PA1_CS256_SP24_Ke_Xu

April 15, 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.

Link: https://drive.google.com/file/d/16gQXMM2UrQsQibiMZ_mPIrazklsK2WDW/view?usp=sl

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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')
```

```
# TODO: Enter the foldername in your Drive where you have saved the unzipped
# assignment folder, e.g. 'cse256/assignments/PA1/'
FOLDERNAME = None
FOLDERNAME = 'CSE256PAs/PA1'
assert FOLDERNAME is not None, "[!] Enter the foldername."

# Now that we've mounted your Drive, this ensures that
# the Python interpreter of the Colab VM can load
# python files from within it.
import sys
sys.path.append('/content/drive/My Drive/{}'.format(FOLDERNAME))

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

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
/content/drive/My Drive/CSE256PAs/PA1
```

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
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)
### YOUR CODE HERE!
# Replace with the actual computation
x = torch.sum(input_sequence_embs, dim=0)

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

```
sequence embedding tensor size:  torch.Size([3, 10])
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 is the loss of word order information. In natural language, the order of words can dramatically change the meaning of a sentence but element-wise addition treats all words equally, aggregating their embeddings without preserving any information about their sequence. This means that sentences with the same words in different orders would result in the same vector representation, potentially leading to ambiguities and inaccuracies in tasks that depend on understanding the precise meaning conveyed by the word order. ##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 $\text{softmax}(x_i) = \frac{e^{x_i}}{\sum_{1 \le j \le n} e^{x_j}}$. 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 $p = \text{softmax}(Wx)$. Let's look at this in the cell below:

[3]:
```python
# 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".

### YOUR CODE HERE
# Replace with the actual computation
import torch.nn.functional as F
probs = F.softmax(torch.matmul(W.transpose(0, 1), 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).

# 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.

# 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.

### YOUR CODE HERE
# Replace with the actual computation
batch_aggregated = torch.sum(batch_embs, dim=1)
batch_projected = torch.matmul(batch_aggregated, W)
batch_probs = F.softmax(batch_projected, 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]:
```
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 6 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] for w in input_sequence.split()]) ###␣
↪MODIFY THIS INDEXING
indices = torch.LongTensor([vocab[w] if w in vocab else vocab['<UNK>'] for w in␣
↪input_sequence.split()])
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]:
```
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()
```

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

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

[8]:
```python
########## 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


########## 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]:

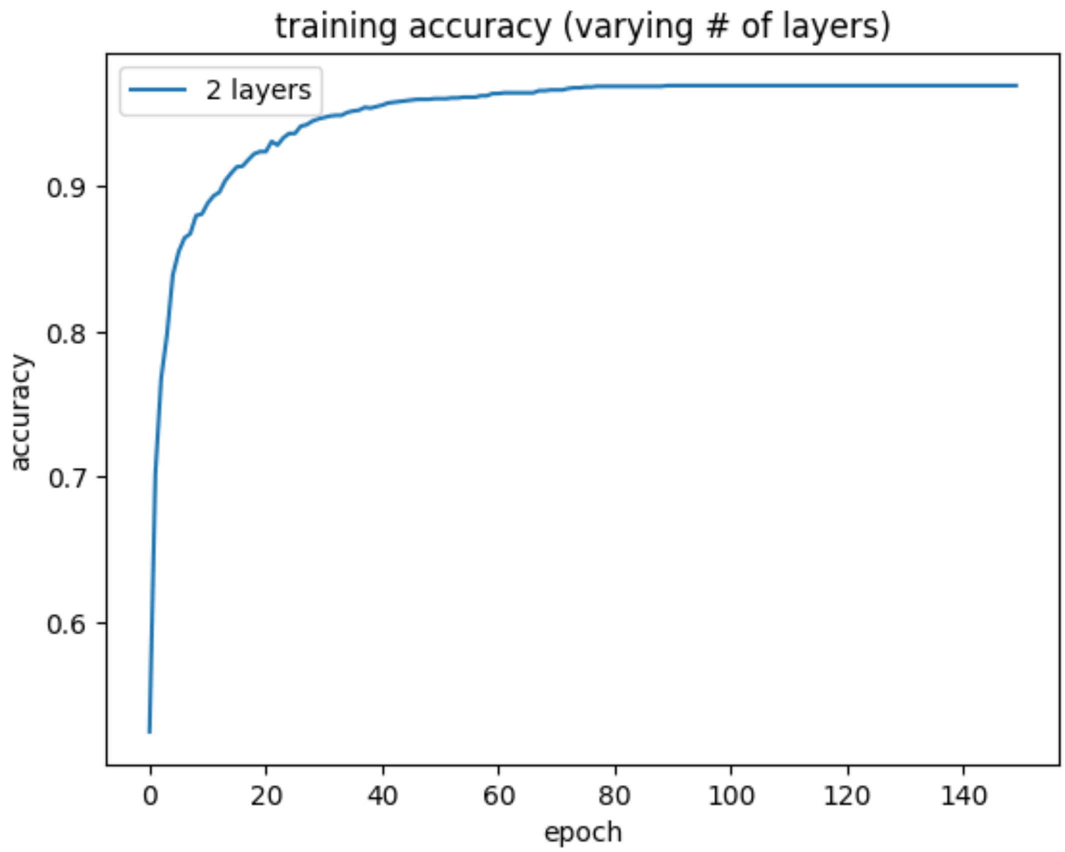
```
######################
#
# 1) Load data splits: the train and test sets
# 2) Train neural networks
# 3) Plot the results
############################
```

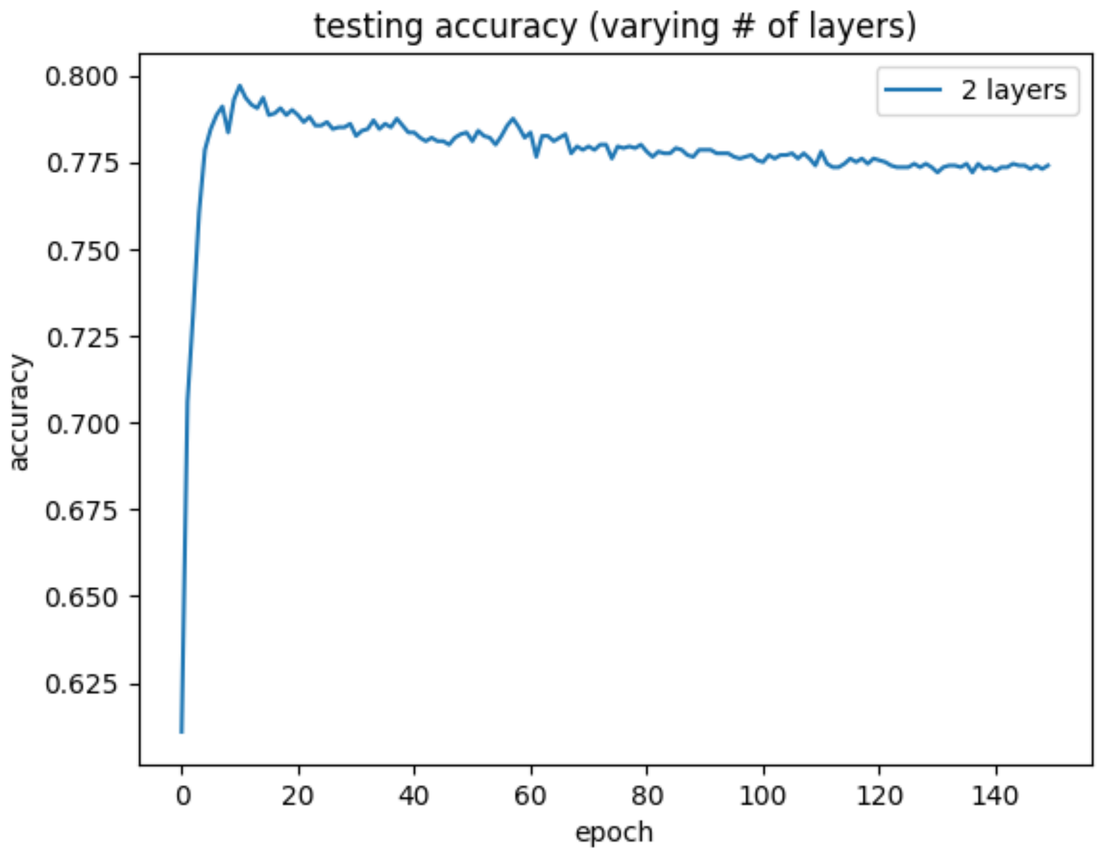
```
start_time = time.time()

# Load the dataset
root_dir = '/content/drive/My Drive/{}/aclImdb/train'.format(FOLDERNAME)
root_dir_test = '/content/drive/My Drive/{}/aclImdb/test'.format(FOLDERNAME)
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")
```

```
Time to load data: 166.29224681854248 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)')
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 0.881    train loss -0.821       test accuracy
0.793   test loss -0.745
Epoch #20:      train accuracy 0.924    train loss -0.887       test accuracy
0.790   test loss -0.767
Epoch #30:      train accuracy 0.947    train loss -0.917       test accuracy
0.786   test loss -0.773
Epoch #40:      train accuracy 0.955    train loss -0.935       test accuracy
0.783   test loss -0.774
Epoch #50:      train accuracy 0.961    train loss -0.947       test accuracy
0.783   test loss -0.776
Epoch #60:      train accuracy 0.964    train loss -0.954       test accuracy
0.782   test loss -0.776
Epoch #70:      train accuracy 0.967    train loss -0.961       test accuracy
0.778   test loss -0.775
Epoch #80:      train accuracy 0.969    train loss -0.965       test accuracy
0.780   test loss -0.776
Epoch #90:      train accuracy 0.970    train loss -0.967       test accuracy
0.778   test loss -0.777
Epoch #100:     train accuracy 0.970    train loss -0.968       test accuracy
0.775   test loss -0.776
Epoch #110:     train accuracy 0.970    train loss -0.969       test accuracy
0.774   test loss -0.776
Epoch #120:     train accuracy 0.970    train loss -0.969       test accuracy
0.776   test loss -0.776
Epoch #130:     train accuracy 0.970    train loss -0.969       test accuracy
0.773   test loss -0.776
Epoch #140:     train accuracy 0.970    train loss -0.969       test accuracy
0.773   test loss -0.776
Epoch #150:     train accuracy 0.970    train loss -0.969       test accuracy
0.774   test loss -0.776
```


training accuracy (varying # of layers)
2 layers
0.9
0.8
0.7
0.6
accuracy
0
20
40
60
80
100
120
140
epoch




