DL_MiniProj

April 14, 2023

1 Submitetd by -

#Pytorch on CIFAR-10 Dataset with Batch Normalisation and Dropout on Convolution Layers output after the activation function

[ ]:
```
# # Install torchvision
# !pip3 install torch==1.2.0+cu92 torchvision==0.4.0+cu92 -f https://download.
↪pytorch.org/whl/torch_stable.html
```

[ ]:
```
'''ResNet in PyTorch.
Reference:
[1] Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun
    Deep Residual Learning for Image Recognition.
[2] https://github.com/kuangliu/pytorch-cifar
[3] https://github.com/abhisikdar/RESNET18-CIFAR10
[4] https://www.srose.biz/wp-content/uploads/2020/08/Batch-Size-and-Epochs.html␣
↪
'''
import torch
import torch.nn as nn
import torch.nn.functional as F
# import torch
from torchvision import datasets
from torchvision import transforms
import matplotlib.pyplot as plt
import torch.nn as nn
import torch.nn.functional as F
import torchvision.models as models
import torch.backends.cudnn as cudnn
import torch
import torch.nn as nn
import torch.optim as optim
import torchvision.datasets as datasets
import torchvision.transforms as transforms
import torch.nn.functional as F
from torchsummary import summary
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
```

```python
from sklearn import decomposition
from sklearn import manifold
from sklearn.metrics import confusion_matrix
from sklearn.metrics import ConfusionMatrixDisplay
import numpy as np
from tqdm import tqdm
import random


class BasicBlock(nn.Module):
    expansion = 1

    def __init__(self, in_planes, planes, stride=1):
        super(BasicBlock, self).__init__()
        self.conv1 = nn.Conv2d(
            in_planes, planes, kernel_size=3, stride=stride, padding=1,␣
↪bias=False)
        self.bn1 = nn.BatchNorm2d(planes)
        self.conv2 = nn.Conv2d(planes, planes, kernel_size=3,
                               stride=1, padding=1, bias=False)
        self.bn2 = nn.BatchNorm2d(planes)

        self.shortcut = nn.Sequential()

        if stride != 1 or in_planes != self.expansion*planes:
            self.shortcut = nn.Sequential(
                nn.Conv2d(in_planes, self.expansion*planes,
                          kernel_size=1, stride=stride, bias=False),
                nn.BatchNorm2d(self.expansion*planes)
            )
        # Dropout after Convolutional BasicBlock
        self.dropout = nn.Dropout(0.25)

    def forward(self, x):
        out = F.relu(self.bn1(self.conv1(x)))
        out = self.dropout(out)
        out = self.bn2(self.conv2(out))
        out += self.shortcut(x)
        out = F.relu(out)
        return out




class ResNet(nn.Module):
    def __init__(self, block, num_blocks, num_classes=10):
        super(ResNet, self).__init__()
```

```
        self.in_planes = 64

        self.conv1 = nn.Conv2d(3, 64, kernel_size=3,
                               stride=1, padding=1, bias=False)
        self.bn1 = nn.BatchNorm2d(64)
        self.layer1 = self._make_layer(block, 64, num_blocks[0], stride=1)
        self.layer2 = self._make_layer(block, 128, num_blocks[1], stride=2)
        self.layer3 = self._make_layer(block, 256, num_blocks[2], stride=2)
        self.layer4 = self._make_layer(block, 512, num_blocks[3], stride=2)
        self.linear = nn.Linear(512*block.expansion, num_classes)
        self.dropout = nn.Dropout(0.25)

    def _make_layer(self, block, planes, num_blocks, stride):
        strides = [stride] + [1]*(num_blocks-1)
        layers = []
        for stride in strides:
            layers.append(block(self.in_planes, planes, stride))
            self.in_planes = planes * block.expansion
        return nn.Sequential(*layers)

    def forward(self, x):
        out = F.relu(self.bn1(self.conv1(x)))
        out = self.dropout(out)
        out = self.layer1(out)
        out = self.layer2(out)
        out = self.layer3(out)
        out = self.layer4(out)
        out = F.avg_pool2d(out, 4)
        out = out.view(out.size(0), -1)
        out = self.linear(out)
        return out


def ResNet18():
    return ResNet(BasicBlock, [2, 2, 2, 2])


def test():
    net = ResNet18()
    y = net(torch.randn(1, 3, 32, 32))
    print(y.size())

device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
layers=[1, 1, 1, 1]
model1 = ResNet(BasicBlock, layers).to(device)
summary(model1, input_size=(3, 32, 32))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1           [-1, 64, 32, 32]           1,728
       BatchNorm2d-2           [-1, 64, 32, 32]             128
           Dropout-3           [-1, 64, 32, 32]               0
            Conv2d-4           [-1, 64, 32, 32]          36,864
       BatchNorm2d-5           [-1, 64, 32, 32]             128
           Dropout-6           [-1, 64, 32, 32]               0
            Conv2d-7           [-1, 64, 32, 32]          36,864
       BatchNorm2d-8           [-1, 64, 32, 32]             128
        BasicBlock-9           [-1, 64, 32, 32]               0
           Conv2d-10          [-1, 128, 16, 16]          73,728
      BatchNorm2d-11          [-1, 128, 16, 16]             256
          Dropout-12          [-1, 128, 16, 16]               0
           Conv2d-13          [-1, 128, 16, 16]         147,456
      BatchNorm2d-14          [-1, 128, 16, 16]             256
           Conv2d-15          [-1, 128, 16, 16]           8,192
      BatchNorm2d-16          [-1, 128, 16, 16]             256
       BasicBlock-17          [-1, 128, 16, 16]               0
           Conv2d-18            [-1, 256, 8, 8]         294,912
      BatchNorm2d-19            [-1, 256, 8, 8]             512
          Dropout-20            [-1, 256, 8, 8]               0
           Conv2d-21            [-1, 256, 8, 8]         589,824
      BatchNorm2d-22            [-1, 256, 8, 8]             512
           Conv2d-23            [-1, 256, 8, 8]          32,768
      BatchNorm2d-24            [-1, 256, 8, 8]             512
       BasicBlock-25            [-1, 256, 8, 8]               0
           Conv2d-26            [-1, 512, 4, 4]       1,179,648
      BatchNorm2d-27            [-1, 512, 4, 4]           1,024
          Dropout-28            [-1, 512, 4, 4]               0
           Conv2d-29            [-1, 512, 4, 4]       2,359,296
      BatchNorm2d-30            [-1, 512, 4, 4]           1,024
           Conv2d-31            [-1, 512, 4, 4]         131,072
      BatchNorm2d-32            [-1, 512, 4, 4]           1,024
       BasicBlock-33            [-1, 512, 4, 4]               0
           Linear-34                   [-1, 10]           5,130
================================================================
Total params: 4,903,242
Trainable params: 4,903,242
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.01
Forward/backward pass size (MB): 8.00
Params size (MB): 18.70
Estimated Total Size (MB): 26.72
----------------------------------------------------------------
```

