assignment1

January 18, 2025

[ ]:
```python
# Imports
import os
import time
import copy

import torch
import torch.nn as nn
import torch.nn.functional as F
from torch.utils.data import DataLoader

import torchvision
from torchvision import datasets, transforms, models
```

[ ]:
```python
train_transform = transforms.Compose([
    transforms.Resize(256),
    transforms.CenterCrop(224),
    transforms.ToTensor(),
    transforms.Normalize((0.4914, 0.4822, 0.4465), (0.2023, 0.1994, 0.2010))
])

test_transform = transforms.Compose([
    transforms.Resize((224, 224)),  # Resize images for AlexNet input
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.5, 0.5, 0.5], std=[0.5, 0.5, 0.5])
])

train_dataset = datasets.CIFAR10('../data', download=True, train=True,␣
 ↪transform=train_transform)
test_dataset = datasets.CIFAR10('../data', train=False, download=True,␣
 ↪transform=test_transform)

train_data, val_data = torch.utils.data.random_split(train_dataset, [40000,␣
 ↪10000])

train_dataloader = DataLoader(train_data, batch_size=16, shuffle=True,␣
 ↪num_workers=2)
```

```
val_dataloader = DataLoader(val_data, batch_size=16, shuffle=False,␣
 ↪num_workers=2)
test_dataloader = DataLoader(test_dataset, batch_size=16, shuffle=False,␣
 ↪num_workers=2)
```

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Files already downloaded and verified
```

[ ]:
```
device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
print(device)
```

```
cuda:0
```

0.0.1 Alexnet

[ ]:
```
class AlexNet(nn.Module):
    def __init__(self, n_classes: int = 10):
        super(AlexNet, self).__init__()

        self.feature_extractors = nn.Sequential(
            nn.Conv2d(3, 96, kernel_size=11, stride=4, padding=2),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=3, stride=2),

            nn.Conv2d(96, 256, kernel_size=5, padding=2),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=3, stride=2),

            nn.Conv2d(256, 384, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),

            nn.Conv2d(384, 384, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),

            nn.Conv2d(384, 256, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=3, stride=2),
        )

        self.adaptive_pool = nn.AdaptiveAvgPool2d((6, 6))

        self.classification = nn.Sequential(
            nn.Flatten(),
            nn.Dropout(),
            nn.Linear(256 * 6 * 6, 4096),
            nn.ReLU(inplace=True),
            nn.Dropout(),
            nn.Linear(4096, 4096),
```

```
            nn.ReLU(inplace=True),
            nn.Linear(4096, n_classes)
        )

    def forward(self, x):
        x = self.feature_extractors(x)
        x = self.adaptive_pool(x)
        x = self.classification(x)

        return x
```

[ ]:
```
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(device)

alexnet = AlexNet().to(device)

criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.SGD(alexnet.parameters(), lr=0.001, momentum=0.9)
```

```
cuda
```

[ ]:
```
def train_model(model, dataloader, criterion, optimizer, num_epochs=25,␣
 ↪weights_name='weight_save', is_inception=False):
    before = time.time()

    val_acc_history = []
    loss_acc_history = []

    best_model_wts = copy.deepcopy(model.state_dict())
    best_acc = 0.0

    for epoch in range(num_epochs):
        epoch_start = time.time()

        print(f"Epoch {epoch}/{num_epochs - 1}")
        print("-"*10)

        for phase in ["train", "val"]:
            if phase == "train":
                model.train()
            else:
                model.eval()

            running_loss = 0.0
            running_corrects = 0

            for imgs, labels in dataloader[phase]:
```

```
                imgs, labels = imgs.to(device), labels.to(device)

                optimizer.zero_grad()

                with torch.set_grad_enabled(phase == "train"):
                    if is_inception and phase == "train":
                        outputs, aux1, aux2 = model(imgs, train=True)
                        loss1 = criterion(outputs, labels)
                        loss2 = criterion(aux1, labels)
                        loss3 = criterion(aux2, labels)
                        loss = loss1 + 0.3 * loss2 + 0.3 * loss3
                    else:
                        outputs = model(imgs)
                        loss = criterion(outputs, labels)

