Introduction

In this project, you will build a neural network of your own design to evaluate the CIFAR-10 dataset. Our target accuracy is 70%, but any accuracy over 50% is a great start. Some of the benchmark results on CIFAR-10 include:

78.9% Accuracy | Deep Belief Networks; Krizhevsky, 2010

90.6% Accuracy | Maxout Networks; Goodfellow et al., 2013

96.0% Accuracy | Wide Residual Networks; Zagoruyko et al., 2016

99.0% Accuracy | GPipe; Huang et al., 2018

98.5% Accuracy | Rethinking Recurrent Neural Networks and other Improvements for ImageClassification; Nguyen et al., 2020

Research with this dataset is ongoing. Notably, many of these networks are quite large and quite expensive to train.

Imports

In [1]:
```
## This cell contains the essential imports you will need – DO NOT CHANGE THE CONTENTS! ##
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
import torchvision
import torchvision.transforms as transforms
import matplotlib.pyplot as plt
import numpy as np
```

Load the Dataset

Specify your transforms as a list first. The transforms module is already loaded as `transforms`.

CIFAR-10 is fortunately included in the torchvision module. Then, you can create your dataset using the `CIFAR10` object from `torchvision.datasets` (the documentation is available here). Make sure to specify `download=True`!

Once your dataset is created, you'll also need to define a `DataLoader` from the `torch.utils.data` module for both the train and the test set.

In [2]:
```
from torch.utils.data import DataLoader
from torchvision.datasets import CIFAR10
```

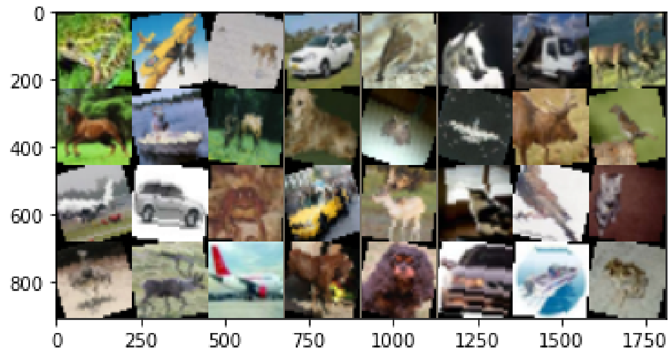
In [3]:
```
dataset_path = "C:\\Users\\Vivek\\Udacity\\DeepLearningUsingPyTorch\\Data\\"
batch_size = 32

torch.manual_seed(42)
np.random.seed(42)

# From https://pytorch.org/vision/stable/models.html
mean = [0.485, 0.456, 0.406]
std = [0.229, 0.224, 0.225]

# Define transforms
# Note to self: Try the RandomCrop or CenterCrop transforms to improve accuracy if needed
transforms_train = transforms.Compose([
                                        transforms.RandomHorizontalFlip(),
                                        transforms.RandomRotation(20),
                                        transforms.Resize(224), # Min size for pretrained
                                        transforms.ToTensor(),
                                        transforms.Normalize(mean=mean, std=std)
                                      ])
transforms_test = transforms.Compose([
                                       transforms.Resize(224),
                                       transforms.ToTensor(),
                                       transforms.Normalize(mean=mean, std=std)
                                     ])

# Create training set and define training dataloader
trainset = CIFAR10(root=dataset_path, train=True, transform=transforms_train, download=True)
trainloader = DataLoader(dataset=trainset, batch_size=batch_size, shuffle=True)

# Create test set and define test dataloader
testset = CIFAR10(root=dataset_path, train=False, transform=transforms_test, download=True)
testloader = DataLoader(dataset=testset, batch_size=batch_size)

# The 10 classes in the dataset
classes = ('plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'ship', 'truck')
```

```
Files already downloaded and verified
Files already downloaded and verified
```

In [4]:
```
# Source: https://pytorch.org/tutorials/beginner/blitz/cifar10_tutorial.html

import matplotlib.pyplot as plt
import numpy as np
import os

# functions to show an image
denormalize = transforms.Compose([
                transforms.Normalize(mean=[-m/s for (m, s) in zip(mean, std)], std=[1.0/s for s in std])
])
```

```python
def imshow(img):
    img = denormalize(img)
    npimg = img.numpy()
    plt.imshow(np.transpose(npimg, (1, 2, 0)))
    plt.show()
```

In [5]:
```python
images, labels = next(iter(trainloader))
imshow(torchvision.utils.make_grid(images))
print(''.join(f"{str(os.linesep) + str(j//8) + ': ' if j%8 == 0 else ', '}{classes[labels[j]]:5s}" for j in range(batch_size)))
```



```
0: frog , plane, deer , car  , bird , horse, truck, deer
1: horse, ship , deer , dog  , frog , plane, deer , bird
2: plane, car  , frog , car  , deer , cat  , bird , cat
3: bird , deer , plane, horse, dog  , car  , ship , frog
```

Explore the Dataset

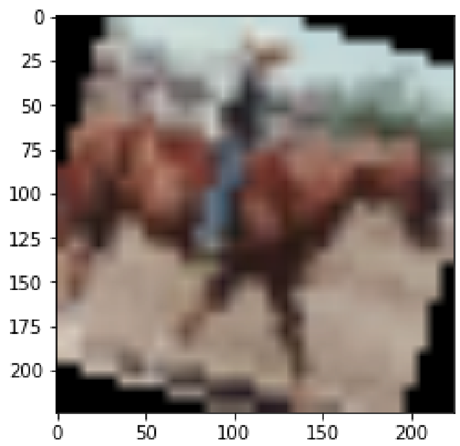
Using matplotlib, numpy, and torch, explore the dimensions of your data.

