CSE 256: NLP UCSD PA1:

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.

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: paste your link here: https://drive.google.com/file/d/1NW9tsO1OMvtdZACRgKyfKojso8rIqDDK/view?usp=sharing

---

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.

Mount your Google Drive to Colab

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

In [ ]:
```
# 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 = 'CSE256_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/
```

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.

In [1]:
```python
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])
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?

One significant limitation of using element-wise addition as a composition function for word embddings is that it does not take the context of the text into consideration. The positioning of words in a sentence result in different contexts, and simply adding up the embeddings ignores the semantics of the sentence. This loss of contextual information can severly affect the performance of downstream tasks, such as sentiment analysis, topic classification, etc., where these element-wise added embeddings are used.

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 $\boldsymbol{x}$ we just computed, we can use the softmax function in combination with a linear projection using a matrix W to transform $\boldsymbol{x}$ into a probability distribution p over the next word, expressed as $p = \text{softmax}(W\boldsymbol{x})$. Let's look at this in the cell below:

In [2]:
```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
```

```python
# Replace with the actual computation
x_ = x.view(1,-1)
projection = torch.matmul(x_,W)
probs = torch.nn.functional.softmax(projection, dim=1)


### 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.

In [3]:
```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
agg_batch_embs = torch.sum(batch_embs, dim=1)
projections = torch.matmul(agg_batch_embs, W)
batch_probs = F.softmax(projections, 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.

In [4]:
```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) # num_embeddings changed from 5 to 6
vocab = {'I': 0, 'like': 1, 'NLP': 2, 'classifiers': 3, '.': 4, '<UNK>': 5}
```

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

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

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.

In [5]:
```
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
```

In [6]:
```
######### 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(
        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]
```

In [7]:
```
########## train_epoch
```

```python
#
# 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, use_cross_entropy=False, learning_rate=0.0001, enable_early_stopping=False, patience=5):
    best_test_accuracy = 0.0
    counter = 0

    # negative log likelihood loss function
    loss_fn = nn.CrossEntropyLoss() if use_cross_entropy else nn.NLLLoss()

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

    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 enable_early_stopping:
            if test_accuracy > best_test_accuracy:
                best_test_accuracy = test_accuracy
                counter = 0
                # Save the model if test accuracy improves
                torch.save(model.state_dict(), 'best_model.pt')
            else:
                counter += 1
```

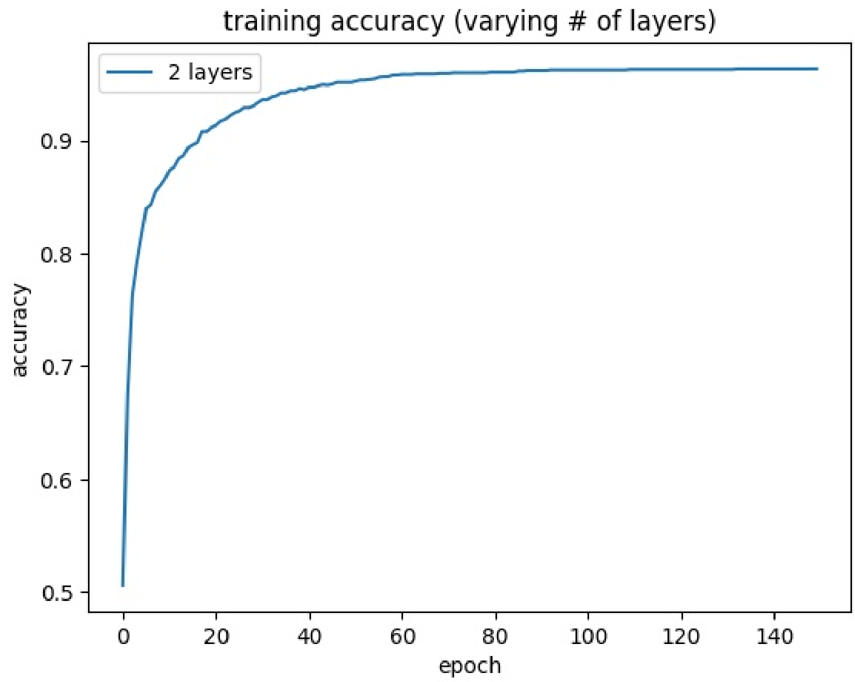
```python
                if counter >= patience:
                    print(f'Early stopping after {patience} epochs without improvement.')
                    break

        if epoch % 10 == 9:
            print(f'Epoch #{epoch+1}: \t train accuracy {train_accuracy:.3f}\t train loss {train_loss:.3f}\t te

    return all_train_accuracy, all_test_accuracy
```

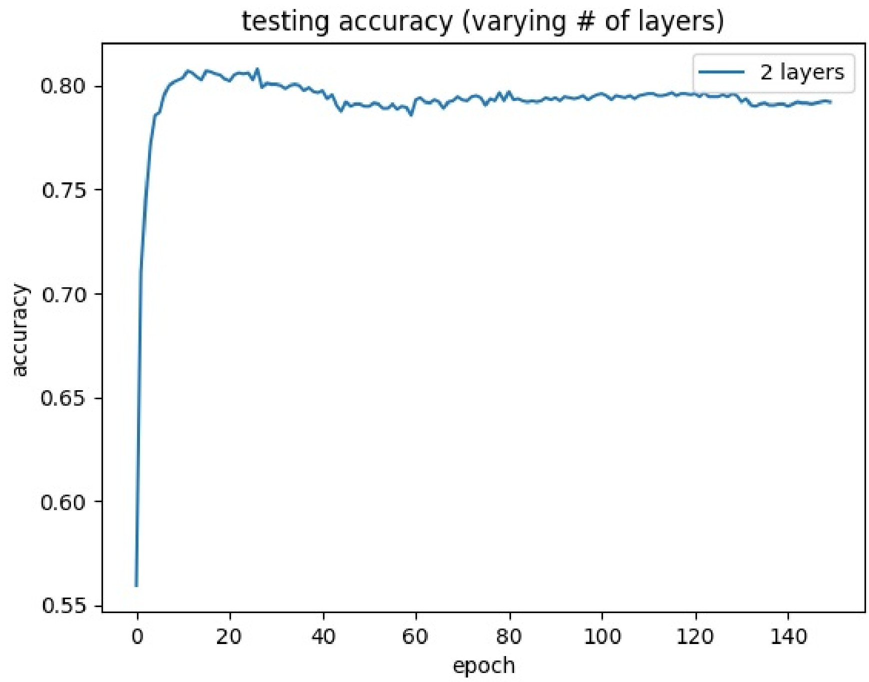
In [8]:
```python
######################
#
# 1) Load data splits: the train and test sets
# 2) Train neural networks
# 3) Plot the results
############################

start_time = time.time()

# Load the dataset
#root_dir = '/content/drive/My Drive/{}/CSE256_PA1/aclImdb/train'.format(FOLDERNAME)
#root_dir_test = '/content/drive/My Drive/{}/CSE256_PA1/aclImdb/test'.format(FOLDERNAME)
root_dir = './CSE256_PA1/aclImdb/train'
root_dir_test = './CSE256_PA1/aclImdb/test'
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_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: 0.5358321666717529 seconds
```

In [9]:
```python
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:
/Users/chinmaysharma/Documents/Jupyter/venv/lib/python3.9/site-packages/urllib3/__init__.py:34: NotOpenSSLWarning: urllib3 v2.0 only supports OpenSSL 1.1.1+, currently the 'ssl' module is compiled with 'LibreSSL 2.8.3'. See: https://github.com/urllib3/urllib3/issues/3020
  warnings.warn(
Epoch #10:       train accuracy 0.866    train loss -0.806       test accuracy 0.802     test loss -0.755
Epoch #20:       train accuracy 0.911    train loss -0.872       test accuracy 0.803     test loss -0.783
Epoch #30:       train accuracy 0.933    train loss -0.904       test accuracy 0.800     test loss -0.787
Epoch #40:       train accuracy 0.945    train loss -0.925       test accuracy 0.796     test loss -0.788
Epoch #50:       train accuracy 0.952    train loss -0.938       test accuracy 0.790     test loss -0.788
Epoch #60:       train accuracy 0.958    train loss -0.948       test accuracy 0.785     test loss -0.788
Epoch #70:       train accuracy 0.960    train loss -0.954       test accuracy 0.794     test loss -0.790
Epoch #80:       train accuracy 0.961    train loss -0.957       test accuracy 0.792     test loss -0.791
Epoch #90:       train accuracy 0.962    train loss -0.960       test accuracy 0.793     test loss -0.791
Epoch #100:      train accuracy 0.963    train loss -0.961       test accuracy 0.795     test loss -0.791
Epoch #110:      train accuracy 0.963    train loss -0.962       test accuracy 0.795     test loss -0.791
Epoch #120:      train accuracy 0.963    train loss -0.963       test accuracy 0.795     test loss -0.791
Epoch #130:      train accuracy 0.963    train loss -0.963       test accuracy 0.795     test loss -0.791
Epoch #140:      train accuracy 0.964    train loss -0.963       test accuracy 0.791     test loss -0.791
Epoch #150:      train accuracy 0.964    train loss -0.963       test accuracy 0.792     test loss -0.791
```