                    _, preds = torch.max(outputs, 1) # _ - max values, and preds - indices -> classes

                    if phase == "train":
                        loss.backward()
                        optimizer.step()

                running_loss += loss.item() * imgs.size(0)
                running_corrects += torch.sum(preds == labels.data)

            epoch_loss = running_loss / len(dataloader[phase].dataset)
            epoch_acc = running_corrects.double() / len(dataloader[phase].dataset)

            elapsed_epoch = time.time() - epoch_start

            print('{} Loss: {:.4f} Acc: {:.4f}'.format(phase, epoch_loss, epoch_acc))
            print("Epoch time taken: ", elapsed_epoch)

            if phase == 'val' and epoch_acc > best_acc:
                best_acc = epoch_acc
                best_model_wts = copy.deepcopy(model.state_dict())
                torch.save(model.state_dict(), weights_name + '.pth')

            if phase == 'val':
                val_acc_history.append(epoch_acc.item())

            if phase == 'train':
                loss_acc_history.append(epoch_loss)

        print()
```

```python
    time_elapsed = time.time() - before
    print('Training complete in {:.0f}m {:.0f}s'.format(time_elapsed // 60, time_elapsed % 60))
    print('Best val Acc: {:4f}'.format(best_acc))
    model.load_state_dict(best_model_wts)
    return model, val_acc_history, loss_acc_history

def test_model(model, dataloader, criterion, optimizer, num_epochs=25, weights_name='weight_save', is_inception=False):
    before = time.time()

    val_acc_history = []
    loss_acc_history = []

    best_model_wts = copy.deepcopy(model.state_dict())
    best_acc = 0.0

    for epoch in range(num_epochs):
        epoch_start = time.time()

        print(f"Epoch {epoch}/{num_epochs - 1}")
        print("-"*10)


        model.eval()

            running_loss = 0.0
            running_corrects = 0

            for imgs, labels in dataloader[phase]:
                imgs, labels = imgs.to(device), labels.to(device)

                optimizer.zero_grad()

                with torch.set_grad_enabled(phase == "train"):
                    if is_inception and phase == "train":
                        outputs, aux1, aux2 = model(imgs, train=True)
                        loss1 = criterion(outputs, labels)
                        loss2 = criterion(aux1, labels)
                        loss3 = criterion(aux2, labels)
                        loss = loss1 + 0.3 * loss2 + 0.3 * loss3
                    else:
                        outputs = model(imgs)
                        loss = criterion(outputs, labels)
```

```
                    _, preds = torch.max(outputs, 1) # _ - max values, and␣
↪preds - indices -> classes

                    if phase == "train":
                        loss.backward()
                        optimizer.step()

                running_loss += loss.item() * imgs.size(0)
                running_corrects += torch.sum(preds == labels.data)

            epoch_loss = running_loss / len(dataloader[phase].dataset)
            epoch_acc = running_corrects.double() / len(dataloader[phase].
↪dataset)

            elapsed_epoch = time.time() - epoch_start

            print('{} Loss: {:.4f} Acc: {:.4f}'.format(phase, epoch_loss,␣
↪epoch_acc))
            print("Epoch time taken: ", elapsed_epoch)

            if phase == 'val' and epoch_acc > best_acc:
                best_acc = epoch_acc
                best_model_wts = copy.deepcopy(model.state_dict())
                torch.save(model.state_dict(), weights_name + '.pth')

            if phase == 'val':
                val_acc_history.append(epoch_acc.item())

            if phase == 'train':
                loss_acc_history.append(epoch_loss)

        print()

    time_elapsed = time.time() - before
    print('Training complete in {:.0f}m {:.0f}s'.format(time_elapsed // 60,␣
↪time_elapsed % 60))
    print('Best val Acc: {:4f}'.format(best_acc))
    model.load_state_dict(best_model_wts)
    return model, val_acc_history, loss_acc_history
```

[ ]:
```
dataloaders = { 'train': train_dataloader, 'val': val_dataloader }

best_model, val_acc_history, loss_acc_history = train_model(alexnet,␣
↪dataloaders, criterion, optimizer, 10, "alex_module_lr_0.001_best")
```