[ ]:
```python
class Model2(nn.Module):
    def __init__(self, block, num_blocks, num_classes=10):
        super(Model2, self).__init__()
        self.in_planes = 16

        self.conv1 = nn.Conv2d(3, 16, kernel_size=3, stride=1, padding=1,␣
 ↪bias=False)
        self.bn1 = nn.BatchNorm2d(16)
        self.layer1 = self._make_layer(block, 16, num_blocks[0], stride=1)
        self.layer2 = self._make_layer(block, 32, num_blocks[1], stride=2)
        self.layer3 = self._make_layer(block, 64, num_blocks[2], stride=2)
        self.avgpool = nn.AdaptiveAvgPool2d((1, 1))
        self.linear = nn.Linear(64, num_classes)

    def _make_layer(self, block, planes, num_blocks, stride):
        downsample = None
        strides = [stride] + [1]*(num_blocks-1)
        layers = []
        for stride in strides:
            layers.append(block(self.in_planes, planes, stride))
            self.in_planes = planes
        return nn.Sequential(*layers)

    def forward(self, x):
        x = F.relu(self.bn1(self.conv1(x)))
        x = self.layer1(x)
        x = self.layer2(x)
        x = self.layer3(x)
        x = self.avgpool(x)
        x = x.view(x.size(0), -1)
        x = self.linear(x)
        return x


device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
layers=[1, 1, 1, 1]
model2 = Model2(BasicBlock, layers).to(device)
summary(model2, input_size=(3, 32, 32))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1           [-1, 16, 32, 32]             432
       BatchNorm2d-2           [-1, 16, 32, 32]              32
            Conv2d-3           [-1, 16, 32, 32]           2,304
       BatchNorm2d-4           [-1, 16, 32, 32]              32
           Dropout-5           [-1, 16, 32, 32]               0
```

```
            Conv2d-6           [-1, 16, 32, 32]           2,304
       BatchNorm2d-7           [-1, 16, 32, 32]              32
        BasicBlock-8           [-1, 16, 32, 32]               0
            Conv2d-9           [-1, 32, 16, 16]           4,608
      BatchNorm2d-10           [-1, 32, 16, 16]              64
          Dropout-11           [-1, 32, 16, 16]               0
           Conv2d-12           [-1, 32, 16, 16]           9,216
      BatchNorm2d-13           [-1, 32, 16, 16]              64
           Conv2d-14           [-1, 32, 16, 16]             512
      BatchNorm2d-15           [-1, 32, 16, 16]              64
       BasicBlock-16           [-1, 32, 16, 16]               0
           Conv2d-17             [-1, 64, 8, 8]          18,432
      BatchNorm2d-18             [-1, 64, 8, 8]             128
          Dropout-19             [-1, 64, 8, 8]               0
           Conv2d-20             [-1, 64, 8, 8]          36,864
      BatchNorm2d-21             [-1, 64, 8, 8]             128
           Conv2d-22             [-1, 64, 8, 8]           2,048
      BatchNorm2d-23             [-1, 64, 8, 8]             128
       BasicBlock-24             [-1, 64, 8, 8]               0
AdaptiveAvgPool2d-25             [-1, 64, 1, 1]               0
           Linear-26                   [-1, 10]             650
================================================================
Total params: 78,042
Trainable params: 78,042
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.01
Forward/backward pass size (MB): 1.75
Params size (MB): 0.30
Estimated Total Size (MB): 2.06
----------------------------------------------------------------
```

[ ]:
```python
# import torch
from torchvision import datasets
from torchvision import transforms
import matplotlib.pyplot as plt
import torch.nn as nn
import torch.nn.functional as F
import torchvision.models as models
import torch.backends.cudnn as cudnn

print('Is CUDA available', torch.cuda.is_available())
print('Torch', torch.__version__, 'CUDA', torch.version.cuda)
print('Device:', torch.device('cuda:0'))
```

```
Is CUDA available False
Torch 2.0.0+cu118 CUDA 11.8
Device: cuda:0
```

2 Data Pre-processing

1. Random cropping, with size 32x32 and padding 4
2. Random horizontal flipping with a probability of 0.5
3. Normalize each image's RGB channel with mean() and std()

[ ]:
```
data_path='../data/'
cifar=datasets.CIFAR10(data_path, train= True, download=True,␣
 ↪transform=transforms.ToTensor())
cifar_val=datasets.CIFAR10(data_path, train=False, download= True,␣
 ↪transform=transforms.ToTensor())
```

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

100%|      | 170498071/170498071 [00:06<00:00, 28370547.93it/s]

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

[ ]:
```
cifar_stack = torch.stack([img for img, _ in cifar], dim=3)
print('Shape of the CIFAR stack is',cifar_stack.shape)
mean= cifar_stack.view(3,-1).mean(dim=1)
std= cifar_stack.view(3,-1).std(dim=1)
print('Mean of training data is', mean)
print('Standard deviation of training data is', std)
```

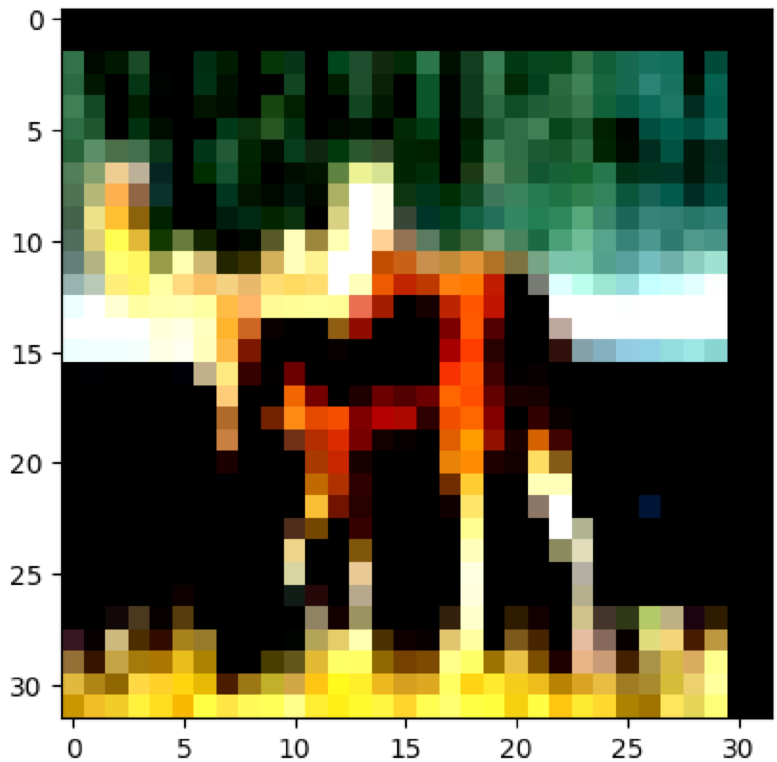
```
Shape of the CIFAR stack is torch.Size([3, 32, 32, 50000])
Mean of training data is tensor([0.4914, 0.4822, 0.4465])
Standard deviation of training data is tensor([0.2470, 0.2435, 0.2616])
```

[ ]:
```
cifar_transformed = datasets.CIFAR10(data_path,train=True,download=False,␣
 ↪transform=transforms.Compose([
                                                                        ␣
 ↪                          transforms.RandomCrop(32, padding=4),
   transforms.RandomHorizontalFlip(p=0.5),transforms.ToTensor(),transforms.
 ↪Normalize(mean,std)
]))
cifar_val_transformed = datasets.CIFAR10(data_path,train=False,download=False,␣
 ↪transform=transforms.Compose([
                                                                        ␣
 ↪                          transforms.RandomCrop(32, padding=4),
   transforms.RandomHorizontalFlip(p=0.5),transforms.ToTensor(),transforms.
 ↪Normalize(mean,std)
]))
```

[ ]:
```
# View images
```

```
img, label = cifar_transformed[28]
plt.imshow(img.permute(1, 2, 0))
plt.show()
```

```
WARNING:matplotlib.image:Clipping input data to the valid range for imshow with
RGB data ([0..1] for floats or [0..255] for integers).
```



#Varied the batch size for training dataset with other parameters fixed to measure the effect of batch size. Now, our Data is ready for Training.