```
Time to train, eval model: 46.318968296051025 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]:
```
### YOUR CODE HERE
import torch
from torch import nn
import torch.nn.functional as F

class NN1(nn.Module):
    def __init__(self, input_size):
        super(NN1, self).__init__()
```

```python
        self.fc1 = nn.Linear(input_size, 2)  # Single layer directly to output

    def forward(self, x):
        x = F.log_softmax(self.fc1(x), dim=1)
        return x

class NN2(nn.Module):
    def __init__(self, input_size, hidden_size=100):
        super(NN2, self).__init__()
        self.fc1 = nn.Linear(input_size, hidden_size)
        self.fc2 = nn.Linear(hidden_size, 2)

    def forward(self, x):
        x = F.relu(self.fc1(x))
        x = F.log_softmax(self.fc2(x), dim=1)
        return x

class NN3(nn.Module):
    def __init__(self, input_size, hidden_size=100):
        super(NN3, self).__init__()
        self.fc1 = nn.Linear(input_size, hidden_size)
        self.fc2 = nn.Linear(hidden_size, hidden_size)
        self.fc3 = nn.Linear(hidden_size, 2)

    def forward(self, x):
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = F.log_softmax(self.fc3(x), dim=1)
        return x

class NN4(nn.Module):
    def __init__(self, input_size, hidden_size=100):
        super(NN4, self).__init__()
        self.fc1 = nn.Linear(input_size, hidden_size)
        self.fc2 = nn.Linear(hidden_size, hidden_size)
        self.fc3 = nn.Linear(hidden_size, hidden_size)
        self.fc4 = nn.Linear(hidden_size, 2)

    def forward(self, x):
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = F.relu(self.fc3(x))
        x = F.log_softmax(self.fc4(x), dim=1)
        return x

input_size = 512
hidden_size = 100
```

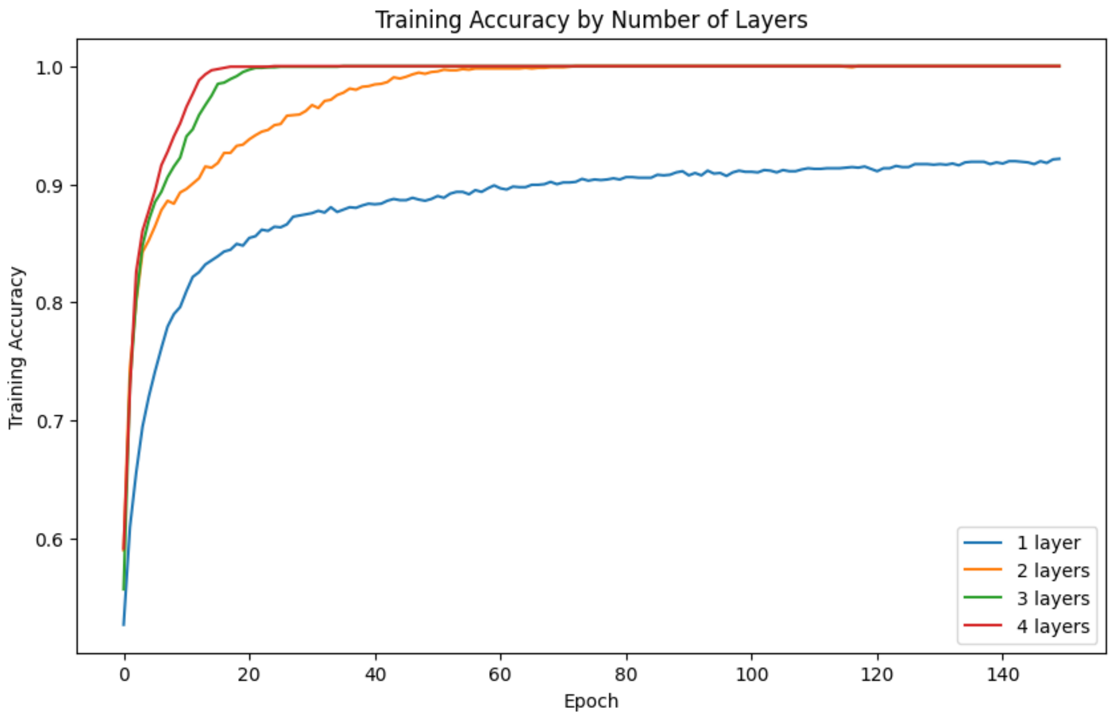
```python
models = [NN1(input_size), NN2(input_size, hidden_size), NN3(input_size,␣
↪hidden_size), NN4(input_size, hidden_size)]
model_names = ['1 layer', '2 layers', '3 layers', '4 layers']

# Dictionaries to hold training and testing accuracies
train_accuracies = {}
test_accuracies = {}

start_time = time.time()

# Loop through each model, train, and collect accuracies
for model, name in zip(models, model_names):
    print(f'\nTraining {name}:')
    train_accuracy, test_accuracy = experiment(model)

    train_accuracies[name] = train_accuracy
    test_accuracies[name] = test_accuracy

end_time = time.time()
elapsed_time = end_time - start_time
print(f"\nTime to train and evaluate all models: {elapsed_time} seconds")

# Plot training accuracies
plt.figure(figsize=(10, 6))
for name in model_names:
    plt.plot(train_accuracies[name], label=f'{name}')
plt.title('Training Accuracy by Number of Layers')
plt.xlabel('Epoch')
plt.ylabel('Training Accuracy')
plt.legend()
plt.show()

# Plot testing accuracies
plt.figure(figsize=(10, 6))
for name in model_names:
    plt.plot(test_accuracies[name], label=f'{name}')
plt.title('Testing Accuracy by Number of Layers')
plt.xlabel('Epoch')
plt.ylabel('Testing Accuracy')
plt.legend()
plt.show()
```