You can view images using the `show5` function defined below – it takes a data loader as an argument. Remember that normalized images will look really weird to you! You may want to try changing your transforms to view images. Typically using no transforms other than `toTensor()` works well for viewing – but not as well for training your network. If `show5` doesn't work, go back and check your code for creating your data loaders and your training/test sets.

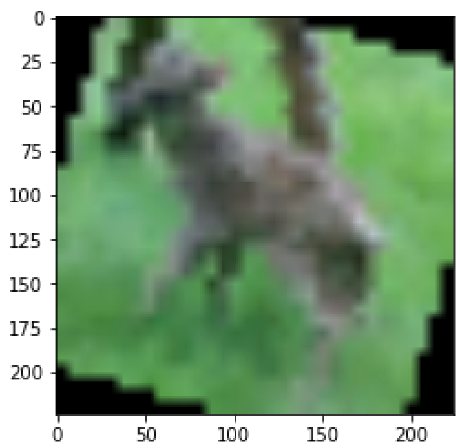
In [6]:
```python
def show5(img_loader):
    dataiter = iter(img_loader)

    batch = next(dataiter)
    labels = batch[1][0:5]
    images = batch[0][0:5]
    for i in range(5):
        print(classes[labels[i]])

        image = denormalize(images[i])
        npimg = image.numpy()
        plt.imshow(np.transpose(npimg, (1, 2, 0)))
        plt.show()
```

In [7]:
```python
# Explore data
print("TRAIN DATA")
show5(trainloader)
print("TEST DATA")
show5(testloader)
```