[ ]:
```
# Parameters
# Model 2 with varying batch sizebatch_size=[256,512]
val_batch_size=100
num_epochs=30
# learning_rate=0.1

dev=torch.device("cuda:0" if torch.cuda.is_available() else "cpu")

max_validation = 0
max_epoch=0
val3_acc=[]
train3_acc=[]
```

```
epochs=[]
from torch.utils.data import DataLoader

#dataloader = DataLoader(dataset, batch_size=32, num_workers=2)
```

[ ]:
```
# Looping over different batch sizes
for batch_no in range(len(batch_size)):
  # Train/Test Data
  # Creating data loaders for training, testing, and validation data with batch␣
 ↪sizes as specified in batch_size list
  train_loader = torch.utils.data.DataLoader(cifar_transformed,␣
 ↪batch_size=batch_size[batch_no], shuffle=True, num_workers=4)
  train_acc_loader = torch.utils.data.DataLoader(cifar_transformed,␣
 ↪batch_size=val_batch_size, shuffle=False, num_workers=4)
  val_loader = torch.utils.data.DataLoader(cifar_val_transformed,␣
 ↪batch_size=val_batch_size, shuffle=False, num_workers=4)

  # Model
  # Creating a ResNet18 model and setting the device where the model will be␣
 ↪trained
  resnet18 = model2
  resnet18 = resnet18.to(dev)
  # Defining loss function and optimizer
  loss_func = torch.nn.CrossEntropyLoss()
  optimizer = torch.optim.SGD(resnet18.parameters(), lr=0.1, momentum=0.9,␣
 ↪weight_decay=5e-4)
  # Learning rate scheduler for optimizer
  scheduler = torch.optim.lr_scheduler.CosineAnnealingLR(optimizer, T_max=100)

  # Looping over number of epochs
  for i in range(num_epochs):
    # Training
    # Looping over batches of data and performing forward and backward pass
    for imgs, labels in train_loader:
      if dev is not None:
        imgs, labels = imgs.to(dev), labels.to(dev)
      out = resnet18(imgs)
      loss = loss_func(out, labels)
      optimizer.zero_grad()
      loss.backward()
      optimizer.step()

    # Initializing counters for calculating accuracy
    correct_val = 0
    total_val = 0
    correct_train_acc = 0
```

```
    total_train_acc = 0

    # Testing
    # Looping over test data batches and calculating accuracy
    with torch.no_grad():
      for imgs, labels in val_loader:
        if dev is not None:
          imgs, labels = imgs.to(dev), labels.to(dev)
        outputs = resnet18(imgs)
        _, predicted = torch.max(outputs, dim=1)
        total_val += labels.shape[0]
        correct_val += int((predicted == labels).sum())
      val3_acc.append(correct_val / total_val)

    # Computing Loss and Accuracy on training data
      for train_acc_imgs, train_acc_labels in train_acc_loader:
        if dev is not None:
          train_acc_imgs, train_acc_labels = train_acc_imgs.to(dev),␣
↪train_acc_labels.to(dev)
        train_acc_out = resnet18(train_acc_imgs)
        _, train_acc_predicted = torch.max(train_acc_out, dim=1)
        total_train_acc += train_acc_labels.shape[0]
        correct_train_acc += int((train_acc_predicted == train_acc_labels).
↪sum())
      train3_acc.append(correct_train_acc / total_train_acc)

      # Saving the model with the highest validation accuracy
      if correct_val / total_val > max_validation:
        max_validation = correct_val / total_val
        max_epoch = i
        torch.save(resnet18, './scratch.pt')

    epochs.append(i)

    # Printing the training and validation accuracy for every epoch
    if i % 1 == 0:
      print("Epoch no %d:\t Train Loss: %f \t Train Accuracy: %f \t Validation␣
↪Accuracy: %f" % (i + 1, float(loss), correct_train_acc / total_train_acc,␣
↪correct_val / total_val))

    # Updating the learning rate using the scheduler


    scheduler.step()

  print(max_validation)
```

```
Epoch no 1:      Train Loss: 1.117293    Train Accuracy: 0.607600
Validation Accuracy: 0.591100
Epoch no 2:      Train Loss: 0.880120    Train Accuracy: 0.660740
Validation Accuracy: 0.634400
Epoch no 3:      Train Loss: 0.806495    Train Accuracy: 0.681340
Validation Accuracy: 0.652000
Epoch no 4:      Train Loss: 0.781968    Train Accuracy: 0.698440
Validation Accuracy: 0.658800
Epoch no 5:      Train Loss: 0.798060    Train Accuracy: 0.723840
Validation Accuracy: 0.702000
Epoch no 6:      Train Loss: 0.684382    Train Accuracy: 0.738480
Validation Accuracy: 0.700100
Epoch no 7:      Train Loss: 0.684458    Train Accuracy: 0.756320
Validation Accuracy: 0.716000
Epoch no 8:      Train Loss: 0.786326    Train Accuracy: 0.757920
Validation Accuracy: 0.720300
Epoch no 9:      Train Loss: 0.643051    Train Accuracy: 0.769080
Validation Accuracy: 0.723400
Epoch no 10:     Train Loss: 0.638852    Train Accuracy: 0.777400
Validation Accuracy: 0.739800
Epoch no 11:     Train Loss: 0.680314    Train Accuracy: 0.775800
Validation Accuracy: 0.719500
Epoch no 12:     Train Loss: 0.664565    Train Accuracy: 0.787920
Validation Accuracy: 0.735700
Epoch no 13:     Train Loss: 0.634847    Train Accuracy: 0.793700
Validation Accuracy: 0.743900
Epoch no 14:     Train Loss: 0.722339    Train Accuracy: 0.788760
Validation Accuracy: 0.745800
Epoch no 15:     Train Loss: 0.618776    Train Accuracy: 0.779600
Validation Accuracy: 0.737700
Epoch no 16:     Train Loss: 0.684180    Train Accuracy: 0.792340
Validation Accuracy: 0.735200
Epoch no 17:     Train Loss: 0.704365    Train Accuracy: 0.796020
Validation Accuracy: 0.749800

Exception ignored in: <function _MultiProcessingDataLoaderIter.__del__ at
0x7f74581b54c0>
Exception ignored in: Traceback (most recent call last):
  File "/usr/local/lib/python3.9/dist-packages/torch/utils/data/dataloader.py",
line 1479, in __del__
    <function _MultiProcessingDataLoaderIter.__del__ at
0x7f74581b54c0>self._shutdown_workers()
Traceback (most recent call last):

  File "/usr/local/lib/python3.9/dist-packages/torch/utils/data/dataloader.py",
line 1479, in __del__
      File "/usr/local/lib/python3.9/dist-
packages/torch/utils/data/dataloader.py", line 1462, in _shutdown_workers
```

```
self._shutdown_workers()
  File "/usr/local/lib/python3.9/dist-packages/torch/utils/data/dataloader.py",
line 1462, in _shutdown_workers
if w.is_alive():
  File "/usr/lib/python3.9/multiprocessing/process.py", line 160, in is_alive
    assert self._parent_pid == os.getpid(), 'can only test a child process'
if w.is_alive():AssertionError
  File "/usr/lib/python3.9/multiprocessing/process.py", line 160, in is_alive
:     assert self._parent_pid == os.getpid(), 'can only test a child process'
AssertionErrorcan only test a child process:
can only test a child process
```