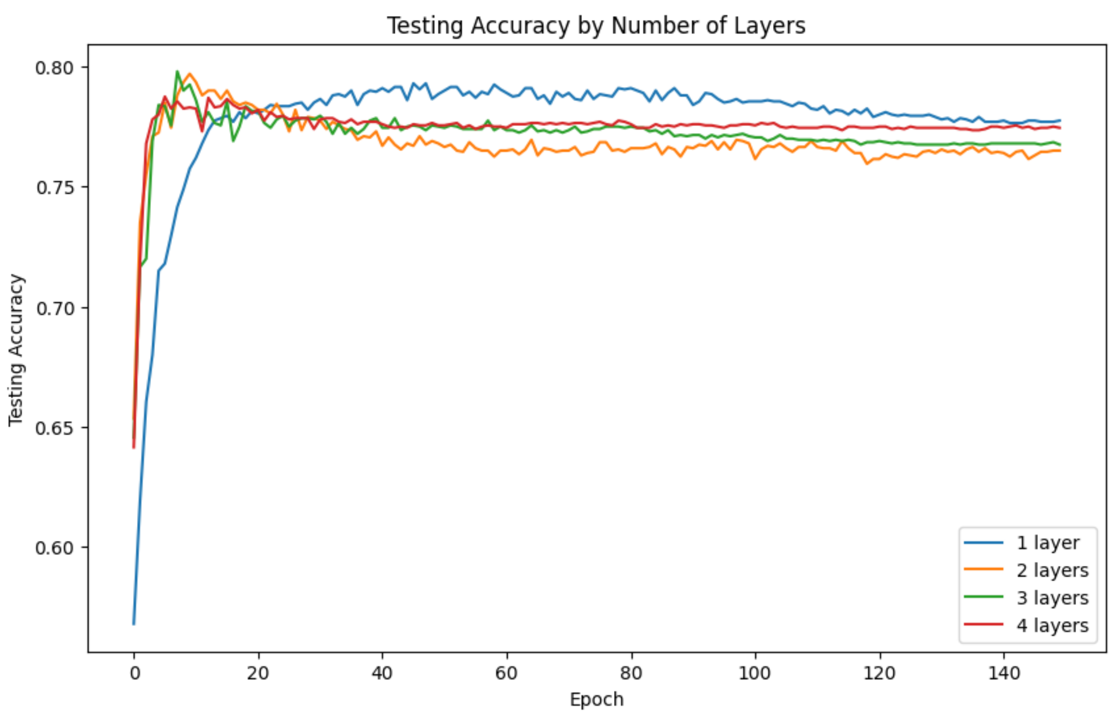
```
Training 1 layer:
Epoch #10:       train accuracy 0.796    train loss 0.497        test accuracy
0.757     test loss 0.548
Epoch #20:       train accuracy 0.848    train loss 0.412        test accuracy
0.781     test loss 0.504
```

```
Epoch #30:       train accuracy 0.875    train loss 0.363        test accuracy
0.785     test loss 0.482
Epoch #40:       train accuracy 0.883    train loss 0.331        test accuracy
0.789     test loss 0.472
Epoch #50:       train accuracy 0.887    train loss 0.309        test accuracy
0.788     test loss 0.469
Epoch #60:       train accuracy 0.899    train loss 0.292        test accuracy
0.790     test loss 0.465
Epoch #70:       train accuracy 0.900    train loss 0.278        test accuracy
0.787     test loss 0.469
Epoch #80:       train accuracy 0.904    train loss 0.267        test accuracy
0.790     test loss 0.470
Epoch #90:       train accuracy 0.911    train loss 0.258        test accuracy
0.788     test loss 0.475
Epoch #100:      train accuracy 0.910    train loss 0.250        test accuracy
0.785     test loss 0.483
Epoch #110:      train accuracy 0.913    train loss 0.244        test accuracy
0.782     test loss 0.485
Epoch #120:      train accuracy 0.913    train loss 0.238        test accuracy
0.779     test loss 0.487
Epoch #130:      train accuracy 0.916    train loss 0.233        test accuracy
0.779     test loss 0.501
Epoch #140:      train accuracy 0.918    train loss 0.228        test accuracy
0.777     test loss 0.503
Epoch #150:      train accuracy 0.921    train loss 0.223        test accuracy
0.777     test loss 0.505

Training 2 layers:
Epoch #10:       train accuracy 0.893    train loss 0.296        test accuracy
0.797     test loss 0.471
Epoch #20:       train accuracy 0.933    train loss 0.195        test accuracy
0.784     test loss 0.516
Epoch #30:       train accuracy 0.962    train loss 0.135        test accuracy
0.778     test loss 0.581
Epoch #40:       train accuracy 0.983    train loss 0.090        test accuracy
0.773     test loss 0.653
Epoch #50:       train accuracy 0.995    train loss 0.058        test accuracy
0.768     test loss 0.756
Epoch #60:       train accuracy 0.998    train loss 0.036        test accuracy
0.765     test loss 0.863
Epoch #70:       train accuracy 0.999    train loss 0.021        test accuracy
0.765     test loss 0.953
Epoch #80:       train accuracy 1.000    train loss 0.012        test accuracy
0.764     test loss 1.078
Epoch #90:       train accuracy 1.000    train loss 0.007        test accuracy
0.766     test loss 1.182
Epoch #100:      train accuracy 1.000    train loss 0.004        test accuracy
0.768     test loss 1.312
```

```
Epoch #110:      train accuracy 1.000    train loss 0.002        test accuracy
0.769     test loss 1.413
Epoch #120:      train accuracy 1.000    train loss 0.001        test accuracy
0.761     test loss 1.509
Epoch #130:      train accuracy 1.000    train loss 0.001        test accuracy
0.764     test loss 1.580
Epoch #140:      train accuracy 1.000    train loss 0.001        test accuracy
0.764     test loss 1.653
Epoch #150:      train accuracy 1.000    train loss 0.000        test accuracy
0.765     test loss 1.737

Training 3 layers:
Epoch #10:       train accuracy 0.922    train loss 0.211        test accuracy
0.792     test loss 0.510
Epoch #20:       train accuracy 0.995    train loss 0.045        test accuracy
0.781     test loss 0.720
Epoch #30:       train accuracy 1.000    train loss 0.009        test accuracy
0.778     test loss 0.961
Epoch #40:       train accuracy 1.000    train loss 0.002        test accuracy
0.778     test loss 1.163
Epoch #50:       train accuracy 1.000    train loss 0.001        test accuracy
0.775     test loss 1.348
Epoch #60:       train accuracy 1.000    train loss 0.000        test accuracy
0.775     test loss 1.495
Epoch #70:       train accuracy 1.000    train loss 0.000        test accuracy
0.772     test loss 1.660
Epoch #80:       train accuracy 1.000    train loss 0.000        test accuracy
0.774     test loss 1.784
Epoch #90:       train accuracy 1.000    train loss 0.000        test accuracy
0.771     test loss 1.911
Epoch #100:      train accuracy 1.000    train loss 0.000        test accuracy
0.771     test loss 2.039
Epoch #110:      train accuracy 1.000    train loss 0.000        test accuracy
0.769     test loss 2.159
Epoch #120:      train accuracy 1.000    train loss 0.000        test accuracy
0.768     test loss 2.279
Epoch #130:      train accuracy 1.000    train loss 0.000        test accuracy
0.767     test loss 2.406
Epoch #140:      train accuracy 1.000    train loss 0.000        test accuracy
0.768     test loss 2.527
Epoch #150:      train accuracy 1.000    train loss 0.000        test accuracy
0.767     test loss 2.648

Training 4 layers:
Epoch #10:       train accuracy 0.952    train loss 0.141        test accuracy
0.783     test loss 0.601
Epoch #20:       train accuracy 1.000    train loss 0.009        test accuracy
0.780     test loss 1.098
```

```
Epoch #30:      train accuracy 1.000    train loss 0.001        test accuracy
0.774    test loss 1.442
Epoch #40:      train accuracy 1.000    train loss 0.000        test accuracy
0.777    test loss 1.662
Epoch #50:      train accuracy 1.000    train loss 0.000        test accuracy
0.775    test loss 1.867
Epoch #60:      train accuracy 1.000    train loss 0.000        test accuracy
0.775    test loss 2.048
Epoch #70:      train accuracy 1.000    train loss 0.000        test accuracy
0.776    test loss 2.214
Epoch #80:      train accuracy 1.000    train loss 0.000        test accuracy
0.777    test loss 2.374
Epoch #90:      train accuracy 1.000    train loss 0.000        test accuracy
0.775    test loss 2.532
Epoch #100:     train accuracy 1.000    train loss 0.000        test accuracy
0.776    test loss 2.676
Epoch #110:     train accuracy 1.000    train loss 0.000        test accuracy
0.774    test loss 2.830
Epoch #120:     train accuracy 1.000    train loss 0.000        test accuracy
0.774    test loss 2.962
Epoch #130:     train accuracy 1.000    train loss 0.000        test accuracy
0.774    test loss 3.097
Epoch #140:     train accuracy 1.000    train loss 0.000        test accuracy
0.775    test loss 3.237
Epoch #150:     train accuracy 1.000    train loss 0.000        test accuracy
0.774    test loss 3.365

Time to train and evaluate all models: 180.06459021568298 seconds
```


Training Accuracy by Number of Layers
Training Accuracy
Epoch
1.0
0.9
0.8
0.7
0.6
0
20
40
60
80
100
120
140
1 layer
2 layers
3 layers
4 layers


Testing Accuracy by Number of Layers
Testing Accuracy
Epoch
0.80
0.75
0.70
0.65
0.60
0
20
40
60
80
100
120
140
1 layer
2 layers
3 layers
4 layers

```
[12]: import torch
from torch import nn
import torch.nn.functional as F

class NN4_Sigmoid_Dropout(nn.Module):
    def __init__(self, input_size, hidden_size=100):
        super(NN4_Sigmoid_Dropout, self).__init__()
        self.fc1 = nn.Linear(input_size, hidden_size)
        self.dropout1 = nn.Dropout(0.5)
        self.fc2 = nn.Linear(hidden_size, hidden_size)
        self.dropout2 = nn.Dropout(0.5)
        self.fc3 = nn.Linear(hidden_size, hidden_size)
        self.dropout3 = nn.Dropout(0.5)
        self.fc4 = nn.Linear(hidden_size, 2)

    def forward(self, x):
        x = torch.sigmoid(self.fc1(x))
        x = self.dropout1(x)
        x = torch.sigmoid(self.fc2(x))
        x = self.dropout2(x)
        x = torch.sigmoid(self.fc3(x))
        x = self.dropout3(x)
        x = F.log_softmax(self.fc4(x), dim=1)
        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.

```
[13]: ### YOUR CODE HERE
input_size = 512
hidden_size = 100
models = [NN1(input_size), NN2(input_size, hidden_size), NN3(input_size,␣
 ↪hidden_size), NN4(input_size, hidden_size), NN4_Sigmoid_Dropout(input_size,␣
 ↪hidden_size)]
model_names = ['1 layer', '2 layers', '3 layers', '4 layers', '4 layers Sigmoid␣
 ↪with Dropout 0.5']

# Dictionaries to hold training and testing accuracies
train_accuracies = {}
test_accuracies = {}

start_time = time.time()
```

```python
# Loop through each model, train, and collect accuracies
for model, name in zip(models, model_names):
    print(f'\nTraining {name}:')
    train_accuracy, test_accuracy = experiment(model)

    train_accuracies[name] = train_accuracy
    test_accuracies[name] = test_accuracy

end_time = time.time()
elapsed_time = end_time - start_time
print(f"\nTime to train and evaluate all models: {elapsed_time} seconds")

# Plot training accuracies
plt.figure(figsize=(10, 6))
for name in model_names:
    plt.plot(train_accuracies[name], label=f'{name}')
plt.title('Training Accuracy by Number of Layers')
plt.xlabel('Epoch')
plt.ylabel('Training Accuracy')
plt.legend()
plt.show()