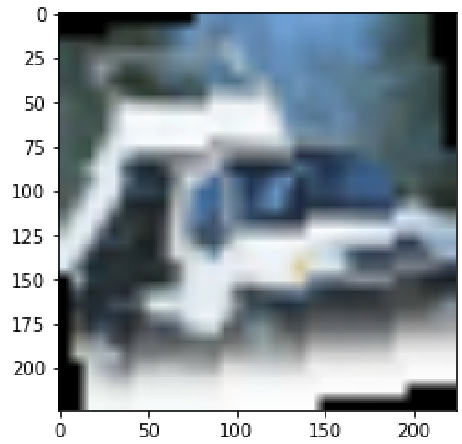
```
TRAIN DATA
horse
```



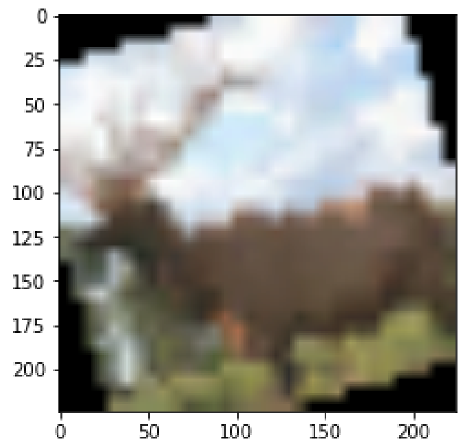
```
deer
```



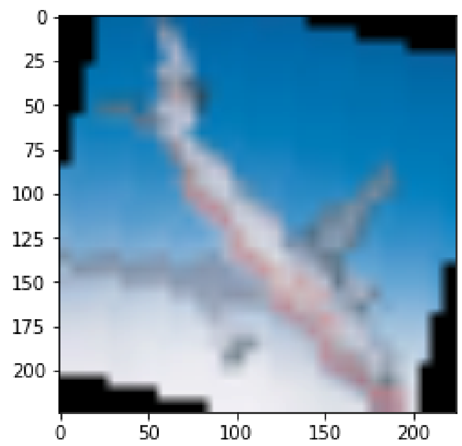
```
truck
```



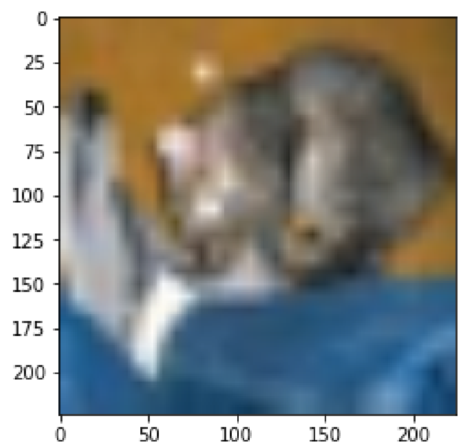
deer



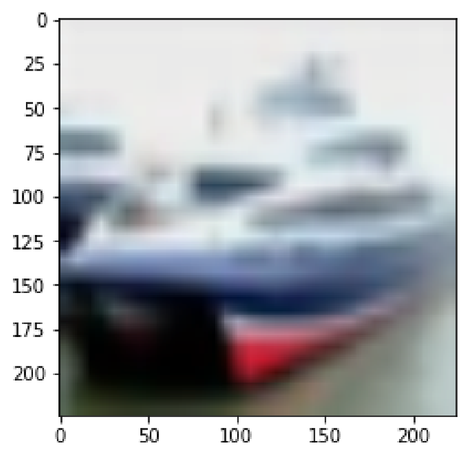
plane



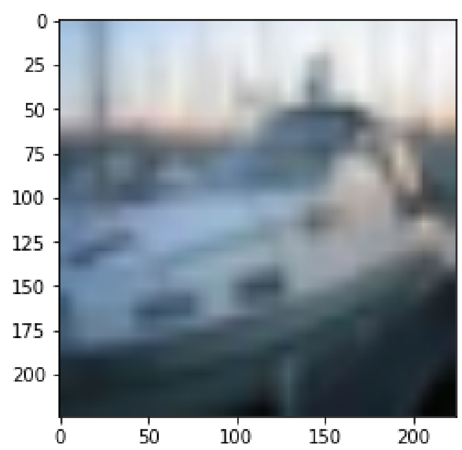
TEST DATA
cat



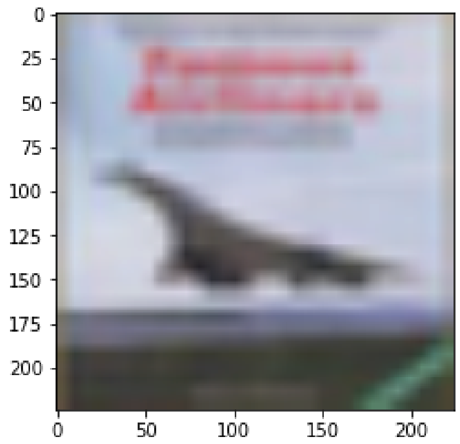
ship



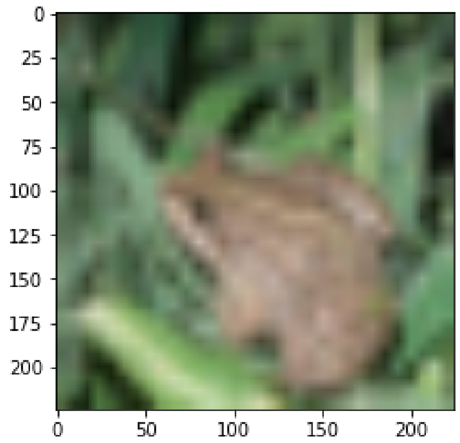
ship



plane



frog



Build your Neural Network

Using the layers in `torch.nn` (which has been imported as `nn`) and the `torch.nn.functional` module (imported as `F`), construct a neural network based on the parameters of the dataset. Feel free to construct a model of any architecture – feedforward, convolutional, or even something more advanced!

In [8]:

```
# NOTE: I also tried to train my own model but the accuracy was not great (51.37%).
# Code and results for that model are after the *Make a recommendation* section

model = torchvision.models.resnet152(pretrained=True)

for param in model.parameters():
    param.requires_grad = False

classifier = nn.Sequential(
                nn.Linear(2048, 1024),
                nn.ReLU(),
                nn.Dropout(p=0.2),
                nn.Linear(1024, 512),
                nn.ReLU(),
                nn.Dropout(p=0.2),
                nn.Linear(512, 10),
                nn.LogSoftmax(dim=1)
             )

model.fc = classifier
```

Specify a loss function and an optimizer, and instantiate the model.

If you use a less common loss function, please note why you chose that loss function in a comment.

In [9]:

```
from torch.optim import Adam
from torch.nn import NLLLoss

optimizer = Adam(params=model.fc.parameters(), lr=0.001)
criterion = NLLLoss()
```

Running your Neural Network

Use whatever method you like to train your neural network, and ensure you record the average loss at each epoch. Don't forget to use `torch.device()` and the `.to()` method for both your model and your data if you are using GPU!

If you want to print your loss during each epoch, you can use the `enumerate` function and print the loss after a set number of batches. 250 batches works well for most people!

In [10]:

```
device = "cuda:0" if torch.cuda.is_available() else "cpu"
model.to(device)
print(f"Using device '{device}'")
```

```
Using device 'cuda:0'
```

In [11]:

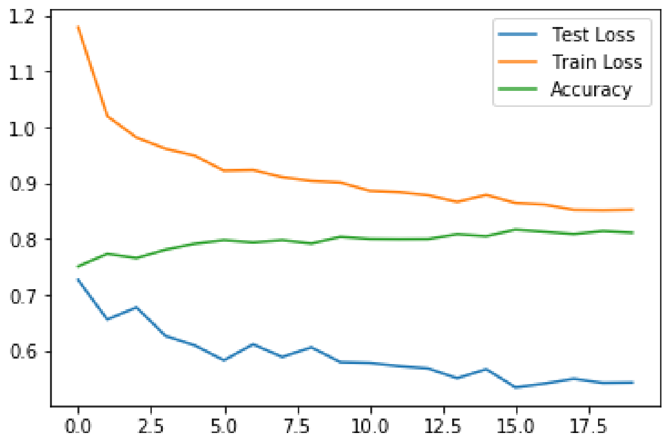
```
EPOCHS = range(20)

per_epoch_train_loss = []
per_epoch_test_loss = []
per_epoch_accuracy = []

for epoch in EPOCHS:
    total_loss = 0

    for batch, (images, labels) in enumerate(trainloader):
        images, labels = images.to(device), labels.to(device)
        optimizer.zero_grad()
```

```
        log_ps = model.forward(images)
        loss = criterion(log_ps, labels)
        loss.backward()
        optimizer.step()

        total_loss += loss

        # if batch%250 == 0:
        #    print(f"Epoch {epoch:2} Batch {batch:4} Loss: {loss:.3f} Avg Loss: {total_loss/float(batch+1):.3f}")

    per_epoch_train_loss.append(total_loss.item()/float(batch+1)) # Per batch loss

    # Compute Test Loss
    with torch.no_grad():
        model.eval()

        total_loss = 0
        total_correct = 0
        count = 0

        for batch, (images, labels) in enumerate(testloader):
            images, labels = images.to(device), labels.to(device)
            log_ps = model.forward(images)
            total_loss += criterion(log_ps, labels)
            ps, pred_label = log_ps.topk(1, dim=1)

            total_correct += torch.sum(pred_label.view(labels.shape) == labels)
            count += len(labels)

        per_epoch_test_loss.append(total_loss.item() / float(batch))
        per_epoch_accuracy.append(100. * total_correct.item() / float(count))
        print(f"Epoch {epoch:2} Train Loss: {per_epoch_train_loss[-1]:.3f} Test Loss: {per_epoch_test_loss[-1]:.3f} Accuracy {per_epoch_accurac

        model.train()

    # Checkpoint at each epoch
    checkpoint_path = f"C:\\Users\\Vivek\\Udacity\\DeepLearningUsingPyTorch\\CIFAR10_classifier_checkpoints\\CIFAR10_classifier_model_epoch{epo
    torch.save(model.state_dict(), checkpoint_path)
```

```
Epoch  0 Train Loss: 1.178 Test Loss: 0.727 Accuracy 75.10%
Epoch  1 Train Loss: 1.020 Test Loss: 0.656 Accuracy 77.35%
Epoch  2 Train Loss: 0.981 Test Loss: 0.678 Accuracy 76.58%
Epoch  3 Train Loss: 0.961 Test Loss: 0.627 Accuracy 78.10%
Epoch  4 Train Loss: 0.949 Test Loss: 0.610 Accuracy 79.16%
Epoch  5 Train Loss: 0.922 Test Loss: 0.583 Accuracy 79.80%
Epoch  6 Train Loss: 0.923 Test Loss: 0.612 Accuracy 79.39%
Epoch  7 Train Loss: 0.911 Test Loss: 0.589 Accuracy 79.80%
Epoch  8 Train Loss: 0.904 Test Loss: 0.606 Accuracy 79.20%
Epoch  9 Train Loss: 0.901 Test Loss: 0.580 Accuracy 80.39%
Epoch 10 Train Loss: 0.886 Test Loss: 0.578 Accuracy 80.00%
Epoch 11 Train Loss: 0.884 Test Loss: 0.573 Accuracy 79.96%
Epoch 12 Train Loss: 0.878 Test Loss: 0.569 Accuracy 79.98%
Epoch 13 Train Loss: 0.866 Test Loss: 0.551 Accuracy 80.85%
Epoch 14 Train Loss: 0.879 Test Loss: 0.567 Accuracy 80.49%
Epoch 15 Train Loss: 0.864 Test Loss: 0.535 Accuracy 81.68%
Epoch 16 Train Loss: 0.862 Test Loss: 0.541 Accuracy 81.29%
Epoch 17 Train Loss: 0.852 Test Loss: 0.550 Accuracy 80.87%
Epoch 18 Train Loss: 0.851 Test Loss: 0.543 Accuracy 81.43%
Epoch 19 Train Loss: 0.852 Test Loss: 0.543 Accuracy 81.13%
```

Plot the training loss (and validation loss/accuracy, if recorded).

In [12]:
```
plt.plot(per_epoch_test_loss)
plt.plot(per_epoch_train_loss)
plt.plot([x/100. for x in per_epoch_accuracy])
plt.legend(["Test Loss", "Train Loss", "Accuracy"])
plt.show()
```



Testing your model

Using the previously created `DataLoader` for the test set, compute the percentage of correct predictions using the highest probability prediction.

If your accuracy is over 70%, great work! This is a hard task to exceed 70% on.

If your accuracy is under 45%, you'll need to make improvements. Go back and check your model architecture, loss function, and optimizer to make sure they're appropriate for an image classification task.

In [13]:
```
# Already did this in the model training.
```

Saving your model

Using `torch.save`, save your model for future loading.

In [14]:
```
model_path = "C:\\Users\\Vivek\\Udacity\\DeepLearningUsingPyTorch\\CIFAR10_classifier_model.pth"
torch.save(model.state_dict(), model_path)
```

Make a Recommendation

Based on your evaluation, what is your recommendation on whether to build or buy? Explain your reasoning below.

In [15]:
```
torch.cuda.get_device_properties(0)
```

Out[15]:
```
_CudaDeviceProperties(name='NVIDIA GeForce GTX 1660 SUPER', major=7, minor=5, total_memory=6143MB, multi_processor_count=22)
```

Recommendation: BUILD

Since this is an image classification problem with typical (commonly seen) classes, there already are several publicly available pre-trained models as well as public datasets. By utilizing the pretrained feature detection portion of these models, we can quickly replace and retrain just the classifier part of the network to get more than 80% accuracy (81.68% on epoch 15). Given that I was able to throw this together in an afternoon with just a 1660 SUPER, we can certainly get better accuracy by looking at the latest research and experimenting with pre-trained image based models other than the RESNET152 that was used here.