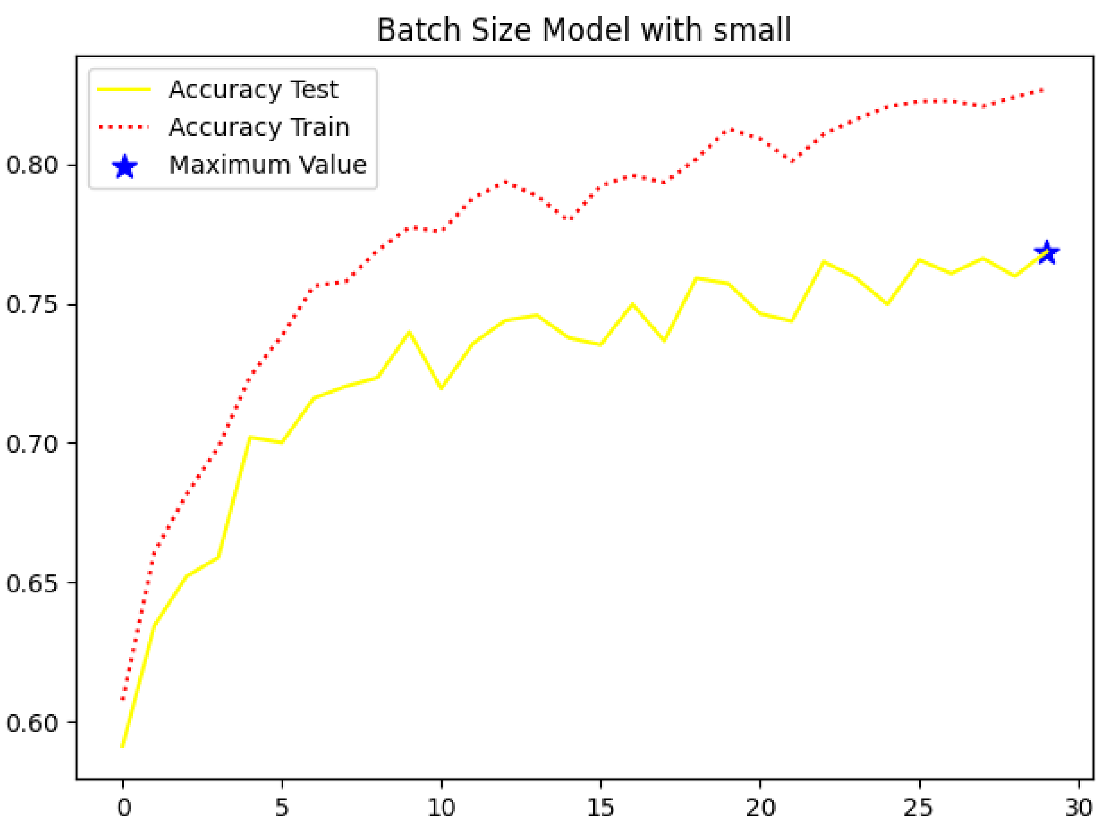
```
Epoch no 18:     Train Loss: 0.537938    Train Accuracy: 0.793420
Validation Accuracy: 0.736600
Epoch no 19:     Train Loss: 0.580487    Train Accuracy: 0.801880
Validation Accuracy: 0.759100
Epoch no 20:     Train Loss: 0.569386    Train Accuracy: 0.812720
Validation Accuracy: 0.757200
Epoch no 21:     Train Loss: 0.514566    Train Accuracy: 0.809180
Validation Accuracy: 0.746400
Epoch no 22:     Train Loss: 0.574617    Train Accuracy: 0.801080
Validation Accuracy: 0.743700
Epoch no 23:     Train Loss: 0.566149    Train Accuracy: 0.810760
Validation Accuracy: 0.765000
Epoch no 24:     Train Loss: 0.550066    Train Accuracy: 0.816040
Validation Accuracy: 0.759300
Epoch no 25:     Train Loss: 0.462372    Train Accuracy: 0.820640
Validation Accuracy: 0.749700
Epoch no 26:     Train Loss: 0.524294    Train Accuracy: 0.822560
Validation Accuracy: 0.765600
Epoch no 27:     Train Loss: 0.528929    Train Accuracy: 0.822680
Validation Accuracy: 0.760800
Epoch no 28:     Train Loss: 0.467284    Train Accuracy: 0.820800
Validation Accuracy: 0.766200
Epoch no 29:     Train Loss: 0.537238    Train Accuracy: 0.824140
Validation Accuracy: 0.759800
```

```
Exception ignored in: <function _MultiProcessingDataLoaderIter.__del__ at
0x7f74581b54c0>
Traceback (most recent call last):
  File "/usr/local/lib/python3.9/dist-packages/torch/utils/data/dataloader.py",
line 1479, in __del__
    self._shutdown_workers()
  File "/usr/local/lib/python3.9/dist-packages/torch/utils/data/dataloader.py",
line 1462, in _shutdown_workers
    if w.is_alive():
  File "/usr/lib/python3.9/multiprocessing/process.py", line 160, in is_alive
    assert self._parent_pid == os.getpid(), 'can only test a child process'
AssertionError: can only test a child process
```

```
Exception ignored in: Exception ignored in: <function
_MultiProcessingDataLoaderIter.__del__ at 0x7f74581b54c0>
<function _MultiProcessingDataLoaderIter.__del__ at 0x7f74581b54c0>Traceback
(most recent call last):
  File "/usr/local/lib/python3.9/dist-packages/torch/utils/data/dataloader.py",
line 1479, in __del__

    Traceback (most recent call last):
self._shutdown_workers()  File "/usr/local/lib/python3.9/dist-
packages/torch/utils/data/dataloader.py", line 1479, in __del__

  File "/usr/local/lib/python3.9/dist-packages/torch/utils/data/dataloader.py",
line 1462, in _shutdown_workers
        self._shutdown_workers()if w.is_alive():

  File "/usr/lib/python3.9/multiprocessing/process.py", line 160, in is_alive
  File "/usr/local/lib/python3.9/dist-packages/torch/utils/data/dataloader.py",
line 1462, in _shutdown_workers
    assert self._parent_pid == os.getpid(), 'can only test a child process'
if w.is_alive():

AssertionError:   File "/usr/lib/python3.9/multiprocessing/process.py", line
160, in is_alive
can only test a child process
assert self._parent_pid == os.getpid(), 'can only test a child process'
AssertionError: Exception ignored in: can only test a child process<function
_MultiProcessingDataLoaderIter.__del__ at 0x7f74581b54c0>

Traceback (most recent call last):
  File "/usr/local/lib/python3.9/dist-packages/torch/utils/data/dataloader.py",
line 1479, in __del__
    self._shutdown_workers()
  File "/usr/local/lib/python3.9/dist-packages/torch/utils/data/dataloader.py",
line 1462, in _shutdown_workers
    if w.is_alive():
  File "/usr/lib/python3.9/multiprocessing/process.py", line 160, in is_alive
    assert self._parent_pid == os.getpid(), 'can only test a child process'
AssertionError: can only test a child process

Epoch no 30:     Train Loss: 0.470613    Train Accuracy: 0.827100
Validation Accuracy: 0.768700
0.7687
```

[ ]:
```
#Small NORMAL
# Plot Train Accuracy vs Test Accuracy
plt.plot(epochs, val3_acc, label="Accuracy Test", color="yellow",␣
↪linestyle='-')
```

```
plt.plot(epochs, train3_acc, label="Accuracy Train", color="red",linestyle=':
↪')
plt.scatter([max_epoch], [max_validation],color="blue", marker="*",␣
↪label="Maximum Value", s=100 )
plt.title("Batch Size Model with small")
plt.legend()
plt.tight_layout()
plt.show()
```



[ ]:
```
# Parameters
#Model 1 with varying batch size
batch_size=[256,512]
val_batch_size=100
num_epochs=10
# learning_rate=0.1

dev=torch.device("cuda:0" if torch.cuda.is_available() else "cpu")

max_validation = 0
max_epoch=0
```

```
val1_acc=[]
train1_acc=[]
epochs=[]
from torch.utils.data import DataLoader

#dataloader = DataLoader(dataset, batch_size=32, num_workers=2)
```

