**CNN** using PyTorch Libraries used: In [155... import torch import torch.nn as nn from torch.autograd import Variable import torch.nn.functional as F import torchvision from torch.utils.data import Dataset, DataLoader import torchvision.transforms as transforms import matplotlib.pyplot as plt 2.1 Loading the FashionMNIST dataset Download the dataset trainSet = torchvision.datasets.FashionMNIST(root='./data', train=True, download=True, transform=transforms.ToTensor()) testSet = torchvision.datasets.FashionMNIST(root='./data', train=False, download=True, transform=transforms.ToTensor()) Make sure you turn on the GPU in Runtime setting, for a better performance. device = torch.device("cuda:0" if torch.cuda.is\_available() else "cpu") Get the train/test loader using DataLoader With batch size --> 100, and Shuffle is TRUE. In [158... | trainLoader = torch.utils.data.DataLoader(trainSet,batch\_size=100,shuffle=True) testLoader = torch.utils.data.DataLoader(testSet,batch\_size=100,shuffle=True) Creating a method to name the class for the label. example: 9 --> Ankle Boot In [159... def outputLabel(label): outputMapping = { 0: "T-shirt/Top", 1: "Trouser", 2: "Pullover", 3: "Dress", 4: "Coat", 5: "Sandal", 6: "Shirt", 7: "Sneaker", 8: "Bag", 9: "Ankle Boot" input = (label.item() if type(label) == torch.Tensor else label) return outputMapping[input] To show a data using matplotlib: image, label = next(iter(trainSet)) plt.imshow(image.squeeze(), cmap="gray") print(label) 9 5 10 15 20 25 10 15 20 2.2 Implementing the Network Building the CNN class: Model Class Name: FashionCNN Layers: 2 sequential layers consist of: Convolution layer with kernal -> 3\*3, padding = 1 (1st layer) & padding = 0 (2nd layer). \* Stride of 1 in both the layer \* Activation function: Relu \* All the functionaltyy is given in forward method that defines the forward pass of CNN. 1. 1st Conv later: input: 28 \* 28 \* 3 and Output : 28 \* 28 \* 32. 2. Max pooling layer: input: 28 \* 28 \* 32 and Output: 14 \* 14 \* 32. 3. 2nd Conv layer: input : 14 \* 14 \* 32 and output: 12 \* 12 \* 64 4. 2nd Max Pooling layer : 12 \* 12 \* 64, output: 6 \* 6 \* 64. At last fully connected layer has 10 output features for 10 types of clothes. In [161... class NeuralNetwork(nn.Module): def \_\_init\_\_(self): super(NeuralNetwork, self).\_\_init\_\_() self.layer1 = nn.Sequential( nn.Conv2d(in\_channels=1, out\_channels=32, kernel\_size=3, padding=1), nn.BatchNorm2d(32), nn.ReLU(), nn.MaxPool2d(kernel\_size=2, stride=2) self.layer2 = nn.Sequential( nn.Conv2d(in\_channels=32, out\_channels=64, kernel\_size=3), nn.BatchNorm2d(64), nn.ReLU(), nn.MaxPool2d(2) self.fc1 = nn.Linear(in\_features=64\*6\*6, out\_features=600) self.drop = nn.Dropout2d(0.25)self.fc2 = nn.Linear(in\_features=600, out\_features=120) self.fc3 = nn.Linear(in\_features=120, out\_features=10) def forward(self, x): out = self.layer1(x)out = self.layer2(out) out = out.view(out.size(0), -1) out = self.fc1(out) out = self.drop(out) out = self.fc2(out) out = self.fc3(out) return out Define CNN by using different architecture to construct model Take a look of the chosen model: In [ ]: | model = NeuralNetwork() model.to(device) #print(model) Firstly, define the learnin rate: In [163... | learningRate = 0.001 Secondly, choose the optimizer in torch. First one we used, is ADAM: In [149... optimizer = torch.optim.Adam(model.parameters(), lr=learningRate) The second optimizer we used is SGD: (Note, you only need to run either the code above or the following one. optimizer = torch.optim.SGD(model.parameters(), lr=learningRate, momentum=0.9) In [164... 2.3 Predicting Let us start training the network with chosen architecture and optimizer, then test it on the testing dataset In [165... error = nn.CrossEntropyLoss() numEpochs = 15count = 0# Lists for visualization of loss and accuracy lossList = [] iterationList = [] accuracyList = [] # List classwise accuracy predictionsList = [] labelsList = [] for epoch in range(numEpochs): for images, labels in trainLoader: # Transfering the images and labels to GPU(if available) images, labels = images.to(device), labels.to(device) train = Variable(images.view(100, 1, 28, 28)) labels = Variable(labels) # Here is --> Forward pass outputs = model(train) loss = error(outputs, labels) # Initializing a gradient as 0 so there is no mixing of gradient among the batches optimizer.zero\_grad() #Propagating the error backward loss.backward() # Optimizing the parameters (Adam Algorithm) optimizer.step() count **+=** 1 # Let us start testing the model: if not (count % 50): total = 0correct = 0 for images, labels in testLoader: images, labels = images.to(device), labels.to(device) labelsList.append(labels) test = Variable(images.view(100, 1, 28, 28)) outputs = model(test) predictions = torch.max(outputs, 1)[1].to(device) predictionsList.append(predictions) correct += (predictions == labels).sum() total += len(labels) accuracy = correct \* 1.0 / total lossList.append(loss.data) iterationList.append(count) accuracyList.append(accuracy) **if not** (count % 500): print("Iteration: {}, Loss: {:.3f}, Accuracy: {:.2%}".format(count, loss.data, accuracy)) Iteration: 500, Loss: 0.265, Accuracy: 86.36% Iteration: 1000, Loss: 0.150, Accuracy: 88.40% Iteration: 1500, Loss: 0.326, Accuracy: 89.72% Iteration: 2000, Loss: 0.320, Accuracy: 90.50% Iteration: 2500, Loss: 0.191, Accuracy: 90.32% Iteration: 3000, Loss: 0.261, Accuracy: 90.05% Iteration: 3500, Loss: 0.337, Accuracy: 90.77% Iteration: 4000, Loss: 0.233, Accuracy: 90.64% Iteration: 4500, Loss: 0.222, Accuracy: 90.64% Iteration: 5000, Loss: 0.110, Accuracy: 90.47% Iteration: 5500, Loss: 0.135, Accuracy: 91.72% Iteration: 6000, Loss: 0.142, Accuracy: 90.32% Iteration: 6500, Loss: 0.182, Accuracy: 90.73% Iteration: 7000, Loss: 0.185, Accuracy: 91.04% Iteration: 7500, Loss: 0.140, Accuracy: 91.18% Iteration: 8000, Loss: 0.127, Accuracy: 90.62% Iteration: 8500, Loss: 0.084, Accuracy: 91.31% Iteration: 9000, Loss: 0.085, Accuracy: 91.31% Plot the loss in iterations: In [168... plt.plot(iterationList, lossList) plt.xlabel("Iterations") plt.ylabel("Loss") plt.show() 0.6 0.5 0.1 2000 4000 6000 Plot the accuracy in iterations: plt.plot(iterationList, accuracyList) plt.xlabel("Iterations") plt.ylabel("Accuracy") plt.show() 0.92 0.90 0.88 98.0 Accuracy 98.0 Accuracy 0.82 0.80 0.78 4000 6000 2000 8000 Iterations Test In [170... model.eval() correct = 0 for images, labels in testLoader: with torch.no\_grad(): # so that computation graph history is not stored images, labels = images.to(device), labels.to(device) # send tensors to GPU outputs = model(images) predictions = outputs.data.max(1)[1] correct += predictions.eq(labels.data).sum() print('Test set accuracy: {:.2f}%'.format(100.0 \* correct / len(testLoader.dataset))) Test set accuracy: 91.46% Auxillary: Getting the accuracy with respect to each classification in the MINST Dataset In [171... | classCorrect = [0. for \_ in range(10)] totalCorrect = [0. for \_ in range(10)] with torch.no\_grad(): for images, labels in testLoader: images, labels = images.to(device), labels.to(device) test = Variable(images) outputs = model(test) predicted = torch.max(outputs, 1)[1] c = (predicted == labels).squeeze() **for** i **in** range(100): label = labels[i] classCorrect[label] += c[i].item() totalCorrect[label] += 1 for i in range(10): print("Accuracy of {}: {:.2f}%".format(outputLabel(i), classCorrect[i] \* 100 / totalCorrect[i])) Accuracy of T-shirt/Top: 82.40% Accuracy of Trouser: 98.50% Accuracy of Pullover: 84.60% Accuracy of Dress: 93.90% Accuracy of Coat: 87.10% Accuracy of Sandal: 98.00% Accuracy of Shirt: 77.60% Accuracy of Sneaker: 97.80% Accuracy of Bag: 97.60% Accuracy of Ankle Boot: 97.10% Among 10 categories, Bag has the highest prediction accuracy, and Shirt has the lowest. In [ ]: def train(dataloader, model, error, optimizer): size = len(dataloader.dataset) model.train() #to know the size of the model i have for batch, (X,y) in enumerate(dataloader): X,y = X.to(device), y.to(device)pred = model(X) loss = error(pred,y)#calculate loss function(predicted, actual) optimizer.zero\_grad() loss.backward() optimizer.step() **if** batch % 100 == 0: loss, current = loss.item(), batch \* len(X) #print("Loss ", loss, " Current ", batch, " of ", size/64) def test(dataloader, model, error): size = len(dataloader.dataset) num\_batches = len(dataloader) model.eval() test\_loss, correct = 0, 0 with torch.no\_grad(): **for** X, y **in** dataloader: X, y = X.to(device), y.to(device)pred = model(X) test\_loss += error(pred, y).item() correct += (pred.argmax(1) == y).type(torch.float).sum().item() test\_loss /= num\_batches correct /= size #print("Accuracy ", 100\*correct, " % " In [ ]: epoches=1 for t in range(epoches): train(trainLoader, model, error, optimizer) test(testLoader, model, error) In [ ]: ### Method to predict using the model def pred\_image(images, model): xb = to\_device(image.unsqueeze(0), device)1 yb = model(xb)\_, preds = torch.max(yb, dim=1) return dataset.classes[preds[0].item()] images, labels = testSet[0] print('Predicted:', pred\_image(images, model),' Actual:', dataset.classes[label]) Predicted: Trouser Actual: Dress Performance metrics In [ ]: |actual=[] predicted=[] for i in range(10): images, labels = testSet[i] a=dataset.classes[labels] b=predict\_image(images, model) if a == 'T-shirt/Top': actual.append(1) elif a == 'Trouser': actual.append(2) elif a == 'Pullover': actual.append(3) elif a == 'Dress': actual.append(4) elif a == 'Coat': actual.append(5) elif a == 'Sandal': actual.append(6) elif a == 'Shirt': actual.append(7) elif a == 'Sneaker': actual.append(8) elif a == 'Bag': actual.append(9) else: actual.append(10) if a == 'T-shirt/Top': predicted.append(1) elif a == 'Trouser': predicted.append(2) elif a == 'Pullover': predicted.append(3) elif a == 'Dress': predicted.append(4) elif a == 'Coat': predicted.append(5) elif a == 'Sandal': predicted.append(6) elif a == 'Shirt': Predicted.append(7) elif a == 'Sneaker': predicted.append(8) elif a == 'Bag': predicted.append(9) predicted.append(10) Performance Metrics In [ ]: from torchmetrics import Accuracy from torchmetrics.functional import auc from torchmetrics import Precision from torchmetrics import Recall from torchmetrics import ROC real = torch.tensor(actual) predicted = torch.tensor(predicted) accuracy = Accuracy() x=accuracy(predicted, real) print("The Accuracy is :",accuracy(predicted, real).item()) print("The AUC is :", auc(predicted, real).item()) precision = Precision() print("The Precision is :", precision(predicted, real).item()) recall = Recall() print("The Precision is :",recall(predicted, real).item()) roc = ROC(pos\_label=1) fpr, tpr, thresholds = roc(predicted, real) print("The ROC is :", recall(predicted, real).item()) print("The TPR is :",tpr.tolist()) print("The FPR is :",fpr.tolist()) The Accuracy is: 0.0 The AUC is: 0.0 The Precision is: 1.0 The Precision is: 0.0 The TPR is: [0, 0] The FPR is: [0.0, 1.0] Conclusion The CNN Architecture defined according to the experiment, has a little bit more smooth loss curve and more stable. For the Architecture, ADAM predicts the accuracy faster. Although, SGD is more stable in loss calculation.