A few notes:

- Using better hardware such as a local machine with 4 or 8 NVidia 3080 or a cloud setup would help further in iterating more quickly.
- The pre-trained model requires an input of minimum size 224 x 224 which is much bigger than our images (32 x 32), so updating the model input shapes and training from scratch might actually not be too slow.
- Creating a representative subset of the dataset would help speed up experimentation
- The graph indicates that both test and train loss are still dropping so it might be interesting to train longer until the model starts overfitting. However, the rate of improvement has dropped significantly (as expected) so it may not be worth spending more time on it.

Pre-trained vs self-built model

Using a pretrained model was very useful in that my GPU only has 6GB of memory and it is very likely that all the weights/biases and gradients of such a large model will probably not fit. Since I'm only retraining a small part that is the classifier, I was able to do it much more quickly.

I also tried training my own model (see below) and was able to get a not that great accuracy of 61.58%. I would probably need to spend some more time improving this model to get anywhere close to the accuracy of the pre-trained network.

Interestingly, the smaller model had higher GPU, CPU as well as disk utilization. While the larger model was around 90% GPU (due to occasional peaks and valleys) and 40% CPU and lower disk use, the smaller model pegged the GPU at 100% with the CPU at 65% and disk at 75%. Perhaps I should have added timing per step to see if the smaller model trains faster and therefore keeps the CPU and disk (dataloader) busy. It is also possible that since I'm retraining only a small part of the larger model, it doesn't have enough compute to keep the GPU at 100%. Might be a good idea to run the NVidia performance analysis tool to validate one of these hypothesis, but any notes from the reviewer would be welcome :)

Attempt at training my own model (not the pretrained one)

In [24]:
```
class CIFARClassifier(nn.Module):
    def __init__(self):
        super(CIFARClassifier, self).__init__()
        self.conv1 = nn.Conv2d(in_channels=3, out_channels=128, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3))
        self.bn1 = nn.BatchNorm2d(128)
        self.conv2 = nn.Conv2d(in_channels=128, out_channels=64, kernel_size=(5, 5), stride=(2, 2), padding=(2, 2))
        self.bn2 = nn.BatchNorm2d(64)
        self.conv3 = nn.Conv2d(in_channels=64, out_channels=32, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1))
        self.bn3 = nn.BatchNorm2d(32)
        self.conv4 = nn.Conv2d(in_channels=32, out_channels=8, kernel_size=(1, 1), stride=(2, 2), padding=(1, 1))
        self.bn4 = nn.BatchNorm2d(8)

        self.classifier = nn.Sequential(
                                nn.Linear(1800, 450),
                                nn.ReLU(),
                                nn.Dropout(p=0.2),
                                nn.Linear(450, 10),
                                nn.LogSoftmax(dim=1)
                          )

    def forward(self, images):
        out = self.conv1(images)
        out = self.bn1(out)
        out = self.conv2(out)
        out = self.bn2(out)
        out = self.conv3(out)
        out = self.bn3(out)
        out = self.conv4(out)
        out = self.bn4(out)
        out = F.relu(out)
        out = F.dropout(out, p=0.2)
        out = self.classifier(out.view(out.shape[0], -1))
        return out

model = CIFARClassifier()
```

Specify a loss function and an optimizer, and instantiate the model.

If you use a less common loss function, please note why you chose that loss function in a comment.

In [25]:
```
from torch.optim import Adam
from torch.nn import NLLLoss

optimizer = Adam(params=model.parameters(), lr=0.001)
# scheduler = MultiStepLR(optimizer, milestones=[1,8], gamma=0.1)
criterion = NLLLoss()
```

Running your Neural Network

Use whatever method you like to train your neural network, and ensure you record the average loss at each epoch. Don't forget to use `torch.device()` and the `.to()` method for both your model and your data if you are using GPU!

If you want to print your loss during each epoch, you can use the `enumerate` function and print the loss after a set number of batches. 250 batches works well for most people!

In [26]:
```
device = "cuda:0" if torch.cuda.is_available() else "cpu"
model.to(device)
print(f"Using device '{device}'")
```

```
Using device 'cuda:0'
```