[ ]:
```
# Loop over different batch sizes for training
for batch_no in range(len(batch_size)):
  # Train/Test Data
  # Create DataLoader objects for training, train accuracy evaluation, and␣
 ↪validation
  train_loader=torch.utils.data.
 ↪DataLoader(cifar_transformed,batch_size=batch_size[batch_no],shuffle=True,␣
 ↪num_workers=4)
  train_acc_loader=torch.utils.data.
 ↪DataLoader(cifar_transformed,batch_size=val_batch_size,shuffle=False,␣
 ↪num_workers=4)
  val_loader = torch.utils.data.DataLoader(cifar_val_transformed,␣
 ↪batch_size=val_batch_size, shuffle=False, num_workers=4)

  # Model
  # Initialize a ResNet18 model, set up loss function, optimizer, and learning␣
 ↪rate scheduler
  resnet18 =model1
  resnet18=resnet18.to(dev)
  loss_func= torch.nn.CrossEntropyLoss()
  optimizer = torch.optim.SGD(resnet18.parameters(), lr=0.1, momentum=0.9,␣
 ↪weight_decay=5e-4)
  scheduler = torch.optim.lr_scheduler.CosineAnnealingLR(optimizer, T_max=100)

  # Loop over epochs
  for i in range(num_epochs):
    # Training
    # Loop over training batches, calculate loss and optimize model parameters
    for imgs, labels in train_loader:
      if dev is not None:
        imgs,labels=imgs.to(dev),labels.to(dev)
      out= resnet18(imgs)
      loss=loss_func(out,labels)
      optimizer.zero_grad()
      loss.backward()
      optimizer.step()

    # Testing
    # Evaluate validation accuracy by looping over validation batches
```

```
    # Calculate training accuracy by looping over train accuracy evaluation␣
↪batches
    correct_val = 0
    total_val = 0
    correct_train_acc=0
    total_train_acc=0
    with torch.no_grad():
      for imgs, labels in val_loader:
        if dev is not None:
          imgs,labels=imgs.to(dev),labels.to(dev)
        outputs = resnet18(imgs)
        _, predicted = torch.max(outputs, dim=1)
        total_val += labels.shape[0]
        correct_val += int((predicted == labels).sum())
      val1_acc.append(correct_val/total_val)

      for train_acc_imgs,train_acc_labels in train_acc_loader:
        if dev is not None:
          train_acc_imgs,train_acc_labels=train_acc_imgs.
↪to(dev),train_acc_labels.to(dev)
        train_acc_out=resnet18(train_acc_imgs)
        _, train_acc_predicted = torch.max(train_acc_out, dim=1)
        total_train_acc += train_acc_labels.shape[0]
        correct_train_acc += int((train_acc_predicted == train_acc_labels).
↪sum())
      train1_acc.append(correct_train_acc/total_train_acc)

      # Save model if validation accuracy is highest so far
      if correct_val/total_val > max_validation:
        max_validation=correct_val/total_val
        max_epoch=i
        torch.save(resnet18,'./scratch.pt' )
    epochs.append(i)

    # Print out loss and accuracy information every epoch
    if i%1==0:
      print("Epoch no %d:\t Train Loss: %f \t Train Accuracy: %f \t Validation␣
↪Accuracy: %f" % (i+1, float(loss), correct_train_acc / total_train_acc,␣
↪correct_val / total_val))

    # Update learning rate with scheduler
    scheduler.step()

  # Print out highest validation accuracy achieved
  print(max_validation)
```

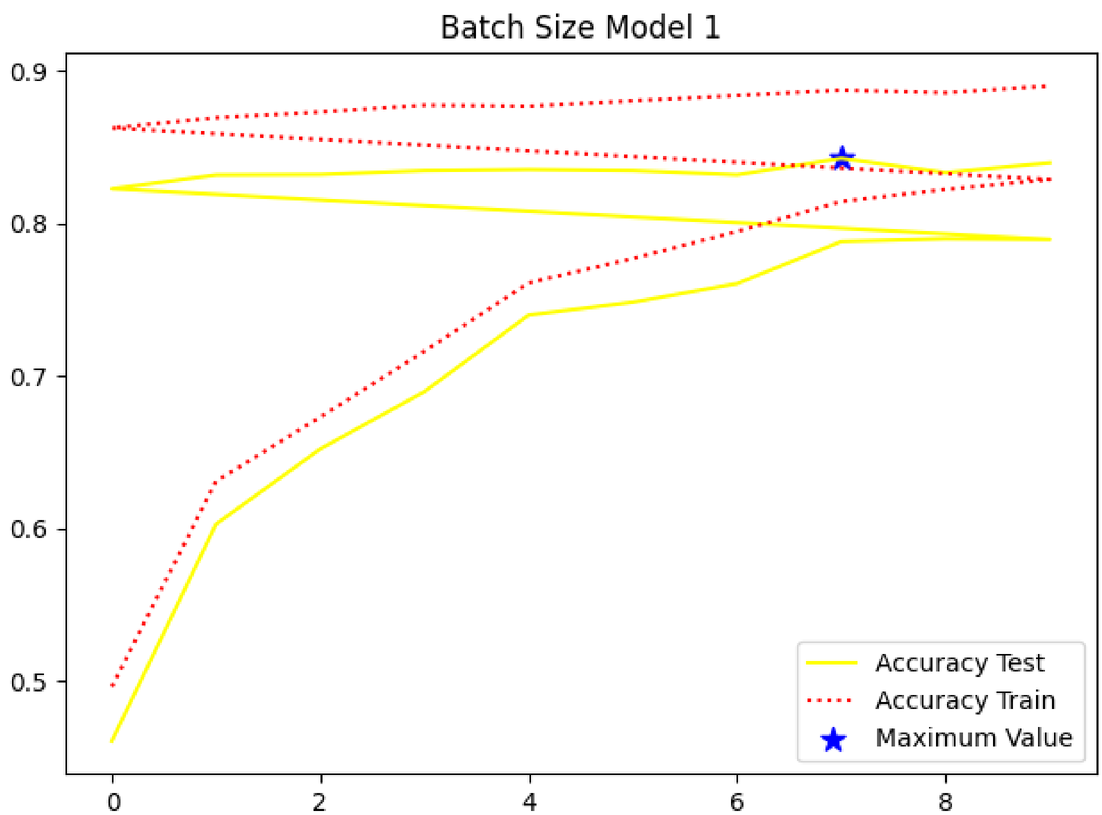
```
/usr/local/lib/python3.9/dist-packages/torch/utils/data/dataloader.py:561:
```

```
UserWarning: This DataLoader will create 4 worker processes in total. Our
suggested max number of worker in current system is 2, which is smaller than
what this DataLoader is going to create. Please be aware that excessive worker
creation might get DataLoader running slow or even freeze, lower the worker
number to avoid potential slowness/freeze if necessary.
  warnings.warn(_create_warning_msg(
```

```
Epoch no 1:      Train Loss: 1.289417    Train Accuracy: 0.496160
Validation Accuracy: 0.460500
Epoch no 2:      Train Loss: 1.235198    Train Accuracy: 0.630820
Validation Accuracy: 0.602700
Epoch no 3:      Train Loss: 1.005832    Train Accuracy: 0.672920
Validation Accuracy: 0.652000
Epoch no 4:      Train Loss: 0.948158    Train Accuracy: 0.716080
Validation Accuracy: 0.689600
Epoch no 5:      Train Loss: 0.650710    Train Accuracy: 0.760900
Validation Accuracy: 0.739800
Epoch no 6:      Train Loss: 0.514321    Train Accuracy: 0.776860
Validation Accuracy: 0.748200
Epoch no 7:      Train Loss: 0.711532    Train Accuracy: 0.794560
Validation Accuracy: 0.760400
Epoch no 8:      Train Loss: 0.677960    Train Accuracy: 0.814220
Validation Accuracy: 0.788000
Epoch no 9:      Train Loss: 0.449751    Train Accuracy: 0.822120
Validation Accuracy: 0.789800
Epoch no 10:     Train Loss: 0.408113    Train Accuracy: 0.828700
Validation Accuracy: 0.789300
0.7898
Epoch no 1:      Train Loss: 0.457710    Train Accuracy: 0.862420
Validation Accuracy: 0.822600
Epoch no 2:      Train Loss: 0.410050    Train Accuracy: 0.869120
Validation Accuracy: 0.831600
Epoch no 3:      Train Loss: 0.359962    Train Accuracy: 0.872840
Validation Accuracy: 0.831900
Epoch no 4:      Train Loss: 0.357708    Train Accuracy: 0.877360
Validation Accuracy: 0.834500
Epoch no 5:      Train Loss: 0.369654    Train Accuracy: 0.876720
Validation Accuracy: 0.835200
Epoch no 6:      Train Loss: 0.329744    Train Accuracy: 0.880240
Validation Accuracy: 0.834500
Epoch no 7:      Train Loss: 0.377844    Train Accuracy: 0.883720
Validation Accuracy: 0.831700
Epoch no 8:      Train Loss: 0.307306    Train Accuracy: 0.887280
Validation Accuracy: 0.842500
Epoch no 9:      Train Loss: 0.381857    Train Accuracy: 0.885560
Validation Accuracy: 0.833200
Epoch no 10:     Train Loss: 0.317745    Train Accuracy: 0.889980
Validation Accuracy: 0.839600
```