# Plot testing accuracies
plt.figure(figsize=(10, 6))
for name in model_names:
    plt.plot(test_accuracies[name], label=f'{name}')
plt.title('Testing Accuracy by Number of Layers')
plt.xlabel('Epoch')
plt.ylabel('Testing Accuracy')
plt.legend()
plt.show()
```

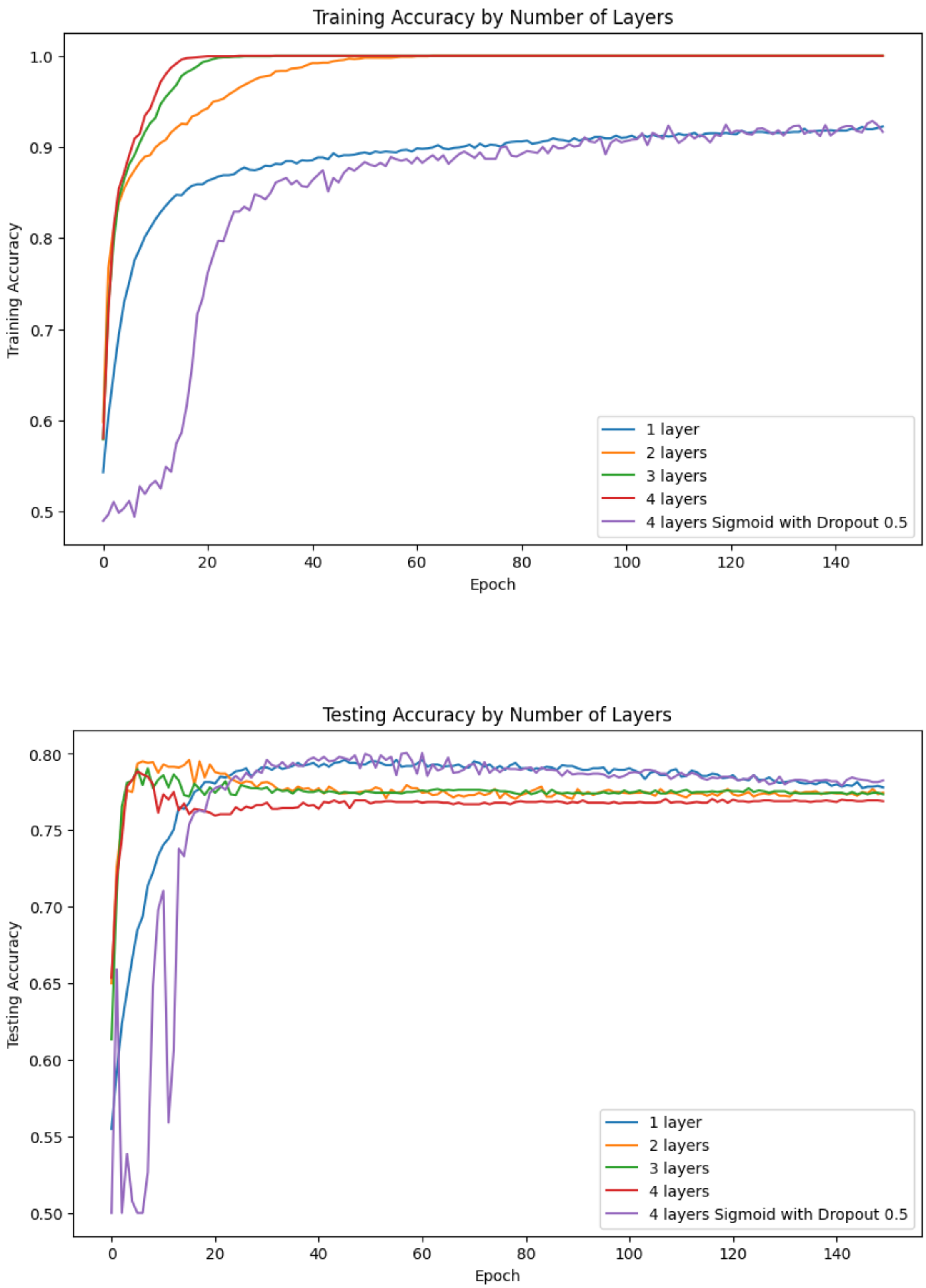
```
Training 1 layer:
Epoch #10:       train accuracy 0.811    train loss 0.496        test accuracy
0.734     test loss 0.565
Epoch #20:       train accuracy 0.859    train loss 0.408        test accuracy
0.781     test loss 0.513
Epoch #30:       train accuracy 0.875    train loss 0.360        test accuracy
0.791     test loss 0.489
Epoch #40:       train accuracy 0.885    train loss 0.329        test accuracy
0.794     test loss 0.476
Epoch #50:       train accuracy 0.893    train loss 0.307        test accuracy
0.793     test loss 0.471
Epoch #60:       train accuracy 0.895    train loss 0.291        test accuracy
0.793     test loss 0.471
Epoch #70:       train accuracy 0.900    train loss 0.278        test accuracy
0.791     test loss 0.470
```

```
Epoch #80:      train accuracy 0.906    train loss 0.267        test accuracy
0.790     test loss 0.473
Epoch #90:      train accuracy 0.906    train loss 0.258        test accuracy
0.792     test loss 0.478
Epoch #100:     train accuracy 0.910    train loss 0.250        test accuracy
0.789     test loss 0.482
Epoch #110:     train accuracy 0.912    train loss 0.243        test accuracy
0.790     test loss 0.485
Epoch #120:     train accuracy 0.915    train loss 0.238        test accuracy
0.784     test loss 0.497
Epoch #130:     train accuracy 0.915    train loss 0.232        test accuracy
0.781     test loss 0.497
Epoch #140:     train accuracy 0.918    train loss 0.227        test accuracy
0.779     test loss 0.502
Epoch #150:     train accuracy 0.922    train loss 0.223        test accuracy
0.778     test loss 0.506

Training 2 layers:
Epoch #10:      train accuracy 0.891    train loss 0.295        test accuracy
0.787     test loss 0.475
Epoch #20:      train accuracy 0.940    train loss 0.187        test accuracy
0.793     test loss 0.509
Epoch #30:      train accuracy 0.974    train loss 0.120        test accuracy
0.781     test loss 0.572
Epoch #40:      train accuracy 0.990    train loss 0.075        test accuracy
0.775     test loss 0.650
Epoch #50:      train accuracy 0.997    train loss 0.045        test accuracy
0.775     test loss 0.763
Epoch #60:      train accuracy 0.999    train loss 0.026        test accuracy
0.777     test loss 0.829
Epoch #70:      train accuracy 1.000    train loss 0.015        test accuracy
0.773     test loss 0.950
Epoch #80:      train accuracy 1.000    train loss 0.008        test accuracy
0.773     test loss 1.049
Epoch #90:      train accuracy 1.000    train loss 0.005        test accuracy
0.770     test loss 1.158
Epoch #100:     train accuracy 1.000    train loss 0.002        test accuracy
0.774     test loss 1.271
Epoch #110:     train accuracy 1.000    train loss 0.001        test accuracy
0.774     test loss 1.392
Epoch #120:     train accuracy 1.000    train loss 0.001        test accuracy
0.777     test loss 1.490
Epoch #130:     train accuracy 1.000    train loss 0.000        test accuracy
0.772     test loss 1.624
Epoch #140:     train accuracy 1.000    train loss 0.000        test accuracy
0.774     test loss 1.755
Epoch #150:     train accuracy 1.000    train loss 0.000        test accuracy
0.774     test loss 1.873
```

```
Training 3 layers:
Epoch #10:      train accuracy 0.926    train loss 0.207        test accuracy
0.783    test loss 0.519
Epoch #20:      train accuracy 0.993    train loss 0.051        test accuracy
0.778    test loss 0.750
Epoch #30:      train accuracy 1.000    train loss 0.010        test accuracy
0.777    test loss 1.007
Epoch #40:      train accuracy 1.000    train loss 0.002        test accuracy
0.775    test loss 1.217
Epoch #50:      train accuracy 1.000    train loss 0.001        test accuracy
0.775    test loss 1.421
Epoch #60:      train accuracy 1.000    train loss 0.000        test accuracy
0.775    test loss 1.573
Epoch #70:      train accuracy 1.000    train loss 0.000        test accuracy
0.776    test loss 1.728
Epoch #80:      train accuracy 1.000    train loss 0.000        test accuracy
0.773    test loss 1.872
Epoch #90:      train accuracy 1.000    train loss 0.000        test accuracy
0.774    test loss 2.006
Epoch #100:     train accuracy 1.000    train loss 0.000        test accuracy
0.776    test loss 2.161
Epoch #110:     train accuracy 1.000    train loss 0.000        test accuracy
0.774    test loss 2.268
Epoch #120:     train accuracy 1.000    train loss 0.000        test accuracy
0.776    test loss 2.410
Epoch #130:     train accuracy 1.000    train loss 0.000        test accuracy
0.775    test loss 2.531
Epoch #140:     train accuracy 1.000    train loss 0.000        test accuracy
0.774    test loss 2.658
Epoch #150:     train accuracy 1.000    train loss 0.000        test accuracy
0.773    test loss 2.791

Training 4 layers:
Epoch #10:      train accuracy 0.942    train loss 0.164        test accuracy
0.761    test loss 0.673
Epoch #20:      train accuracy 0.999    train loss 0.012        test accuracy
0.761    test loss 1.077
Epoch #30:      train accuracy 1.000    train loss 0.001        test accuracy
0.766    test loss 1.430
Epoch #40:      train accuracy 1.000    train loss 0.000        test accuracy
0.766    test loss 1.713
Epoch #50:      train accuracy 1.000    train loss 0.000        test accuracy
0.769    test loss 1.909
Epoch #60:      train accuracy 1.000    train loss 0.000        test accuracy
0.769    test loss 2.082
Epoch #70:      train accuracy 1.000    train loss 0.000        test accuracy
0.767    test loss 2.266
```

```
Epoch #80:      train accuracy 1.000    train loss 0.000        test accuracy
0.769    test loss 2.447
Epoch #90:      train accuracy 1.000    train loss 0.000        test accuracy
0.768    test loss 2.606
Epoch #100:     train accuracy 1.000    train loss 0.000        test accuracy
0.768    test loss 2.759
Epoch #110:     train accuracy 1.000    train loss 0.000        test accuracy
0.768    test loss 2.914
Epoch #120:     train accuracy 1.000    train loss 0.000        test accuracy
0.768    test loss 3.049
Epoch #130:     train accuracy 1.000    train loss 0.000        test accuracy
0.769    test loss 3.195
Epoch #140:     train accuracy 1.000    train loss 0.000        test accuracy
0.769    test loss 3.331
Epoch #150:     train accuracy 1.000    train loss 0.000        test accuracy
0.769    test loss 3.456