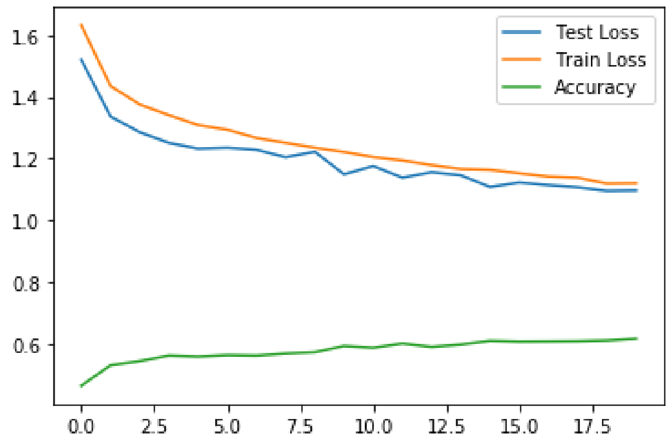
In [27]:
```
EPOCHS = range(20)

per_epoch_train_loss = []
per_epoch_test_loss = []
per_epoch_accuracy = []

for epoch in EPOCHS:
    total_loss = 0

    for batch, (images, labels) in enumerate(trainloader):
        images, labels = images.to(device), labels.to(device)
        optimizer.zero_grad()
        log_ps = model.forward(images)
        loss = criterion(log_ps, labels)
        loss.backward()
        optimizer.step()

        total_loss += loss

        if batch%250 == 0:
            print(f"Epoch {epoch:2} Batch {batch:4} Loss: {loss:.3f} Avg Loss: {total_loss/float(batch+1):.3f}")

    per_epoch_train_loss.append(total_loss.item()/float(batch+1)) # Per batch loss

    # Compute Test Loss
    with torch.no_grad():
        model.eval()

        total_loss = 0
        total_correct = 0
        count = 0

        for batch, (images, labels) in enumerate(testloader):
            images, labels = images.to(device), labels.to(device)
            log_ps = model.forward(images)
            total_loss += criterion(log_ps, labels)
            ps, pred_label = log_ps.topk(1, dim=1)

            total_correct += torch.sum(pred_label.view(labels.shape) == labels)
            count += len(labels)

        per_epoch_test_loss.append(total_loss.item() / float(batch))
        per_epoch_accuracy.append(100. * total_correct.item() / float(count))
        print(f"Epoch {epoch:2} Train Loss: {per_epoch_train_loss[-1]:.3f} Test Loss: {per_epoch_test_loss[-1]:.3f} Accuracy {per_epoch_accurac

        model.train()
```

```
Epoch  0 Batch    0 Loss: 2.320 Avg Loss: 2.320
Epoch  0 Batch  250 Loss: 1.611 Avg Loss: 1.859
Epoch  0 Batch  500 Loss: 1.593 Avg Loss: 1.782
Epoch  0 Batch  750 Loss: 1.358 Avg Loss: 1.726
Epoch  0 Batch 1000 Loss: 1.428 Avg Loss: 1.691
Epoch  0 Batch 1250 Loss: 1.261 Avg Loss: 1.663
Epoch  0 Batch 1500 Loss: 1.364 Avg Loss: 1.636
Epoch  0 Train Loss: 1.633 Test Loss: 1.521 Accuracy 46.26%
Epoch  1 Batch    0 Loss: 1.207 Avg Loss: 1.207
Epoch  1 Batch  250 Loss: 1.802 Avg Loss: 1.480
Epoch  1 Batch  500 Loss: 1.194 Avg Loss: 1.458
Epoch  1 Batch  750 Loss: 1.391 Avg Loss: 1.454
Epoch  1 Batch 1000 Loss: 1.444 Avg Loss: 1.446
Epoch  1 Batch 1250 Loss: 1.367 Avg Loss: 1.441
Epoch  1 Batch 1500 Loss: 1.212 Avg Loss: 1.436
Epoch  1 Train Loss: 1.436 Test Loss: 1.337 Accuracy 52.93%
Epoch  2 Batch    0 Loss: 1.276 Avg Loss: 1.276
Epoch  2 Batch  250 Loss: 1.515 Avg Loss: 1.379
Epoch  2 Batch  500 Loss: 1.616 Avg Loss: 1.382
Epoch  2 Batch  750 Loss: 1.361 Avg Loss: 1.379
Epoch  2 Batch 1000 Loss: 1.399 Avg Loss: 1.378
Epoch  2 Batch 1250 Loss: 1.337 Avg Loss: 1.376
Epoch  2 Batch 1500 Loss: 1.067 Avg Loss: 1.375
Epoch  2 Train Loss: 1.376 Test Loss: 1.286 Accuracy 54.25%
Epoch  3 Batch    0 Loss: 1.788 Avg Loss: 1.788
Epoch  3 Batch  250 Loss: 1.273 Avg Loss: 1.367
Epoch  3 Batch  500 Loss: 1.492 Avg Loss: 1.355
Epoch  3 Batch  750 Loss: 1.203 Avg Loss: 1.348
Epoch  3 Batch 1000 Loss: 1.445 Avg Loss: 1.351
Epoch  3 Batch 1250 Loss: 1.273 Avg Loss: 1.343
Epoch  3 Batch 1500 Loss: 0.860 Avg Loss: 1.340
Epoch  3 Train Loss: 1.341 Test Loss: 1.251 Accuracy 56.05%
Epoch  4 Batch    0 Loss: 1.761 Avg Loss: 1.761
Epoch  4 Batch  250 Loss: 1.428 Avg Loss: 1.319