```
Time to train, eval model: 10.604265928268433 seconds
```

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().

In [10]:
```
### YOUR CODE HERE
```

In [11]:
```
### 1 layer
class NN1(nn.Module):
    def __init__(self, input_size):
        super().__init__()
        self.fc1 = nn.Linear(input_size, 2)

    # Define the forward pass of the neural network.
    # x: The input tensor.
    def forward(self, x):
        x = self.fc1(x)
        x = F.softmax(x, dim=1)  # Apply Softmax to obtain output probabilities.
        return x

start_time = time.time()
```

```python
# train neural networks
print('\n1 layers:')
nn1_train_accuracy, nn1_test_accuracy = experiment(NN1(input_size=512))

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

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

```
1 layers:
Epoch #10:       train accuracy 0.778    train loss -0.652       test accuracy 0.764     test loss -0.637
Epoch #20:       train accuracy 0.822    train loss -0.712       test accuracy 0.791     test loss -0.685
Epoch #30:       train accuracy 0.843    train loss -0.747       test accuracy 0.797     test loss -0.711
Epoch #40:       train accuracy 0.855    train loss -0.771       test accuracy 0.797     test loss -0.728
Epoch #50:       train accuracy 0.864    train loss -0.788       test accuracy 0.800     test loss -0.740
Epoch #60:       train accuracy 0.872    train loss -0.802       test accuracy 0.808     test loss -0.749
Epoch #70:       train accuracy 0.878    train loss -0.813       test accuracy 0.809     test loss -0.756
Epoch #80:       train accuracy 0.883    train loss -0.822       test accuracy 0.806     test loss -0.761
Epoch #90:       train accuracy 0.890    train loss -0.830       test accuracy 0.808     test loss -0.765
Epoch #100:      train accuracy 0.891    train loss -0.836       test accuracy 0.807     test loss -0.768
Epoch #110:      train accuracy 0.894    train loss -0.842       test accuracy 0.808     test loss -0.770
Epoch #120:      train accuracy 0.898    train loss -0.847       test accuracy 0.809     test loss -0.772
Epoch #130:      train accuracy 0.900    train loss -0.851       test accuracy 0.808     test loss -0.774
Epoch #140:      train accuracy 0.904    train loss -0.855       test accuracy 0.807     test loss -0.775
Epoch #150:      train accuracy 0.907    train loss -0.859       test accuracy 0.809     test loss -0.776
Time to train, eval model: 5.5231032371521 seconds
```

In [12]:

```python
### 2 layers
start_time = time.time()

# train neural networks
print('\n2 layers:')
nn2_train_accuracy, nn2_test_accuracy = experiment(NN2(input_size=512, hidden_size=100))
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 0.863    train loss -0.806       test accuracy 0.801     test loss -0.757
Epoch #20:       train accuracy 0.904    train loss -0.869       test accuracy 0.807     test loss -0.783
Epoch #30:       train accuracy 0.927    train loss -0.899       test accuracy 0.803     test loss -0.787
Epoch #40:       train accuracy 0.943    train loss -0.919       test accuracy 0.793     test loss -0.786
Epoch #50:       train accuracy 0.950    train loss -0.933       test accuracy 0.794     test loss -0.785
Epoch #60:       train accuracy 0.956    train loss -0.944       test accuracy 0.790     test loss -0.784
Epoch #70:       train accuracy 0.959    train loss -0.951       test accuracy 0.786     test loss -0.783
Epoch #80:       train accuracy 0.961    train loss -0.956       test accuracy 0.789     test loss -0.784
Epoch #90:       train accuracy 0.962    train loss -0.959       test accuracy 0.791     test loss -0.785
Epoch #100:      train accuracy 0.963    train loss -0.961       test accuracy 0.789     test loss -0.786
Epoch #110:      train accuracy 0.965    train loss -0.963       test accuracy 0.788     test loss -0.785
Epoch #120:      train accuracy 0.965    train loss -0.964       test accuracy 0.787     test loss -0.784
Epoch #130:      train accuracy 0.965    train loss -0.964       test accuracy 0.784     test loss -0.784
Epoch #140:      train accuracy 0.965    train loss -0.965       test accuracy 0.783     test loss -0.784
Epoch #150:      train accuracy 0.965    train loss -0.965       test accuracy 0.785     test loss -0.784
Time to train, eval model: 10.408082962036133 seconds
```

In [13]:

```python
### 3 layers
class NN3(nn.Module):
    def __init__(self, input_size, hidden_size):
        super().__init__()
        self.fc1 = nn.Linear(input_size, hidden_size)
        self.fc2 = nn.Linear(hidden_size, hidden_size)
        self.fc3 = nn.Linear(hidden_size, 2)

    # Define the forward pass of the neural network.
    # x: The input tensor.
    def forward(self, x):
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        x = F.softmax(x, dim=1)
        return x


start_time = time.time()

# train neural networks
print('\n3 layers:')
nn3_train_accuracy, nn3_test_accuracy = experiment(NN3(input_size=512, hidden_size=100))
end_time = time.time()
elapsed_time = end_time - start_time

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

```
3 layers:
Epoch #10:      train accuracy 0.898    train loss -0.867      test accuracy 0.799     test loss -0.787
Epoch #20:      train accuracy 0.944    train loss -0.931      test accuracy 0.793     test loss -0.790
Epoch #30:      train accuracy 0.959    train loss -0.954      test accuracy 0.791     test loss -0.788
Epoch #40:      train accuracy 0.962    train loss -0.961      test accuracy 0.786     test loss -0.786
Epoch #50:      train accuracy 0.965    train loss -0.964      test accuracy 0.785     test loss -0.783
Epoch #60:      train accuracy 0.965    train loss -0.964      test accuracy 0.782     test loss -0.785
Epoch #70:      train accuracy 0.966    train loss -0.965      test accuracy 0.783     test loss -0.785
Epoch #80:      train accuracy 0.966    train loss -0.966      test accuracy 0.785     test loss -0.789
Epoch #90:      train accuracy 0.966    train loss -0.966      test accuracy 0.785     test loss -0.789
Epoch #100:     train accuracy 0.966    train loss -0.966      test accuracy 0.785     test loss -0.788
Epoch #110:     train accuracy 0.967    train loss -0.967      test accuracy 0.790     test loss -0.785
Epoch #120:     train accuracy 0.967    train loss -0.967      test accuracy 0.788     test loss -0.786
Epoch #130:     train accuracy 0.967    train loss -0.967      test accuracy 0.789     test loss -0.787
Epoch #140:     train accuracy 0.967    train loss -0.967      test accuracy 0.787     test loss -0.787
Epoch #150:     train accuracy 0.967    train loss -0.967      test accuracy 0.787     test loss -0.787
Time to train, eval model: 12.805835962295532 seconds
```

In [14]:

```python
### 4 layers
class NN4(nn.Module):
    def __init__(self, input_size, hidden_size, activation_function='relu', dropout_prob=0):
        super().__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)
        self.activation = nn.ReLU() if activation_function == 'relu' else nn.Sigmoid()
        self.dropout1 = nn.Dropout(p=dropout_prob)
        self.dropout2 = nn.Dropout(p=dropout_prob)
        self.dropout3 = nn.Dropout(p=dropout_prob)

    # Define the forward pass of the neural network.
    # x: The input tensor.
    def forward(self, x):
        x = self.activation(self.fc1(x))
        x = self.dropout1(x)
        x = self.activation(self.fc2(x))
        x = self.dropout2(x)
        x = self.activation(self.fc3(x))
        x = self.dropout3(x)
        x = self.fc4(x)
        x = F.softmax(x, dim=1)
        return x
```

In [15]:

```python
# 4 layers with ReLU activation and without dropout
start_time = time.time()

# train neural networks
print('\n4 layers:')
nn4_train_accuracy, nn4_test_accuracy = experiment(NN4(input_size=512, hidden_size=100))
end_time = time.time()
elapsed_time = end_time - start_time

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

```
4 layers:
Epoch #10:      train accuracy 0.916    train loss -0.899      test accuracy 0.799     test loss -0.794
Epoch #20:      train accuracy 0.952    train loss -0.949      test accuracy 0.803     test loss -0.798
Epoch #30:      train accuracy 0.959    train loss -0.958      test accuracy 0.797     test loss -0.796
Epoch #40:      train accuracy 0.960    train loss -0.959      test accuracy 0.797     test loss -0.795
Epoch #50:      train accuracy 0.962    train loss -0.961      test accuracy 0.801     test loss -0.798
Epoch #60:      train accuracy 0.963    train loss -0.963      test accuracy 0.798     test loss -0.798
Epoch #70:      train accuracy 0.963    train loss -0.963      test accuracy 0.797     test loss -0.798
Epoch #80:      train accuracy 0.964    train loss -0.963      test accuracy 0.799     test loss -0.798
Epoch #90:      train accuracy 0.964    train loss -0.964      test accuracy 0.794     test loss -0.794
Epoch #100:     train accuracy 0.964    train loss -0.964      test accuracy 0.796     test loss -0.794
Epoch #110:     train accuracy 0.964    train loss -0.964      test accuracy 0.796     test loss -0.795
Epoch #120:     train accuracy 0.958    train loss -0.957      test accuracy 0.786     test loss -0.783
Epoch #130:     train accuracy 0.965    train loss -0.965      test accuracy 0.794     test loss -0.793
Epoch #140:     train accuracy 0.965    train loss -0.965      test accuracy 0.794     test loss -0.793
Epoch #150:     train accuracy 0.965    train loss -0.965      test accuracy 0.794     test loss -0.794
Time to train, eval model: 14.845610857009888 seconds
```