```
Epoch 0/9
----------
```

```
train Loss: 2.0135 Acc: 0.2407
Epoch time taken:  45.38444709777832
val Loss: 1.5777 Acc: 0.4127
Epoch time taken:  56.587465047836304

Epoch 1/9
----------
train Loss: 1.5045 Acc: 0.4480
Epoch time taken:  46.45918655395508
val Loss: 1.3588 Acc: 0.5123
Epoch time taken:  58.114521741867065

Epoch 2/9
----------
train Loss: 1.2674 Acc: 0.5418
Epoch time taken:  46.46684455871582
val Loss: 1.1886 Acc: 0.5846
Epoch time taken:  58.427972078323364

Epoch 3/9
----------
train Loss: 1.0672 Acc: 0.6230
Epoch time taken:  45.707512855529785
val Loss: 0.9426 Acc: 0.6617
Epoch time taken:  56.95591640472412

Epoch 4/9
----------
train Loss: 0.8980 Acc: 0.6823
Epoch time taken:  45.81937289237976
val Loss: 0.8689 Acc: 0.6925
Epoch time taken:  57.10862588882446

Epoch 5/9
----------
train Loss: 0.7840 Acc: 0.7263
Epoch time taken:  45.236807107925415
val Loss: 0.7904 Acc: 0.7244
Epoch time taken:  57.10383439064026

Epoch 6/9
----------
train Loss: 0.6890 Acc: 0.7583
Epoch time taken:  46.259265422821045
val Loss: 0.7091 Acc: 0.7535
Epoch time taken:  57.395973682403564

Epoch 7/9
```

```
----------
train Loss: 0.6079 Acc: 0.7903
Epoch time taken:  46.08885908126831
val Loss: 0.6299 Acc: 0.7803
Epoch time taken:  58.04206895828247

Epoch 8/9
----------
train Loss: 0.5359 Acc: 0.8129
Epoch time taken:  46.20888042449951
val Loss: 0.6449 Acc: 0.7825
Epoch time taken:  57.510289907455444

Epoch 9/9
----------
train Loss: 0.4687 Acc: 0.8361
Epoch time taken:  46.156208515167236
val Loss: 0.6552 Acc: 0.7823
Epoch time taken:  57.26388740539551

