HW4 DeepLearning

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1 Part 1

1. A DenseNet network involves each layer receiving input from all of the previous layers. The advantages of this is that it leads to networks that require much fewer layers, and smaller parameter sizes allowing to achieve similar levels of accuracy. Disadvantages of a DenseNet is that there will be more connections between layers leading to more required computations and possibly to overfitting.

2. Inception module allows for multiple different sized convolutions to occur simultaneously within a given layer. The advantages of this include exploring multiple possible convolutions to determine which size would be best for the data you plan to use. Once again disadvantges include an increase in the computational time because the model now needs to look at many different convolutional sizes for each layer and decide which to emphasize.

3. Three different loss functions used for autoenconders can be made using different regularization for example, l1 norm or l2 norm. Can use a loss function that uses the jacobian regularization for example in a Denoiseing autoencoder. Loss functions can be a binary cross entropy based loss function. Or a Mean Squared Error based loss function. You can also use a classification loss branch, where one branch looks at loss for classification and the other does simple binary cross entropy loss.

4. In a sparse autoenconder, you go through the network and set some activations of the hidden layers to zero both on the encoding and decoding side of the network.

5. Denoising autoencoder works by adding noise first to the input to the algorithm and then training it to pull out the original image, this can be done by increasing the dimensionality of the image by creating redundant representation. This helps the network resist small perturbations.

6. Segmentation involves breaking an image components into separate classes. In semantic segmentation the divisions are based on different classes ie road, sheep, sky. And in instance classification, each instance of a class is separately classified ie goat1, goat2 etc.

7. One way of object detection is using a sliding window detector which uses a sliding window and for each window you test if object is there or not. Second way is region proposal based networks, which involves a region being proposed using a selective search and then these regions are sent to a CNN. Third way we discussed is YOLO which using small bounding boxes and classifies and detects in a single CNN.

8. Non max suppression is a technique used for object detection. The method uses the IOU to remove boxes that have a high overlap such that only a single box that best describes the detection of the object remains. It is an iterative algorithm that essentially compares the box with the highest confidence with the rest, removing them based on if the IOU is greater than a threshold.

9. In RCNN regions proposed using selective search are then sent to a CNN, but they are very time consuming because many bounding boxes are sent. In Fast-RCNN, they feed image to convolutional map to get features then get regional proposals from the features and then classification. Faster-RCNN gets rid of regional proposal part altogether by using a region proposal network to do it.

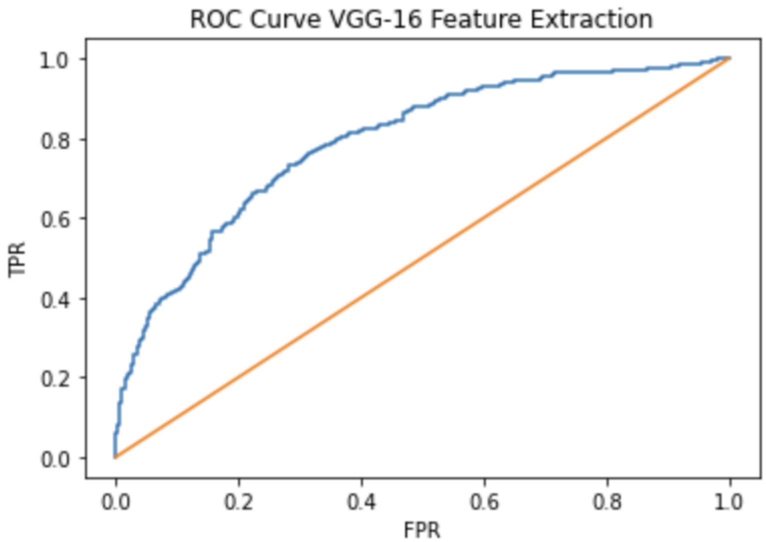
10. YOLO (you only look once) predicts the bounding box and image classification all in a single convolutional network. It does it by dividing the image into multiple small boxes and within it having bounding boxes, these boxes are then classified.

11. As described in the Faster-RCNN paper assigned for this class a way to measure detection accuracy is mAP or mean Average Precision. It calculates the mean precision value based on recall between 0 and 1 for a particular detection square.

2 Part 2: Models, VGG-16

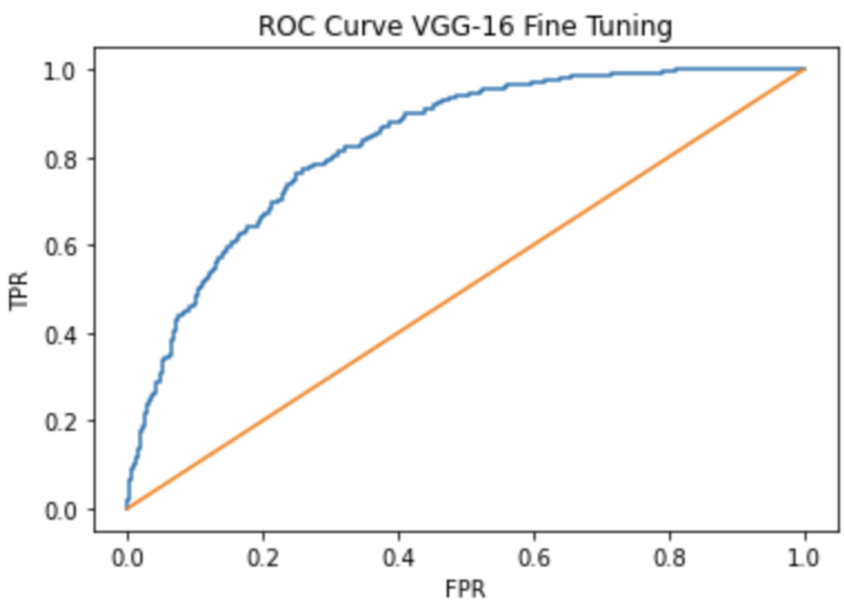
In the VGG models for training I used a binary cross entropy loss function with learning rate of 10^{-5} using the Adam optimizer. I used the cosine similarity measurement to compute the similarity between model outputs for the image pairs.

2.1 ROC curve for feature extraction from VGG-16



In this section I took a pretrained VGG-16 network and removed the last layer of it. Then ran the lfw pairs through it and used the cosine angle similarity to determine the similarity values for each pair. This is highlighted in the ROC curve above. The AUC for this was: .7914

2.2 ROC curve for fine tuning from VGG-16

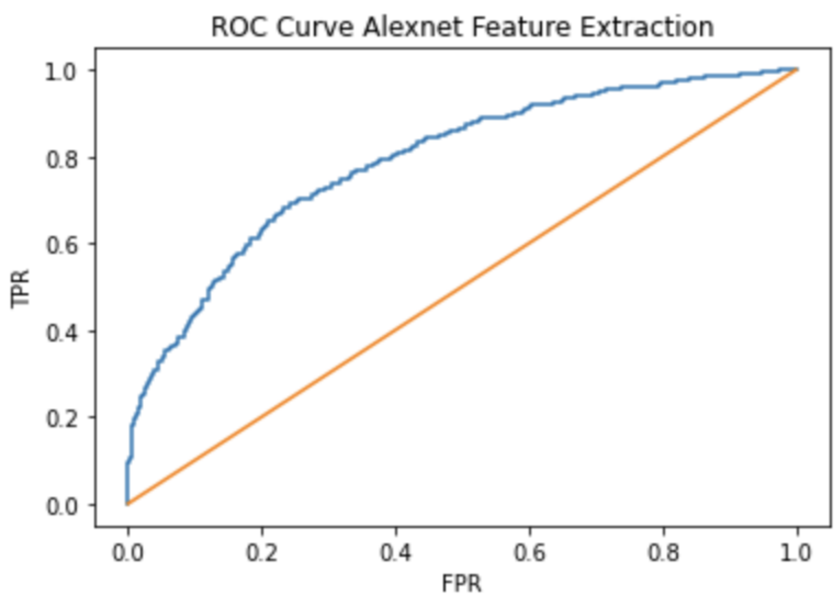


In this section I performed fine tuning of the VGG network, this involved loading the pretrained weights of the model removing the last layer of the model and then training on the dataset for 10 epochs. Training was fed in batches of 60 pairs. The AUC was:.83 , I experienced better performance on the fine-tuned model especially after increasing it up to 10 epochs.

3 Part 2: Models, Alexnet

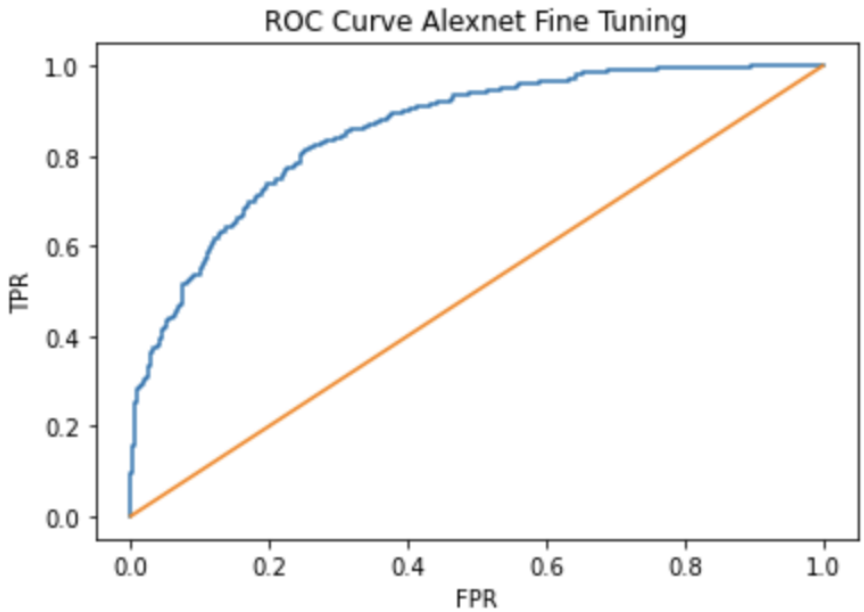
In the Alexnet models I used a binary cross entropy loss function with learning rate of 10^{-4} using the Adam optimizer. I used the cosine similarity measurement to compute the similarity between model outputs for the image pairs.

2.3 Feature Extraction from Alexnet



In this section I took a pretrained Alexnet network and removed the last layer of it. Then ran the lfw pairs through it and used the cosine similarity to determine the similarity values for each pair. This was used in a binary cross entropy loss function as described earlier. This is highlighted in the ROC curve above. The AUC for this was: .79.

2.4 Fine Tuning Alexnet



In this section I performed fine tuning of the Alexnet model, this involved loading the pre-trained weights of the model and then training on the dataset for only 2 epochs. Training was fed in batches of 40 pairs. The AUC was: .85 , I experienced better performance on the fine tuned model and it was interesting to see that smaller epochs gave better results. This probably helped keep the model from over fitting. **This model was my greatest performing one.**

4 Appended Code and References to code

Here is all the code for my work. I wrote everything in python using the framework pytorch on google COLABs Using the GPU setting for faster running. Data was imported using the sklearn libraries and was verified to resemble the lfw dataset.

HW4_Final

April 29, 2021

[1]:
```
#HW 4 Vedant Jain



import torch
import torch.nn as nn
import matplotlib.pyplot as plt
from torch.utils.data import Dataset,DataLoader
import torchvision.transforms as transforms
from torchvision.transforms import ToPILImage
import torch.nn.functional as F
import numpy as np
import os
import random
import sys
from PIL import Image

import torchvision.models as models

from sklearn.metrics import roc_curve, auc
```

[2]:
```
torch.cuda.is_available()
```

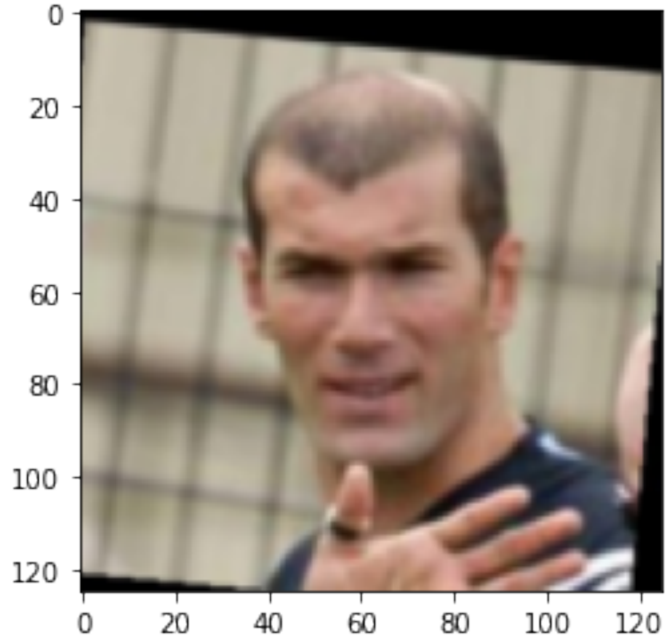
[2]:
```
True
```

[3]:
```
#%% load in the images

from sklearn.datasets import fetch_lfw_pairs
lfw_train = fetch_lfw_pairs(subset='train',color=True, slice_=(slice(0, 250),␣
 ↪slice(0, 250)))
lfw_test = fetch_lfw_pairs(subset='test',color=True, slice_=(slice(0, 250),␣
 ↪slice(0, 250)))
```

[4]:
```
first = lfw_train.pairs[1099,0,:,:,:]
second = lfw_train.pairs[1099,1,:,:,:]
lfw_train.pairs.shape
```

[4]:
```
(2200, 2, 125, 125, 3)
```

[5]:
```
plt.imshow(second.astype('uint8'))
plt.show()
```



[6]:
```
#%% preprocess image
preprocess = transforms.Compose([
    transforms.ToPILImage(),
    transforms.Resize(256),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225]),
])

#input_tensor = preprocess(singleImage.astype(np.uint8))
```

[7]:
```
#%% get labels and individual images
trainLabels = lfw_train.target
testLabels = lfw_test.target
```

[8]:
```
#%% throw into dataloader:

class NumbersDataset(Dataset):
    def __init__(self,trainSel):
        self.trainingData = trainSel
        if trainSel == 1:
            self.numEntries = len(trainLabels)
```

```
        else:
            self.numEntries = len(testLabels)

    def __len__(self):
        return self.numEntries

    def __getitem__(self, idx):
        if self.trainingData == 1:
            singleImage = lfw_train.pairs[idx,0,:,:,:]
            image1 = preprocess(singleImage.astype(np.uint8))
            secondImage = lfw_train.pairs[idx,1,:,:,:]
            image2 = preprocess(secondImage.astype(np.uint8))
            label = trainLabels[idx]
            return image1, image2, label
        else:
            singleImage = lfw_test.pairs[idx,0,:,:,:]
            image1 = preprocess(singleImage.astype(np.uint8))
            secondImage = lfw_test.pairs[idx,1,:,:,:]
            image2 = preprocess(secondImage.astype(np.uint8))
            label = testLabels[idx]
            return image1, image2, label
```

[9]:
```
#%% load the dataset
train_set = NumbersDataset(1)
test_set = NumbersDataset(0)
train_loader = DataLoader(train_set, batch_size=50, shuffle=True, num_workers=0)
test_loader = DataLoader(test_set, batch_size=1, shuffle=False, num_workers=0)
```

[10]:
```
torch.cuda.is_available()
```

[10]: True

trueLabel = []; predLabel = [];

for i,data in enumerate(test_loader, 0): model.train(mode=False) image1s,image2s,labels=data image1s = image1s.to(device) image2s = image2s.to(device) labels = labels.to(device) trueLabel.append(labels.cpu().numpy()) with torch.no_grad(): output = model(image1s) output2 = model(image2s) #getLabels.append(output) cos = nn.CosineSimilarity(dim=1, eps=1e-6) cos_sim = cos(output, output2) predLabel.append(cos_sim.cpu().numpy()) #print(i)

[11]:
```
#%%
def train(train_loader, model, loss_fn, optimizer):
    for i, data in enumerate(train_loader):
        model.train(mode=True)
        image1s,image2s,labels=data
        labels = labels.to(torch.float32)
```

```
        image1s = image1s.to(device)
        image2s = image2s.to(device)
        labels = labels.to(device)
        optimizer.zero_grad()

        # Compute prediction error
        output = model(image1s)
        output2 = model(image2s)
    #getLabels.append(output)
        cos = nn.CosineSimilarity(dim=1, eps=1e-8)
        cos_sim = cos(output, output2)
        predVal = cos_sim

        # print(predVal)
        # print('True value: ')
        # print(labels)

        loss = loss_fn(predVal, labels)
        #print(loss)

        # Backpropagation
        loss.backward()
        optimizer.step()
    print('one Epoch done')


def test(dataloader, model):
    trueLabel = [];
    predLabel = [];
    model.train(mode=False)
    model.eval()
    with torch.no_grad():
        for i, data in enumerate(dataloader):
            image1s,image2s,labels=data
            #labels = labels.to(torch.float32)
            image1s = image1s.to(device)
            image2s = image2s.to(device)
            #labels = labels.to(device)
            output = model(image1s)
            output2 = model(image2s)
            #trueLabel.append(labels.cpu().numpy())
            cos = nn.CosineSimilarity(dim=1, eps=1e-6)
            cos_sim = cos(output, output2)
            predLabel.append(cos_sim.cpu().numpy())
            trueLabel.append(labels)
    return trueLabel, predLabel
```

[12]:

```
#%% reset Dataset
train_set = NumbersDataset(1)
test_set = NumbersDataset(0)
train_loader = DataLoader(train_set, batch_size=60, shuffle=True, num_workers=0)
test_loader = DataLoader(test_set, batch_size=1, shuffle=False, num_workers=0)
```

[13]:

```
#%% define model to use here its VGG
#model = torch.hub.load('pytorch/vision:v0.6.0', 'alexnet', pretrained=True)
model = models.vgg16(pretrained=True)
model.eval()
new_classifier = nn.Sequential(*list(model.classifier.children())[:-1])
model.classifier = new_classifier
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
model.to(device)
```

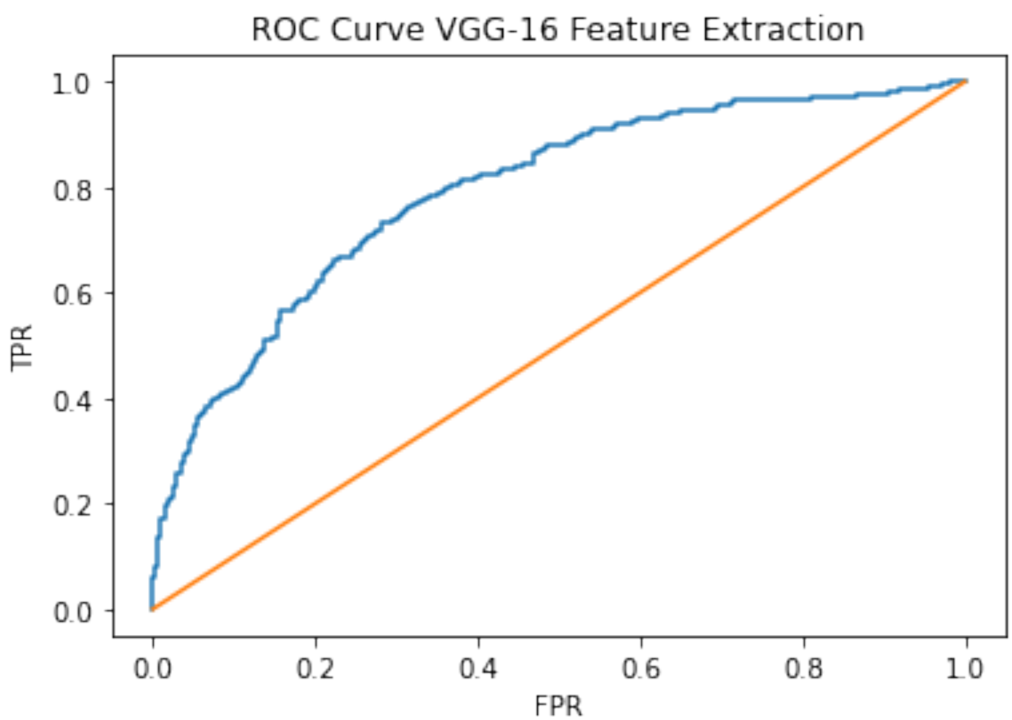
[13]:

```
VGG(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU(inplace=True)
    (2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (3): ReLU(inplace=True)
    (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (5): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (6): ReLU(inplace=True)
    (7): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (8): ReLU(inplace=True)
    (9): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (10): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (11): ReLU(inplace=True)
    (12): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (13): ReLU(inplace=True)
    (14): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (15): ReLU(inplace=True)
    (16): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (17): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (18): ReLU(inplace=True)
    (19): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (20): ReLU(inplace=True)
    (21): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (22): ReLU(inplace=True)
    (23): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (24): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (25): ReLU(inplace=True)
```

```
    (26): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (27): ReLU(inplace=True)
    (28): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (29): ReLU(inplace=True)
    (30): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(7, 7))
  (classifier): Sequential(
    (0): Linear(in_features=25088, out_features=4096, bias=True)
    (1): ReLU(inplace=True)
    (2): Dropout(p=0.5, inplace=False)
    (3): Linear(in_features=4096, out_features=4096, bias=True)
    (4): ReLU(inplace=True)
    (5): Dropout(p=0.5, inplace=False)
  )
)
```

