='relu', dropout_prob=0.5):
        super().__init__()
        self.activation = activation
        self.num_layers = num_layers
        self.dropout_prob = dropout_prob
        layers = []
        sizes = [512, 256, 128, 64, 2]

        print(sizes)
        for i in range(num_layers):
            layers.append(nn.Linear(sizes[i], sizes[i+1]))
            if activation == 'relu':
                layers.append(nn.ReLU())
            elif activation == 'sigmoid':
                layers.append(nn.Sigmoid())
            if dropout_prob > 0:
                layers.append(nn.Dropout(dropout_prob))

        self.layers = nn.Sequential(*layers[:-1])  # Exclude the last␣
↪activation or dropout for the output layer

    def forward(self, x):
        for layer in self.layers:
            x = layer(x)
        x = F.softmax(x, dim=1)  # Apply Softmax to obtain output probabilities.
        return x

model_pyramid = NN_pyramid(num_layers=4, activation='relu')
```

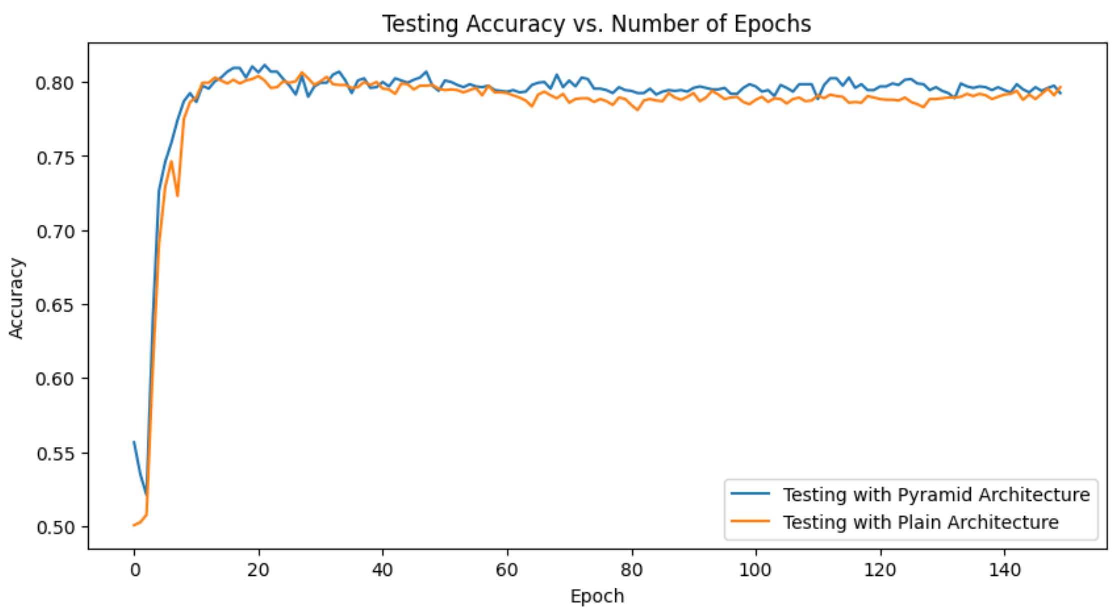
```
model_plain = CustomNN(input_size=512, hidden_size=128, num_layers=4,␣
 ↪activation='relu', dropout_prob=0.5)
train_pyramid, test_pyramid = experiment(model_pyramid)
train_plain, test_plain = experiment(model_plain)

pyramid_train_accuracies = [np.mean(epoch_acc) for epoch_acc in␣
 ↪zip(train_pyramid)]
pyramid_test_accuracies = [np.mean(epoch_acc) for epoch_acc in␣
 ↪zip(test_pyramid)]

plain_train_accuracies = [np.mean(epoch_acc) for epoch_acc in zip(train_plain)]
plain_test_accuracies = [np.mean(epoch_acc) for epoch_acc in zip(test_plain)]


# Plot training accuracies
plt.figure(figsize=(10, 5))
plt.plot(pyramid_train_accuracies, label='Training with Pyramid Architecture')
plt.plot(plain_train_accuracies, label='Training with Plain Architecture')
plt.title('Training Accuracy vs. Number of Epochs')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.show()