Epoch  4 Batch  500 Loss: 0.876 Avg Loss: 1.306
Epoch  4 Batch  750 Loss: 1.516 Avg Loss: 1.311
Epoch  4 Batch 1000 Loss: 1.045 Avg Loss: 1.311
Epoch  4 Batch 1250 Loss: 0.980 Avg Loss: 1.312
Epoch  4 Batch 1500 Loss: 1.175 Avg Loss: 1.309
Epoch  4 Train Loss: 1.309 Test Loss: 1.232 Accuracy 55.70%
Epoch  5 Batch    0 Loss: 1.227 Avg Loss: 1.227
Epoch  5 Batch  250 Loss: 1.079 Avg Loss: 1.278
Epoch  5 Batch  500 Loss: 1.095 Avg Loss: 1.285
Epoch  5 Batch  750 Loss: 1.392 Avg Loss: 1.291
Epoch  5 Batch 1000 Loss: 1.231 Avg Loss: 1.296
Epoch  5 Batch 1250 Loss: 1.462 Avg Loss: 1.296
Epoch  5 Batch 1500 Loss: 1.140 Avg Loss: 1.294
Epoch  5 Train Loss: 1.294 Test Loss: 1.235 Accuracy 56.20%
Epoch  6 Batch    0 Loss: 1.314 Avg Loss: 1.314
Epoch  6 Batch  250 Loss: 1.250 Avg Loss: 1.262
Epoch  6 Batch  500 Loss: 1.154 Avg Loss: 1.263
Epoch  6 Batch  750 Loss: 1.119 Avg Loss: 1.267
Epoch  6 Batch 1000 Loss: 1.740 Avg Loss: 1.271
Epoch  6 Batch 1250 Loss: 1.389 Avg Loss: 1.267
Epoch  6 Batch 1500 Loss: 0.991 Avg Loss: 1.267
Epoch  6 Train Loss: 1.267 Test Loss: 1.228 Accuracy 56.04%
Epoch  7 Batch    0 Loss: 1.166 Avg Loss: 1.166
Epoch  7 Batch  250 Loss: 1.143 Avg Loss: 1.265
Epoch  7 Batch  500 Loss: 1.411 Avg Loss: 1.252
Epoch  7 Batch  750 Loss: 1.381 Avg Loss: 1.251
Epoch  7 Batch 1000 Loss: 1.189 Avg Loss: 1.252
Epoch  7 Batch 1250 Loss: 1.276 Avg Loss: 1.251
Epoch  7 Batch 1500 Loss: 0.834 Avg Loss: 1.251
Epoch  7 Train Loss: 1.251 Test Loss: 1.204 Accuracy 56.75%
Epoch  8 Batch    0 Loss: 1.105 Avg Loss: 1.105
Epoch  8 Batch  250 Loss: 1.348 Avg Loss: 1.238
Epoch  8 Batch  500 Loss: 0.974 Avg Loss: 1.233
Epoch  8 Batch  750 Loss: 1.127 Avg Loss: 1.236
Epoch  8 Batch 1000 Loss: 0.960 Avg Loss: 1.233
Epoch  8 Batch 1250 Loss: 1.234 Avg Loss: 1.234
Epoch  8 Batch 1500 Loss: 1.000 Avg Loss: 1.235
Epoch  8 Train Loss: 1.235 Test Loss: 1.222 Accuracy 57.17%
Epoch  9 Batch    0 Loss: 0.954 Avg Loss: 0.954
Epoch  9 Batch  250 Loss: 0.920 Avg Loss: 1.207
Epoch  9 Batch  500 Loss: 1.259 Avg Loss: 1.225
Epoch  9 Batch  750 Loss: 1.603 Avg Loss: 1.225
Epoch  9 Batch 1000 Loss: 0.929 Avg Loss: 1.226
Epoch  9 Batch 1250 Loss: 0.866 Avg Loss: 1.223
Epoch  9 Batch 1500 Loss: 1.212 Avg Loss: 1.221
Epoch  9 Train Loss: 1.221 Test Loss: 1.149 Accuracy 59.18%
Epoch 10 Batch    0 Loss: 1.056 Avg Loss: 1.056
Epoch 10 Batch  250 Loss: 1.271 Avg Loss: 1.213
Epoch 10 Batch  500 Loss: 1.319 Avg Loss: 1.203
Epoch 10 Batch  750 Loss: 1.218 Avg Loss: 1.203
Epoch 10 Batch 1000 Loss: 1.276 Avg Loss: 1.203
Epoch 10 Batch 1250 Loss: 1.275 Avg Loss: 1.205
Epoch 10 Batch 1500 Loss: 1.021 Avg Loss: 1.204
Epoch 10 Train Loss: 1.205 Test Loss: 1.176 Accuracy 58.60%
Epoch 11 Batch    0 Loss: 1.598 Avg Loss: 1.598
Epoch 11 Batch  250 Loss: 1.187 Avg Loss: 1.193
Epoch 11 Batch  500 Loss: 1.723 Avg Loss: 1.202
Epoch 11 Batch  750 Loss: 1.348 Avg Loss: 1.193
Epoch 11 Batch 1000 Loss: 1.345 Avg Loss: 1.192
Epoch 11 Batch 1250 Loss: 1.115 Avg Loss: 1.192
Epoch 11 Batch 1500 Loss: 1.558 Avg Loss: 1.194
Epoch 11 Train Loss: 1.194 Test Loss: 1.138 Accuracy 60.02%
Epoch 12 Batch    0 Loss: 1.181 Avg Loss: 1.181
Epoch 12 Batch  250 Loss: 1.335 Avg Loss: 1.174
Epoch 12 Batch  500 Loss: 1.175 Avg Loss: 1.176
Epoch 12 Batch  750 Loss: 1.431 Avg Loss: 1.177