Training 4 layers Sigmoid with Dropout 0.5:
Epoch #10:      train accuracy 0.528    train loss 0.699        test accuracy
0.698    test loss 0.688
Epoch #20:      train accuracy 0.734    train loss 0.579        test accuracy
0.774    test loss 0.576
Epoch #30:      train accuracy 0.848    train loss 0.369        test accuracy
0.787    test loss 0.452
Epoch #40:      train accuracy 0.856    train loss 0.343        test accuracy
0.797    test loss 0.449
Epoch #50:      train accuracy 0.878    train loss 0.297        test accuracy
0.800    test loss 0.459
Epoch #60:      train accuracy 0.882    train loss 0.289        test accuracy
0.787    test loss 0.475
Epoch #70:      train accuracy 0.895    train loss 0.266        test accuracy
0.792    test loss 0.483
Epoch #80:      train accuracy 0.889    train loss 0.263        test accuracy
0.789    test loss 0.496
Epoch #90:      train accuracy 0.903    train loss 0.248        test accuracy
0.786    test loss 0.512
Epoch #100:     train accuracy 0.905    train loss 0.236        test accuracy
0.785    test loss 0.517
Epoch #110:     train accuracy 0.913    train loss 0.227        test accuracy
0.785    test loss 0.532
Epoch #120:     train accuracy 0.924    train loss 0.212        test accuracy
0.785    test loss 0.549
Epoch #130:     train accuracy 0.918    train loss 0.207        test accuracy
0.785    test loss 0.559
Epoch #140:     train accuracy 0.912    train loss 0.222        test accuracy
0.782    test loss 0.580
Epoch #150:     train accuracy 0.916    train loss 0.209        test accuracy
0.782    test loss 0.596
```

```
Time to train and evaluate all models: 243.20409536361694 seconds
```



Analysis and discussion here (< 5 sentences) : The training accuracy graph indicates that models with more layers tend to overfit, as seen with the three-layer network achieving the highest training accuracy but then plateauing. The four-layer network with dropout regularisation doesn't achieve as high training accuracy as the others, likely due to its regularization effect preventing overfitting. In contrast, the testing accuracy graph shows that the models with two and three layers have similar performance and generalize well after a certain number of epochs. The four-layer network with dropout has significantly improved testing performance compared to the same network without dropout, indicating the effectiveness of dropout in combating overfitting.

3.2 Question 2.2 Activation functions (20 points)

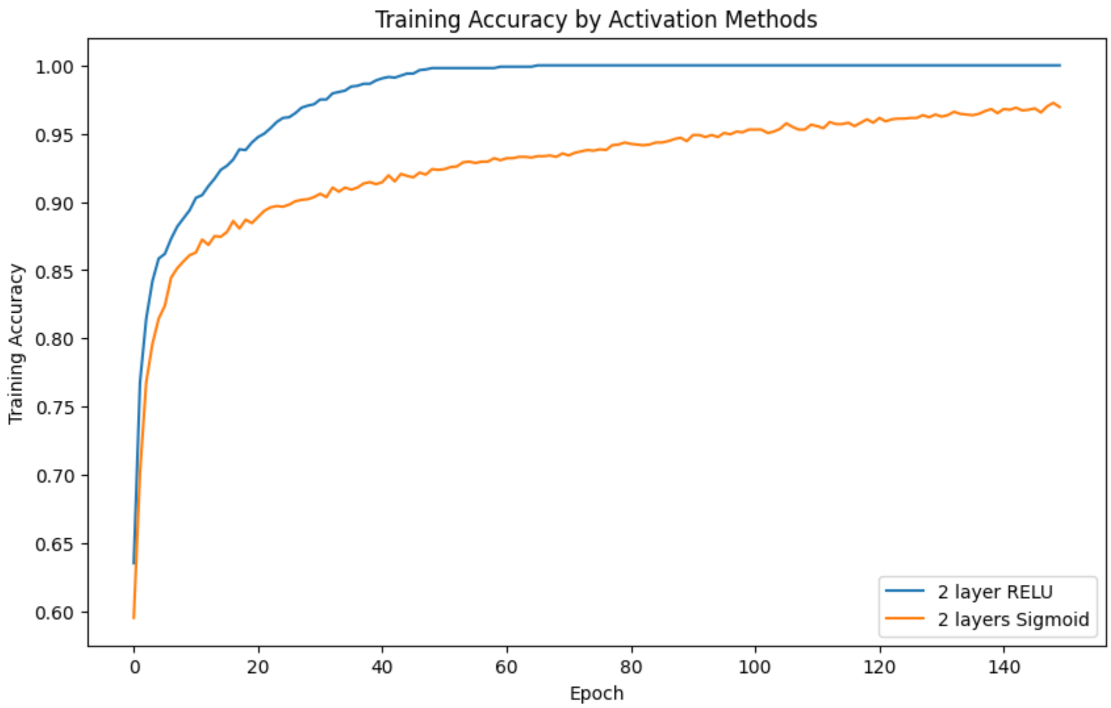
Generate two plots where the y-axis is the accuracy and the x-axis is the # of epochs. The first plot should include 2 curves that show the training accuracy when using the ReLU versus sigmoid activation functions. The second plot should include 2 curves that show the testing accuracy when using the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

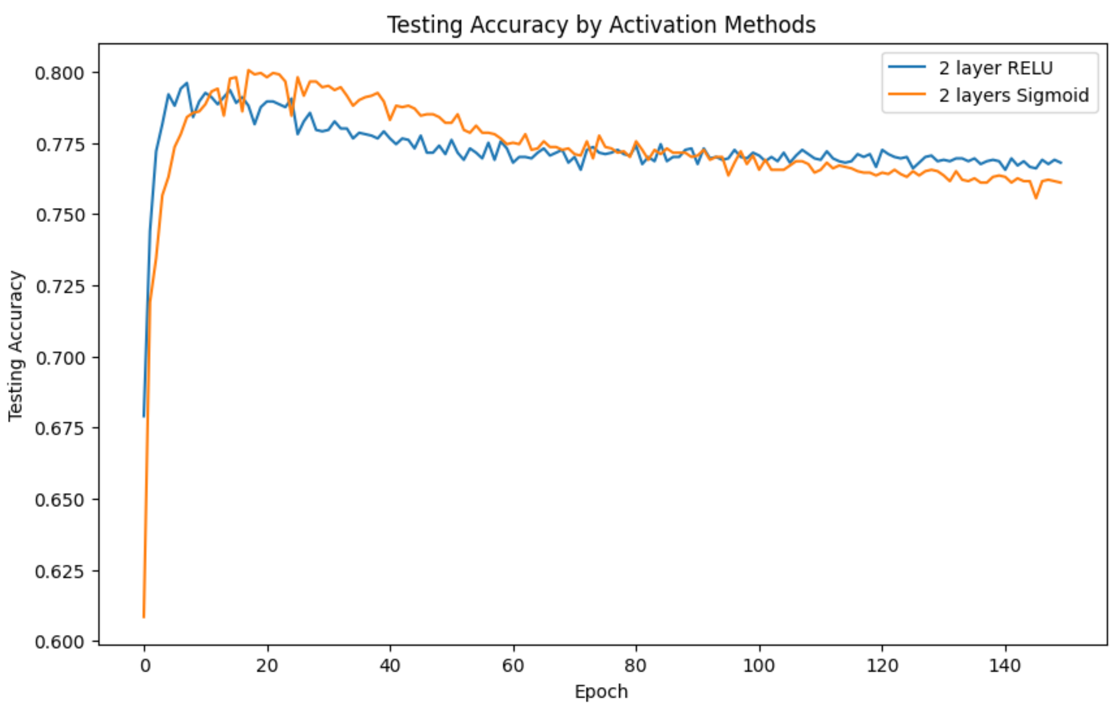
[14]:
```
### YOUR CODE HERE
class NN2_Sigmoid(nn.Module):
    def __init__(self, input_size, hidden_size=100):
        super(NN2_Sigmoid, self).__init__()
        self.fc1 = nn.Linear(input_size, hidden_size)
        self.fc2 = nn.Linear(hidden_size, 2)

    def forward(self, x):
        x = torch.sigmoid(self.fc1(x))
        x = F.log_softmax(self.fc2(x), dim=1)
        return x

input_size = 512
hidden_size = 100
models = [NN2(input_size), NN2_Sigmoid(input_size, hidden_size)]
model_names = ['2 layer RELU', '2 layers Sigmoid']

# Dictionaries to hold training and testing accuracies
train_accuracies = {}
test_accuracies = {}

start_time = time.time()

# Loop through each model, train, and collect accuracies
for model, name in zip(models, model_names):
    print(f'\nTraining {name}:')
    train_accuracy, test_accuracy = experiment(model)
```

```python
    train_accuracies[name] = train_accuracy
    test_accuracies[name] = test_accuracy

end_time = time.time()
elapsed_time = end_time - start_time
print(f"\nTime to train and evaluate all models: {elapsed_time} seconds")

# Plot training accuracies
plt.figure(figsize=(10, 6))
for name in model_names:
    plt.plot(train_accuracies[name], label=f'{name}')
plt.title('Training Accuracy by Activation Methods')
plt.xlabel('Epoch')
plt.ylabel('Training Accuracy')
plt.legend()
plt.show()

# Plot testing accuracies
plt.figure(figsize=(10, 6))
for name in model_names:
    plt.plot(test_accuracies[name], label=f'{name}')
plt.title('Testing Accuracy by Activation Methods')
plt.xlabel('Epoch')
plt.ylabel('Testing Accuracy')
plt.legend()
plt.show()
```

```
Training 2 layer RELU:
Epoch #10:       train accuracy 0.894    train loss 0.289        test accuracy
0.789     test loss 0.473
Epoch #20:       train accuracy 0.944    train loss 0.184        test accuracy
0.787     test loss 0.503
Epoch #30:       train accuracy 0.972    train loss 0.119        test accuracy
0.779     test loss 0.592
Epoch #40:       train accuracy 0.989    train loss 0.076        test accuracy
0.779     test loss 0.668
Epoch #50:       train accuracy 0.998    train loss 0.046        test accuracy
0.771     test loss 0.775
Epoch #60:       train accuracy 0.999    train loss 0.027        test accuracy
0.773     test loss 0.861
Epoch #70:       train accuracy 1.000    train loss 0.015        test accuracy
0.768     test loss 0.990
Epoch #80:       train accuracy 1.000    train loss 0.008        test accuracy
0.770     test loss 1.074
Epoch #90:       train accuracy 1.000    train loss 0.005        test accuracy
0.773     test loss 1.193
```