Training complete in 10m 1s
Best val Acc: 0.782500
```

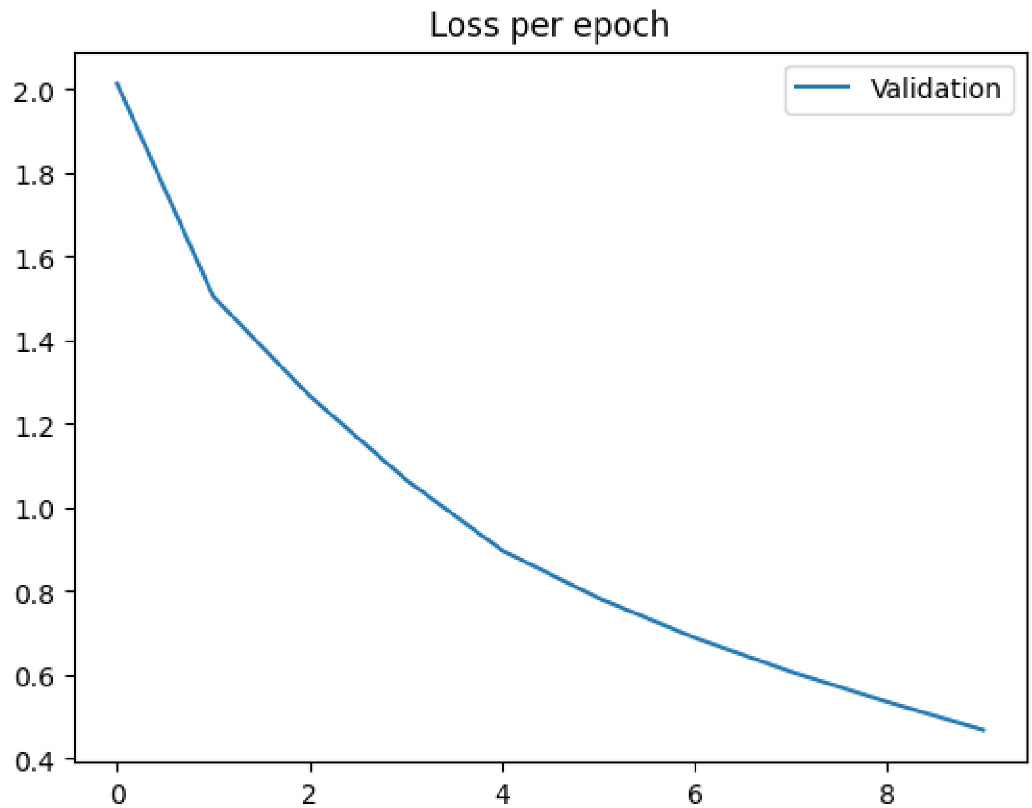
[ ]:

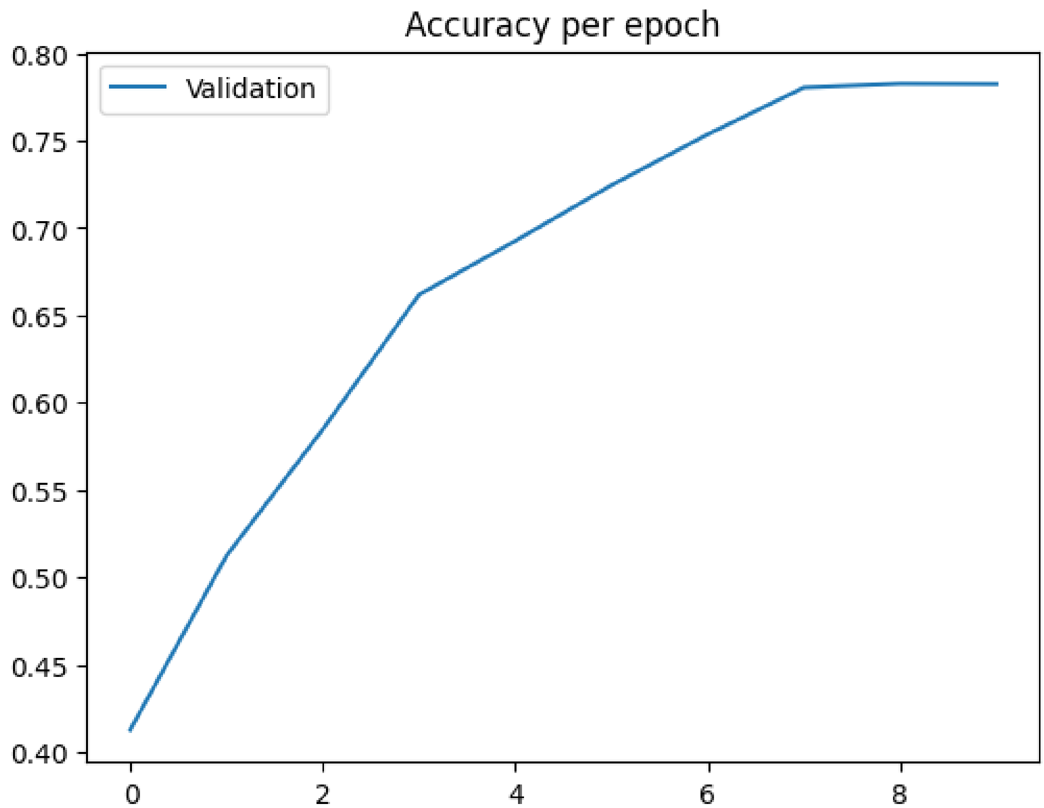
```
import matplotlib.pyplot as plt

def plot_data(val_acc_history, loss_acc_history):
    plt.plot(loss_acc_history, label = 'Validation')
    plt.title('Loss per epoch')
    plt.legend()
    plt.show()
    plt.plot(val_acc_history, label = 'Validation')
    plt.title('Accuracy per epoch')
    plt.legend()
    plt.show()
```

[ ]:

```
plot_data(val_acc_history, loss_acc_history)
```


Loss per epoch
Validation
2.0
1.8
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0
2
4
6
8



[ ]:
```

```

[ ]:
```
from torchsummary import summary

summary(alexnet, input_size=(3, 224, 224))
```

```
---------------------------------------------------------------------------
ModuleNotFoundError                       Traceback (most recent call last)
Cell In[10], line 1
----> 1 from torchsummary import summary
      3 summary(alexnet, input_size=(3, 224, 224))

ModuleNotFoundError: No module named 'torchsummary'
```

0.0.2 GoogleNet

[ ]:
```
class Inception(nn.Module):
    def __init__(self, in_planes, n1x1, n3x3red, n3x3, n5x5red, n5x5,␣
 ↪pool_planes):
```

```
        # red -> reduce
        super(Inception, self).__init__()

        self.in_planes      = in_planes
        self.n1x1           = n1x1
        self.n3x3red        = n3x3red
        self.n3x3           = n3x3
        self.n5x5red        = n5x5red
        self.n5x5           = n5x5
        self.pool_planes    = pool_planes

        # 1x1 conv branch
        self.b1 = nn.Sequential(
            nn.Conv2d(in_planes, n1x1, kernel_size=1),
            nn.BatchNorm2d(n1x1),
            nn.ReLU(inplace=True),
        )

        # 1x1 conv -> 3x3 conv branch
        self.b2 = nn.Sequential(
            nn.Conv2d(in_planes, n3x3red, kernel_size=1),
            nn.BatchNorm2d(n3x3red),
            nn.ReLU(inplace=True),

            nn.Conv2d(n3x3red, n3x3, kernel_size=3, padding=1),
            nn.BatchNorm2d(n3x3),
            nn.ReLU(inplace=True),
        )

        # 1x1 conv -> 5x5 conv branch
        # Inceptionv1, it uses 5x5 conv (keeping same logic as per assignment␣
↪base)
        # but if we want to replicate the paper carefully -> we would need to␣
↪replace it
        # omitting and using two 3x3 conv (which was formulated in Inceptionv2␣
↪paper)
        self.b3 = nn.Sequential(
            nn.Conv2d(in_planes, n5x5red, kernel_size=1),
            nn.BatchNorm2d(n5x5red),
            nn.ReLU(inplace=True),

            nn.Conv2d(n5x5red, n5x5, kernel_size=3, padding=1),
            nn.BatchNorm2d(n5x5),
            nn.ReLU(inplace=True),

            nn.Conv2d(n5x5, n5x5, kernel_size=3, padding=1),
            nn.BatchNorm2d(n5x5),
```

```
            nn.ReLU(inplace=True),
        )

        # 3x3 pool -> 1x1 conv branch
        self.b4 = nn.Sequential(
            nn.MaxPool2d(kernel_size=3, stride=1, padding=1),
            nn.Conv2d(in_planes, pool_planes, kernel_size=1),
            nn.BatchNorm2d(pool_planes),
            nn.ReLU(inplace=True),
        )

    def forward(self, x):
        y1 = self.b1(x)
        y2 = self.b2(x)
        y3 = self.b3(x)
        y4 = self.b4(x)

        return torch.cat([y1, y2, y3, y4], dim=1)
```

[ ]:

```
class GoogleNet(nn.Module):
    def __init__(self, n_classes: int = 1000):
        super(GoogleNet, self).__init__()

        self.pre_layers = nn.Sequential(
            nn.Conv2d(3, 64, kernel_size=7, stride=2, padding=3),
            nn.BatchNorm2d(64),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=3, stride=2, padding=1),

            nn.Conv2d(64, 192, kernel_size=3, padding=1),
            nn.BatchNorm2d(192),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=3, stride=2, padding=1),
        )

        self.a3 = Inception(192,  64,  96, 128, 16, 32, 32)
        self.b3 = Inception(256, 128, 128, 192, 32, 96, 64)

        self.maxpool = nn.MaxPool2d(kernel_size=3, stride=2, padding=1)

        self.a4 = Inception(480, 192,  96, 208, 16,  48,  64)