In [16]:

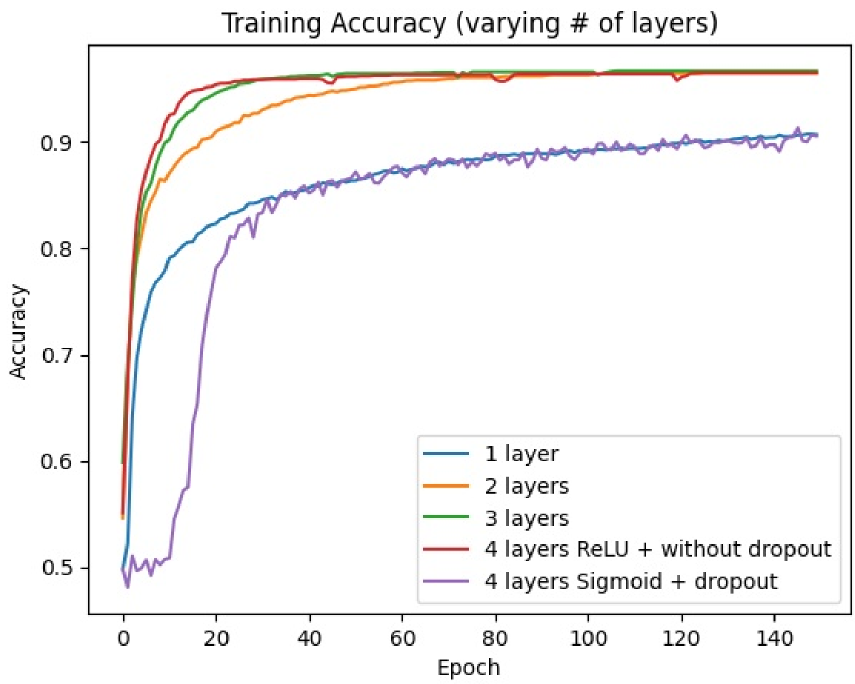
```python
### 4 layers with sigmoid activation and dropout
start_time = time.time()

# train neural networks
print('\n4 layers with sigmoid activation and dropout:')
nn4_train_accuracy_sigmoid_dropout, nn4_test_accuracy_sigmoid_dropout = experiment(NN4(input_size=512, hidden_s
end_time = time.time()
elapsed_time = end_time - start_time

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

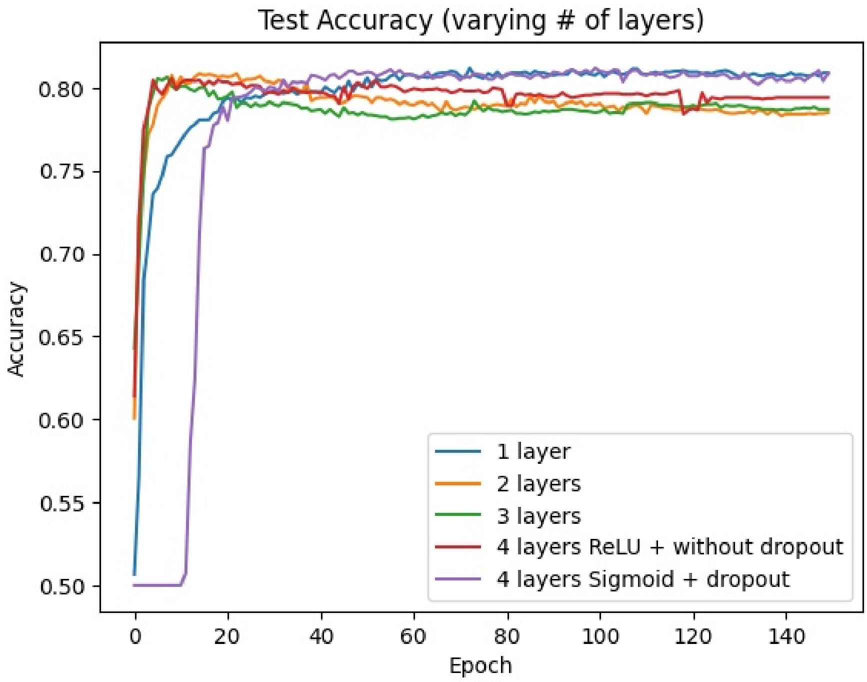
```
4 layers with sigmoid activation and dropout:
Epoch #10:      train accuracy 0.507    train loss -0.502       test accuracy 0.500     test loss -0.505
Epoch #20:      train accuracy 0.760    train loss -0.656       test accuracy 0.788     test loss -0.669
Epoch #30:      train accuracy 0.832    train loss -0.804       test accuracy 0.800     test loss -0.782
Epoch #40:      train accuracy 0.859    train loss -0.843       test accuracy 0.807     test loss -0.797
Epoch #50:      train accuracy 0.866    train loss -0.858       test accuracy 0.808     test loss -0.803
Epoch #60:      train accuracy 0.877    train loss -0.867       test accuracy 0.808     test loss -0.804
Epoch #70:      train accuracy 0.880    train loss -0.876       test accuracy 0.807     test loss -0.805
Epoch #80:      train accuracy 0.887    train loss -0.880       test accuracy 0.805     test loss -0.805
Epoch #90:      train accuracy 0.893    train loss -0.889       test accuracy 0.807     test loss -0.805
Epoch #100:     train accuracy 0.893    train loss -0.891       test accuracy 0.812     test loss -0.806
Epoch #110:     train accuracy 0.898    train loss -0.896       test accuracy 0.808     test loss -0.805
Epoch #120:     train accuracy 0.893    train loss -0.889       test accuracy 0.807     test loss -0.804
Epoch #130:     train accuracy 0.900    train loss -0.899       test accuracy 0.806     test loss -0.805
Epoch #140:     train accuracy 0.897    train loss -0.896       test accuracy 0.805     test loss -0.805
Epoch #150:     train accuracy 0.905    train loss -0.902       test accuracy 0.808     test loss -0.805
Time to train, eval model: 16.052730798721313 seconds
```

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.

In [17]:
```python
# plot training accuracy
plt.plot(nn1_train_accuracy, label='1 layer')
plt.plot(nn2_train_accuracy, label='2 layers')
plt.plot(nn3_train_accuracy, label='3 layers')
plt.plot(nn4_train_accuracy, label='4 layers ReLU + without dropout')
plt.plot(nn4_train_accuracy_sigmoid_dropout, label='4 layers Sigmoid + dropout')
plt.title('Training Accuracy (varying # of layers)')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend()
plt.show()

# plot testing accuracy
plt.plot(nn1_test_accuracy, label='1 layer')
plt.plot(nn2_test_accuracy, label='2 layers')
plt.plot(nn3_test_accuracy, label='3 layers')
plt.plot(nn4_test_accuracy, label='4 layers ReLU + without dropout')
plt.plot(nn4_test_accuracy_sigmoid_dropout, label='4 layers Sigmoid + dropout')
plt.title('Test Accuracy (varying # of layers)')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend()
plt.show()
```





Analysis and discussion here (< 5 sentences) :

We can observe that the training accuracy for all 4 models (with different number of layers) initially increases and then stabilizes with increasing epochs. The training accuracy for models with 2, 3 and 4 layers converges to similar values, while training accuracy was lower for model with just 1 layer. However, this trend is reversed in the test accuracy as the model with 1 layer achieves the highest test accuracy after 150 epochs. Whereas, the models with 2, 3 and 4 layers coverge to a lower test accuracy. This shows that although deeper models with 2,3 or 4 layers fit the training data well, they fail to generalize on the unseen test data, which indicates that the deeper models are overfitting on the training data.

However, we can observe that the training and testing accuracy of the 4 layers model with sigmoid activation and dropout layers is similar to the 1 layer model. The gap between the training and testing accuracy of the 4 layers model with sigmoid activation and dropout layers is less compared to the 4 layer model with relu activation and no dropout. This reduction in disparity between the training and testing accuracy of the 4 layers model with sigmoid activation and dropout layers can be attributed to the dropout layers with probability 0.5. This demonstrates the regularization capability of dropout layers which prevents models from overfitting on the training data.

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.

In [18]:
```
### 2 layers custom model
class NN2_custom(nn.Module):
    def __init__(self, input_size, hidden_size, activation_function='relu', dropout_prob=0):
        super().__init__()
        self.fc1 = nn.Linear(input_size, hidden_size)
        self.fc2 = nn.Linear(hidden_size, 2)
        self.activation = nn.ReLU() if activation_function == 'relu' else nn.Sigmoid()
        self.dropout = nn.Dropout(p=dropout_prob)

    # Define the forward pass of the neural network.
    # x: The input tensor.
    def forward(self, x):
        x = self.activation(self.fc1(x))
        x = self.fc2(x)
        x = F.softmax(x, dim=1)
        return x
```

In [19]:
```
### 2 layers with ReLU
```

```
start_time = time.time()

# train neural networks
print('\n2 layers with ReLU:')
nn2_train_accuracy_relu, nn2_test_accuracy_relu = experiment(NN2_custom(input_size=512, hidden_size=100, activa
end_time = time.time()
elapsed_time = end_time - start_time

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

```
2 layers with ReLU:
Epoch #10:       train accuracy 0.872    train loss -0.809       test accuracy 0.806     test loss -0.758
Epoch #20:       train accuracy 0.909    train loss -0.871       test accuracy 0.805     test loss -0.782
Epoch #30:       train accuracy 0.930    train loss -0.902       test accuracy 0.806     test loss -0.788
Epoch #40:       train accuracy 0.946    train loss -0.923       test accuracy 0.799     test loss -0.788
Epoch #50:       train accuracy 0.955    train loss -0.938       test accuracy 0.793     test loss -0.787
Epoch #60:       train accuracy 0.957    train loss -0.948       test accuracy 0.791     test loss -0.788
Epoch #70:       train accuracy 0.959    train loss -0.953       test accuracy 0.797     test loss -0.790
Epoch #80:       train accuracy 0.961    train loss -0.958       test accuracy 0.797     test loss -0.790
Epoch #90:       train accuracy 0.963    train loss -0.960       test accuracy 0.796     test loss -0.788
Epoch #100:      train accuracy 0.964    train loss -0.963       test accuracy 0.797     test loss -0.789
Epoch #110:      train accuracy 0.964    train loss -0.963       test accuracy 0.795     test loss -0.789
Epoch #120:      train accuracy 0.965    train loss -0.964       test accuracy 0.789     test loss -0.787
Epoch #130:      train accuracy 0.965    train loss -0.964       test accuracy 0.788     test loss -0.787
Epoch #140:      train accuracy 0.965    train loss -0.965       test accuracy 0.789     test loss -0.789
Epoch #150:      train accuracy 0.965    train loss -0.965       test accuracy 0.790     test loss -0.789
Time to train, eval model: 10.094784021377563 seconds
```

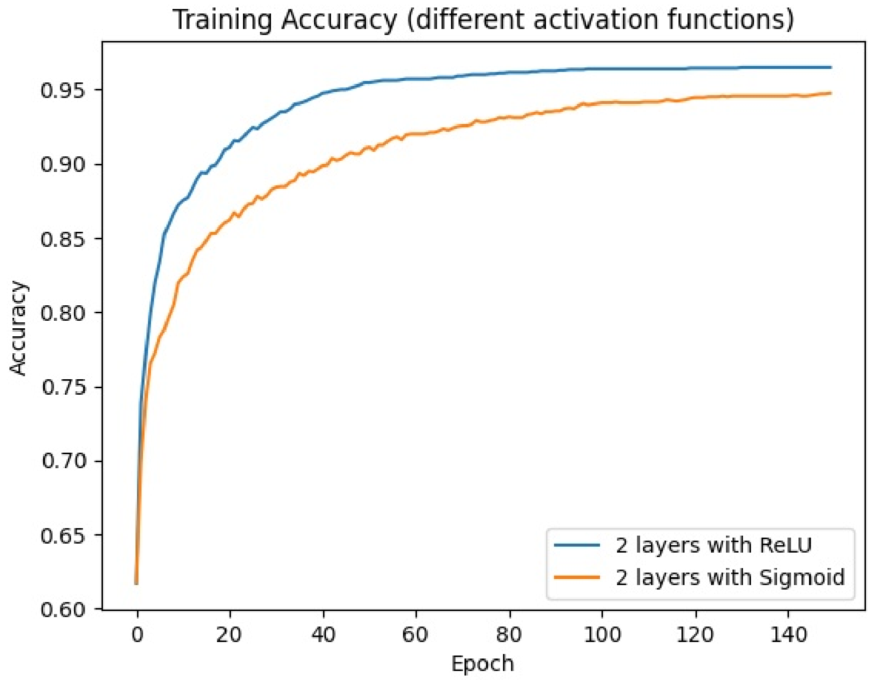
In [20]:

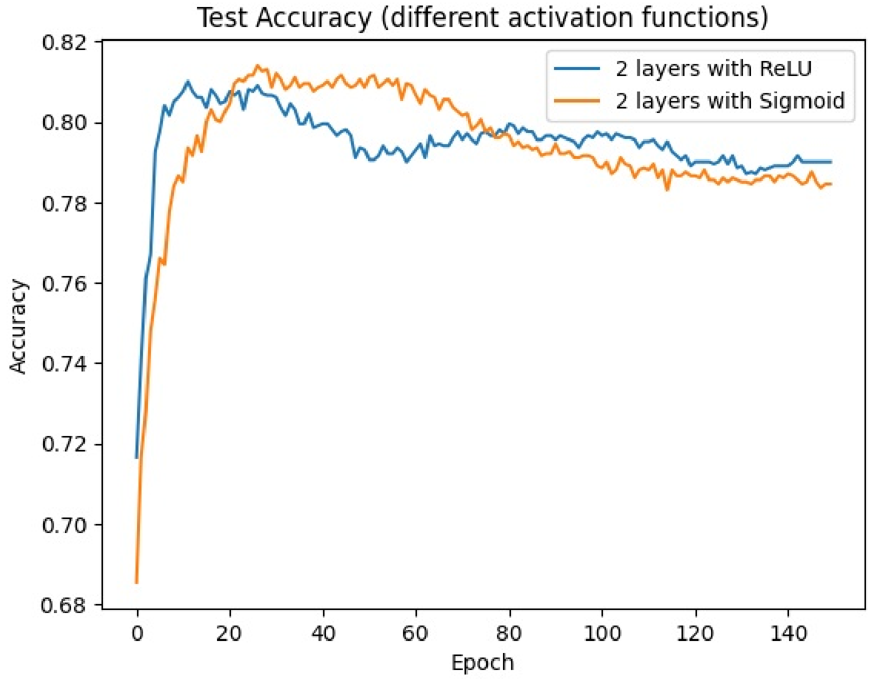
```
### 2 layers with Sigmoid

start_time = time.time()

# train neural networks
print('\n2 layers with Sigmoid:')
nn2_train_accuracy_sigmoid, nn2_test_accuracy_sigmoid = experiment(NN2_custom(input_size=512, hidden_size=100, a
end_time = time.time()
elapsed_time = end_time - start_time

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

```
2 layers with Sigmoid:
Epoch #10:       train accuracy 0.820    train loss -0.693       test accuracy 0.786     test loss -0.675
Epoch #20:       train accuracy 0.860    train loss -0.795       test accuracy 0.802     test loss -0.750
Epoch #30:       train accuracy 0.882    train loss -0.837       test accuracy 0.808     test loss -0.775
Epoch #40:       train accuracy 0.896    train loss -0.862       test accuracy 0.808     test loss -0.784
Epoch #50:       train accuracy 0.910    train loss -0.878       test accuracy 0.808     test loss -0.789
Epoch #60:       train accuracy 0.920    train loss -0.890       test accuracy 0.809     test loss -0.791
Epoch #70:       train accuracy 0.925    train loss -0.901       test accuracy 0.802     test loss -0.791
Epoch #80:       train accuracy 0.930    train loss -0.909       test accuracy 0.797     test loss -0.790
Epoch #90:       train accuracy 0.935    train loss -0.917       test accuracy 0.792     test loss -0.789
Epoch #100:      train accuracy 0.941    train loss -0.923       test accuracy 0.789     test loss -0.786
Epoch #110:      train accuracy 0.942    train loss -0.927       test accuracy 0.788     test loss -0.785
Epoch #120:      train accuracy 0.944    train loss -0.931       test accuracy 0.786     test loss -0.785
Epoch #130:      train accuracy 0.946    train loss -0.935       test accuracy 0.785     test loss -0.784
Epoch #140:      train accuracy 0.946    train loss -0.937       test accuracy 0.786     test loss -0.783
Epoch #150:      train accuracy 0.948    train loss -0.940       test accuracy 0.784     test loss -0.782
Time to train, eval model: 10.169013261795044 seconds
```

In [21]:

```
# plot training accuracy
plt.plot(nn2_train_accuracy_relu, label='2 layers with ReLU')
plt.plot(nn2_train_accuracy_sigmoid, label='2 layers with Sigmoid')
plt.title('Training Accuracy (different activation functions)')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend()
plt.show()