0.8425

```
[ ]:  # Plot Train Accuracy vs Test Accuracy
      plt.plot(epochs, val1_acc, label="Accuracy Test", color="yellow",␣
     ↪linestyle='-')
      plt.plot(epochs, train1_acc, label="Accuracy Train", color="red",linestyle=':
     ↪')
      plt.scatter([max_epoch], [max_validation],color="blue", marker="*",␣
     ↪label="Maximum Value", s=100 )
      plt.title("Batch Size Model 1")
      plt.legend()
      plt.tight_layout()
      plt.show()
```



#Varied the learning rate [0.1, 0.01, 0.001, 0.0001] on fixed batch size and fixed no of epoch to observe the effect of varying the epoch size Results for lr = 0.1 have been shown above

```
[ ]: #Model1 WITH DIFFERENT LEARNING RATE
     # Parameters
     batch_size=512
     val_batch_size=100
```

```
num_epochs=10
learning_rate=[0.01, 0.001, 0.0001]

dev=torch.device("cuda:0" if torch.cuda.is_available() else "cpu")

max_validation = 0
max_epoch=0
val2_acc=[]
train2_acc=[]
epochs=[]
```

[ ]:

```
# Loop over different learning rates
for lr_no in range(len(learning_rate)):

  # Data loaders for training, training accuracy evaluation, and validation
  train_loader = torch.utils.data.DataLoader(cifar_transformed,␣
↪batch_size=batch_size, shuffle=True, num_workers=4)
  train_acc_loader = torch.utils.data.DataLoader(cifar_transformed,␣
↪batch_size=val_batch_size, shuffle=False, num_workers=4)
  val_loader = torch.utils.data.DataLoader(cifar_val_transformed,␣
↪batch_size=val_batch_size, shuffle=False, num_workers=4)

  # Create model, move it to device
  resnet18 = model1
  resnet18 = resnet18.to(dev)

  # Define loss function, optimizer and scheduler
  loss_func = torch.nn.CrossEntropyLoss()
  optimizer = torch.optim.SGD(resnet18.parameters(), lr=learning_rate[lr_no],␣
↪momentum=0.9, weight_decay=5e-4)
  scheduler = torch.optim.lr_scheduler.CosineAnnealingLR(optimizer, T_max=100)

  # Loop over epochs
  for i in range(num_epochs):
    # Training
    for imgs, labels in train_loader:
      if dev is not None:
        imgs, labels = imgs.to(dev), labels.to(dev)
      out = resnet18(imgs)
      loss = loss_func(out, labels)
      optimizer.zero_grad()
      loss.backward()
      optimizer.step()

    # Evaluation of validation accuracy
    correct_val = 0
    total_val = 0
```

```
    # Evaluation of training accuracy
    correct_train_acc = 0
    total_train_acc = 0

    # Testing
    with torch.no_grad():
      for imgs, labels in val_loader:
        if dev is not None:
          imgs, labels = imgs.to(dev), labels.to(dev)
        outputs = resnet18(imgs)
        _, predicted = torch.max(outputs, dim=1)
        total_val += labels.shape[0]
        correct_val += int((predicted == labels).sum())
      val2_acc.append(correct_val/total_val)

      # Compute loss and accuracy on training data
      for train_acc_imgs, train_acc_labels in train_acc_loader:
        if dev is not None:
          train_acc_imgs, train_acc_labels = train_acc_imgs.to(dev),␣
↪train_acc_labels.to(dev)
        train_acc_out = resnet18(train_acc_imgs)
        _, train_acc_predicted = torch.max(train_acc_out, dim=1)
        total_train_acc += train_acc_labels.shape[0]
        correct_train_acc += int((train_acc_predicted == train_acc_labels).
↪sum())
      train2_acc.append(correct_train_acc/total_train_acc)

      # Track best validation accuracy and corresponding epoch
      if correct_val/total_val > max_validation:
        max_validation = correct_val/total_val
        max_epoch = i

    epochs.append(i)

    # Print training and validation accuracy every epoch
    if i%1==0:
      print("Epoch no %d:\t Train Loss: %f \t Train Accuracy: %f \t Validation␣
↪Accuracy: %f" % (i+1, float(loss), correct_train_acc / total_train_acc,␣
↪correct_val / total_val))

    # Update learning rate using the scheduler
    scheduler.step()

  print(max_validation)
```

```
Epoch no 1:       Train Loss: 1.559082    Train Accuracy: 0.424980
Validation Accuracy: 0.435500
```

```
Epoch no 2:      Train Loss: 1.350326    Train Accuracy: 0.510760
Validation Accuracy: 0.506000
Epoch no 3:      Train Loss: 1.219319    Train Accuracy: 0.566680
Validation Accuracy: 0.554100
Epoch no 4:      Train Loss: 1.080049    Train Accuracy: 0.623520
Validation Accuracy: 0.605900
Epoch no 5:      Train Loss: 0.976655    Train Accuracy: 0.656920
Validation Accuracy: 0.643600
Epoch no 6:      Train Loss: 0.984496    Train Accuracy: 0.679920
Validation Accuracy: 0.655500
Epoch no 7:      Train Loss: 0.829843    Train Accuracy: 0.703400
Validation Accuracy: 0.673000
Epoch no 8:      Train Loss: 0.801193    Train Accuracy: 0.714540
Validation Accuracy: 0.686800
Epoch no 9:      Train Loss: 0.682460    Train Accuracy: 0.721560
Validation Accuracy: 0.689100
Epoch no 10:     Train Loss: 0.690344    Train Accuracy: 0.742400
Validation Accuracy: 0.704600
0.7046
Epoch no 1:      Train Loss: 0.650053    Train Accuracy: 0.761120
Validation Accuracy: 0.718800
Epoch no 2:      Train Loss: 0.731430    Train Accuracy: 0.762540
Validation Accuracy: 0.726800
Epoch no 3:      Train Loss: 0.659601    Train Accuracy: 0.767140
Validation Accuracy: 0.727200
Epoch no 4:      Train Loss: 0.657767    Train Accuracy: 0.765040
Validation Accuracy: 0.730200
Epoch no 5:      Train Loss: 0.614757    Train Accuracy: 0.765460
Validation Accuracy: 0.735000
Epoch no 6:      Train Loss: 0.607678    Train Accuracy: 0.768680
Validation Accuracy: 0.728900
```

