image_classifier_on_cifar_10

December 11, 2022

##Image Classification on CIFAR-10 In this problem we will explore different deep learning architectures for image classification on the CIFAR-10 dataset. Make sure that you are familiar with torch `Tensor`s, two-dimensional convolutions (`nn.Conv2d`) and fully-connected layers (`nn.Linear`), ReLU non-linearities (`F.relu`), pooling (`nn.MaxPool2d`), and tensor reshaping (`view`).

We will use Colab because it has free GPU runtimes available; GPUs can accelerate training times for this problem by 10-100x. **You will need to enable the GPU runtime to use it**. To do so, click "Runtime" above and then "Change runtime type". There under hardware accelerator choose "GPU".

This notebook provides some starter code for the CIFAR-10 problem on HW4, including a completed training loop to assist with some of the Pytorch setup. You'll need to modify this code to implement the layers required for the assignment, but this provides a working training loop to start from.

Note: GPU runtimes are limited on Colab. Limit your training to short-running jobs (around 20mins or less) and spread training out over time, if possible. Colab WILL limit your usage of GPU time, so plan ahead and be prepared to take breaks during training. We also suggest performing your early coding/sweeps on a small fraction of the dataset (~10%) to minimize training time and GPU usage.

[1]:
```
import torch
from torch import nn

from typing import Tuple, Union, List, Callable
from torch.optim import SGD
import torchvision
from torch.utils.data import DataLoader, TensorDataset, random_split
import matplotlib.pyplot as plt
from tqdm import tqdm, trange
```

Let's verify that we are using a gpu:

[ ]:
```
assert torch.cuda.is_available(), "GPU is not available, check the directions␣
↪above (or disable this assertion to use CPU)"

DEVICE = "cuda" if torch.cuda.is_available() else "cpu"
print(DEVICE)  # this should print out CUDA
```

```
cuda
```

To use the GPU you will need to send both the model and data to a device; this transfers the model from its default location on CPU to the GPU.

Note that torch operations on Tensors will fail if they are not located on the same device.

```
model = model.to(DEVICE)  # Sending a model to GPU

for x, y in tqdm(data_loader):
  x, y = x.to(DEVICE), y.to(DEVICE)
```

When reading tensors you may need to send them back to cpu, you can do so with `x = x.cpu()`.

Let's load CIFAR-10 data. This is how we load datasets using PyTorch in the real world!

[ ]:
```
train_dataset = torchvision.datasets.CIFAR10("./data", train=True,␣
 ↪download=True, transform=torchvision.transforms.ToTensor())
test_dataset = torchvision.datasets.CIFAR10("./data", train=False,␣
 ↪download=True, transform=torchvision.transforms.ToTensor())
```

```
Downloading https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz to
./data/cifar-10-python.tar.gz

  0%|          | 0/170498071 [00:00<?, ?it/s]

Extracting ./data/cifar-10-python.tar.gz to ./data
Files already downloaded and verified
```

Here, we'll use the torch `DataLoader` to wrap our datasets. `DataLoaders` handle batching, shuffling, and iterating over data; they can also be useful for building more complex input pipelines that perform transfoermations such as data augmentation.

[ ]:
```
batch_size = 128

#train_dataset, _ = random_split(train_dataset, [int(0.1 * len(train_dataset)),␣
 ↪int( 0.9 * len(train_dataset))])

train_dataset, val_dataset = random_split(train_dataset, [int(0.9 *␣
 ↪len(train_dataset)), int( 0.1 * len(train_dataset))])

# Create separate dataloaders for the train, test, and validation set
train_loader = DataLoader(
    train_dataset,
    batch_size=batch_size,
    shuffle=True
)

val_loader = DataLoader(
    val_dataset,
    batch_size=batch_size,
    shuffle=True
)
```

```
test_loader = DataLoader(
    test_dataset,
    batch_size=batch_size,
    shuffle=True
)
```

[ ]:
```
def linear_model() -> nn.Module:
  """Instantiate a linear model and send it to device."""
  model =  nn.Sequential(
            nn.Flatten(),
            nn.Linear(d, 10)
         )
  return model.to(DEVICE)
```

Let's define a method to train this model using SGD as our optimizer.

[ ]:
```
def train(
    model: nn.Module, optimizer: SGD,
    train_loader: DataLoader, val_loader: DataLoader,
    epochs: int = 20
    )-> Tuple[List[float], List[float], List[float], List[float]]:
  """
  Trains a model for the specified number of epochs using the loaders.

  Returns:
    Lists of training loss, training accuracy, validation loss, validation␣
↪accuracy for each epoch.
  """

  loss = nn.CrossEntropyLoss()
  train_losses = []
  train_accuracies = []
  val_losses = []
  val_accuracies = []
  for e in range(epochs):
    model.train()
    train_loss = 0.0
    train_acc = 0.0

    # Main training loop; iterate over train_loader. The loop
    # terminates when the train loader finishes iterating, which is one epoch.
    for (x_batch, labels) in train_loader:
      x_batch, labels = x_batch.to(DEVICE), labels.to(DEVICE)
      optimizer.zero_grad()
      labels_pred = model(x_batch)
      batch_loss = loss(labels_pred, labels)
```

```
      train_loss = train_loss + batch_loss.item()

      labels_pred_max = torch.argmax(labels_pred, 1)
      batch_acc = torch.sum(labels_pred_max == labels)
      train_acc = train_acc + batch_acc.item()

      batch_loss.backward()
      optimizer.step()
    train_losses.append(train_loss / len(train_loader))
    train_accuracies.append(train_acc / (batch_size * len(train_loader)))

    # Validation loop; use .no_grad() context manager to save memory.
    model.eval()
    val_loss = 0.0
    val_acc = 0.0

    with torch.no_grad():
      for (v_batch, labels) in val_loader:
        v_batch, labels = v_batch.to(DEVICE), labels.to(DEVICE)
        labels_pred = model(v_batch)
        v_batch_loss = loss(labels_pred, labels)
        val_loss = val_loss + v_batch_loss.item()

        v_pred_max = torch.argmax(labels_pred, 1)
        batch_acc = torch.sum(v_pred_max == labels)
        val_acc = val_acc + batch_acc.item()
      val_losses.append(val_loss / len(val_loader))
      val_accuracies.append(val_acc / (batch_size * len(val_loader)))

  return train_losses, train_accuracies, val_losses, val_accuracies
```