```
Epoch #100:      train accuracy 1.000    train loss 0.002        test accuracy
0.771    test loss 1.320
Epoch #110:      train accuracy 1.000    train loss 0.001        test accuracy
0.769    test loss 1.459
Epoch #120:      train accuracy 1.000    train loss 0.001        test accuracy
0.766    test loss 1.603
Epoch #130:      train accuracy 1.000    train loss 0.000        test accuracy
0.768    test loss 1.724
Epoch #140:      train accuracy 1.000    train loss 0.000        test accuracy
0.768    test loss 1.827
Epoch #150:      train accuracy 1.000    train loss 0.000        test accuracy
0.768    test loss 1.963

Training 2 layers Sigmoid:
Epoch #10:       train accuracy 0.861    train loss 0.424        test accuracy
0.786    test loss 0.501
Epoch #20:       train accuracy 0.884    train loss 0.305        test accuracy
0.799    test loss 0.454
Epoch #30:       train accuracy 0.903    train loss 0.257        test accuracy
0.794    test loss 0.460
Epoch #40:       train accuracy 0.913    train loss 0.227        test accuracy
0.789    test loss 0.487
Epoch #50:       train accuracy 0.923    train loss 0.206        test accuracy
0.782    test loss 0.510
Epoch #60:       train accuracy 0.930    train loss 0.191        test accuracy
0.774    test loss 0.540
Epoch #70:       train accuracy 0.935    train loss 0.177        test accuracy
0.773    test loss 0.576
Epoch #80:       train accuracy 0.944    train loss 0.167        test accuracy
0.770    test loss 0.618
Epoch #90:       train accuracy 0.945    train loss 0.158        test accuracy
0.770    test loss 0.635
Epoch #100:      train accuracy 0.953    train loss 0.148        test accuracy
0.770    test loss 0.676
Epoch #110:      train accuracy 0.957    train loss 0.141        test accuracy
0.764    test loss 0.703
Epoch #120:      train accuracy 0.958    train loss 0.133        test accuracy
0.763    test loss 0.738
Epoch #130:      train accuracy 0.964    train loss 0.127        test accuracy
0.765    test loss 0.770
Epoch #140:      train accuracy 0.965    train loss 0.118        test accuracy
0.763    test loss 0.804
Epoch #150:      train accuracy 0.970    train loss 0.112        test accuracy
0.761    test loss 0.840

Time to train and evaluate all models: 84.39417600631714 seconds
```


Training Accuracy by Activation Methods
Training Accuracy
Epoch
2 layer RELU
2 layers Sigmoid
1.00
0.95
0.90
0.85
0.80
0.75
0.70
0.65
0.60
0
20
40
60
80
100
120
140


Testing Accuracy by Activation Methods
Testing Accuracy
Epoch
2 layer RELU
2 layers Sigmoid
0.800
0.775
0.750
0.725
0.700
0.675
0.650
0.625
0.600
0
20
40
60
80
100
120
140

Analysis and discussion here (< 5 sentences) : The training accuracy plot reveals that the network with ReLU activation converges faster and achieves marginally higher accuracy compared to the sigmoid network. In testing accuracy, both ReLU and sigmoid display similar patterns of convergence, with ReLU having a slight advantage. The ReLU's performance suggests it might be more effective at capturing complex patterns in this context. However, the close performance on the testing set suggests that both activation functions are capable of similar generalization from the training data, and the choice may depend on the specific characteristics of the dataset and the training dynamics.

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.

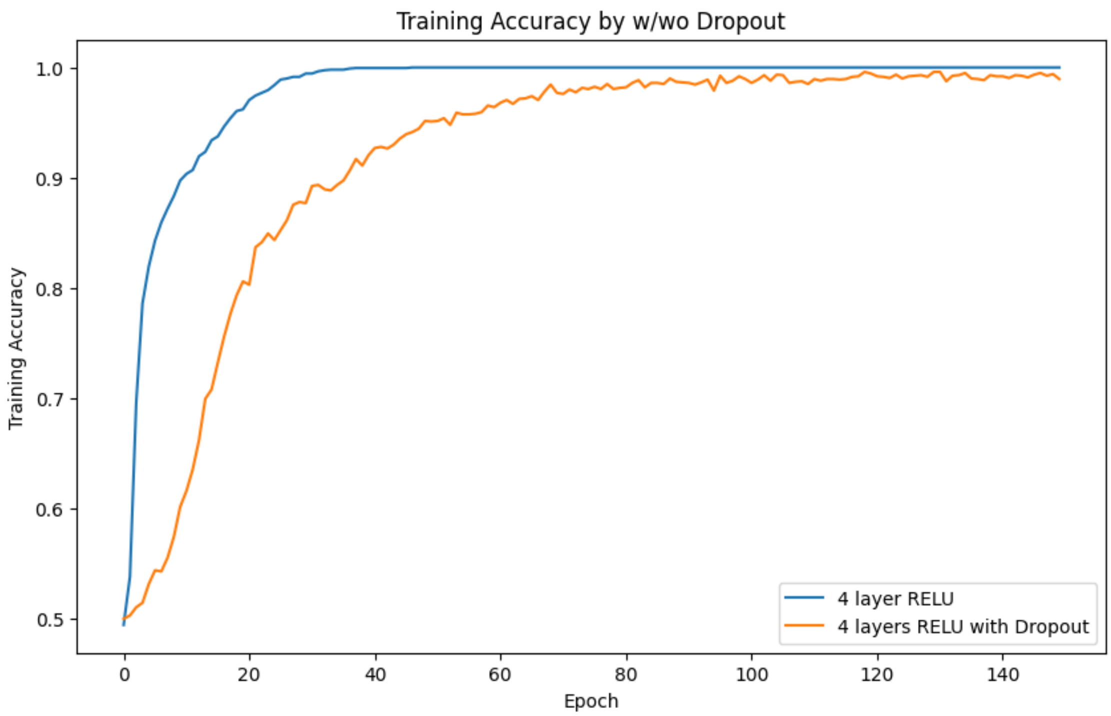
[15]:
```python
### YOUR CODE HERE
class NN4_Dropout(nn.Module):
    def __init__(self, input_size, hidden_size=100):
        super(NN4_Dropout, self).__init__()
        self.fc1 = nn.Linear(input_size, hidden_size)
        self.dropout1 = nn.Dropout(0.5)
        self.fc2 = nn.Linear(hidden_size, hidden_size)
        self.dropout2 = nn.Dropout(0.5)
        self.fc3 = nn.Linear(hidden_size, hidden_size)
        self.dropout3 = nn.Dropout(0.5)
        self.fc4 = nn.Linear(hidden_size, 2)

    def forward(self, x):
        x = F.relu(self.fc1(x))
        x = self.dropout1(x)
        x = F.relu(self.fc2(x))
        x = self.dropout2(x)
        x = F.relu(self.fc3(x))
        x = self.dropout3(x)
        x = F.log_softmax(self.fc4(x), dim=1)
        return x

input_size = 512
hidden_size = 36
models = [NN4(input_size, hidden_size), NN4_Dropout(input_size, hidden_size)]
model_names = ['4 layer RELU', '4 layers RELU with Dropout']

# Dictionaries to hold training and testing accuracies
train_accuracies = {}
test_accuracies = {}
```

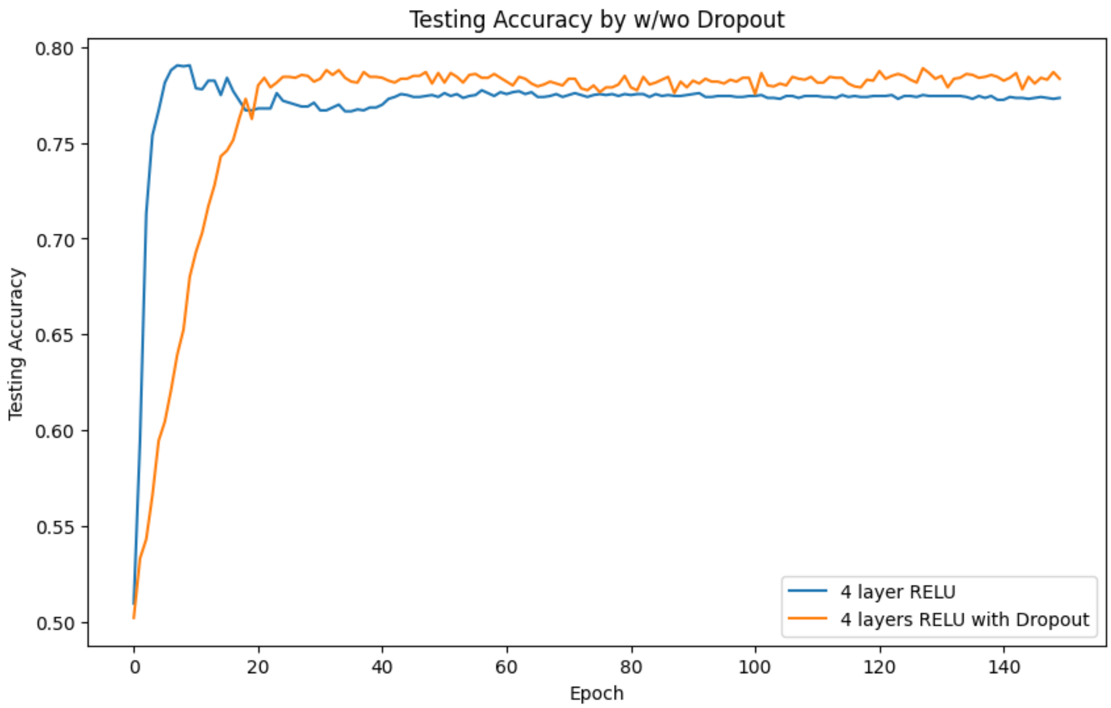
```python
start_time = time.time()

# Loop through each model, train, and collect accuracies
for model, name in zip(models, model_names):
    print(f'\nTraining {name}:')
    train_accuracy, test_accuracy = experiment(model)

    train_accuracies[name] = train_accuracy
    test_accuracies[name] = test_accuracy

end_time = time.time()
elapsed_time = end_time - start_time
print(f"\nTime to train and evaluate all models: {elapsed_time} seconds")