# plot testing accuracy
plt.plot(nn2_test_accuracy_relu, label='2 layers with ReLU')
plt.plot(nn2_test_accuracy_sigmoid, label='2 layers with Sigmoid')
plt.title('Test Accuracy (different activation functions)')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend()
plt.show()
```





Analysis and discussion here (< 5 sentences) :

The training accuracy for both models nearly stabilize around the 150 epoch mark. The 2 layer model with ReLU activation achieves a higher training accuracy compared to the 2 layer model with sigmoid activation. On the other hand, the testing accuracy of both the models had significant variablility but at later epochs the 2 layer model with ReLU activation had higher test accuracy than the 2 layer model with sigmoid activation. This shows that the 2 layer model with ReLU activation fits the training data well and with enough training epochs reduces overfitting on the training data. This is understandable as ReLU does sparse activation and mitigates the vanishing gradient problem, which aids the model's ability to generalize. Whereas, the 2 layer model with sigmoid activation tends to overfit on the training data at later epochs.

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.

In [22]:
```
### 4 layers without dropout
start_time = time.time()

# train neural networks
print('\n4 layers without dropout:')
nn4_train_accuracy_no_dropout, nn4_test_accuracy_no_dropout = experiment(NN4(input_size=512, hidden_size=36))
```

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

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

```
4 layers without dropout:
Epoch #10:       train accuracy 0.873    train loss -0.843       test accuracy 0.808     test loss -0.782
Epoch #20:       train accuracy 0.930    train loss -0.914       test accuracy 0.807     test loss -0.796
Epoch #30:       train accuracy 0.945    train loss -0.939       test accuracy 0.803     test loss -0.797
Epoch #40:       train accuracy 0.951    train loss -0.948       test accuracy 0.797     test loss -0.795
Epoch #50:       train accuracy 0.952    train loss -0.951       test accuracy 0.797     test loss -0.795
Epoch #60:       train accuracy 0.954    train loss -0.953       test accuracy 0.799     test loss -0.794
Epoch #70:       train accuracy 0.955    train loss -0.954       test accuracy 0.798     test loss -0.794
Epoch #80:       train accuracy 0.955    train loss -0.954       test accuracy 0.798     test loss -0.795
Epoch #90:       train accuracy 0.955    train loss -0.954       test accuracy 0.798     test loss -0.795
Epoch #100:      train accuracy 0.955    train loss -0.954       test accuracy 0.797     test loss -0.795
Epoch #110:      train accuracy 0.955    train loss -0.954       test accuracy 0.796     test loss -0.795
Epoch #120:      train accuracy 0.955    train loss -0.954       test accuracy 0.796     test loss -0.795
Epoch #130:      train accuracy 0.958    train loss -0.958       test accuracy 0.791     test loss -0.791
Epoch #140:      train accuracy 0.958    train loss -0.958       test accuracy 0.791     test loss -0.791
Epoch #150:      train accuracy 0.958    train loss -0.958       test accuracy 0.791     test loss -0.791
Time to train, eval model: 11.329285144805908 seconds
```

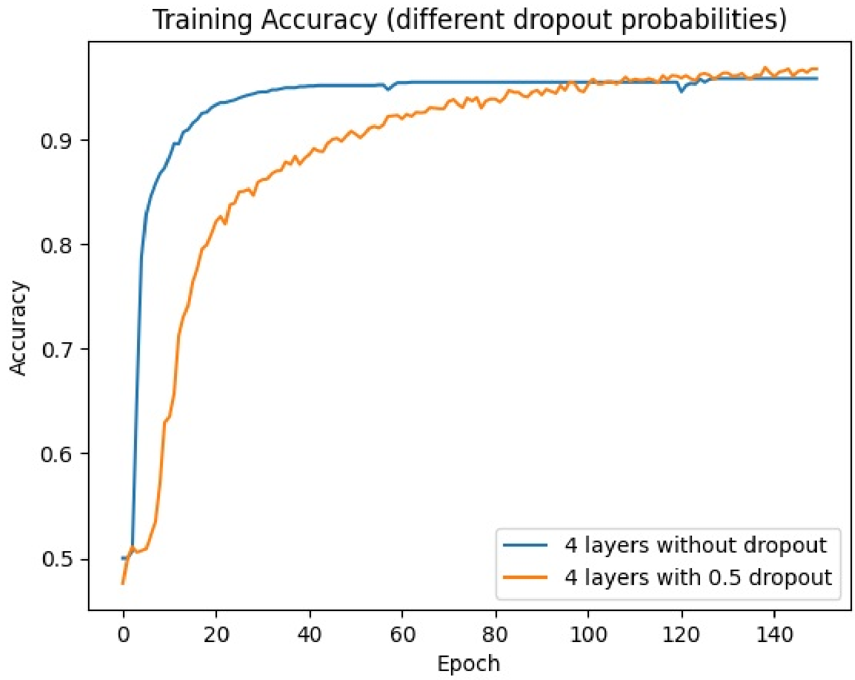
In [23]:

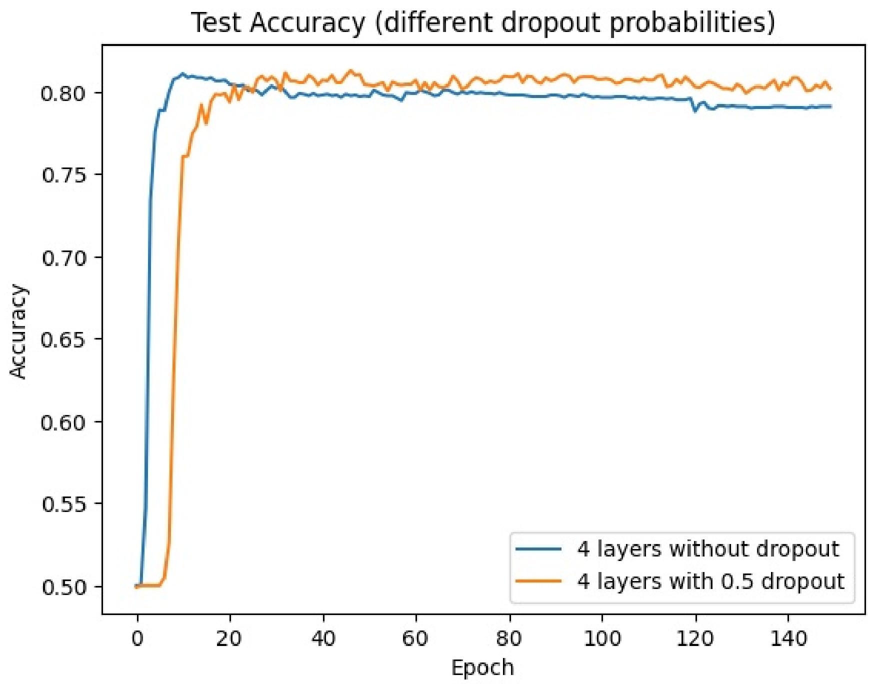
```
### 4 layers with 0.5 dropout
start_time = time.time()

# train neural networks
print('\n4 layers with 0.5 dropout:')
nn4_train_accuracy_dropout, nn4_test_accuracy_dropout = experiment(NN4(input_size=512, hidden_size=36, dropout_
end_time = time.time()
elapsed_time = end_time - start_time

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

```
4 layers with 0.5 dropout:
Epoch #10:       train accuracy 0.629    train loss -0.553       test accuracy 0.705     test loss -0.570
Epoch #20:       train accuracy 0.810    train loss -0.766       test accuracy 0.799     test loss -0.774
Epoch #30:       train accuracy 0.859    train loss -0.835       test accuracy 0.809     test loss -0.800
Epoch #40:       train accuracy 0.881    train loss -0.867       test accuracy 0.804     test loss -0.804
Epoch #50:       train accuracy 0.908    train loss -0.899       test accuracy 0.804     test loss -0.803
Epoch #60:       train accuracy 0.923    train loss -0.914       test accuracy 0.804     test loss -0.804
Epoch #70:       train accuracy 0.929    train loss -0.925       test accuracy 0.806     test loss -0.804
Epoch #80:       train accuracy 0.939    train loss -0.936       test accuracy 0.809     test loss -0.807
Epoch #90:       train accuracy 0.947    train loss -0.944       test accuracy 0.806     test loss -0.807
Epoch #100:      train accuracy 0.946    train loss -0.944       test accuracy 0.807     test loss -0.807
Epoch #110:      train accuracy 0.956    train loss -0.952       test accuracy 0.808     test loss -0.807
Epoch #120:      train accuracy 0.961    train loss -0.958       test accuracy 0.806     test loss -0.807
Epoch #130:      train accuracy 0.964    train loss -0.961       test accuracy 0.804     test loss -0.805
Epoch #140:      train accuracy 0.964    train loss -0.963       test accuracy 0.805     test loss -0.805
Epoch #150:      train accuracy 0.968    train loss -0.966       test accuracy 0.802     test loss -0.803
Time to train, eval model: 11.91307806968689 seconds
```

In [24]:

```
# plot training accuracy
plt.plot(nn4_train_accuracy_no_dropout, label='4 layers without dropout')
plt.plot(nn4_train_accuracy_dropout, label='4 layers with 0.5 dropout')
plt.title('Training Accuracy (different dropout probabilities)')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend()
plt.show()

# plot testing accuracy
plt.plot(nn4_test_accuracy_no_dropout, label='4 layers without dropout')
plt.plot(nn4_test_accuracy_dropout, label='4 layers with 0.5 dropout')
plt.title('Test Accuracy (different dropout probabilities)')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend()
plt.show()
```





Analysis and discussion here (< 5 sentences) :

We can observe that the training accuracy of the 4 layer model with and without dropout layers is similar. However, on the test set, the model with dropout performs better than the model without dropout. This represents the ability of dropout to serve as a regularization technique which prevents overfitting. Since the model without dropout had lower testing accuracy than model with dropout, despite having simiar training accuracy, makes it evident that adding a dropout probability of 0.5 helped in preventing overfitting by the model.