[ ]:
```
def evaluate(
    model: nn.Module, loader: DataLoader
) -> Tuple[float, float]:
  """Computes test loss and accuracy of model on loader."""
  loss = nn.CrossEntropyLoss()
  model.eval()
  test_loss = 0.0
  test_acc = 0.0
  with torch.no_grad():
    for (batch, labels) in loader:
      batch, labels = batch.to(DEVICE), labels.to(DEVICE)
      y_batch_pred = model(batch)
      batch_loss = loss(y_batch_pred, labels)
      test_loss = test_loss + batch_loss.item()

      pred_max = torch.argmax(y_batch_pred, 1)
```

```
        batch_acc = torch.sum(pred_max == labels)
        test_acc = test_acc + batch_acc.item()
    test_loss = test_loss / len(loader)
    test_acc = test_acc / (batch_size * len(loader))
    return test_loss, test_acc
```

[ ]:
```
def fully_connected(M: int) -> nn.Module:
  model = nn.Sequential(
      nn.Flatten(),
      nn.Linear(3072, M),
      nn.ReLU(),
      nn.Linear(M, 10)
  )

  return model.to(DEVICE)
```

[ ]:
```
def fully_connected_tune_hyperparams(train_loader: DataLoader,
                                      val_loader: DataLoader,
                                     model_fn:Callable[[], nn.Module]):
  num_iterations = 10
  best_loss = torch.inf
  best_lr = 0.0
  best_M = 0.0
  best_momentum = 0.0

  val_losses = []
  momentums_array = []
  learning_rates = []
  M_array = []

  Ms = torch.pow(2, torch.arange(5, 11))
  momentums = torch.linspace(10 ** (-6), 10 ** (-1), num_iterations)
  lrs = torch.linspace(10 ** (-6), 10 ** (-1), num_iterations)

  for M in Ms:
    for learning_rate in lrs:
      for momentum in momentums:
        print(f"lr : {learning_rate}, momentum : {momentum}, M : {M}")
        model = model_fn(M)
        optim = SGD(model.parameters(), learning_rate, momentum = momentum)

        train_loss, train_acc, val_loss, val_acc = train(
            model, optim, train_loader, val_loader, epochs = 20
        )

        val_losses.append(min(val_loss))
        learning_rates.append(learning_rate)
```

```
        momentums_array.append(momentum)
        M_array.append(M)

    indices = torch.argsort(torch.tensor(val_losses))[:5]

    return torch.tensor(M_array)[indices], torch.tensor(learning_rates)[indices],␣
 ↪torch.tensor(momentums_array)[indices]
```

[ ]:
```
best_M, best_lr, best_momentum = fully_connected_tune_hyperparams(train_loader,␣
 ↪val_loader, fully_connected)
```

[ ]:
```
print(f"M : {best_M}, learning_rate = {best_lr}, momentum = {best_momentum}")
```

```
M : tensor([ 128,  128, 1024,  512, 1024]), learning_rate = tensor([0.0778,
0.0667, 0.0333, 0.1000, 0.0556]), momentum = tensor([0.0444, 0.0667, 0.0889,
0.0222, 0.0667])
```

[ ]:
```
best_M = torch.tensor([128, 128, 1024, 512, 1024])
best_lr = torch.tensor([0.0778, 0.0667, 0.0333, 0.1000, 0.0556])
best_momentum = torch.tensor([0.0444, 0.0667, 0.0889, 0.0222, 0.0667])
model1 = fully_connected(best_M[0])
model2 = fully_connected(best_M[1])
model3 = fully_connected(best_M[2])
model4 = fully_connected(best_M[3])
model5 = fully_connected(best_M[4])
optimizer_1 = SGD(model1.parameters(), best_lr[0], momentum = best_momentum[0])
optimizer_2 = SGD(model2.parameters(), best_lr[1], momentum = best_momentum[1])
optimizer_3 = SGD(model3.parameters(), best_lr[2], momentum = best_momentum[2])
optimizer_4 = SGD(model4.parameters(), best_lr[3], momentum = best_momentum[3])
optimizer_5 = SGD(model5.parameters(), best_lr[4], momentum = best_momentum[4])
```

[ ]:
```
train_loss, train_accuracy, val_loss, val_accuracy = train(
    model1, optimizer_1, train_loader, val_loader, 40)

train_loss_2, train_accuracy_2, val_loss_2, val_accuracy_2 = train(
    model2, optimizer_2, train_loader, val_loader, 40)

train_loss_3, train_accuracy_3, val_loss_3, val_accuracy_3 = train(
    model3, optimizer_3, train_loader, val_loader, 40)

train_loss_4, train_accuracy_4, val_loss_4, val_accuracy_4 = train(
    model4, optimizer_4, train_loader, val_loader, 40)

train_loss_5, train_accuracy_5, val_loss_5, val_accuracy_5 = train(
    model5, optimizer_5, train_loader, val_loader, 40)
```

printing out the test accuracy version of the fully connected linear neural network and saving the arrays of the test_acc and losses

[ ]:
```
a5a_train_losses = [train_loss, train_loss_2, train_loss_3, train_loss_4,␣
↪train_loss_5]
a5a_train_accuracies = [train_accuracy, train_accuracy_2, train_accuracy_3,␣
↪train_accuracy_4, train_accuracy_5]
a5a_val_losses = [val_loss, val_loss_2, val_loss_3, val_loss_4, val_loss_5]
a5a_val_accuracies = [val_accuracy, val_accuracy_2, val_accuracy_3,␣
↪val_accuracy_4, val_accuracy_5]
print(a5a_train_losses)
print(a5a_train_accuracies)
print(a5a_val_losses)
print(a5a_val_accuracies)
```