[ ]:
```
#Model2 WITH DIFFERENT LR
# Parameters
batch_size=512
val_batch_size=100
num_epochs=10
learning_rate=[0.01, 0.001, 0.0001]

dev=torch.device("cuda:0" if torch.cuda.is_available() else "cpu")

max_validation = 0
max_epoch=0
valsmall_acc=[]
trainsmall_acc=[]
epochs=[]
```

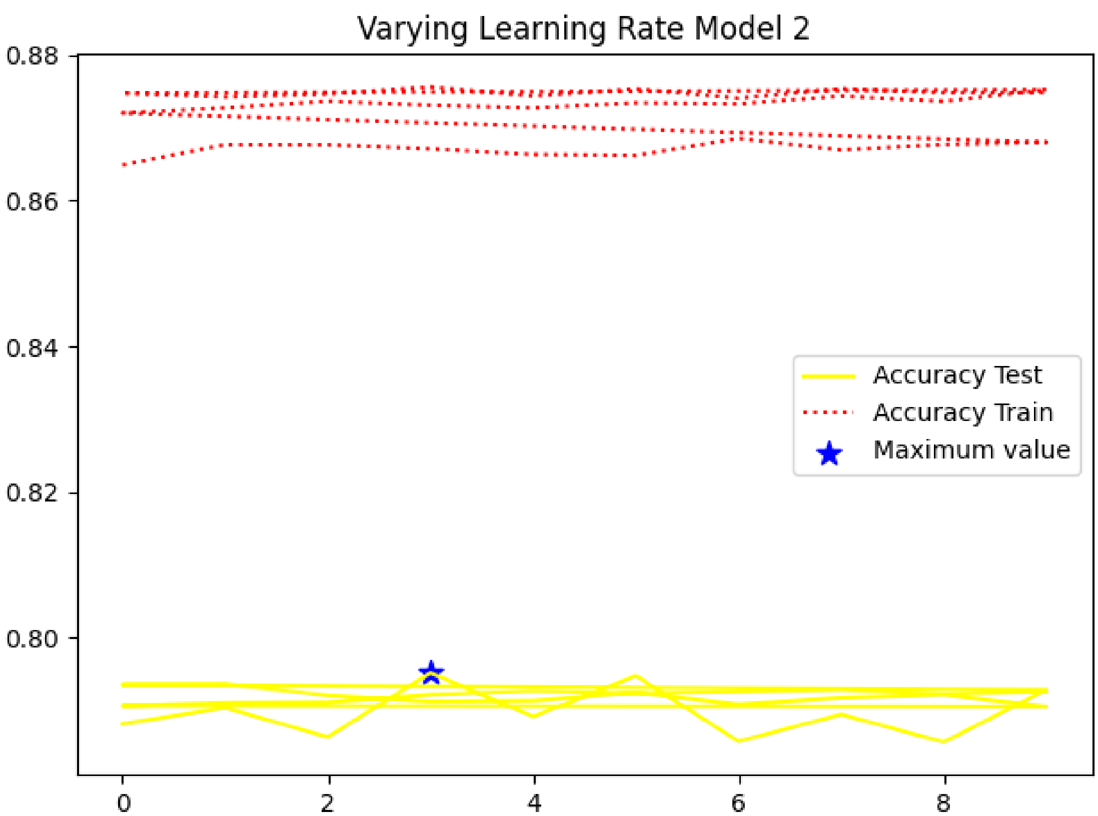
```
for lr_no in range(len(learning_rate)):
  # Train/Test Data
  train_loader=torch.utils.data.
↪DataLoader(cifar_transformed,batch_size=batch_size,shuffle=True,␣
↪num_workers=4)
  train_acc_loader=torch.utils.data.
↪DataLoader(cifar_transformed,batch_size=val_batch_size,shuffle=False,␣
↪num_workers=4)
  val_loader = torch.utils.data.DataLoader(cifar_val_transformed,␣
↪batch_size=val_batch_size, shuffle=False, num_workers=4)

  # Model
  resnet18 =model2
  resnet18=resnet18.to(dev)
  loss_func= torch.nn.CrossEntropyLoss()
  optimizer = torch.optim.SGD(resnet18.parameters(), lr=learning_rate[lr_no],␣
↪momentum=0.9, weight_decay=5e-4)
  scheduler = torch.optim.lr_scheduler.CosineAnnealingLR(optimizer, T_max=100)

  for i in range(num_epochs):
    # Training
    for imgs, labels in train_loader:
      if dev is not None:
        imgs,labels=imgs.to(dev),labels.to(dev)
      out= resnet18(imgs)
      loss=loss_func(out,labels)
      optimizer.zero_grad()
      loss.backward()
      optimizer.step()

    correct_val = 0
    total_val = 0
    correct_train_acc=0
    total_train_acc=0
    # Testing
    with torch.no_grad():
      for imgs, labels in val_loader:
        if dev is not None:
          imgs,labels=imgs.to(dev),labels.to(dev)
        outputs = resnet18(imgs)
        _, predicted = torch.max(outputs, dim=1)
        total_val += labels.shape[0]
        correct_val += int((predicted == labels).sum())
      valsmall_acc.append(correct_val/total_val)

    # Compute Loss and Accuracy on training data
      for train_acc_imgs,train_acc_labels in train_acc_loader:
```

```
        if dev is not None:
          train_acc_imgs,train_acc_labels=train_acc_imgs.
↪to(dev),train_acc_labels.to(dev)
        train_acc_out=resnet18(train_acc_imgs)
        _, train_acc_predicted = torch.max(train_acc_out, dim=1)
        total_train_acc += train_acc_labels.shape[0]
        correct_train_acc += int((train_acc_predicted == train_acc_labels).
↪sum())
        # minibatch_acc = accuracy(train_acc, train_acc_labels,1)[0]
        # print("Top-1 training accuracy for minibatch", minibatch_acc)
      trainsmall_acc.append(correct_train_acc/total_train_acc)


      if correct_val/total_val > max_validation:
        max_validation=correct_val/total_val
        max_epoch=i
    epochs.append(i)



    if i%1==0:
      print("Epoch no %d:\t Train Loss: %f \t Train Accuracy: %f \t Validation␣
↪Accuracy: %f" % (i+1, float(loss), correct_train_acc / total_train_acc,␣
↪correct_val / total_val))

    scheduler.step()

  print(max_validation)
```

```
Epoch no 1:      Train Loss: 0.304700    Train Accuracy: 0.864900
Validation Accuracy: 0.788100
Epoch no 2:      Train Loss: 0.414667    Train Accuracy: 0.867700
Validation Accuracy: 0.790300
Epoch no 3:      Train Loss: 0.459256    Train Accuracy: 0.867680
Validation Accuracy: 0.786300
Epoch no 4:      Train Loss: 0.312795    Train Accuracy: 0.867120
Validation Accuracy: 0.795100
Epoch no 5:      Train Loss: 0.333094    Train Accuracy: 0.866340
Validation Accuracy: 0.789100
Epoch no 6:      Train Loss: 0.387988    Train Accuracy: 0.866200
Validation Accuracy: 0.794700
Epoch no 7:      Train Loss: 0.316807    Train Accuracy: 0.868560
Validation Accuracy: 0.785700
Epoch no 8:      Train Loss: 0.402478    Train Accuracy: 0.866960
Validation Accuracy: 0.789400
Epoch no 9:      Train Loss: 0.446762    Train Accuracy: 0.867720
Validation Accuracy: 0.785600
```

```
Epoch no 10:     Train Loss: 0.334962    Train Accuracy: 0.868020
Validation Accuracy: 0.792800
0.7951
Epoch no 1:      Train Loss: 0.341429    Train Accuracy: 0.872020
Validation Accuracy: 0.793500
Epoch no 2:      Train Loss: 0.277920    Train Accuracy: 0.872760
Validation Accuracy: 0.793600
Epoch no 3:      Train Loss: 0.356231    Train Accuracy: 0.873660
Validation Accuracy: 0.792000
Epoch no 4:      Train Loss: 0.394408    Train Accuracy: 0.873120
Validation Accuracy: 0.791200
Epoch no 5:      Train Loss: 0.320152    Train Accuracy: 0.872760
Validation Accuracy: 0.791300
Epoch no 6:      Train Loss: 0.338917    Train Accuracy: 0.873440
Validation Accuracy: 0.792400
Epoch no 7:      Train Loss: 0.368553    Train Accuracy: 0.873300
Validation Accuracy: 0.790800
Epoch no 8:      Train Loss: 0.351268    Train Accuracy: 0.874360
Validation Accuracy: 0.791700
Epoch no 9:      Train Loss: 0.363321    Train Accuracy: 0.873640
Validation Accuracy: 0.792100
Epoch no 10:     Train Loss: 0.312656    Train Accuracy: 0.875260
Validation Accuracy: 0.790500
0.7951
Epoch no 1:      Train Loss: 0.327647    Train Accuracy: 0.874780
Validation Accuracy: 0.790600
Epoch no 2:      Train Loss: 0.379745    Train Accuracy: 0.874240
Validation Accuracy: 0.791000
Epoch no 3:      Train Loss: 0.310425    Train Accuracy: 0.874660
Validation Accuracy: 0.791100
Epoch no 4:      Train Loss: 0.346937    Train Accuracy: 0.875620
Validation Accuracy: 0.792100
Epoch no 5:      Train Loss: 0.336440    Train Accuracy: 0.874380
Validation Accuracy: 0.792600
Epoch no 6:      Train Loss: 0.274691    Train Accuracy: 0.875360
Validation Accuracy: 0.792300
Epoch no 7:      Train Loss: 0.365223    Train Accuracy: 0.874080
Validation Accuracy: 0.792500
Epoch no 8:      Train Loss: 0.344389    Train Accuracy: 0.875380
Validation Accuracy: 0.792800
Epoch no 9:      Train Loss: 0.303088    Train Accuracy: 0.874840
Validation Accuracy: 0.792200
Epoch no 10:     Train Loss: 0.323907    Train Accuracy: 0.874840
Validation Accuracy: 0.792500
0.7951
```