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} Train on a larger dataset.

3} Increase the regularization strength.

Explanation (< 5 sentences) here: :

Training on larger dataset: A larger dataset can accomodate more variety of data. So training the Neural Network classifier on a larger dataset will allow the model to learn more generalized features of the data. This will help in reducing overfitting on the samples present in the training set, and imporved generalization performance on the unseen data in the test set.

Increase the regularization strength: This will penalize large weights in the model which prevents model from giving too much importance to only certain features. Additionally, penalizing large weights assists model in learning a smoother decision boundary between classes which is less susceptible to noise in training data. These will promote the model's ability to generalize well on unseen data and prevent overfitting on training data. Hence, reducing the gap between training and testing accuracy.

Part 3: Exploration (20 points)

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.

In [25]:
```
### YOUR CODE HERE
```

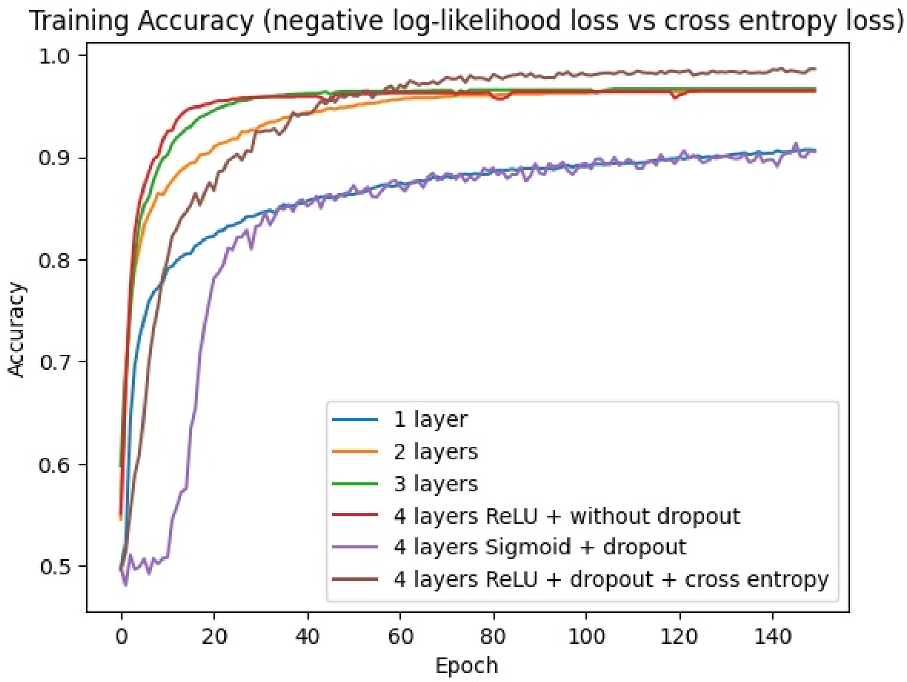
Cross Entropy Loss

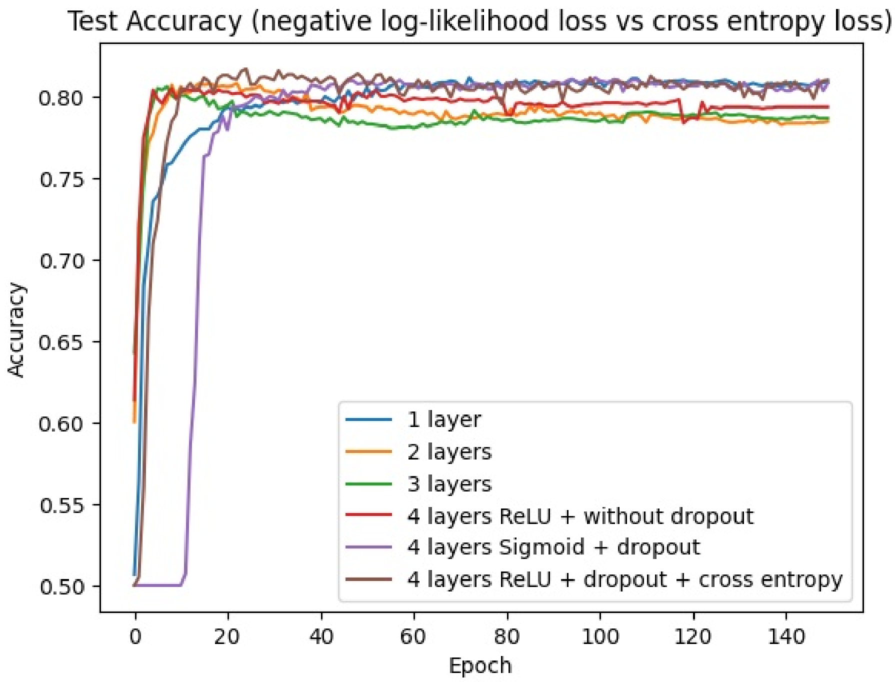
In [26]:
```
### 4 layers with dropout and cross entropy loss
start_time = time.time()

# train neural networks
print('\n4 layers with dropout and cross entropy loss:')
nn4_train_accuracy_cross_entropy, nn4_test_accuracy_cross_entropy = experiment(NN4(input_size=512, hidden_size=
                                                                                use_cross_entropy=True)

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

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

```
4 layers with dropout and cross entropy loss:
Epoch #10:       train accuracy 0.782    train loss 0.545        test accuracy 0.789     test loss 0.529
Epoch #20:       train accuracy 0.875    train loss 0.446        test accuracy 0.814     test loss 0.492
Epoch #30:       train accuracy 0.925    train loss 0.394        test accuracy 0.811     test loss 0.493
Epoch #40:       train accuracy 0.943    train loss 0.374        test accuracy 0.811     test loss 0.496
Epoch #50:       train accuracy 0.962    train loss 0.354        test accuracy 0.812     test loss 0.496
Epoch #60:       train accuracy 0.965    train loss 0.350        test accuracy 0.806     test loss 0.499
Epoch #70:       train accuracy 0.975    train loss 0.340        test accuracy 0.808     test loss 0.500
Epoch #80:       train accuracy 0.975    train loss 0.338        test accuracy 0.795     test loss 0.507
Epoch #90:       train accuracy 0.979    train loss 0.335        test accuracy 0.807     test loss 0.500
Epoch #100:      train accuracy 0.983    train loss 0.331        test accuracy 0.806     test loss 0.501
Epoch #110:      train accuracy 0.981    train loss 0.332        test accuracy 0.809     test loss 0.500
Epoch #120:      train accuracy 0.984    train loss 0.330        test accuracy 0.807     test loss 0.504
Epoch #130:      train accuracy 0.984    train loss 0.330        test accuracy 0.804     test loss 0.504
Epoch #140:      train accuracy 0.983    train loss 0.330        test accuracy 0.808     test loss 0.503
Epoch #150:      train accuracy 0.987    train loss 0.327        test accuracy 0.810     test loss 0.500
Time to train, eval model: 15.786219120025635 seconds
```

In [27]:
```
# plot training accuracy
plt.plot(nn1_train_accuracy, label='1 layer')
plt.plot(nn2_train_accuracy, label='2 layers')
plt.plot(nn3_train_accuracy, label='3 layers')
plt.plot(nn4_train_accuracy, label='4 layers ReLU + without dropout')
plt.plot(nn4_train_accuracy_sigmoid_dropout, label='4 layers Sigmoid + dropout')
plt.plot(nn4_train_accuracy_cross_entropy, label='4 layers ReLU + dropout + cross entropy')
plt.title('Training Accuracy (negative log-likelihood loss vs cross entropy loss)')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend()
plt.show()

# plot testing accuracy
plt.plot(nn1_test_accuracy, label='1 layer')
plt.plot(nn2_test_accuracy, label='2 layers')
plt.plot(nn3_test_accuracy, label='3 layers')
plt.plot(nn4_test_accuracy, label='4 layers ReLU + without dropout')
plt.plot(nn4_test_accuracy_sigmoid_dropout, label='4 layers Sigmoid + dropout')
plt.plot(nn4_test_accuracy_cross_entropy, label='4 layers ReLU + dropout + cross entropy')
plt.title('Test Accuracy (negative log-likelihood loss vs cross entropy loss)')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
```