[2]:

```
a5a_train_losses = [[1.9725063104521146, 1.797321759502996, 1.7197425345128232,
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```

```
a5a_train_accuracies = [[0.2847567471590909, 0.3592196377840909, 0.
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```

```
a5a_val_losses = [[1.8702658593654633, 1.7845394730567932, 1.7281279534101486,
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4899368584156036, 1.5330430418252945, 1.5105597645044326, 1.
```
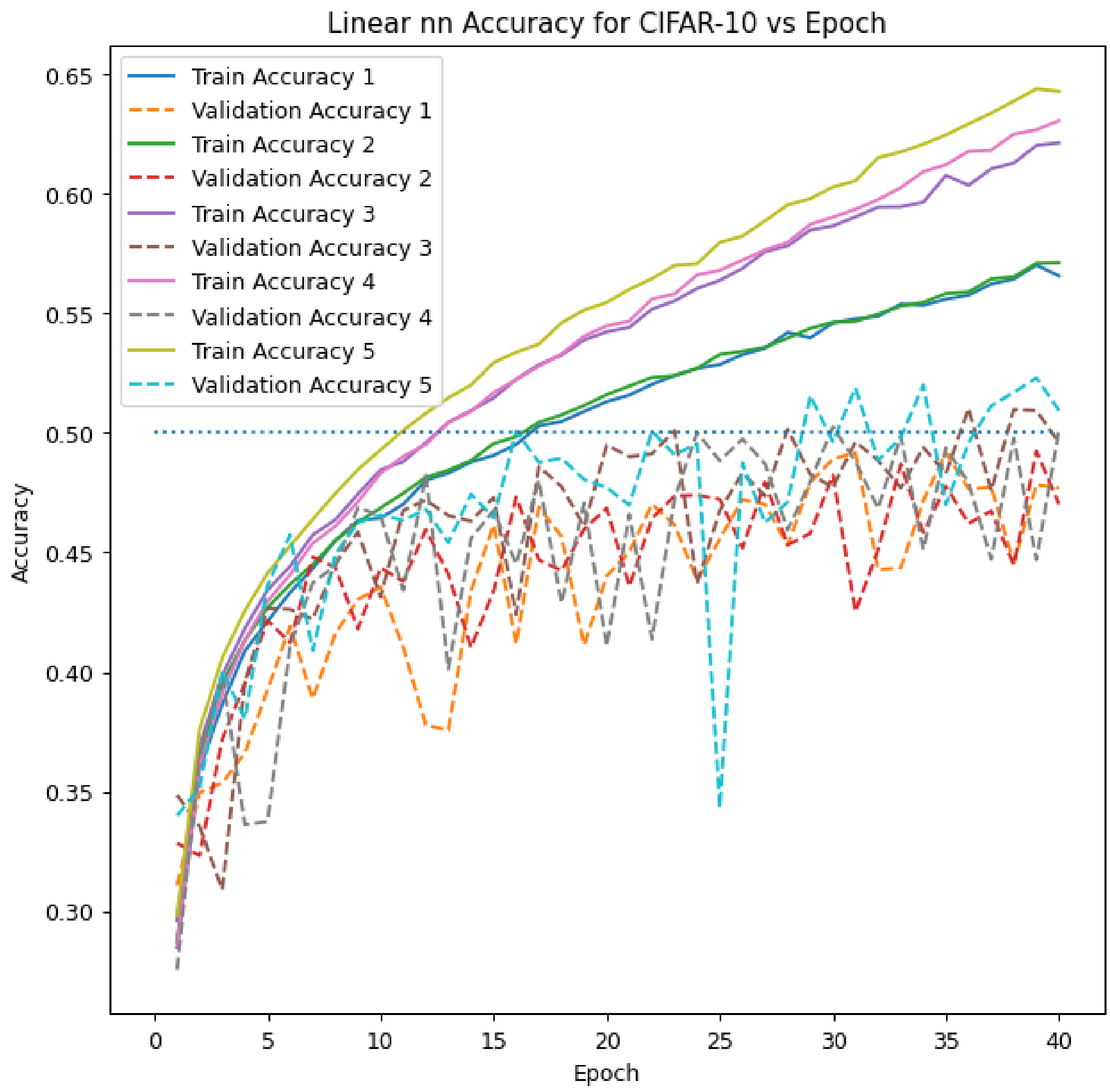

```
a5a_val_accuracies = [[0.310546875, 0.3494140625, 0.353515625, 0.366015625, 0.3923828125, 0.419140625, 0.388671875, 0.416015625, 0.4302734375, 0.435546875, 0.4103515625, 0.377734375, 0.3755859375, 0.433984375, 0.4615234375, 0.41171875, 0.4689453125, 0.456640625, 0.4111328125, 0.4400390625, 0.4501953125, 0.4701171875, 0.4615234375, 0.43828125, 0.4556640625, 0.4720703125, 0.4701171875, 0.4529296875, 0.479296875, 0.4890625, 0.491796875, 0.4427734375, 0.4435546875, 0.4716796875, 0.491796875, 0.4765625, 0.47734375, 0.445703125, 0.4783203125, 0.476953125], [0.3283203125, 0.323046875, 0.371875, 0.3951171875, 0.421484375, 0.4123046875, 0.448046875, 0.44375, 0.41796875, 0.4435546875, 0.437890625, 0.4595703125, 0.4408203125, 0.41015625, 0.433984375, 0.4732421875, 0.446875, 0.4423828125, 0.459765625, 0.4685546875, 0.4357421875, 0.4642578125, 0.4736328125, 0.4740234375, 0.472265625, 0.4517578125, 0.4794921875, 0.453125, 0.4580078125, 0.482421875, 0.4251953125, 0.451171875, 0.4869140625, 0.4583984375, 0.477734375, 0.462109375, 0.4673828125, 0.4447265625, 0.4923828125, 0.4701171875], [0.3484375, 0.3353515625, 0.3087890625, 0.3958984375, 0.4265625, 0.426171875, 0.4220703125, 0.4451171875, 0.45859375, 0.43125, 0.467578125, 0.471875, 0.4654296875, 0.4630859375, 0.473046875, 0.4240234375, 0.4859375, 0.4775390625, 0.4609375, 0.494921875, 0.4900390625, 0.4912109375, 0.5009765625, 0.4369140625, 0.467578125, 0.483203125, 0.4736328125, 0.5015625, 0.4826171875, 0.47734375, 0.4962890625, 0.4884765625, 0.476953125, 0.4939453125, 0.4830078125, 0.5103515625, 0.47578125, 0.509765625, 0.509375, 0.4958984375], [0.275390625, 0.365625, 0.398828125, 0.3361328125, 0.3373046875, 0.4107421875, 0.4373046875, 0.4443359375, 0.46875, 0.4654296875, 0.4341796875, 0.4822265625, 0.401171875, 0.455859375, 0.467578125, 0.4451171875, 0.4802734375, 0.4287109375, 0.470703125, 0.4107421875, 0.466015625, 0.413671875, 0.47265625, 0.5001953125, 0.48828125, 0.4974609375, 0.487109375, 0.459375, 0.4796875, 0.5025390625, 0.4880859375, 0.468359375, 0.498828125, 0.451171875, 0.49375, 0.4791015625, 0.4470703125, 0.4978515625, 0.446875, 0.5013671875], [0.33984375, 0.3513671875, 0.400390625, 0.3802734375, 0.4361328125, 0.457421875, 0.4087890625, 0.44921875, 0.4625, 0.465625, 0.4634765625, 0.46796875, 0.4541015625, 0.4744140625, 0.464453125, 0.50078125, 0.4876953125, 0.489453125, 0.48046875, 0.4771484375, 0.4697265625, 0.50078125, 0.4908203125, 0.4955078125, 0.34296875, 0.4875, 0.4625, 0.47109375, 0.515625, 0.4962890625, 0.5189453125, 0.4884765625, 0.498046875, 0.5201171875, 0.469921875, 0.4958984375, 0.511328125, 0.5169921875, 0.523046875, 0.509375]]
```

[7]:

```
epochs = range(1, 41)
plt.figure(figsize=(8, 8), dpi=90)
plt.plot(epochs, a5a_train_accuracies[0], label="Train Accuracy 1")
plt.plot(epochs, a5a_val_accuracies[0], label="Validation Accuracy 1", linestyle = "dashed")

plt.plot(epochs, a5a_train_accuracies[1], label="Train Accuracy 2",)
plt.plot(epochs, a5a_val_accuracies[1], label="Validation Accuracy 2", linestyle = "dashed")
```

```
plt.plot(epochs, a5a_train_accuracies[2], label="Train Accuracy 3")
plt.plot(epochs, a5a_val_accuracies[2], label="Validation Accuracy 3",␣
 ↪linestyle = "dashed")

plt.plot(epochs, a5a_train_accuracies[3], label="Train Accuracy 4")
plt.plot(epochs, a5a_val_accuracies[3], label="Validation Accuracy 4",␣
 ↪linestyle = "dashed")

plt.plot(epochs, a5a_train_accuracies[4], label="Train Accuracy 5")
plt.plot(epochs, a5a_val_accuracies[4], label="Validation Accuracy 5",␣
 ↪linestyle = "dashed")

plt.plot([0, 40], [0.5, 0.5], linestyle = "dotted")
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.legend(loc = "upper left")
plt.title("Linear nn Accuracy for CIFAR-10 vs Epoch")
plt.show()
```



[ ]:
```
_, test_acc_1 = evaluate(model1, test_loader)
_, test_acc_2 = evaluate(model2, test_loader)
_, test_acc_3 = evaluate(model3, test_loader)
_, test_acc_4 = evaluate(model4, test_loader)
_, test_acc_5 = evaluate(model5, test_loader)
print(f"Test Accuracy: {test_acc_1}")
print(f"Test Accuracy: {test_acc_2}")
print(f"Test Accuracy: {test_acc_3}")
print(f"Test Accuracy: {test_acc_4}")
print(f"Test Accuracy: {test_acc_5}")
```

```
Test Accuracy: 0.482001582278481
Test Accuracy: 0.463310917721519
Test Accuracy: 0.5046479430379747
```

```
Test Accuracy: 0.5000988924050633
Test Accuracy: 0.5026700949367089
```

Test accuracies for the convolutional model

Test Accuracy: 0.482001582278481 \ Test Accuracy: 0.463310917721519 \ Test Accuracy: 0.5046479430379747 \ Test Accuracy: 0.5000988924050633 \ Test Accuracy: 0.5026700949367089 \

convolutional neural network

```
[ ]: def convolutional(M: int, k: int, N: int) -> nn.Module:
       model = nn.Sequential(
           nn.Conv2d(in_channels = 3, out_channels = M, kernel_size = k),
           nn.ReLU(),
           nn.MaxPool2d(kernel_size = N),
           nn.Flatten(),
           nn.Linear(in_features = M * (((33 - k) // 14) ** 2), out_features = 10)
       )

       return model.to(DEVICE)
```

i changed some of the hyperparameter ranges which hopefully work? print out test accuracies, this is the one i submit

```
[ ]: def a5b_conv_param_search(train_loader: DataLoader,
                             val_loader: DataLoader,
                             model_fn:Callable[[], nn.Module]):
       num_iter = 6
       epochs = 35

       Ms = torch.pow(2, torch.arange(5, 11))
       lr = torch.linspace(10 ** (-5), 10 ** (-1), 6)
       momentums = torch.linspace(0.3, 0.9, num_iter)
       k = 5
       N = 14

       stored_Ms = []
       stored_lrs = []
       stored_momentums = []
       stored_ks = []
       stored_Ns = []

       stored_val_losses = []

       i = 1
       for M in Ms:
         for momentum in momentums:
           print(f"({i}): trying M: {M}, lr: {lr}, momentum: {momentum}, k: {k}, N:␣
     ↪{N}")
```

```
        i += 1

        model = model_fn(M.item(), k, N)
        optim = SGD(model.parameters(), lr, momentum=momentum)

        train_loss, train_acc, val_loss, val_acc = train(
          model,
          optim,
          train_loader,
          val_loader,
          epochs=35
          )

        stored_Ms.append(M)
        stored_lrs.append(lr)
        stored_momentums.append(momentum)
        stored_ks.append(k)
        stored_Ns.append(N)

        stored_val_losses.append(min(val_loss))

    indices = torch.argsort(torch.tensor(stored_val_losses))[:5]

    return torch.tensor(stored_Ms)[indices], torch.tensor(stored_lrs)[indices],␣
  ↪torch.tensor(stored_momentums)[indices], torch.tensor(stored_ks)[indices],␣
  ↪torch.tensor(stored_Ns)[indices]
```

[8]:
```
a5b_stored_best_Ms = torch.tensor([1024, 1024, 1024, 1024, 1024])
a5b_stored_best_lrs = torch.tensor([0.0800, 0.0200, 0.0600, 0.0400, 0.0600])
a5b_stored_best_momentums = torch.tensor([0.6600, 0.9000, 0.6600, 0.7800, 0.
  ↪7800])
a5b_stored_best_ks = torch.tensor([5, 5, 5, 5, 5])
a5b_stored_best_Ns = torch.tensor([14, 14, 14, 14, 14])
```

[ ]:
```
model_1 = convolutional(a5b_stored_best_Ms[0], 5, 14)
model_2 = convolutional(a5b_stored_best_Ms[1], 5, 14)
model_3 = convolutional(a5b_stored_best_Ms[2], 5, 14)
model_4 = convolutional(a5b_stored_best_Ms[3], 5, 14)
model_5 = convolutional(a5b_stored_best_Ms[4], 5, 14)
optimizer_1 = SGD(model_1.parameters(), a5b_stored_best_lrs[0], momentum =␣
  ↪a5b_stored_best_momentums[0])
optimizer_2 = SGD(model_2.parameters(), a5b_stored_best_lrs[1], momentum =␣
  ↪a5b_stored_best_momentums[1])
optimizer_3 = SGD(model_3.parameters(), a5b_stored_best_lrs[2], momentum =␣
  ↪a5b_stored_best_momentums[2])
optimizer_4 = SGD(model_4.parameters(), a5b_stored_best_lrs[3], momentum =␣
  ↪a5b_stored_best_momentums[3])
```

```
optimizer_5 = SGD(model_5.parameters(), a5b_stored_best_lrs[4], momentum =␣
 ↪a5b_stored_best_momentums[4])
```

[ ]:
```
train_loss, train_accuracy, val_loss, val_accuracy = train(
    model_1, optimizer_1, train_loader, val_loader, 40)
train_loss_2, train_accuracy_2, val_loss_2, val_accuracy_2 = train(
    model_2, optimizer_2, train_loader, val_loader, 40)
train_loss_3, train_accuracy_3, val_loss_3, val_accuracy_3 = train(
    model_3, optimizer_3, train_loader, val_loader, 40)
train_loss_4, train_accuracy_4, val_loss_4, val_accuracy_4 = train(
    model_4, optimizer_4, train_loader, val_loader, 40)
train_loss_5, train_accuracy_5, val_loss_5, val_accuracy_5 = train(
    model_5, optimizer_5, train_loader, val_loader, 40)
```

[ ]:
```
a5b_train_losses = [train_loss, train_loss_2, train_loss_3, train_loss_4,␣
 ↪train_loss_5]
a5b_train_accuracies = [train_accuracy, train_accuracy_2, train_accuracy_3,␣
 ↪train_accuracy_4, train_accuracy_5]
a5b_val_losses = [val_loss, val_loss_2, val_loss_3, val_loss_4, val_loss_5]
a5b_val_accuracies = [val_accuracy, val_accuracy_2, val_accuracy_3,␣
 ↪val_accuracy_4, val_accuracy_5]
print(a5b_train_losses)
print(a5b_train_accuracies)
print(a5b_val_losses)
print(a5b_val_accuracies)
```

[9]:

```
a5b_train_losses = [[1.7784075506708839, 1.4377309486947276, 1.3318312188441104, 1.256117377599532, 1.2131349754265763, 1.165010241791606, 1.1315156819129533, 1.0927815461023287, 1.067361811006611, 1.032843084836548, 1.0164639875292778, 1.0026831239123235, 0.9725683295929973, 0.9623517433012073, 0.9416735792024569, 0.929081183265556, 0.9112594906579364, 0.8971708113835617, 0.8868081810122187, 0.8760893813927065, 0.8583813939582218, 0.8465221698649905, 0.8371764629740607, 0.8270039958032694, 0.8068326415324752, 0.8058258941905065, 0.7924882585013454, 0.7809077186340635, 0.7764605971222575, 0.7632395376197316, 0.7551901332018051, 0.7397001309489663, 0.7324953003024514, 0.7249096497385339, 0.7214435895227573, 0.7128545575859871, 0.7084208750589327, 0.6912736768241633, 0.6846137275411324, 0.6765748827125538], [1.7129530452869155, 1.4160366505384445, 1.3081939521838317, 1.2264667002653533, 1.1849401945417577, 1.1345273632217536, 1.100427525456656, 1.0695301641456105, 1.044029350815849, 1.0068540894849733, 1.0018949700011448, 0.9726522146639499, 0.9483239469541744, 0.9359955574301156, 0.9096493250267073, 0.8947688027877699, 0.8792217228222977, 0.8682330728254535, 0.8597941588271748, 0.8364319152791392, 0.8369351261380044, 0.8131101586940613, 0.7951103138991378, 0.7858532552014698, 0.77134573798288, 0.7632630074566061, 0.7609321969476613, 0.7479772021655332, 0.7304134815084663, 0.7262372079898011, 0.7004650619558312, 0.6953222519633445, 0.6768327269025824, 0.679365751502866, 0.6630337655713613, 0.6589514759623192, 0.644906466149471, 0.6439351193098859, 0.6489429016682234, 0.6253396835686131], [1.7365920645269481, 1.4410851750184188, 1.3343578776852651, 1.2686960981650786, 1.2178432804278352, 1.1748396720398555, 1.1359420068223367, 1.100056325678121, 1.0745525578544899, 1.0560869743878192, 1.027101598510688, 1.00450223447247, 0.9877210648899729, 0.9693884869868105, 0.9506288920952515, 0.9412067065184767, 0.9163380661471323, 0.9102237063714049, 0.8903572628782555, 0.8747815503315493, 0.8562733581797644, 0.8512817873534831, 0.8363145398484035, 0.827913474291563, 0.8142581102861599, 0.8114488407630812, 0.7870432382280176, 0.7911911948838017, 0.7704978085715662, 0.762684249911796, 0.7545380224897102, 0.7475036723031239, 0.7256888585503806, 0.7208380074324933, 0.7169048419560898, 0.696293955668807, 0.69480115827173, 0.691177300600843, 0.6817119765857403, 0.6688155281272802], [1.72902572425929, 1.428882451558655, 1.326429053802382, 1.2552997202358462, 1.2112315845760433, 1.15574713897976, 1.124009239233353, 1.1021092390133576, 1.06770095737143, 1.0394391590221361, 1.0182694338939406, 0.9927973769266497, 
```

```
a5b_train_accuracies = [[0.3799715909090909, 0.4929421164772727, 0.
↪5354447798295454, 0.5599698153409091, 0.5757723721590909, 0.
↪5972123579545454, 0.6101296164772727, 0.6247114701704546, 0.
↪6323908025568182, 0.6470836292613636, 0.6540305397727273, 0.
↪6573819247159091, 0.66796875, 0.6691450639204546, 0.677734375, 0.
↪6809303977272727, 0.6888982599431818, 0.6916281960227273, 0.
↪6978204900568182, 0.69921875, 0.7071422230113636, 0.7091841264204546, 0.
↪7132013494318182, 0.7162420099431818, 0.7246315696022727, 0.724609375, 0.
↪7271173650568182, 0.7320445667613636, 0.7357066761363636, 0.
↪7401899857954546, 0.7420099431818182, 0.7446067116477273, 0.750244140625, 0.
↪7515980113636364, 0.7524192116477273, 0.7565030184659091, 0.
↪7576127485795454, 0.7630060369318182, 0.7660910866477273, 0.766357421875],␣
↪[0.3916237571022727, 0.5060147372159091, 0.5419921875, 0.5774369673295454, 0.
↪5899325284090909, 0.6071111505681818, 0.621337890625, 0.633544921875, 0.
↪6412020596590909, 0.6545188210227273, 0.6566273082386364, 0.
↪6675470525568182, 0.6758478338068182, 0.6823064630681818, 0.
↪6902965198863636, 0.6956232244318182, 0.7002618963068182, 0.
↪7047230113636364, 0.7078524502840909, 0.7139559659090909, 0.714111328125, 0.
↪7229669744318182, 0.7294034090909091, 0.7327547940340909, 0.
↪7359952059659091, 0.7401677911931818, 0.7412997159090909, 0.
↪7433194247159091, 0.7513316761363636, 0.7529962713068182, 0.
↪7606977982954546, 0.7652476917613636, 0.7703524502840909, 0.
↪7686434659090909, 0.7754572088068182, 0.7729714133522727, 0.
↪7798295454545454, 0.7784090909090909, 0.7783203125, 0.7852672230113636], [0.
↪387451171875, 0.4929865056818182, 0.5359330610795454, 0.5577281605113636, 0.
↪5773703835227273, 0.5941938920454546, 0.6086869673295454, 0.
↪6210049715909091, 0.6332341974431818, 0.6369406960227273, 0.
↪6466841264204546, 0.6575150923295454, 0.6613325639204546, 0.
↪6683460582386364, 0.6767134232954546, 0.6792436079545454, 0.
↪6880104758522727, 0.6888316761363636, 0.6959561434659091, 0.
↪7016379616477273, 0.7094060724431818, 0.7094948508522727, 0.
↪7144664417613636, 0.7195712002840909, 0.7215243252840909, 0.
↪7230335582386364, 0.7341752485795454, 0.728759765625, 0.7379483309659091, 0.
↪7393465909090909, 0.7425204190340909, 0.7445401278409091, 0.
↪7535733309659091, 0.7549050071022727, 0.7549493963068182, 0.
↪7643821022727273, 0.7654252485795454, 0.7632501775568182, 0.
↪7665127840909091, 0.771240234375], [0.38682972301136365, 0.
↪49882368607954547, 0.5385520241477273, 0.5657848011363636, 0.
↪5819424715909091, 0.6000088778409091, 0.6109952059659091, 0.
↪6215154474431818, 0.6325905539772727, 0.6442427201704546, 0.
```

```
a5b_val_losses = [[1.5655976742506028, 1.3963831067085266, 1.3190482884645462,
1.285090345144272, 1.1842646718025207, 1.1781110033392905, 1.
2044517546892166, 1.1658358544111251, 1.1269395604729653, 1.144325076043606,
1.1231994420289992, 1.1455506503582, 1.0182002529501915, 1.1665931209921836,
1.0535438820719718, 1.0705567941069603, 1.0929344102740288, 1.
0644094094634056, 1.0451778545975685, 1.1074789851903915, 1.
0092910081148148, 1.0704100653529167, 1.0773278638720512, 1.033614307641983,
0.9371625527739524, 1.080445683002472, 1.016153635084629, 1.
0667413741350174, 0.9933030039072037, 1.0601032644510269, 1.
0384751126170157, 1.0301920726895333, 1.1099111706018447, 0.
9841205686330795, 1.0587839752435684, 1.0171958848834037, 1.047957293689251,
1.0233655765652656, 1.0458671301603317, 0.9734011679887772], [1.
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098723790049553, 1.0578299179673194, 1.1890966176986695, 1.0396249800920487,
1.1020448744297027, 1.0826002940535546, 1.0647443428635597, 0.
9958298683166504, 1.0413264989852906, 1.1108571588993073, 1.047364141047001,
0.981288594007492, 1.0091863930225373, 1.0793118178844452, 1.
0274139031767846, 0.9688847586512566, 0.9372925609350204, 1.
0202151879668235, 0.945965439081192, 1.0281192481517791, 0.9344085216522217,
0.9610651835799218, 0.9212571680545807, 0.9983295381069184, 0.
9096237152814866, 0.9598172143101692, 0.9618901014328003, 0.
9990213632583618, 1.0358095958828926, 1.0074639916419983, 1.
0772795021533965, 0.9557497963309288, 0.9335545226931572], [1.
6622334122657776, 1.4224862158298492, 1.3248430237174034, 1.
2902903407812119, 1.2557401299476623, 1.216827616095543, 1.2077743530273437,
1.1106926679611206, 1.0985313400626182, 1.1716050073504447, 1.
0718852132558823, 1.0947488024830818, 1.0802558809518814, 1.014692023396492,
1.1370791003108025, 1.0089283376932143, 1.0844287991523742, 1.
0406236931681634, 1.0600083231925965, 1.0517213016748428, 1.073353184759617,
1.0146382302045822, 1.0162255316972733, 1.1008418381214142, 0.
9819896250963212, 1.1750887580215932, 1.0170021563768388, 1.
0390363916754723, 1.0438886180520057, 1.050899587571621, 1.084867125749588,
0.9853161200881004, 1.018677568435669, 1.0252774998545646, 1.
071724571287632, 0.9546704187989234, 0.9214951977133751, 1.007592961192131,
1.0354547321796417, 0.9933191135525703], [1.5239570379257201, 1.
4112355917692185, 1.3159384429454803, 1.330892312526703, 1.344026692211628,
1.1783560037612915, 1.2067612037062645, 1.1922819584608078, 1.
137100425362587, 1.125764176249504, 1.100405828654766, 1.104533815383911, 1.
0344666063785553, 1.0425182223320006, 1.1271056443452836, 1.
0592205673456192, 1.0610340416431427, 1.039922794699669, 1.2394075393676758,
```

```
a5b_val_accuracies = [[0.42265625, 0.487109375, 0.5255859375, 0.5509765625, 0.57109375, 0.5796875, 0.5466796875, 0.58359375, 0.612109375, 0.597265625, 0.598046875, 0.590625, 0.6349609375, 0.5982421875, 0.634375, 0.619921875, 0.6158203125, 0.631640625, 0.633984375, 0.616796875, 0.641796875, 0.6357421875, 0.629296875, 0.64296875, 0.6673828125, 0.627734375, 0.651171875, 0.63359375, 0.6494140625, 0.62265625, 0.6466796875, 0.637890625, 0.6330078125, 0.6611328125, 0.6353515625, 0.6609375, 0.6478515625, 0.6578125, 0.6439453125, 0.6720703125], [0.4427734375, 0.5025390625, 0.5419921875, 0.540234375, 0.591015625, 0.5763671875, 0.584765625, 0.6095703125, 0.6255859375, 0.5662109375, 0.630859375, 0.60859375, 0.614453125, 0.613671875, 0.6529296875, 0.634765625, 0.6248046875, 0.63359375, 0.6462890625, 0.6423828125, 0.6216796875, 0.6423828125, 0.6587890625, 0.6740234375, 0.6490234375, 0.6740234375, 0.64609375, 0.6689453125, 0.66328125, 0.6796875, 0.6560546875, 0.67734375, 0.66484375, 0.665234375, 0.65859375, 0.6466796875, 0.6521484375, 0.64609375, 0.6775390625, 0.6791015625], [0.386328125, 0.4859375, 0.5177734375, 0.5322265625, 0.5455078125, 0.5705078125, 0.5654296875, 0.6076171875, 0.6115234375, 0.5767578125, 0.623828125, 0.6197265625, 0.612890625, 0.6431640625, 0.590234375, 0.6443359375, 0.6134765625, 0.635546875, 0.6271484375, 0.6328125, 0.623828125, 0.637890625, 0.63515625, 0.61953125, 0.6482421875, 0.60390625, 0.6509765625, 0.6380859375, 0.637890625, 0.6416015625, 0.63203125, 0.65859375, 0.6583984375, 0.6423828125, 0.6306640625, 0.6666015625, 0.6796875, 0.6560546875, 0.6513671875, 0.646484375], [0.4494140625, 0.48984375, 0.521484375, 0.5119140625, 0.51875, 0.5791015625, 0.571875, 0.5775390625, 0.591015625, 0.6185546875, 0.6275390625, 0.6146484375, 0.6373046875, 0.6318359375, 0.5962890625, 0.62734375, 0.6265625, 0.6330078125, 0.573828125, 0.6451171875, 0.6271484375, 0.6365234375, 0.6373046875, 0.664453125, 0.6416015625, 0.6287109375, 0.6615234375, 0.6568359375, 0.659765625, 0.6576171875, 0.657421875, 0.6517578125, 0.651171875, 0.67578125, 0.6337890625, 0.6458984375, 0.651953125, 0.6654296875, 0.6212890625, 0.684765625], [0.4728515625, 0.5126953125, 0.5005859375, 0.5474609375, 0.579296875, 0.5685546875, 0.6068359375, 0.612109375, 0.6017578125, 0.61015625, 0.6166015625, 0.6294921875, 0.6103515625, 0.6416015625, 0.6423828125, 0.648046875, 0.632421875, 0.634375, 0.6599609375, 0.6232421875, 0.64765625, 0.6578125, 0.620703125, 0.635546875, 0.6513671875, 0.6595703125, 0.6525390625, 0.64921875, 0.631640625, 0.6568359375, 0.66484375, 0.6640625, 0.6595703125, 0.666015625, 0.6607421875, 0.6580078125, 0.6408203125, 0.636328125, 0.655078125, 0.62578125]]
```

[ ]:
```
print(max(val_accuracy))
print(max(val_accuracy_2))
print(max(val_accuracy_3))
print(max(val_accuracy_4))
print(max(val_accuracy_5))
```

[ ]:
```
_, test_acc_1 = evaluate(model_1, test_loader)
_, test_acc_2 = evaluate(model_2, test_loader)
```

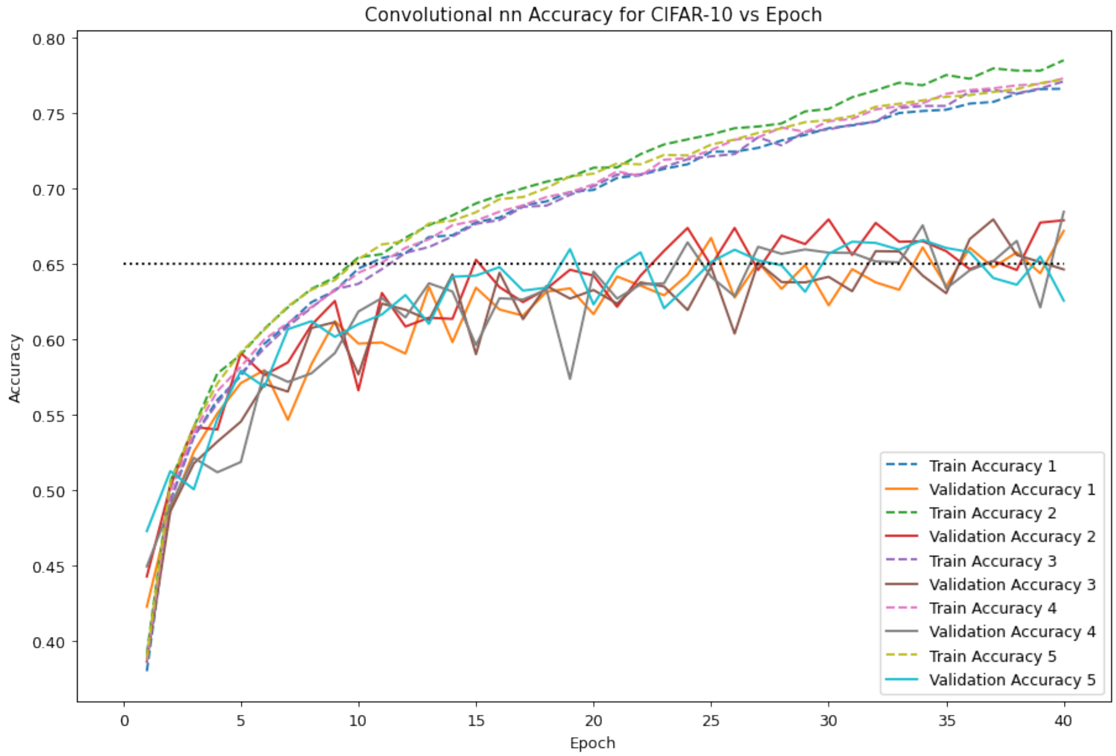
```
_, test_acc_3 = evaluate(model_3, test_loader)
_, test_acc_4 = evaluate(model_4, test_loader)
_, test_acc_5 = evaluate(model_5, test_loader)
print(f"Test Accuracy: {test_acc_1}")
print(f"Test Accuracy: {test_acc_2}")
print(f"Test Accuracy: {test_acc_3}")
print(f"Test Accuracy: {test_acc_4}")
print(f"Test Accuracy: {test_acc_5}")
```

```
Test Accuracy: 0.6798852848101266
Test Accuracy: 0.6870055379746836
Test Accuracy: 0.6590189873417721
Test Accuracy: 0.6926424050632911
Test Accuracy: 0.646064082278481
```

Test accuracies for the convolutional model

Test Accuracy: 0.6798852848101266 \ Test Accuracy: 0.6870055379746836 \ Test Accuracy: 0.6590189873417721 \ Test Accuracy: 0.6926424050632911 \ Test Accuracy: 0.646064082278481 \

[11]:
```
epochs = range(1, 41)
plt.figure(figsize=(12, 8), dpi=90)
plt.plot(epochs, a5b_train_accuracies[0], label="Train Accuracy 1", linestyle =␣
↪"dashed")
plt.plot(epochs, a5b_val_accuracies[0], label="Validation Accuracy 1")

plt.plot(epochs, a5b_train_accuracies[1], label="Train Accuracy 2",linestyle =␣
↪"dashed")
plt.plot(epochs, a5b_val_accuracies[1], label="Validation Accuracy 2")

plt.plot(epochs, a5b_train_accuracies[2], label="Train Accuracy 3", linestyle =␣
↪"dashed")
plt.plot(epochs, a5b_val_accuracies[2], label="Validation Accuracy 3")

plt.plot(epochs, a5b_train_accuracies[3], label="Train Accuracy 4", linestyle =␣
↪"dashed")
plt.plot(epochs, a5b_val_accuracies[3], label="Validation Accuracy 4")

plt.plot(epochs, a5b_train_accuracies[4], label="Train Accuracy 5", linestyle =␣
↪"dashed")
plt.plot(epochs, a5b_val_accuracies[4], label="Validation Accuracy 5")

plt.plot([0, 40], [0.65, 0.65], linestyle = "dotted", color = "black")
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.legend(loc = "lower right")
plt.title("Convolutional nn Accuracy for CIFAR-10 vs Epoch")
plt.show()
```



Convolutional nn Accuracy for CIFAR-10 vs Epoch
Accuracy
Epoch
0.80
0.75
0.70
0.65
0.60
0.55
0.50
0.45
0.40
0
5
10
15
20
25
30
35
40
Train Accuracy 1
Validation Accuracy 1
Train Accuracy 2
Validation Accuracy 2
Train Accuracy 3
Validation Accuracy 3
Train Accuracy 4
Validation Accuracy 4
Train Accuracy 5
Validation Accuracy 5