        # auxilary classifier 1
        self.aux1_avgpool = nn.AvgPool2d(kernel_size=5, stride=3)
        self.aux1_conv = nn.Conv2d(512, 128, kernel_size=1, stride=1)
        self.aux1_bn = nn.BatchNorm2d(128)
        self.aux1_fc1 = nn.Linear(4 * 4 * 128, 1024)
```

```
        self.aux1_dropout = nn.Dropout(p=0.7) # 70% ratio
        self.aux1_fc2 = nn.Linear(1024, n_classes)

        self.b4 = Inception(512, 160, 112, 224, 24,  64,  64)
        self.c4 = Inception(512, 128, 128, 256, 24,  64,  64)
        self.d4 = Inception(512, 112, 144, 288, 32,  64,  64)

        # auxilary classifier 2
        self.aux2_avgpool = nn.AvgPool2d(kernel_size=5, stride=3)
        self.aux2_conv = nn.Conv2d(528, 128, kernel_size=1, stride=1)
        self.aux2_bn = nn.BatchNorm2d(128)
        self.aux2_fc1 = nn.Linear(4 * 4 * 128, 1024)
        self.aux2_dropout = nn.Dropout(p=0.7) # 70% ratio
        self.aux2_fc2 = nn.Linear(1024, n_classes)

        self.e4 = Inception(528, 256, 160, 320, 32, 128, 128)

        self.a5 = Inception(832, 256, 160, 320, 32, 128, 128)
        self.b5 = Inception(832, 384, 192, 384, 48, 128, 128)

        self.avgpool = nn.AvgPool2d(kernel_size=7, stride=1)
        self.linear  = nn.Linear(1024, n_classes)


    def forward(self, x, train=False):
        aux1, aux2 = 0, 0

        out = self.pre_layers(x)
        out = self.a3(out)
        out = self.b3(out)
        out = self.maxpool(out)
        out = self.a4(out)

        if train:
            aux1 = self.aux1_avgpool(out)
            aux1 = F.relu(self.aux1_bn(self.aux1_conv(aux1)))
            aux1 = torch.flatten(aux1, 1)
            aux1 = self.aux1_dropout(F.relu(self.aux1_fc1(aux1)))
            aux1 = self.aux1_fc2(aux1)

        out = self.b4(out)
        out = self.c4(out)
        out = self.d4(out)

        if train:
            aux2 = self.aux2_avgpool(out)
            aux2 = F.relu(self.aux2_bn(self.aux2_conv(aux2)))
```

```
            aux2 = torch.flatten(aux2, 1)
            aux2 = self.aux2_dropout(F.relu(self.aux2_fc1(aux2)))
            aux2 = self.aux2_fc2(aux2)

        out = self.e4(out)
        out = self.maxpool(out)
        out = self.a5(out)
        out = self.b5(out)
        out = self.avgpool(out)
        out = torch.flatten(out, 1)
        out = self.linear(out)

        if train:
            return out, aux1, aux2

        return out
```

[ ]:
```
googlenet = GoogleNet(n_classes=10).to(device)
criterion2 = nn.CrossEntropyLoss()
optimizer2 = torch.optim.SGD(googlenet.parameters(), momentum=0.9, lr=0.001)
```

[ ]:
```
dataloaders = { 'train': train_dataloader, 'val': val_dataloader }

best_model2, val_acc_history2, loss_acc_history2 = train_model(googlenet,␣
 ↪dataloaders, criterion2, optimizer2, 15, "googlenet_module_lr_0.001_best",␣
 ↪is_inception=True)
```

```
Epoch 0/14
----------
train Loss: 2.4234 Acc: 0.4574
Epoch time taken:  172.69162821769714
val Loss: 1.0698 Acc: 0.6113
Epoch time taken:  183.46275758743286

Epoch 1/14
----------
train Loss: 1.6325 Acc: 0.6568
Epoch time taken:  183.61280632019043
val Loss: 0.7921 Acc: 0.7247
Epoch time taken:  195.3561086654663