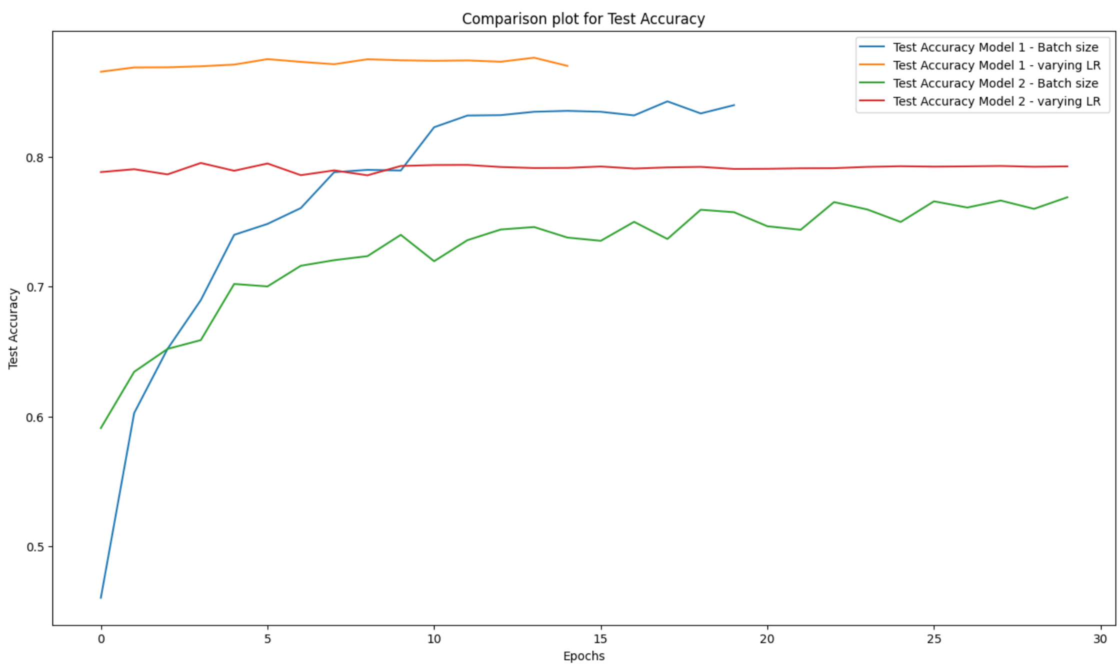
[ ]:
```
# Plot Train Accuracy vs Test Accuracy
plt.plot(epochs, valsmall_acc, label="Accuracy Test", color="yellow",␣
 ↪linestyle='-')
plt.plot(epochs, trainsmall_acc, label="Accuracy Train",␣
 ↪color="red",linestyle=':')
plt.scatter([max_epoch], [max_validation],color="blue", marker="*",␣
 ↪label="Maximum value", s=100 )
plt.title("Varying Learning Rate Model 2")
plt.legend()
plt.tight_layout()
plt.show()
```



Comparison of above models with varying parameters

[ ]:
```
#Create a figure and axis object with a size of 16x9
fig, ax = plt.subplots(figsize=(16,9))

#Set the title of the plot
plt.title('Comparison plot for Test Accuracy')

#Plot the test accuracy data for each model and label them accordingly
```

```
plt.plot(val1_acc, label='Test Accuracy Model 1 - Batch size')
plt.plot(val2_acc, label='Test Accuracy Model 1 - varying LR')
plt.plot(val3_acc, label='Test Accuracy Model 2 - Batch size')
plt.plot(valsmall_acc, label='Test Accuracy Model 2 - varying LR ')

#Add a legend to the plot
plt.legend()

#Set the x-label and y-label of the plot
plt.xlabel("Epochs")
plt.ylabel("Test Accuracy")

#Display the plot
plt.show()
```



[ ]:
```
# Create a figure and axis object with the specified size
fig, ax = plt.subplots(figsize=(16,9))

# Set the title of the plot
plt.title('Comparison plot for Train Accuracy')

# Plot the train accuracy values for each experiment using the plot function of␣
↪matplotlib
plt.plot(train1_acc, label='Train Accuracy Model 1 - Batch size')
plt.plot(train2_acc, label='Train Accuracy Model 1 - varying LR')
```

```
plt.plot(train3_acc, label='Train Accuracy Model 2 - Batch size')
plt.plot(trainsmall_acc, label='Train Accuracy Model 2 - varying LR ')

# Set the legend for the plot
plt.legend()

# Set the x and y labels for the plot
plt.xlabel("Epochs")
plt.ylabel("Train Accuracy")

# Display the plot
plt.show()
```