Epoch 12 Batch 1000 Loss: 1.098 Avg Loss: 1.176
Epoch 12 Batch 1250 Loss: 1.361 Avg Loss: 1.173
```

```
Epoch 12 Batch 1500 Loss: 1.206 Avg Loss: 1.178
Epoch 12 Train Loss: 1.179 Test Loss: 1.156 Accuracy 58.89%
Epoch 13 Batch    0 Loss: 1.334 Avg Loss: 1.334
Epoch 13 Batch  250 Loss: 1.412 Avg Loss: 1.164
Epoch 13 Batch  500 Loss: 1.574 Avg Loss: 1.165
Epoch 13 Batch  750 Loss: 1.704 Avg Loss: 1.165
Epoch 13 Batch 1000 Loss: 1.288 Avg Loss: 1.169
Epoch 13 Batch 1250 Loss: 1.082 Avg Loss: 1.171
Epoch 13 Batch 1500 Loss: 1.254 Avg Loss: 1.167
Epoch 13 Train Loss: 1.166 Test Loss: 1.146 Accuracy 59.68%
Epoch 14 Batch    0 Loss: 1.304 Avg Loss: 1.304
Epoch 14 Batch  250 Loss: 0.758 Avg Loss: 1.132
Epoch 14 Batch  500 Loss: 1.011 Avg Loss: 1.155
Epoch 14 Batch  750 Loss: 1.062 Avg Loss: 1.156
Epoch 14 Batch 1000 Loss: 1.247 Avg Loss: 1.160
Epoch 14 Batch 1250 Loss: 1.869 Avg Loss: 1.162
Epoch 14 Batch 1500 Loss: 1.162 Avg Loss: 1.166
Epoch 14 Train Loss: 1.163 Test Loss: 1.108 Accuracy 60.84%
Epoch 15 Batch    0 Loss: 1.372 Avg Loss: 1.372
Epoch 15 Batch  250 Loss: 1.278 Avg Loss: 1.158
Epoch 15 Batch  500 Loss: 0.995 Avg Loss: 1.158
Epoch 15 Batch  750 Loss: 1.159 Avg Loss: 1.154
Epoch 15 Batch 1000 Loss: 0.829 Avg Loss: 1.149
Epoch 15 Batch 1250 Loss: 0.891 Avg Loss: 1.150
Epoch 15 Batch 1500 Loss: 1.061 Avg Loss: 1.153
Epoch 15 Train Loss: 1.152 Test Loss: 1.122 Accuracy 60.60%
Epoch 16 Batch    0 Loss: 1.154 Avg Loss: 1.154
Epoch 16 Batch  250 Loss: 1.100 Avg Loss: 1.135
Epoch 16 Batch  500 Loss: 1.220 Avg Loss: 1.136
Epoch 16 Batch  750 Loss: 1.080 Avg Loss: 1.135
Epoch 16 Batch 1000 Loss: 1.006 Avg Loss: 1.140
Epoch 16 Batch 1250 Loss: 1.313 Avg Loss: 1.140
Epoch 16 Batch 1500 Loss: 0.844 Avg Loss: 1.141
Epoch 16 Train Loss: 1.142 Test Loss: 1.114 Accuracy 60.65%
Epoch 17 Batch    0 Loss: 1.206 Avg Loss: 1.206
Epoch 17 Batch  250 Loss: 0.983 Avg Loss: 1.127
Epoch 17 Batch  500 Loss: 1.257 Avg Loss: 1.134
Epoch 17 Batch  750 Loss: 0.889 Avg Loss: 1.136
Epoch 17 Batch 1000 Loss: 1.154 Avg Loss: 1.137
Epoch 17 Batch 1250 Loss: 1.087 Avg Loss: 1.142
Epoch 17 Batch 1500 Loss: 1.229 Avg Loss: 1.139
Epoch 17 Train Loss: 1.138 Test Loss: 1.107 Accuracy 60.72%
Epoch 18 Batch    0 Loss: 0.840 Avg Loss: 0.840
Epoch 18 Batch  250 Loss: 1.138 Avg Loss: 1.112
Epoch 18 Batch  500 Loss: 1.337 Avg Loss: 1.119
Epoch 18 Batch  750 Loss: 1.284 Avg Loss: 1.125
Epoch 18 Batch 1000 Loss: 0.942 Avg Loss: 1.117
Epoch 18 Batch 1250 Loss: 0.880 Avg Loss: 1.119
Epoch 18 Batch 1500 Loss: 1.076 Avg Loss: 1.120
Epoch 18 Train Loss: 1.119 Test Loss: 1.095 Accuracy 60.96%
Epoch 19 Batch    0 Loss: 1.066 Avg Loss: 1.066
Epoch 19 Batch  250 Loss: 1.449 Avg Loss: 1.090
Epoch 19 Batch  500 Loss: 1.107 Avg Loss: 1.113
Epoch 19 Batch  750 Loss: 1.576 Avg Loss: 1.119
Epoch 19 Batch 1000 Loss: 1.165 Avg Loss: 1.122
Epoch 19 Batch 1250 Loss: 0.922 Avg Loss: 1.122
Epoch 19 Batch 1500 Loss: 0.991 Avg Loss: 1.120
Epoch 19 Train Loss: 1.120 Test Loss: 1.096 Accuracy 61.58%
```

Plot the training loss (and validation loss/accuracy, if recorded).

In [28]:
```
plt.plot(per_epoch_test_loss)
plt.plot(per_epoch_train_loss)
plt.plot([x/100. for x in per_epoch_accuracy])
plt.legend(["Test Loss", "Train Loss", "Accuracy"])
plt.show()
```



In [ ]: