Machine Learning Essentials SS25 - Exercise Sheet 5

Instructions

- T0D0 's indicate where you need to complete the implementations.
- You may use external resources, but write your own solutions.
- Provide concise, but comprehensible comments to explain what your code does.
- Code that's unnecessarily extensive and/or not well commented will not be scored.

Exercise 1

Exercise 2

```
In [1]: import matplotlib.pyplot as plt
        import numpy as np
        # TODO: Import the stuff you need from torch and torchvision
        import torch
        from torchvision import transforms
        from torchvision.datasets import FashionMNIST
        from torch.utils.data import random_split, DataLoader
        from torch import nn, optim
        0.000
        If you stay in ML-related fields, you will likely be working on a server
        always remember to set the number of CPU (or even GPU) threads you're usi
        might sometimes use all available threads by default, which will lead to
        also want to use some of the threads.
        # Example of limiting CPU threads:
        # import os
        # os.environ["OMP NUM THREADS"] = "15"
        # os.environ["MKL NUM THREADS"] = "15"
        # torch.set_num_threads(15) # If you only want to use PyTorch threads
```

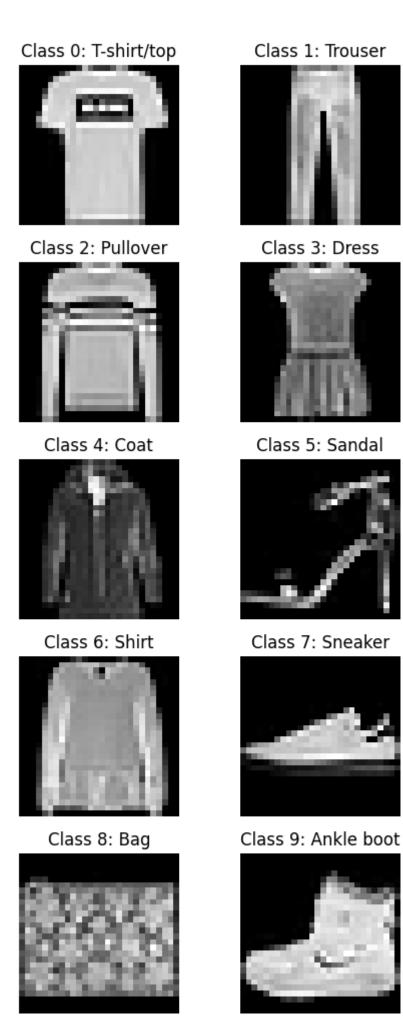
Out[1]: '"\nIf you stay in ML-related fields, you will likely be working on a se rver or cluster. If you do so,\nalways remember to set the number of CPU (or even GPU) threads you\'re using, as Jupyter notebooks or Python scri pts \nmight sometimes use all available threads by default, which will lead to unhappy colleagues or classmates that\nalso want to use some of the threads.\n'

```
In [2]: num_workers = 8
```

2.1

```
In [3]: # TODO: Define transformations
    # Given statistics of training set:
    mu_train = 0.286
```

```
std train = 0.353
        transform = transforms.Compose([
            transforms.ToTensor(),
            transforms.Normalize((mu train,), (std train,))
        ])
        # TODO: Load FashionMNIST train/testsets
        train dataset full = FashionMNIST(
            root='./data',
            train=True,
            download=True,
            transform=transform
        test_dataset = FashionMNIST(
            root='./data',
            train=False,
            download=True,
            transform=transform
        )
        print(f"Full training dataset size: {len(train_dataset_full)}")
        print(f"Test dataset size: {len(test_dataset)}")
       Full training dataset size: 60000
       Test dataset size: 10000
In [4]: # TODO: Create 5x2 subplot grid w/ example image for each class
        fig, axes = plt.subplots(5, 2, figsize=(5, 10))
        for i in range(10):
            img = np.where(train_dataset_full.targets == i)[0][0]
            img_tensor = train_dataset_full[img][0]
            img_array = img_tensor.numpy().squeeze()
            ax = axes[i // 2, i % 2]
            ax.imshow(img array, cmap='gray')
            ax.set_title(f'Class {i}: {train_dataset_full.classes[i]}')
            ax.axis('off')
        plt.tight_layout()
        plt.show()
```



2.2

```
In [6]: # TODO: Define your model architecture: A class called MLP that inherits
        class MLP(nn.Module):
            def __init__(self, input_size=28*28, k=10, hidden_size=128, output_si
                super(MLP, self). init ()
                layers = []
                layers.append(nn.Linear(input size, hidden size))
                layers.append(nn.ReLU())
                for in range(k):
                    layers.append(nn.Linear(hidden_size, hidden_size))
                    layers.append(nn.ReLU())
                layers.append(nn.Linear(hidden_size, output_size))
                self.model = nn.Sequential(*layers)
            def forward(self, x):
                x = x.view(x.size(0), -1)
                return nn.functional.softmax(self.model(x), dim=1)
        # TODO: Define appropriate loss
        criterion = nn.CrossEntropyLoss()
```

2.3

```
In [7]: BATCH_SIZE_DEFAULT = 2048 # TODO: Set your default batch size. The capital
         #TODO: Define DataLoaders for training, validation, and test sets
         train loader = DataLoader(
             train dataset,
             batch_size=BATCH_SIZE_DEFAULT,
             shuffle=True,
             num_workers=num_workers
         validation loader = DataLoader(
             validation_dataset,
             batch_size=BATCH_SIZE_DEFAULT,
             shuffle=False,
             num_workers=num_workers
         test loader = DataLoader(
             test_dataset,
             batch_size=BATCH_SIZE_DEFAULT,
             shuffle=False,
             num_workers=num_workers
In [14]: | def calculate accuracy(outputs, labels):
```

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Calculate accuracy given model outputs and true labels.

```
_, predicted = torch.max(outputs.data, 1) # Prediction = class with h
    total = labels.size(0)
    correct = (predicted == labels).sum().item() #.item() converts a sing
    return correct / total
def train model(model, criterion, optimizer, train loader, val loader, nu
   # Device configuration: if available use GPU (needs CUDA installed an
   device = torch.device('cuda' if torch.cuda.is available() else 'cpu')
   model.to(device)
   print(f"Training on device: {device}")
   # TODO: Define training loop that for each epoch iterates over all mi
   # Record and return the training&validation loss and accuracy for eac
   train_losses = []
   val_losses = []
   train_accuracies = []
   val accuracies = []
   for epoch in range(num epochs):
       # mini batches
       model.train()
        running_loss = 0.0
        running accuracy = 0.0
        for _ , (images, labels) in enumerate(train_loader):
            images, labels = images.to(device), labels.to(device)
            optimizer.zero grad()
            outputs = model(images)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()
            running_loss += loss.item()
            running_accuracy += calculate_accuracy(outputs, labels)
        train_loss = running_loss / len(train_loader)
        train losses.append(train loss)
        train_accuracy = running_accuracy / len(train_loader)
        train_accuracies.append(train_accuracy)
       model.eval()
        with torch.no grad():
            running_val_acc = 0.0
            running_val_loss = 0.0
            for _, (images, labels) in enumerate(val_loader):
                images, labels = images.to(device), labels.to(device)
                outputs = model(images)
                running_val_acc += calculate_accuracy(outputs, labels)
                loss = criterion(outputs, labels)
                running_val_loss += loss.item()
            val_accuracy = running_val_acc / len(val_loader)
            val_accuracies.append(val_accuracy)
```

```
val_loss = running_val_loss / len(val_loader)
val_losses.append(val_loss)

print(f'Epoch [{epoch+1}/{num_epochs}], '
    f'Train Loss: {train_loss:.4f}, Train Accuracy: {train_accuracy: {val_accuracy:.4f}')

return train_losses, val_losses, train_accuracies, val_accuracies
```

2.4

```
In [16]: # TODO: Define hyperparameter grid for tuning
         k = [2, 5, 10]
         hidden size = [32, 64, 128, 256]
         batch size = [256, 512, 1024, BATCH SIZE DEFAULT]
         # fixed hybperparameters
         num epochs = 100
         input size = 28 * 28
         output_size = 10
         default k = 2
         default hidden size = 64
         # TODO: For each hyperparameter setting, instantiate model&optimizer,
         # train the model, and store the results for evaluation later
         results k adam = {}
         results k sgd = {}
         for k value in k:
             model adam = MLP(input size=input size, k=k value, hidden size=defaul
             model sgd = MLP(input size=input size, k=k value, hidden size=default
             optimizer adam = optim.Adam(model adam.parameters())
             optimizer sgd = optim.SGD(model sgd.parameters(), lr=0.01, momentum=0
             print(f"Training model with k={k value} using Adam optimizer")
             train_losses_adam, val_losses_adam, train_accuracies_adam, val_accura
                 model adam, criterion, optimizer adam, train loader, validation l
             results_k_adam[k_value] = {
                 'train losses': train losses adam,
                 'val losses': val losses adam,
                 'train_accuracies': train_accuracies_adam,
                 'val_accuracies': val_accuracies_adam
             print(f"Training model with k={k value} using SGD optimizer")
             train losses sgd, val losses sgd, train accuracies sgd, val accuracie
                 model sgd, criterion, optimizer sgd, train loader, validation loa
             results_k_sgd[k_value] = {
                 'train_losses': train_losses_sgd,
                 'val losses': val losses sgd,
                 'train accuracies': train accuracies sgd,
                 'val accuracies': val accuracies sgd
             }
```

```
Epoch [93/100], Train Loss: 1.6367, Train Accuracy: 0.8293, Val Accuracy:
0.8144
Epoch [94/100], Train Loss: 1.6365, Train Accuracy: 0.8291, Val Accuracy:
0.8146
Epoch [95/100], Train Loss: 1.6359, Train Accuracy: 0.8299, Val Accuracy:
0.8154
Epoch [96/100], Train Loss: 1.6353, Train Accuracy: 0.8307, Val Accuracy:
0.8148
Epoch [97/100], Train Loss: 1.6354, Train Accuracy: 0.8303, Val Accuracy:
0.8146
Epoch [98/100], Train Loss: 1.6347, Train Accuracy: 0.8310, Val Accuracy:
0.8158
Epoch [99/100], Train Loss: 1.6352, Train Accuracy: 0.8303, Val Accuracy:
0.8139
Epoch [100/100], Train Loss: 1.6346, Train Accuracy: 0.8311, Val Accuracy:
0.8146
```

```
In [ ]: results batch size adam = {}
         results batch size sgd = {}
         for batch size value in batch size:
             train_loader = DataLoader(
                 train dataset,
                 batch size=batch size value,
                 shuffle=True,
                 num workers=num workers
             validation loader = DataLoader(
                 validation_dataset,
                 batch size=batch size value,
                 shuffle=False,
                 num workers=num workers
             )
             model_adam = MLP(input_size=input_size, k=default_k, hidden_size=defa
             model sgd = MLP(input size=input size, k=default k, hidden size=defau
             optimizer adam = optim.Adam(model adam.parameters())
             optimizer_sgd = optim.SGD(model_sgd.parameters(), lr=0.01, momentum=0
             print(f"Training model with batch size={batch size value} using Adam
             train_losses_adam, val_losses_adam, train_accuracies_adam, val_accura
                 model adam, criterion, optimizer adam, train loader, validation l
             results_batch_size_adam[batch_size_value] = {
                 'train losses': train losses adam,
                 'val_losses': val_losses_adam,
                 'train accuracies': train accuracies adam,
                 'val accuracies': val accuracies adam
             }
             print(f"Training model with batch size={batch size value} using SGD o
             train_losses_sgd, val_losses_sgd, train_accuracies_sgd, val_accuracie
                 model sgd, criterion, optimizer sgd, train loader, validation loa
             results_batch_size_sgd[batch_size_value] = {
                 'train losses': train losses sgd,
                 'val_losses': val_losses_sgd,
                 'train_accuracies': train_accuracies_sgd,
                 'val_accuracies': val_accuracies_sgd
             }
In [26]: # TODO: Plot evolution of validation accuracy for each hyperparameter set
         def plot results(results, title):
             plt.figure(figsize=(12, 8))
             for key, value in results.items():
                 plt.plot(value['val_accuracies'], label=f'k={key}' if 'k' in titl
             plt.title(title)
             plt.xlabel('Epochs')
             plt.ylabel('Validation Accuracy')
             plt.legend()
             plt.grid()
             plt.show()
In [27]: print(results hidden size adam.values())
```

dict values([{'train losses': [2.2086666584014893, 1.9124801301956176, 1.7 935973978042603, 1.72051860332489, 1.694562406539917, 1.682826418876648, 1 .6749101448059083, 1.6701427459716798, 1.6660133695602417, 1.6606020832061 767, 1.6582284259796143, 1.654193000793457, 1.6505397081375122, 1.64865959 16748046, 1.6456811761856078, 1.6433111333847046, 1.6431246423721313, 1.64 10329580307006, 1.639166374206543, 1.6387004518508912, 1.636634693145752, 1.6357011032104491, 1.6344984722137452, 1.6333588504791259, 1.633451471328 7354, 1.6324427127838135, 1.6314708805084228, 1.6311833572387695, 1.631136 1360549927, 1.6294871520996095, 1.6280263662338257, 1.628728461265564, 1.6 28010950088501, 1.6270203542709352, 1.626003670692444, 1.6255670881271362, 1.6252462577819824, 1.6239779281616211, 1.6247189807891846, 1.623516893386 841, 1.6220717096328736, 1.6221473979949952, 1.6217905855178834, 1.6206709 09881592, 1.621665015220642, 1.620404977798462, 1.6200374460220337, 1.6192 26861000061, 1.6188181447982788, 1.6207627058029175, 1.6185651588439942, 1 .6174710083007813, 1.6185905027389527, 1.6174226474761964, 1.6162547159194 947, 1.6161060428619385, 1.616579875946045, 1.6157733583450318, 1.61605782 5088501, 1.6145689010620117, 1.6145924568176269, 1.6161954832077026, 1.613 6467695236205, 1.6136060762405395, 1.61245361328125, 1.6124424171447753, 1 .6127238750457764, 1.6125553417205811, 1.5989297389984132, 1.5895776271820 068, 1.5872467470169067, 1.5843375873565675, 1.5835417604446411, 1.5823227 977752685, 1.5816703748703003, 1.5788419914245606, 1.577428879737854, 1.57 79587650299072, 1.575684952735901, 1.5744591999053954, 1.574035406112671, 1.575721492767334, 1.5733262538909911, 1.5704761028289795, 1.5713236427307 13, 1.570775146484375, 1.5690933561325073, 1.5688835525512694, 1.568105053 9016723, 1.5691445922851563, 1.567627387046814, 1.5675666999816895, 1.5689 304780960083, 1.5655420160293578, 1.5661112785339355, 1.5647973251342773, 1.5636361598968507, 1.565658574104309, 1.5642124795913697, 1.5649220705032 35], 'val losses': [2.042501163482666, 1.8264740705490112, 1.7542208433151 245, 1.7088290691375732, 1.6928551912307739, 1.6849909782409669, 1.6776272 535324097, 1.6743304491043092, 1.6712412118911744, 1.6643535852432252, 1.6 61929988861084, 1.6596421957015992, 1.6569008827209473, 1.6552968263626098 , 1.6532380819320678, 1.6524292707443238, 1.6528838872909546, 1.6504288673 40088, 1.6493853330612183, 1.6483260631561278, 1.6475474119186402, 1.64641 55197143555, 1.6466788053512573, 1.6463876724243165, 1.64597647190094, 1.6 441298961639403, 1.6441519737243653, 1.6478918313980102, 1.644204187393188 5, 1.6439706325531005, 1.6434713363647462, 1.640738320350647, 1.6407545328 140258, 1.6428239822387696, 1.6413987874984741, 1.640782403945923, 1.64034 28077697755, 1.6401729583740234, 1.6410790920257567, 1.6383211612701416, 1 .6387939453125, 1.6380725860595704, 1.637694787979126, 1.6388476848602296, 1.6379369497299194, 1.6392048835754394, 1.638838768005371, 1.6370249032974 242, 1.6387346744537354, 1.6372810363769532, 1.6382737398147582, 1.6382448 91166687, 1.6364982366561889, 1.6359021425247193, 1.6355789184570313, 1.63 6524748802185, 1.6367555856704712, 1.6367313861846924, 1.6350367546081543, 1.635895037651062, 1.636530613899231, 1.6349081516265869, 1.63478548526763 91, 1.6347235918045044, 1.6350157737731934, 1.6345439672470092, 1.63439512 25280762, 1.6264461278915405, 1.613888192176819, 1.6134798049926757, 1.608 5321187973023, 1.6052253007888795, 1.6037676572799682, 1.6024924993515015, 1.6042128086090088, 1.6016602277755738, 1.6005648374557495, 1.599534845352 173, 1.5989341497421266, 1.5986332654953004, 1.6011247396469117, 1.5982038 974761963, 1.5968698263168335, 1.5972932815551757, 1.597111463546753, 1.59 81909036636353, 1.5965644359588622, 1.5957716464996339, 1.5960610389709473 , 1.5958025455474854, 1.594939661026001, 1.598764419555664, 1.595660853385 9253, 1.5944181680679321, 1.5943343877792358, 1.594592523574829, 1.5951914 548873902, 1.596961998939514, 1.595246434211731, 1.5945375442504883], 'tra in accuracies': [0.347799233490566, 0.5920327240566038, 0.6811265477594339 , 0.7601923643867924, 0.7769136939858491, 0.7859559257075471, 0.7929105247 641509, 0.796893794221698, 0.8004057340801887, 0.8055081810141509, 0.80682 74616745283, 0.811510539504717, 0.8145688384433963, 0.8168720518867925, 0. 8199705188679245, 0.8218256191037736, 0.8217891362028301, 0.82375663325471 69, 0.8256360554245283, 0.8258118366745283, 0.8277760170990567, 0.82920216

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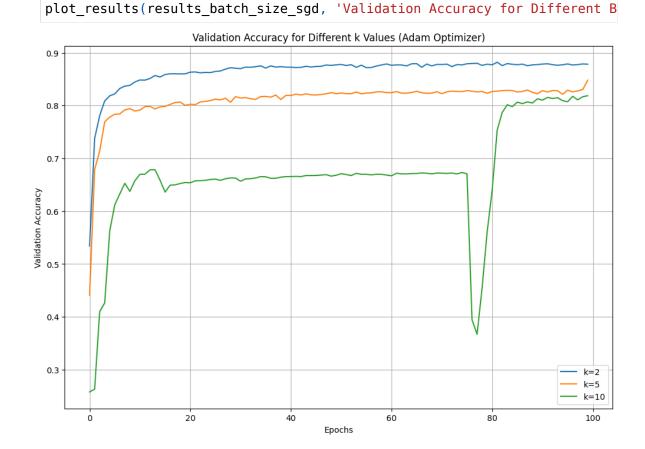
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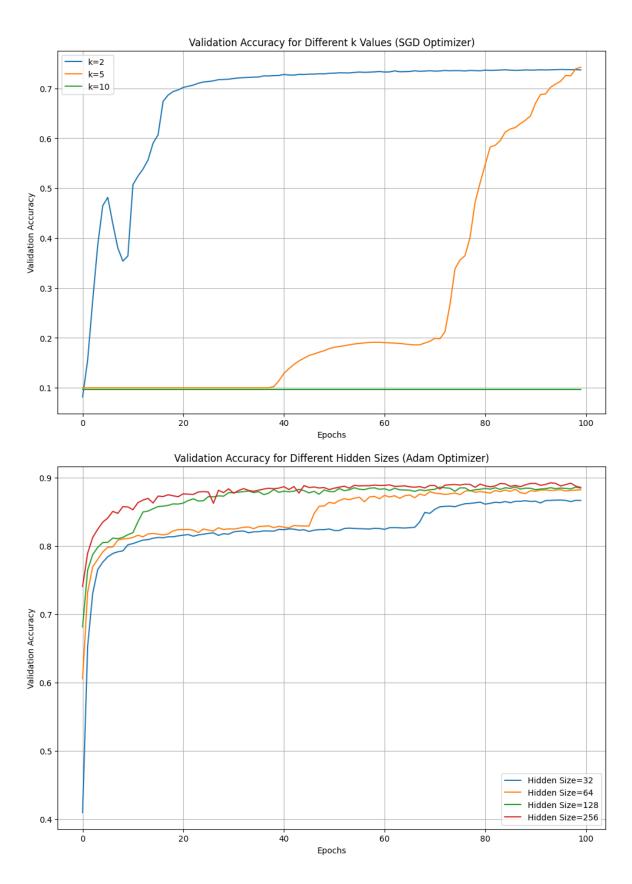
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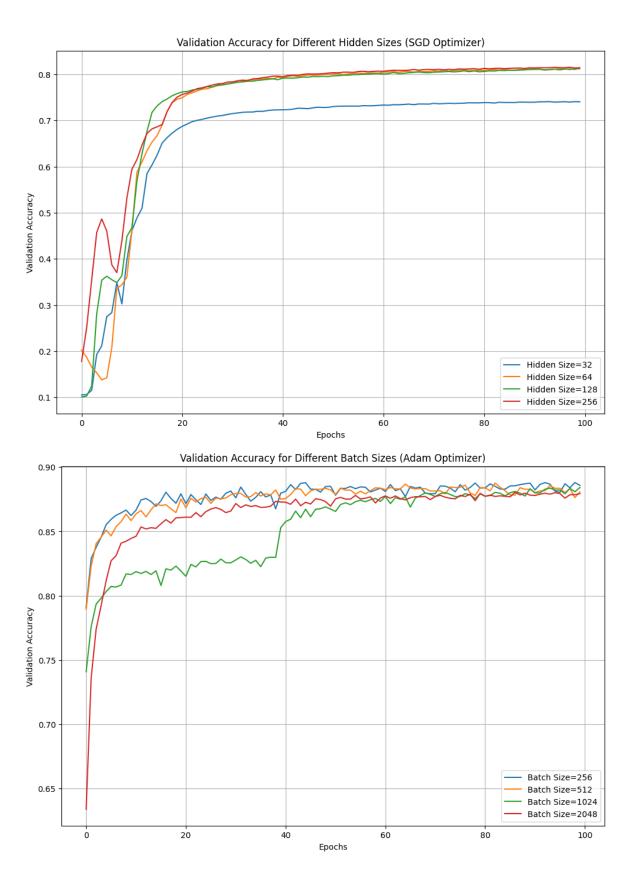
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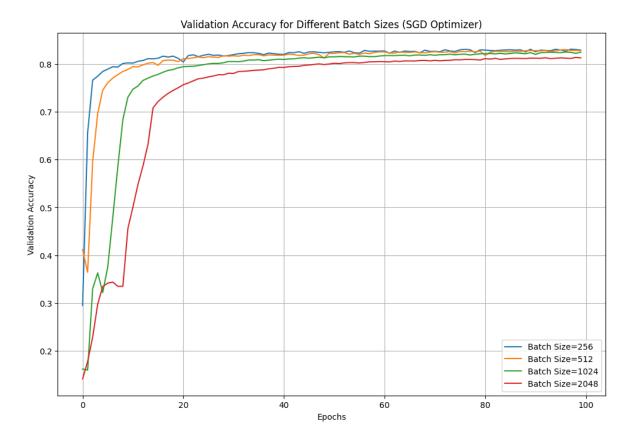
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In [28]: plot_results(results_k_adam, 'Validation Accuracy for Different k Values plot_results(results_k_sgd, 'Validation Accuracy for Different k Values (plot_results(results_hidden_size_adam, 'Validation Accuracy for Different plot_results(results_hidden_size_sgd, 'Validation Accuracy for Different plot_results(results_batch_size_adam, 'Validation Accuracy for Different









TODO: Justify which batch size and learning rate combination you will go with.

For the Batch Size it seems to not make a large difference for the convergence. Smaller Batch size seems to converge faster but you make much more mini opitmization steps, which results in this behavior, so we choose 1024, because 2048 performed slightly worse, if we choose the batch size too small the training takes longer because the CPU and GPU communication takes longer.

For the hidden size 64 performed equally well compared to the others, but we will choose 128 because, the learning seems to not go beyond the 0.75 accurracy mark, and a larger network maybe helps to achieve better accuracies and learns the underlying distribution better.

For the hidden layers k, we choose 5. It seems sufficient to use 2, but we choose more for the same reason as before.

But we train for more epochs than before

2.4

```
In [32]: # TODO: Train model w/ best hyperparameters for SGD and compare to defaul
best_k = 5
best_hidden_size = 128
best_batch_size = 1024

train_loader = DataLoader(
    train_dataset,
    batch_size=best_batch_size,
    shuffle=True,
    num_workers=12
```

```
validation_loader = DataLoader(
   validation_dataset,
   batch_size=best_batch_size,
   shuffle=False,
   num_workers=12
)

model_best_sgd = MLP(input_size=input_size, k=best_k, hidden_size=best_hi
   optimizer_best_sgd = optim.SGD(model_best_sgd.parameters(), lr=0.01, mome

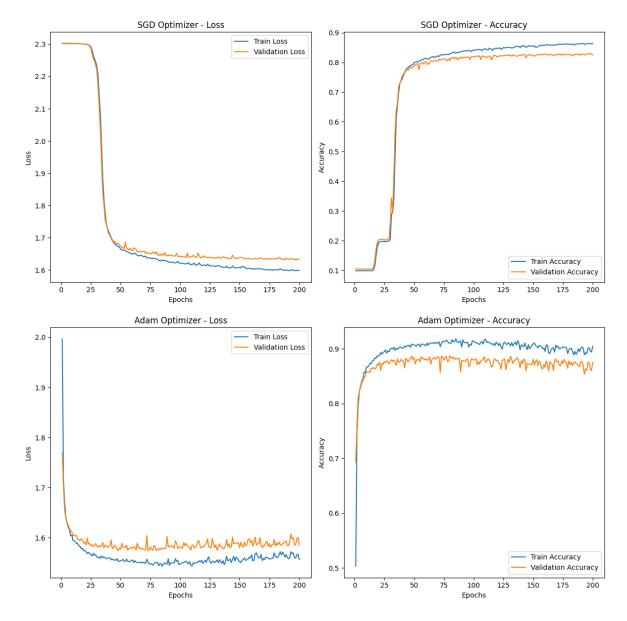
print("Training model with best hyperparameters using SGD optimizer")

train_losses_best_sgd, val_losses_best_sgd, train_accuracies_best_sgd, va
   model_best_sgd, criterion, optimizer_best_sgd, train_loader, validati

model_best_adam = MLP(input_size=input_size, k=best_k, hidden_size=best_h
   optimizer_best_adam = optim.Adam(model_best_adam.parameters())

print("Training model with best hyperparameters using Adam optimizer")
   train_losses_best_adam, val_losses_best_adam, train_accuracies_best_adam,
        model_best_adam, criterion, optimizer_best_adam, train_loader, valida
```

```
Epoch [189/200], Train Loss: 1.5663, Train Accuracy: 0.8948, Val Accuracy:
        0.8675
        Epoch [190/200], Train Loss: 1.5610, Train Accuracy: 0.9001, Val Accuracy:
        0.8766
        Epoch [191/200], Train Loss: 1.5580, Train Accuracy: 0.9032, Val Accuracy:
        0.8769
        Epoch [192/200], Train Loss: 1.5597, Train Accuracy: 0.9014, Val Accuracy:
        Epoch [193/200], Train Loss: 1.5721, Train Accuracy: 0.8889, Val Accuracy:
        0.8535
        Epoch [194/200], Train Loss: 1.5682, Train Accuracy: 0.8928, Val Accuracy:
        0.8631
        Epoch [195/200], Train Loss: 1.5699, Train Accuracy: 0.8912, Val Accuracy:
        0.8608
        Epoch [196/200], Train Loss: 1.5605, Train Accuracy: 0.9007, Val Accuracy:
        Epoch [197/200], Train Loss: 1.5596, Train Accuracy: 0.9016, Val Accuracy:
        0.8749
        Epoch [198/200], Train Loss: 1.5655, Train Accuracy: 0.8957, Val Accuracy:
        0.8636
        Epoch [199/200], Train Loss: 1.5672, Train Accuracy: 0.8940, Val Accuracy:
        0.8604
        Epoch [200/200], Train Loss: 1.5567, Train Accuracy: 0.9044, Val Accuracy:
        0.8749
In [33]: # TODO: Plot "learning curves" of the best SGD model and the Adam model
         def plot learning curves(train losses, val losses, train accuracies, val
             epochs = range(1, len(train losses) + 1)
             plt.figure(figsize=(12, 6))
             plt.subplot(1, 2, 1)
             plt.plot(epochs, train_losses, label='Train Loss')
             plt.plot(epochs, val losses, label='Validation Loss')
             plt.title(f'{title} - Loss')
             plt.xlabel('Epochs')
             plt.ylabel('Loss')
             plt.legend()
             plt.subplot(1, 2, 2)
             plt.plot(epochs, train_accuracies, label='Train Accuracy')
             plt.plot(epochs, val accuracies, label='Validation Accuracy')
             plt.title(f'{title} - Accuracy')
             plt.xlabel('Epochs')
             plt.ylabel('Accuracy')
             plt.legend()
             plt.tight layout()
             plt.show()
         plot_learning_curves(train_losses_best_sgd, val_losses_best_sgd, train_ac
         plot learning curves(train losses best adam, val losses best adam, train
```



TODO: Based on plots, compare (mini-batch) SGD and Adam, select overall best Model Select Adam because overall performance is better

```
In [34]: #TODO: Evaluate the best model on the test set, print the test/train/vali
         def evaluate_model(model, test_loader, train_loader, validation_loader):
             device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
             model.to(device)
             model.eval()
             test_accuracy = 0.0
             train_accuracy = 0.0
             validation_accuracy = 0.0
             with torch.no_grad():
                 for images, labels in test loader:
                     images, labels = images.to(device), labels.to(device)
                     outputs = model(images)
                     test_accuracy += calculate_accuracy(outputs, labels)
                 for images, labels in train loader:
                     images, labels = images.to(device), labels.to(device)
                     outputs = model(images)
```

```
train_accuracy += calculate_accuracy(outputs, labels)
for images, labels in validation_loader:
    images, labels = images.to(device), labels.to(device)
    outputs = model(images)
    validation_accuracy += calculate_accuracy(outputs, labels)

test_accuracy /= len(test_loader)
    train_accuracy /= len(train_loader)
    validation_accuracy /= len(validation_loader)

return test_accuracy, train_accuracy, validation_accuracy

test_acc_best, train_acc_best, val_acc_best = evaluate_model(
    model_best_adam, test_loader, train_loader, validation_loader
)

print(f"Adam best model test accuracy: {test_acc_best:.4f}")
print(f"Adam best model train accuracy: {train_acc_best:.4f}")
print(f"Adam best model validation accuracy: {val_acc_best:.4f}")
```

Adam best model test accuracy: 0.8069

Adam best model train accuracy: 0.9016

Adam best model validation accuracy: 0.8749

TODO: Briefly discuss your results.

Adam converged faster than SGD and also had a steeper learning curve. SGD took more epochs to achieve higher accuracies compared to Adam. With more epochs, the results maybe would have been better, but this network is not designed for image classification, odher models would achieve better results.