# Plot testing accuracies
plt.figure(figsize=(10, 5))
plt.plot(pyramid_test_accuracies, label='Testing with Pyramid Architecture')
plt.plot(plain_test_accuracies, label='Testing with Plain Architecture')
plt.title('Testing Accuracy vs. Number of Epochs')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```

```
[512, 256, 128, 64, 2]
[512, 128, 128, 128, 2]
Epoch #10:       train accuracy 0.818    train loss -0.774       test accuracy
0.792     test loss -0.767
Epoch #20:       train accuracy 0.878    train loss -0.865       test accuracy
0.810     test loss -0.801
Epoch #30:       train accuracy 0.919    train loss -0.910       test accuracy
0.797     test loss -0.796
Epoch #40:       train accuracy 0.938    train loss -0.931       test accuracy
0.796     test loss -0.799
Epoch #50:       train accuracy 0.952    train loss -0.947       test accuracy
0.794     test loss -0.795
Epoch #60:       train accuracy 0.960    train loss -0.957       test accuracy
```

```
0.794     test loss -0.794
Epoch #70:       train accuracy 0.968    train loss -0.966       test accuracy
0.796     test loss -0.795
Epoch #80:       train accuracy 0.969    train loss -0.968       test accuracy
0.794     test loss -0.794
Epoch #90:       train accuracy 0.971    train loss -0.969       test accuracy
0.793     test loss -0.794
Epoch #100:      train accuracy 0.972    train loss -0.972       test accuracy
0.798     test loss -0.796
Epoch #110:      train accuracy 0.972    train loss -0.972       test accuracy
0.798     test loss -0.795
Epoch #120:      train accuracy 0.976    train loss -0.975       test accuracy
0.794     test loss -0.796
Epoch #130:      train accuracy 0.977    train loss -0.976       test accuracy
0.796     test loss -0.796
Epoch #140:      train accuracy 0.978    train loss -0.977       test accuracy
0.796     test loss -0.795
Epoch #150:      train accuracy 0.977    train loss -0.976       test accuracy
0.792     test loss -0.794
Epoch #10:       train accuracy 0.779    train loss -0.739       test accuracy
0.786     test loss -0.756
Epoch #20:       train accuracy 0.867    train loss -0.853       test accuracy
0.802     test loss -0.799
Epoch #30:       train accuracy 0.903    train loss -0.898       test accuracy
0.798     test loss -0.795
Epoch #40:       train accuracy 0.933    train loss -0.926       test accuracy
0.800     test loss -0.797
Epoch #50:       train accuracy 0.944    train loss -0.940       test accuracy
0.795     test loss -0.796
Epoch #60:       train accuracy 0.955    train loss -0.951       test accuracy
0.793     test loss -0.794
Epoch #70:       train accuracy 0.963    train loss -0.960       test accuracy
0.792     test loss -0.792
Epoch #80:       train accuracy 0.965    train loss -0.964       test accuracy
0.788     test loss -0.788
Epoch #90:       train accuracy 0.969    train loss -0.967       test accuracy
0.790     test loss -0.790
Epoch #100:      train accuracy 0.969    train loss -0.969       test accuracy
0.785     test loss -0.787
Epoch #110:      train accuracy 0.969    train loss -0.968       test accuracy
0.787     test loss -0.788
Epoch #120:      train accuracy 0.974    train loss -0.973       test accuracy
0.789     test loss -0.789
Epoch #130:      train accuracy 0.973    train loss -0.973       test accuracy
0.788     test loss -0.789
Epoch #140:      train accuracy 0.973    train loss -0.972       test accuracy
0.790     test loss -0.790
Epoch #150:      train accuracy 0.976    train loss -0.976       test accuracy
```

```
0.796     test loss -0.793
```





Analysis and discussion here (< 15 sentences) : In this experiment, two neural network architectures were compared: one with a pyramid structure that gradually reduces the size of its layers, and another with a plain structure having equal-sized layers. Both architectures used ReLU activations and incorporated dropout.

The training accuracy plot reveals that both models perform almost identically throughout the training process, with neither showing a clear advantage over the other. In terms of testing accuracy, again, both models exhibit comparable performance across epochs, suggesting that the pyramid architecture did not provide a significant benefit in this context.

Given these results, it could be hypothesized that the complexity of the task does not require the representational power that a pyramid structure might offer, or that the data is not sufficiently complex to benefit from the increased depth and reduction in dimensionality. The dropout used in both models could also be compensating for any overfitting, leveling the playing field between the two architectures.

Therefore, although the pyramid architecture is often touted for its ability to capture more abstract representations in deeper layers with fewer neurons, in this specific instance, it did not demonstrate superior performance compared to a plain architecture. This suggests that simply changing the architecture to a pyramid form, in the absence of other modifications or a more complex dataset, might not always lead to improved performance.

Submission Instructions

1. Click the Save button at the top of the Jupyter Notebook.
2. Select Cell -> All Output -> Clear. This will clear all the outputs from all cells (but will keep the content of all cells).
3. Select Cell -> Run All. This will run all the cells in order, and will take several minutes.
4. Once you've rerun everything, select File -> Download as -> PDF via LaTeX (If you have trouble using "PDF via LaTex", you can also save the webpage as pdf. Make sure all your solutions are displayed in the pdf, it's okay if the provided codes get cut off because lines are not wrapped in code cells).
5. Look at the PDF file and make sure all your solutions are there, displayed correctly. The PDF is the only thing your graders will see!
6. Submit your PDF on Gradescope.