Epoch 2/14
----------
train Loss: 1.2436 Acc: 0.7496
Epoch time taken:  182.33090734481812
val Loss: 0.6466 Acc: 0.7769
Epoch time taken:  193.7907247543335
```

```
Epoch 3/14
----------
train Loss: 1.0081 Acc: 0.8036
Epoch time taken:  184.68632078170776
val Loss: 0.6049 Acc: 0.7924
Epoch time taken:  195.99578499794006

Epoch 4/14
----------
train Loss: 0.8500 Acc: 0.8391
Epoch time taken:  178.20713710784912
val Loss: 0.5122 Acc: 0.8266
Epoch time taken:  188.99292850494385

Epoch 5/14
----------
train Loss: 0.7223 Acc: 0.8676
Epoch time taken:  181.87393379211426
val Loss: 0.5775 Acc: 0.8083
Epoch time taken:  193.4015302658081

Epoch 6/14
----------
train Loss: 0.6113 Acc: 0.8913
Epoch time taken:  181.41607284545898
val Loss: 0.5318 Acc: 0.8263
Epoch time taken:  192.69333863258362

Epoch 7/14
----------
train Loss: 0.5086 Acc: 0.9169
Epoch time taken:  181.01730632781982
val Loss: 0.5040 Acc: 0.8378
Epoch time taken:  191.86808967590332

Epoch 8/14
----------
train Loss: 0.4337 Acc: 0.9331
Epoch time taken:  190.95056748390198
val Loss: 0.5289 Acc: 0.8374
Epoch time taken:  202.66059041023254

Epoch 9/14
----------
train Loss: 0.3637 Acc: 0.9476
Epoch time taken:  178.64172840118408
val Loss: 0.5135 Acc: 0.8453
Epoch time taken:  190.4009120464325
```

```
Epoch 10/14
----------
train Loss: 0.3086 Acc: 0.9594
Epoch time taken:  184.20845460891724
val Loss: 0.5255 Acc: 0.8471
Epoch time taken:  195.55805325508118

Epoch 11/14
----------
train Loss: 0.2741 Acc: 0.9645
Epoch time taken:  184.33273363113403
val Loss: 0.5261 Acc: 0.8510
Epoch time taken:  195.67002081871033

Epoch 12/14
----------
train Loss: 0.2362 Acc: 0.9710
Epoch time taken:  183.36810159683228
val Loss: 0.5652 Acc: 0.8513
Epoch time taken:  194.72251725196838

Epoch 13/14
----------
train Loss: 0.2071 Acc: 0.9766
Epoch time taken:  181.2397439479828
val Loss: 0.5110 Acc: 0.8615
Epoch time taken:  192.87545657157898

Epoch 14/14
----------
train Loss: 0.1720 Acc: 0.9822
Epoch time taken:  178.27705192565918
val Loss: 0.5692 Acc: 0.8538
Epoch time taken:  189.90931248664856

Training complete in 48m 21s
Best val Acc: 0.861500
```

[ ]:
```
!python main.py
```

```
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Epoch 0/9
----------
train Loss: 2.2641 Acc: 0.1323
Epoch time taken:  51.62145519256592
val Loss: 2.0536 Acc: 0.2422
```

```
Epoch time taken:  62.22923135757446

Epoch 1/9
----------
train Loss: 1.8374 Acc: 0.3173
Epoch time taken:  51.751463651657104
val Loss: 1.5916 Acc: 0.4099
Epoch time taken:  61.78646755218506

Epoch 2/9
----------
train Loss: 1.4905 Acc: 0.4525
Epoch time taken:  51.90189504623413
val Loss: 1.3701 Acc: 0.5012
Epoch time taken:  62.61916399002075

Epoch 3/9
----------
train Loss: 1.3018 Acc: 0.5260
Epoch time taken:  51.57613921165466
val Loss: 1.2488 Acc: 0.5496
Epoch time taken:  62.414655923843384

Epoch 4/9
----------
train Loss: 1.1465 Acc: 0.5909
Epoch time taken:  51.91716265678406
val Loss: 1.0747 Acc: 0.6149
Epoch time taken:  62.40043020248413