# Plot training accuracies
plt.figure(figsize=(10, 6))
for name in model_names:
    plt.plot(train_accuracies[name], label=f'{name}')
plt.title('Training Accuracy by w/wo Dropout')
plt.xlabel('Epoch')
plt.ylabel('Training Accuracy')
plt.legend()
plt.show()

# Plot testing accuracies
plt.figure(figsize=(10, 6))
for name in model_names:
    plt.plot(test_accuracies[name], label=f'{name}')
plt.title('Testing Accuracy by w/wo Dropout')
plt.xlabel('Epoch')
plt.ylabel('Testing Accuracy')
plt.legend()
plt.show()
```

```
Training 4 layer RELU:
Epoch #10:       train accuracy 0.897    train loss 0.271        test accuracy
0.790     test loss 0.486
Epoch #20:       train accuracy 0.962    train loss 0.130        test accuracy
0.767     test loss 0.672
Epoch #30:       train accuracy 0.995    train loss 0.043        test accuracy
0.771     test loss 0.916
Epoch #40:       train accuracy 1.000    train loss 0.011        test accuracy
0.768     test loss 1.259
Epoch #50:       train accuracy 1.000    train loss 0.002        test accuracy
0.774     test loss 1.516
Epoch #60:       train accuracy 1.000    train loss 0.001        test accuracy
```

```
0.776     test loss 1.795
Epoch #70:       train accuracy 1.000    train loss 0.000        test accuracy
0.774     test loss 2.021
Epoch #80:       train accuracy 1.000    train loss 0.000        test accuracy
0.775     test loss 2.231
Epoch #90:       train accuracy 1.000    train loss 0.000        test accuracy
0.775     test loss 2.434
Epoch #100:      train accuracy 1.000    train loss 0.000        test accuracy
0.774     test loss 2.629
Epoch #110:      train accuracy 1.000    train loss 0.000        test accuracy
0.774     test loss 2.810
Epoch #120:      train accuracy 1.000    train loss 0.000        test accuracy
0.774     test loss 3.000
Epoch #130:      train accuracy 1.000    train loss 0.000        test accuracy
0.774     test loss 3.194
Epoch #140:      train accuracy 1.000    train loss 0.000        test accuracy
0.772     test loss 3.370
Epoch #150:      train accuracy 1.000    train loss 0.000        test accuracy
0.773     test loss 3.541

Training 4 layers RELU with Dropout:
Epoch #10:       train accuracy 0.602    train loss 0.671        test accuracy
0.680     test loss 0.668
Epoch #20:       train accuracy 0.806    train loss 0.477        test accuracy
0.762     test loss 0.515
Epoch #30:       train accuracy 0.877    train loss 0.325        test accuracy
0.782     test loss 0.481
Epoch #40:       train accuracy 0.920    train loss 0.239        test accuracy
0.784     test loss 0.520
Epoch #50:       train accuracy 0.951    train loss 0.155        test accuracy
0.786     test loss 0.593
Epoch #60:       train accuracy 0.964    train loss 0.113        test accuracy
0.784     test loss 0.703
Epoch #70:       train accuracy 0.977    train loss 0.071        test accuracy
0.780     test loss 0.840
Epoch #80:       train accuracy 0.982    train loss 0.059        test accuracy
0.785     test loss 1.005
Epoch #90:       train accuracy 0.987    train loss 0.043        test accuracy
0.779     test loss 1.112
Epoch #100:      train accuracy 0.990    train loss 0.033        test accuracy
0.784     test loss 1.264
Epoch #110:      train accuracy 0.985    train loss 0.040        test accuracy
0.784     test loss 1.324
Epoch #120:      train accuracy 0.995    train loss 0.021        test accuracy
0.782     test loss 1.467
Epoch #130:      train accuracy 0.996    train loss 0.018        test accuracy
0.783     test loss 1.515
Epoch #140:      train accuracy 0.992    train loss 0.029        test accuracy
```

```
0.784     test loss 1.636
Epoch #150:      train accuracy 0.990    train loss 0.024        test accuracy
0.783     test loss 1.737

Time to train and evaluate all models: 107.53877091407776 seconds
```





Analysis and discussion here (< 5 sentences) : The training accuracy plot demonstrates that the four-layer network without dropout achieves higher training accuracy more rapidly compared to the same network with dropout. This suggests that dropout regularizes the model by limiting its capacity to overfit to the training data. On the testing accuracy plot, both models initially show similar accuracy, but as epochs increase, the model with dropout maintains a more consistent accuracy. This consistency indicates effective regularization, which helps the model generalize better without reducing its overall performance on unseen data. Hence, while dropout seems to slow down learning, it leads to a model that is more robust to variations in the data.

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 :

- Train on a larger dataset.
- Increase the regularization strength.

Explanation (< 5 sentences) here: : Overfitting occurs when a model is too complex relative to the amount and noisiness of the input data, capturing spurious patterns that fail to generalize to other data sets. More data and stronger regularization both work to smooth out these issues, improving model performance on new, unseen datasets (testing accuracy) relative to the performance on the training dataset. Adding more hidden units, conversely, might increase the model's complexity and potentially lead to more overfitting, not less.

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.

[16]:
```
### YOUR CODE HERE

# Learning Rate Scheduling
import torch
import torch.nn as nn
import torch.optim as optim
from torch.optim.lr_scheduler import StepLR

def experiment_steplr(model):
    loss_fn = nn.NLLLoss()
    optimizer = torch.optim.Adam(model.parameters(), lr=0.0001)
    scheduler = StepLR(optimizer, step_size=30, gamma=0.1)  # Adjust lr every␣
 ↪30 epochs

    all_train_accuracy = []
    average_train_loss = []
    all_test_accuracy = []
    average_test_loss = []

    for epoch in range(150):
        train_accuracy, train_loss = train_epoch(train_loader, model, loss_fn,␣
 ↪optimizer)
        all_train_accuracy.append(train_accuracy)
        average_train_loss.append(train_loss)

        test_accuracy, test_loss = eval_epoch(test_loader, model, loss_fn,␣
 ↪optimizer)
        all_test_accuracy.append(test_accuracy)
        average_test_loss.append(test_loss)

        scheduler.step()  # Update the learning rate

        if epoch % 10 == 9:
```

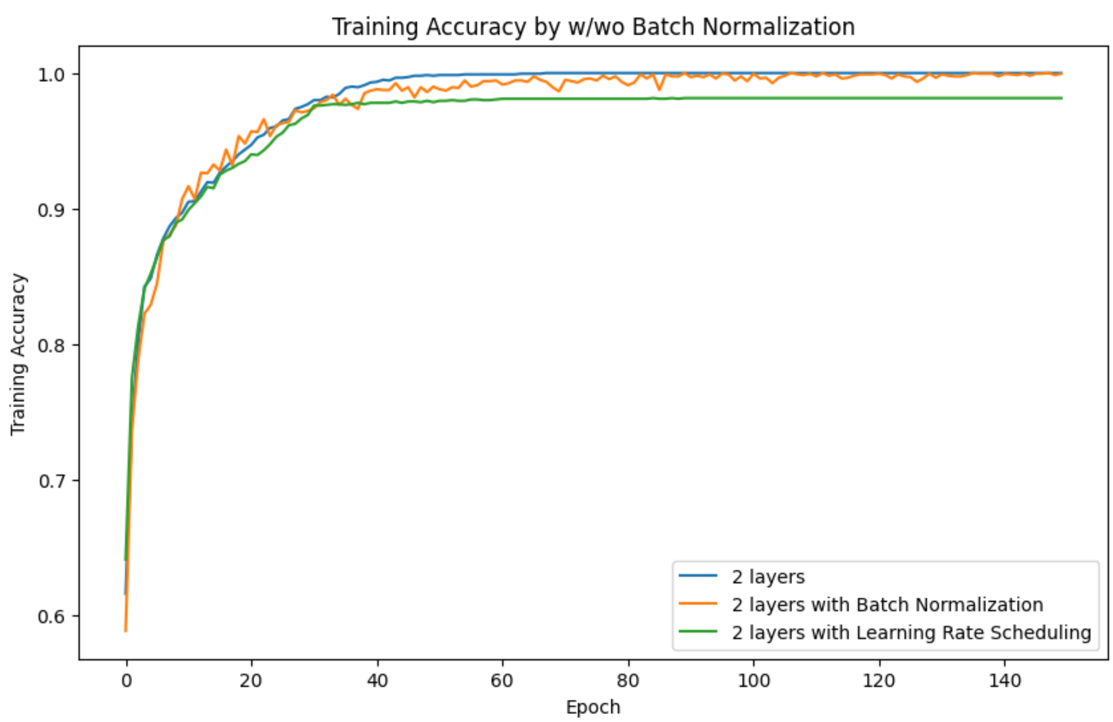
```
            print(f'Epoch #{epoch+1}: \t train accuracy {train_accuracy:.3f} \t␣
↪train loss {train_loss:.3f} \t test accuracy {test_accuracy:.3f} \t test␣
↪loss {test_loss:.3f}')

    return all_train_accuracy, all_test_accuracy

# Batch Normalization
class NN2_BatchNorm(nn.Module):
    def __init__(self, input_size, hidden_size=100):
        super(NN2_BatchNorm, self).__init__()
        self.fc1 = nn.Linear(input_size, hidden_size)
        self.bn1 = nn.BatchNorm1d(hidden_size)
        self.fc2 = nn.Linear(hidden_size, 2)

    def forward(self, x):
        x = F.relu(self.bn1(self.fc1(x)))
        x = F.log_softmax(self.fc2(x), dim=1)
        return x

input_size = 512
hidden_size = 100
models = [NN2(input_size, hidden_size), NN2_BatchNorm(input_size, hidden_size),␣
↪NN2(input_size, hidden_size)]
model_names = ['2 layers', '2 layers with Batch Normalization', '2 layers with␣
↪Learning Rate Scheduling']

# Dictionaries to hold training and testing accuracies
train_accuracies = {}
test_accuracies = {}

start_time = time.time()