```
plt.legend()
plt.show()
```





Analysis and discussion :

The first optimization I attempted was replacing negative log-likelihood loss function with cross-entropy loss function. Cross entropy loss tends to provide better gradients during backpropagation compared to directly using the negative log-likelihood loss. This allows more stable and efficient training of neural networks. We can see that the 4 layer model with ReLU activation and dropout which was trained with cross-entropy loss had the highest training accuracy. However, its testing accuracy remained similar to earlier 4 layer models. This represents the overfitting on training data done by this model. Therefore, to prevent overfitting I tried early stopping in the next section.

In [ ]:

1. Early stopping

In [28]:

```
### 4 layers with dropout, cross entropy loss and early stopping
start_time = time.time()

# train neural networks
print('\n4 layers with dropout, cross entropy loss and early stopping:')
nn4_train_accuracy_early_stop, nn4_test_accuracy_early_stop = experiment(NN4(input_size=512, hidden_size=100, d
                                                                             use_cross_entropy=True, enable_early_s
end_time = time.time()
elapsed_time = end_time - start_time
```

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

```
4 layers with dropout, cross entropy loss and early stopping:
Epoch #10:      train accuracy 0.772    train loss 0.564        test accuracy 0.775     test loss 0.548
Epoch #20:      train accuracy 0.869    train loss 0.446        test accuracy 0.807     test loss 0.497
Epoch #30:      train accuracy 0.916    train loss 0.402        test accuracy 0.807     test loss 0.498
Epoch #40:      train accuracy 0.947    train loss 0.370        test accuracy 0.805     test loss 0.502
Epoch #50:      train accuracy 0.961    train loss 0.354        test accuracy 0.808     test loss 0.500
Epoch #60:      train accuracy 0.972    train loss 0.342        test accuracy 0.799     test loss 0.506
Epoch #70:      train accuracy 0.973    train loss 0.340        test accuracy 0.801     test loss 0.504
Epoch #80:      train accuracy 0.975    train loss 0.337        test accuracy 0.800     test loss 0.509
Early stopping after 50 epochs without improvement.
Time to train, eval model: 8.915257215499878 seconds
```

Analysis and discussion :

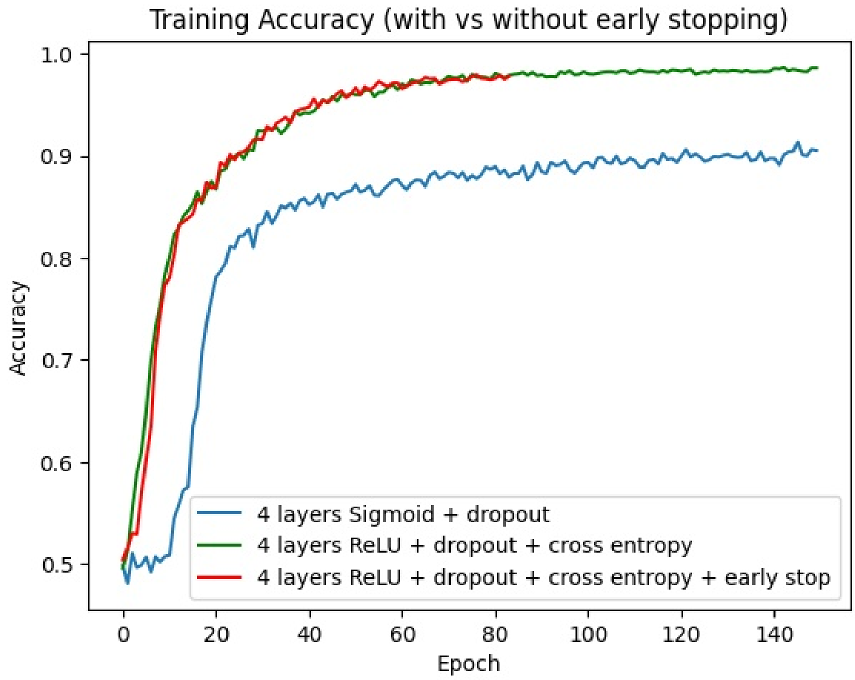
Early Stopping is a regularization method that stops training when parameter updates no longer yeild improvement on the test set. It prevents overfitting by stopping the training before the model starts to overfit to the training data. This encourages the model to learn more generalizable patterns from the training data. It makes sense to apply early stopping since we only have 2000 samples in the training set and the model tends to overfit the training data at later epochs.

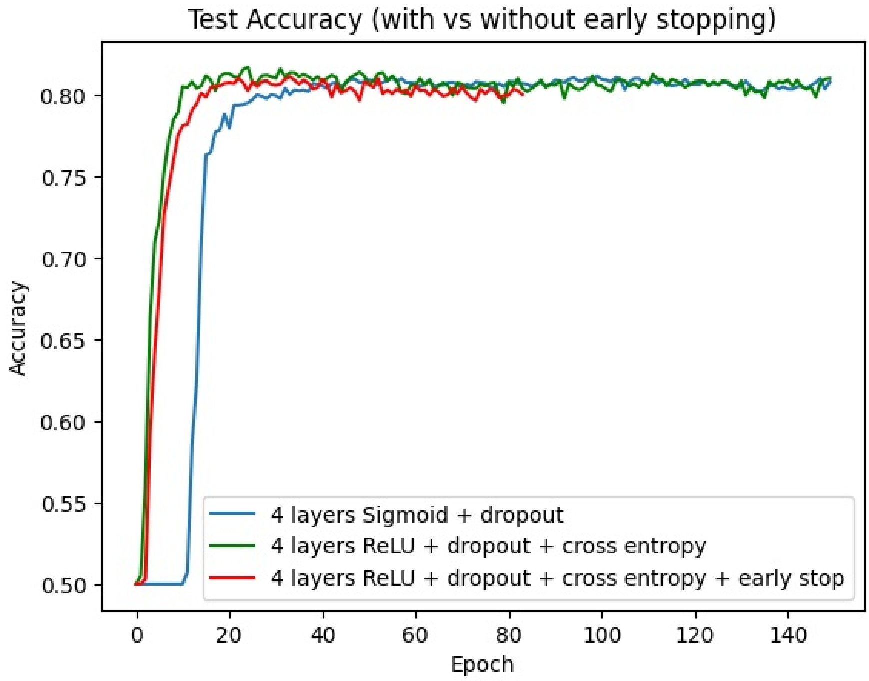
Here, I used the 4 layer model with ReLU activation, dropout and cross-entropy loss. In the experiment function, I implemented code changes that monitor the model's performance on the testing set and stops the training when the test accuracy does not improve for a certain number of epochs. Here we stop after 50 epochs, i.e. best test accuracy was achieved at Epoch #30, we monitored up until Epoch #80 (so 80 didn't printed) and then stopped since further training the model did not produce better test accuracy. But with more training, the training accuracy would have kept improving as the model would have overfitted on the training data.

The model parameters at Epoch #30 that produced the higest test accuracy were also saved, which can be later be loaded as the final model.

In [44]:

```
# plot training accuracy
#plt.plot(nn1_train_accuracy, label='1 layer')
#plt.plot(nn2_train_accuracy, label='2 layers')
#plt.plot(nn3_train_accuracy, label='3 layers')
#plt.plot(nn4_train_accuracy, label='4 layers ReLU + without dropout')
plt.plot(nn4_train_accuracy_sigmoid_dropout, label='4 layers Sigmoid + dropout')
plt.plot(nn4_train_accuracy_cross_entropy, label='4 layers ReLU + dropout + cross entropy', c='green')
plt.plot(nn4_train_accuracy_early_stop, label='4 layers ReLU + dropout + cross entropy + early stop', c='r')
plt.title('Training Accuracy (with vs without early stopping)')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend()
plt.show()

# plot testing accuracy
#plt.plot(nn1_test_accuracy, label='1 layer')
#plt.plot(nn2_test_accuracy, label='2 layers')
#plt.plot(nn3_test_accuracy, label='3 layers')
#plt.plot(nn4_test_accuracy, label='4 layers ReLU + without dropout')
plt.plot(nn4_test_accuracy_sigmoid_dropout, label='4 layers Sigmoid + dropout')
plt.plot(nn4_test_accuracy_cross_entropy, label='4 layers ReLU + dropout + cross entropy', c='green')
plt.plot(nn4_test_accuracy_early_stop, label='4 layers ReLU + dropout + cross entropy + early stop', c='r')
plt.title('Test Accuracy (with vs without early stopping)')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend()
plt.show()
```





I plotted the training and test accuracy for 4 layer models with regularization techniques. All these models have similar performance on the test set. But, we can observe that the 4 layer model with relu activation, dropout, cross entropy and early stopping has highest test accuracy, i.e. the best set of parameters, around Epoch #30.

Now, if we compare the training accuracy and test accuracy graph beyond Epoch #30, the training accuarcy keeps increasing but the test accuracy flattens. This demonstrates that with more training the model just overfits on the training data and doesn't learn to generalize and perform well on the unseen test data. Thus, training for additional epochs is not benefitial and early stopping will prevent overfitting.

In [ ]:

2. Batch Normalization

In [48]:

```
class NN4BatchNorm(nn.Module):
    def __init__(self, input_size, hidden_size, activation_function='relu', dropout_prob=0):
        super().__init__()
        self.fc1 = nn.Linear(input_size, hidden_size)
        self.bn1 = nn.BatchNorm1d(hidden_size)
        self.fc2 = nn.Linear(hidden_size, hidden_size)
        self.bn2 = nn.BatchNorm1d(hidden_size)
        self.fc3 = nn.Linear(hidden_size, hidden_size)
        self.bn3 = nn.BatchNorm1d(hidden_size)
        self.fc4 = nn.Linear(hidden_size, 2)
        self.activation = nn.ReLU() if activation_function == 'relu' else nn.Sigmoid()
        self.dropout1 = nn.Dropout(p=dropout_prob)
        self.dropout2 = nn.Dropout(p=dropout_prob)
```

```
        self.dropout3 = nn.Dropout(p=dropout_prob)

    def forward(self, x):
        x = self.activation(self.bn1(self.fc1(x)))
        x = self.dropout1(x)
        x = self.activation(self.bn2(self.fc2(x)))
        x = self.dropout2(x)
        x = self.activation(self.bn3(self.fc3(x)))
        x = self.dropout3(x)
        x = self.fc4(x)
        x = F.softmax(x, dim=1)
        return x
```

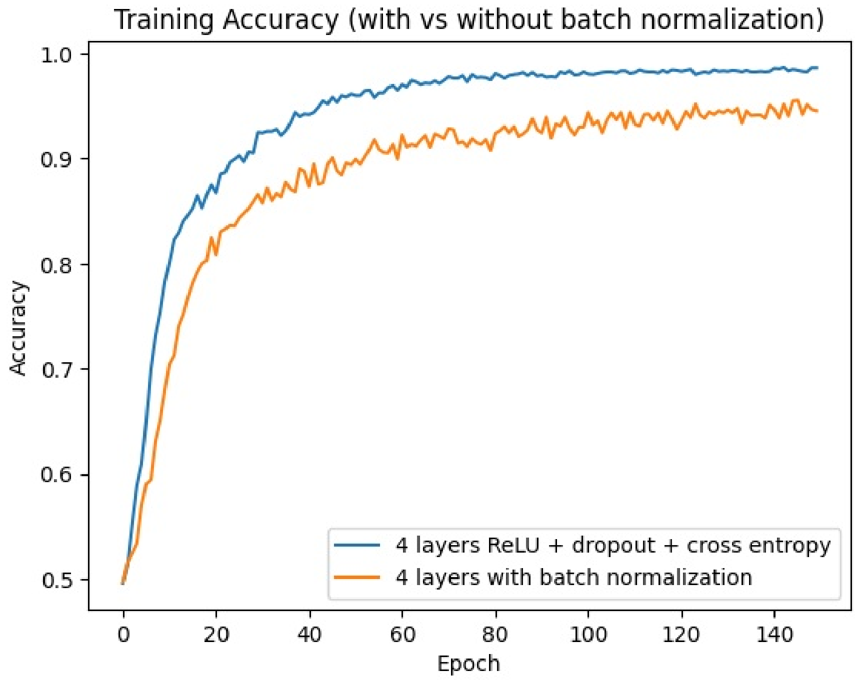
In [49]:

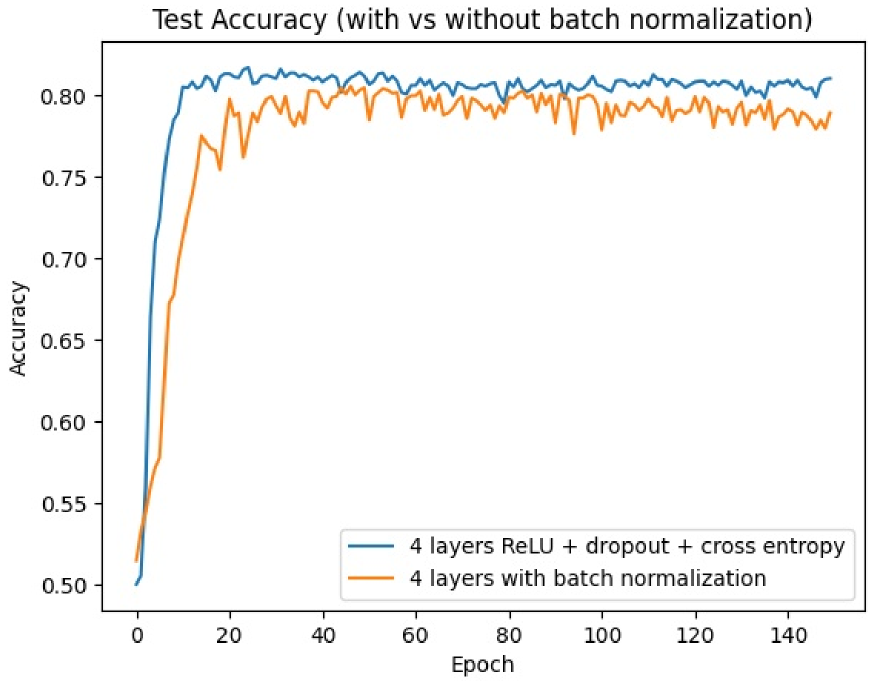
```
### 4 layers without batch normalization
start_time = time.time()

# train neural networks
print('\n4 layers without batch normalization:')
nn4_train_accuracy_batch_norm, nn4_test_accuracy_batch_norm = experiment(NN4BatchNorm(input_size=512, hidden_si
end_time = time.time()
elapsed_time = end_time - start_time

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

```
4 layers without batch normalization:
Epoch #10:       train accuracy 0.679    train loss 0.621        test accuracy 0.698     test loss 0.619
Epoch #20:       train accuracy 0.825    train loss 0.499        test accuracy 0.779     test loss 0.531
Epoch #30:       train accuracy 0.866    train loss 0.452        test accuracy 0.799     test loss 0.506
Epoch #40:       train accuracy 0.888    train loss 0.425        test accuracy 0.802     test loss 0.503
Epoch #50:       train accuracy 0.894    train loss 0.419        test accuracy 0.805     test loss 0.501
Epoch #60:       train accuracy 0.899    train loss 0.412        test accuracy 0.800     test loss 0.503
Epoch #70:       train accuracy 0.919    train loss 0.394        test accuracy 0.797     test loss 0.508
Epoch #80:       train accuracy 0.908    train loss 0.400        test accuracy 0.789     test loss 0.515
Epoch #90:       train accuracy 0.927    train loss 0.383        test accuracy 0.800     test loss 0.507
Epoch #100:      train accuracy 0.930    train loss 0.380        test accuracy 0.794     test loss 0.511
Epoch #110:      train accuracy 0.944    train loss 0.368        test accuracy 0.793     test loss 0.511
Epoch #120:      train accuracy 0.928    train loss 0.381        test accuracy 0.791     test loss 0.512
Epoch #130:      train accuracy 0.944    train loss 0.368        test accuracy 0.792     test loss 0.514
Epoch #140:      train accuracy 0.951    train loss 0.362        test accuracy 0.788     test loss 0.518
Epoch #150:      train accuracy 0.946    train loss 0.368        test accuracy 0.789     test loss 0.514
Time to train, eval model: 51.044286012649536 seconds
```

In [50]:

```
# plot training accuracy
plt.plot(nn4_train_accuracy_cross_entropy, label='4 layers ReLU + dropout + cross entropy')
plt.plot(nn4_train_accuracy_batch_norm, label='4 layers with batch normalization')
plt.title('Training Accuracy (with vs without batch normalization)')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend()
plt.show()

# plot testing accuracy
plt.plot(nn4_test_accuracy_cross_entropy, label='4 layers ReLU + dropout + cross entropy')
plt.plot(nn4_test_accuracy_batch_norm, label='4 layers with batch normalization')
plt.title('Test Accuracy (with vs without batch normalization)')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend()
plt.show()
```





Analysis and discussion here :

Batch normalization normalizes the activations of each layer during training which ensures inputs to each layer are consistent. It assists the model to learn more generalizable features from the data. Here, I have compared the 4 layer model with ReLU activation, dropout and cross entropy loss, and another version of this model which has batch normalization.

We can see that the model with batch normalization has lower training accuracy compared to the model without batch normalization. However, both these models have comparable test accuracy, i.e. around 0.79-0.80. The gap between the training and test accuarcy was reduced in the model with batch normalization. Whereas, the model without batch normalization has a larger difference in training and test accuarcy. This demostrates the ability of batch normalization to prevent overfitting on training data and allow model to improve performance on unseen test data.

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.

In [ ]:

```
```