[14]:

```
trueLabel, predLabel = test(test_loader, model)
fpr, tpr, thresholds = roc_curve(trueLabel, predLabel)
plt.plot(fpr, tpr)
plt.plot(np.linspace(0,1,100),np.linspace(0,1,100))
plt.title('ROC Curve VGG-16 Feature Extraction')
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.show()
```



[15]:
```python
aucVal = auc(fpr, tpr)
aucVal
```

[15]: 0.791432

[16]:
```python
loss_fn = nn.BCELoss()
optimizer = torch.optim.Adam(model.parameters(), lr=1e-5) #loss earlier was 1e-4

epochs = 10

#%%

for t in range(epochs):
    print(f"Epoch {t+1}\n-------------------------------")
    train(train_loader, model, loss_fn, optimizer)
print("Done!")
```

```
Epoch 1
-------------------------------
one Epoch done
Epoch 2
-------------------------------
one Epoch done
Epoch 3
-------------------------------
one Epoch done
Epoch 4
-------------------------------
one Epoch done
Epoch 5
-------------------------------
one Epoch done
Epoch 6
-------------------------------
one Epoch done
Epoch 7
-------------------------------
one Epoch done
Epoch 8
-------------------------------
one Epoch done
Epoch 9
-------------------------------
one Epoch done
Epoch 10
```

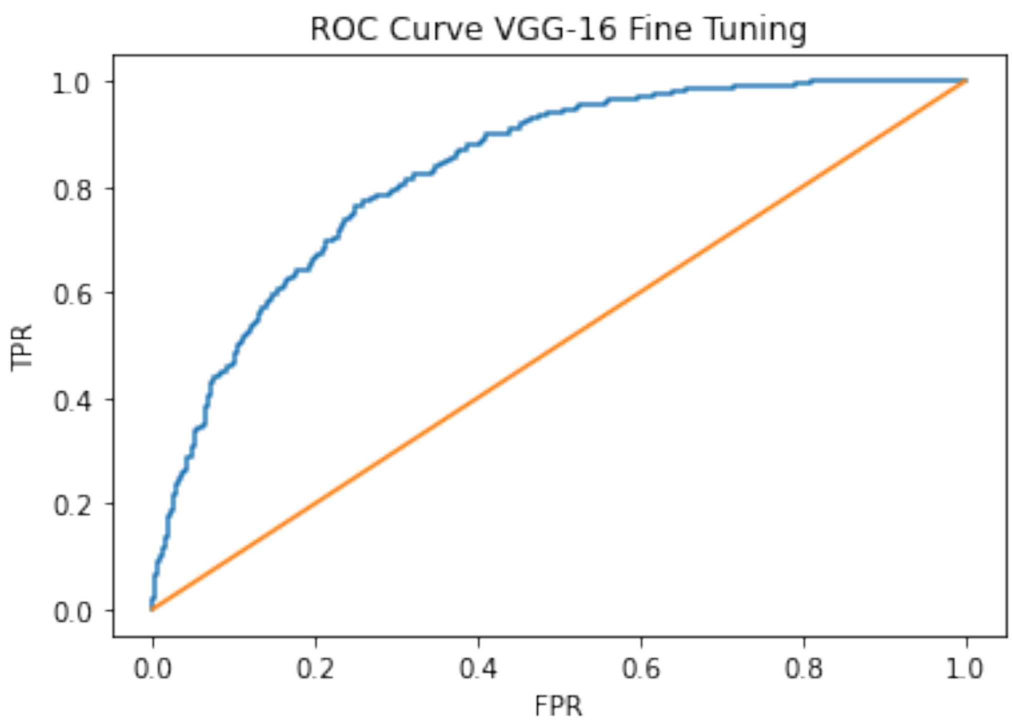
```
-------------------------------
one Epoch done
Done!
```