# Loop through each model, train, and collect accuracies
for model, name in zip(models, model_names):
    print(f'\nTraining {name}:')
    if name == '2 layers with Learning Rate Scheduling':
      train_accuracy, test_accuracy = experiment_steplr(model)
    else:
      train_accuracy, test_accuracy = experiment(model)

    train_accuracies[name] = train_accuracy
    test_accuracies[name] = test_accuracy

end_time = time.time()
elapsed_time = end_time - start_time
print(f"\nTime to train and evaluate all models: {elapsed_time} seconds")
```

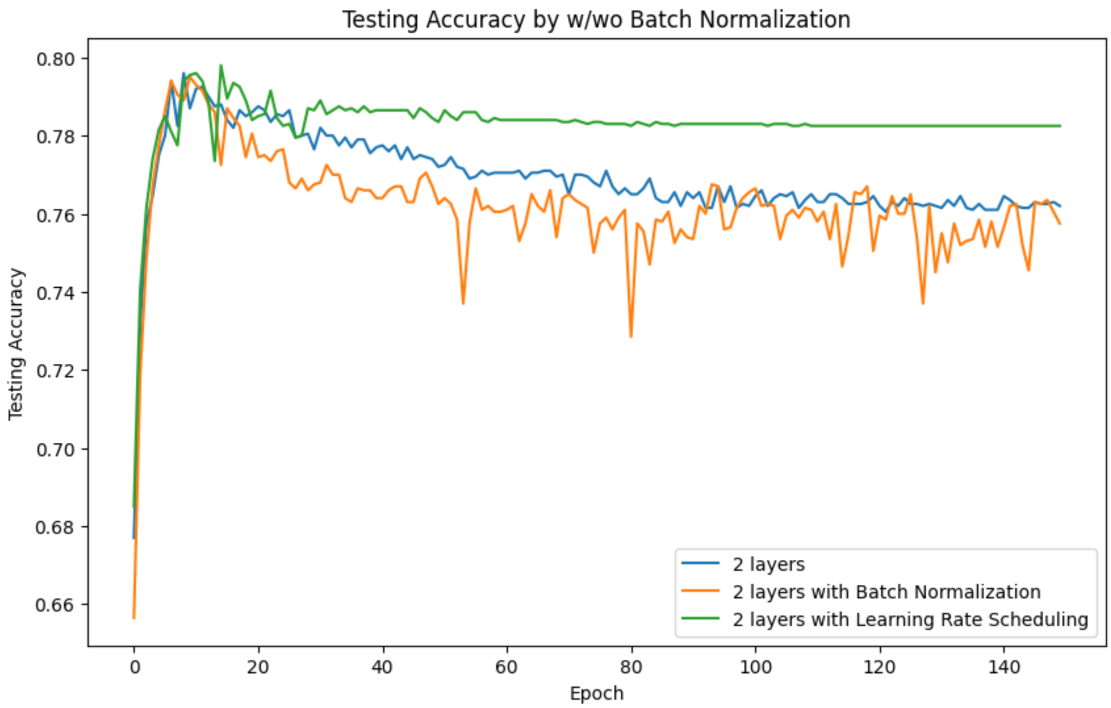
```python
# Plot training accuracies
plt.figure(figsize=(10, 6))
for name in model_names:
    plt.plot(train_accuracies[name], label=f'{name}')
plt.title('Training Accuracy by w/wo Batch Normalization')
plt.xlabel('Epoch')
plt.ylabel('Training Accuracy')
plt.legend()
plt.show()

# Plot testing accuracies
plt.figure(figsize=(10, 6))
for name in model_names:
    plt.plot(test_accuracies[name], label=f'{name}')
plt.title('Testing Accuracy by w/wo Batch Normalization')
plt.xlabel('Epoch')
plt.ylabel('Testing Accuracy')
plt.legend()
plt.show()
```

```
Training 2 layers:
Epoch #10:        train accuracy 0.897    train loss 0.292        test accuracy
0.787     test loss 0.476
Epoch #20:        train accuracy 0.944    train loss 0.182        test accuracy
0.786     test loss 0.516
Epoch #30:        train accuracy 0.977    train loss 0.116        test accuracy
0.776     test loss 0.571
Epoch #40:        train accuracy 0.993    train loss 0.071        test accuracy
0.777     test loss 0.671
Epoch #50:        train accuracy 0.998    train loss 0.042        test accuracy
0.772     test loss 0.781
Epoch #60:        train accuracy 0.999    train loss 0.024        test accuracy
0.770     test loss 0.857
Epoch #70:        train accuracy 1.000    train loss 0.013        test accuracy
0.770     test loss 0.958
Epoch #80:        train accuracy 1.000    train loss 0.007        test accuracy
0.766     test loss 1.078
Epoch #90:        train accuracy 1.000    train loss 0.004        test accuracy
0.765     test loss 1.196
Epoch #100:       train accuracy 1.000    train loss 0.002        test accuracy
0.762     test loss 1.336
Epoch #110:       train accuracy 1.000    train loss 0.001        test accuracy
0.765     test loss 1.434
Epoch #120:       train accuracy 1.000    train loss 0.001        test accuracy
0.764     test loss 1.586
Epoch #130:       train accuracy 1.000    train loss 0.000        test accuracy
0.762     test loss 1.678
```

```
Epoch #140:      train accuracy 1.000    train loss 0.000        test accuracy
0.761    test loss 1.805
Epoch #150:      train accuracy 1.000    train loss 0.000        test accuracy
0.762    test loss 1.926

Training 2 layers with Batch Normalization:
Epoch #10:       train accuracy 0.907    train loss 0.271        test accuracy
0.795    test loss 0.463
Epoch #20:       train accuracy 0.948    train loss 0.165        test accuracy
0.780    test loss 0.484
Epoch #30:       train accuracy 0.972    train loss 0.104        test accuracy
0.767    test loss 0.526
Epoch #40:       train accuracy 0.987    train loss 0.065        test accuracy
0.764    test loss 0.618
Epoch #50:       train accuracy 0.990    train loss 0.048        test accuracy
0.762    test loss 0.680
Epoch #60:       train accuracy 0.995    train loss 0.032        test accuracy
0.760    test loss 0.754
Epoch #70:       train accuracy 0.987    train loss 0.042        test accuracy
0.764    test loss 0.772
Epoch #80:       train accuracy 0.994    train loss 0.027        test accuracy
0.761    test loss 0.807
Epoch #90:       train accuracy 1.000    train loss 0.016        test accuracy
0.754    test loss 0.847
Epoch #100:      train accuracy 0.994    train loss 0.021        test accuracy
0.765    test loss 0.870
Epoch #110:      train accuracy 1.000    train loss 0.012        test accuracy
0.761    test loss 0.912
Epoch #120:      train accuracy 0.999    train loss 0.010        test accuracy
0.750    test loss 0.979
Epoch #130:      train accuracy 0.997    train loss 0.015        test accuracy
0.745    test loss 1.037
Epoch #140:      train accuracy 0.998    train loss 0.011        test accuracy
0.751    test loss 0.963
Epoch #150:      train accuracy 1.000    train loss 0.006        test accuracy
0.757    test loss 1.008

Training 2 layers with Learning Rate Scheduling:
Epoch #10:       train accuracy 0.892    train loss 0.302        test accuracy
0.795    test loss 0.468
Epoch #20:       train accuracy 0.935    train loss 0.196        test accuracy
0.784    test loss 0.520
Epoch #30:       train accuracy 0.969    train loss 0.128        test accuracy
0.786    test loss 0.576
Epoch #40:       train accuracy 0.978    train loss 0.114        test accuracy
0.786    test loss 0.583
Epoch #50:       train accuracy 0.979    train loss 0.109        test accuracy
0.783    test loss 0.591
```

```
Epoch #60:       train accuracy 0.981    train loss 0.103        test accuracy
0.784     test loss 0.602
Epoch #70:       train accuracy 0.981    train loss 0.102        test accuracy
0.783     test loss 0.603
Epoch #80:       train accuracy 0.981    train loss 0.101        test accuracy
0.783     test loss 0.604
Epoch #90:       train accuracy 0.982    train loss 0.101        test accuracy
0.783     test loss 0.605
Epoch #100:      train accuracy 0.982    train loss 0.101        test accuracy
0.783     test loss 0.605
Epoch #110:      train accuracy 0.982    train loss 0.100        test accuracy
0.782     test loss 0.605
Epoch #120:      train accuracy 0.982    train loss 0.100        test accuracy
0.782     test loss 0.605
Epoch #130:      train accuracy 0.982    train loss 0.100        test accuracy
0.782     test loss 0.606
Epoch #140:      train accuracy 0.982    train loss 0.100        test accuracy
0.782     test loss 0.606
Epoch #150:      train accuracy 0.982    train loss 0.100        test accuracy
0.782     test loss 0.606

Time to train and evaluate all models: 144.76883625984192 seconds
```





Analysis and discussion here (< 15 sentences) : It is evident that all models achieve high training accuracy over time, but their testing accuracy does not improve in tandem. This indicates overfitting, especially for the model without batch normalization or learning rate scheduling, which shows a testing accuracy that peaks and then starts to decrease as the epochs increase. The model with batch normalization appears to stabilize the training slightly better than the one without it, but ultimately it too shows signs of overfitting, as seen by the gap between training and testing accuracy and the decrease in testing accuracy after a certain number of epochs. The model with learning rate scheduling shows the best testing accuracy overall, although the improvement is modest. It seems to slightly mitigate overfitting as the testing accuracy does not degrade as much as with the other models. However, the plateau in testing accuracy despite further training suggests that simply adjusting the learning rate is not enough to continue to improve the generalization of the model. In all cases, while training accuracy approaches or reaches 100%, the testing accuracy is significantly lower, highlighting the models' inability to generalize well from their training data to unseen data. This could be improved by employing techniques such as data augmentation, more sophisticated learning rate schedules, early stopping, or by exploring more complex models that may capture the nuances of the data better without overfitting.

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.