[17]:

```
trueLabel, predLabel = test(test_loader, model)
```

[18]:

```
#roc curve graph
fpr, tpr, thresholds = roc_curve(trueLabel, predLabel)
plt.plot(fpr, tpr)
plt.plot(np.linspace(0,1,100),np.linspace(0,1,100))
plt.title('ROC Curve VGG-16 Fine Tuning')
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.show()
```



[19]:

```
aucVal = auc(fpr, tpr)
aucVal
```

[19]: 0.83124

[20]:

```
#%% reset Dataset
train_set = NumbersDataset(1)
test_set = NumbersDataset(0)
train_loader = DataLoader(train_set, batch_size=40, shuffle=True, num_workers=0)
```

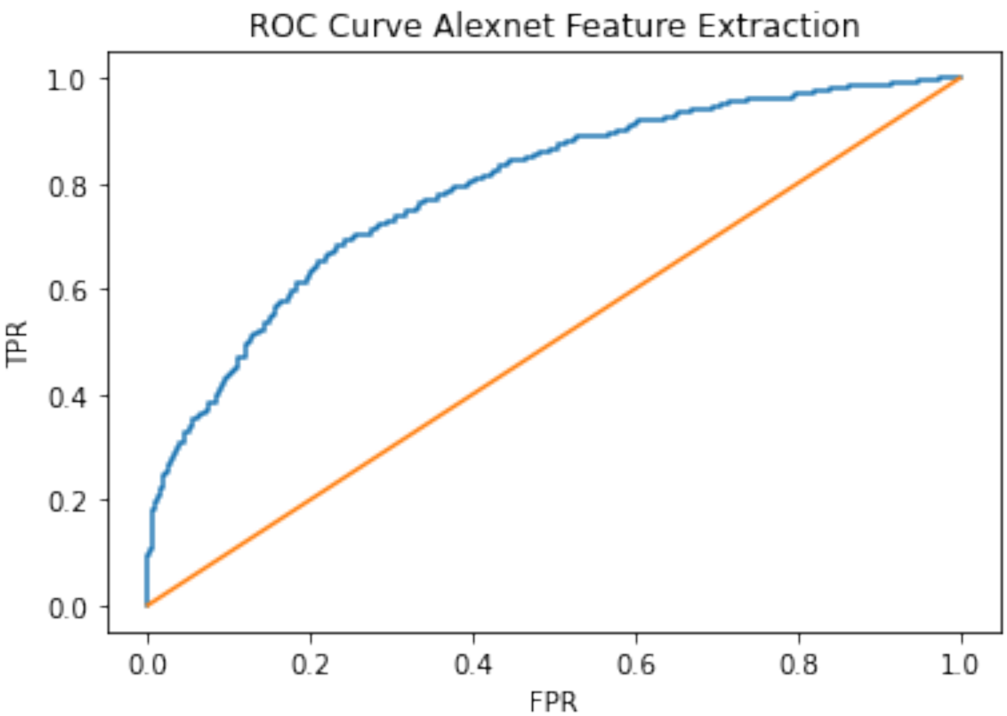
```
test_loader = DataLoader(test_set, batch_size=1, shuffle=False, num_workers=0)
```

[27]:
```
#%% define model to use
#model = torch.hub.load('pytorch/vision:v0.6.0', 'alexnet', pretrained=True)
#model = models.vgg16(pretrained=True)
model2 = models.alexnet(pretrained=True)
model2.eval()
new_classifier = nn.Sequential(*list(model2.classifier.children())[:-1])
model2.classifier = new_classifier
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
model2.to(device)
```

[27]:
```
AlexNet(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(11, 11), stride=(4, 4), padding=(2, 2))
    (1): ReLU(inplace=True)
    (2): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (3): Conv2d(64, 192, kernel_size=(5, 5), stride=(1, 1), padding=(2, 2))
    (4): ReLU(inplace=True)
    (5): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (6): Conv2d(192, 384, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (7): ReLU(inplace=True)
    (8): Conv2d(384, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (9): ReLU(inplace=True)
    (10): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (11): ReLU(inplace=True)
    (12): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1,
ceil_mode=False)
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(6, 6))
  (classifier): Sequential(
    (0): Dropout(p=0.5, inplace=False)
    (1): Linear(in_features=9216, out_features=4096, bias=True)
    (2): ReLU(inplace=True)
    (3): Dropout(p=0.5, inplace=False)
    (4): Linear(in_features=4096, out_features=4096, bias=True)
    (5): ReLU(inplace=True)
  )
)
```

[22]:
```
trueLabel, predLabel = test(test_loader, model2)
#roc curve graph
fpr, tpr, thresholds = roc_curve(trueLabel, predLabel)
plt.plot(fpr, tpr)
plt.plot(np.linspace(0,1,100),np.linspace(0,1,100))
```

```
plt.title('ROC Curve Alexnet Feature Extraction')
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.show()
```



[23]:
```
aucVal = auc(fpr, tpr)
aucVal
```

[23]: 0.7899160000000001

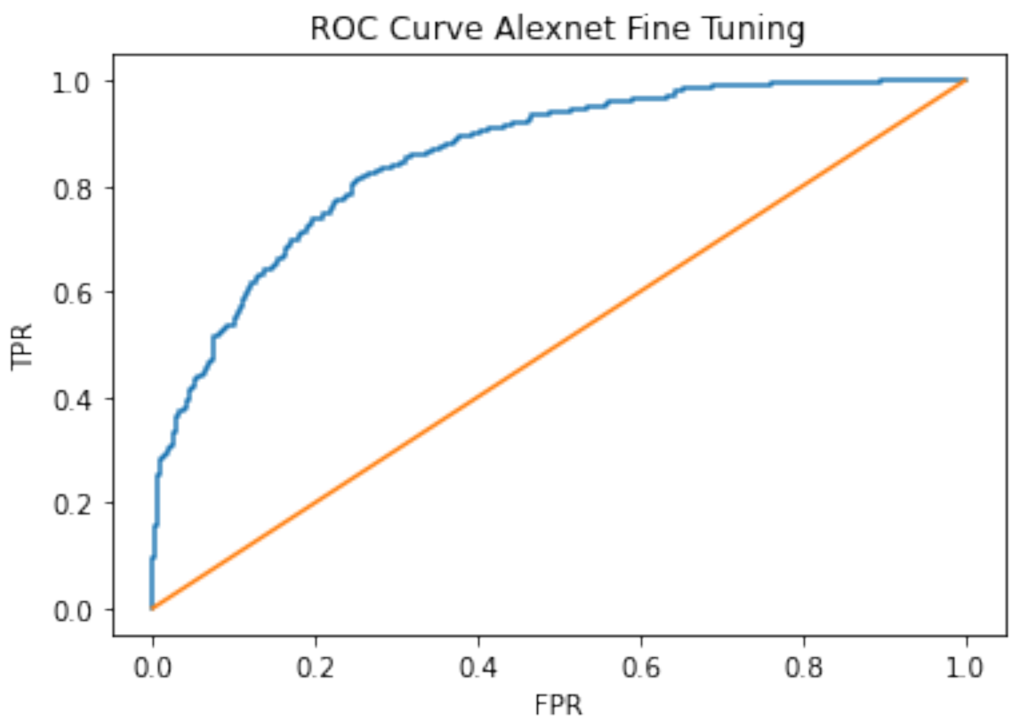
[28]:
```
loss_fn = nn.BCELoss()
optimizer = torch.optim.Adam(model2.parameters(), lr=1e-4) #loss earlier was␣
↪1e-4

epochs = 2

#%%

for t in range(epochs):
    print(f"Epoch {t+1}\n-------------------------------")
    train(train_loader, model2, loss_fn, optimizer)
print("Done!")
```

```
Epoch 1
```

```
-------------------------------
one Epoch done
Epoch 2
-------------------------------
one Epoch done
Done!
```

[29]:

```python
trueLabel, predLabel = test(test_loader, model2)
#roc curve graph
fpr, tpr, thresholds = roc_curve(trueLabel, predLabel)
plt.plot(fpr, tpr)
plt.plot(np.linspace(0,1,100),np.linspace(0,1,100))
plt.title('ROC Curve Alexnet Fine Tuning')
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.show()
```



[26]:

```python
aucVal = auc(fpr, tpr)
aucVal
```

[26]: 0.8529159999999999

[26]:

[26]:

```
```

[26]:

```
```