Epoch 5/9
----------
train Loss: 0.9963 Acc: 0.6480
Epoch time taken:  51.65522599220276
val Loss: 0.8993 Acc: 0.6814
Epoch time taken:  62.81190323829651

Epoch 6/9
----------
train Loss: 0.8701 Acc: 0.6946
Epoch time taken:  52.54066777229309
val Loss: 0.8183 Acc: 0.7139
Epoch time taken:  63.20818471908569

Epoch 7/9
----------
train Loss: 0.7721 Acc: 0.7322
Epoch time taken:  51.60240316390991
```

```
val Loss: 0.7652 Acc: 0.7293
Epoch time taken:  62.076316356658936

Epoch 8/9
----------
train Loss: 0.6963 Acc: 0.7557
Epoch time taken:  51.09913969039917
val Loss: 0.7591 Acc: 0.7346
Epoch time taken:  61.33423590660095

Epoch 9/9
----------
train Loss: 0.6226 Acc: 0.7835
Epoch time taken:  51.20476937294006
val Loss: 0.7160 Acc: 0.7526
Epoch time taken:  61.71939969062805

Training complete in 10m 58s
Best val Acc: 0.752600
Epoch 0/14
----------
train Loss: 2.4002 Acc: 0.4646
Epoch time taken:  168.51746582984924
val Loss: 1.1035 Acc: 0.5970
Epoch time taken:  179.94041776657104

Epoch 1/14
----------
train Loss: 1.6191 Acc: 0.6599
Epoch time taken:  181.56514859199524
val Loss: 0.7557 Acc: 0.7368
Epoch time taken:  192.90568470954895

Epoch 2/14
----------
train Loss: 1.2408 Acc: 0.7515
Epoch time taken:  179.04786229133606
val Loss: 0.6785 Acc: 0.7627
Epoch time taken:  190.50202417373657

Epoch 3/14
----------
train Loss: 1.0238 Acc: 0.8006
Epoch time taken:  180.41774654388428
val Loss: 0.6075 Acc: 0.7872
Epoch time taken:  191.56561660766602

Epoch 4/14
```

```
----------
train Loss: 0.8616 Acc: 0.8372
Epoch time taken:  181.3175983428955
val Loss: 0.5307 Acc: 0.8205
Epoch time taken:  192.75254821777344

Epoch 5/14
----------
train Loss: 0.7280 Acc: 0.8679
Epoch time taken:  180.54843950271606
val Loss: 0.4816 Acc: 0.8355
Epoch time taken:  192.2288851737976

Epoch 6/14
----------
train Loss: 0.6160 Acc: 0.8934
Epoch time taken:  186.26038765907288
val Loss: 0.4445 Acc: 0.8528
Epoch time taken:  199.24184322357178

Epoch 7/14
----------
train Loss: 0.5221 Acc: 0.9136
Epoch time taken:  181.910804271698
val Loss: 0.5417 Acc: 0.8320
Epoch time taken:  192.69080519676208

Epoch 8/14
----------
train Loss: 0.4456 Acc: 0.9289
Epoch time taken:  181.51540064811707
val Loss: 0.4915 Acc: 0.8438
Epoch time taken:  193.0899212360382

Epoch 9/14
----------
train Loss: 0.3752 Acc: 0.9451
Epoch time taken:  180.71139454841614
val Loss: 0.4835 Acc: 0.8515
Epoch time taken:  192.32903361320496

Epoch 10/14
----------
train Loss: 0.3161 Acc: 0.9579
Epoch time taken:  179.48733019828796
val Loss: 0.5588 Acc: 0.8413
Epoch time taken:  190.06542658805847
```

```
Epoch 11/14
----------
train Loss: 0.2695 Acc: 0.9675
Epoch time taken:  182.03052949905396
val Loss: 0.5710 Acc: 0.8392
Epoch time taken:  193.60909152030945

Epoch 12/14
----------
train Loss: 0.2315 Acc: 0.9736
Epoch time taken:  189.5867133140564
val Loss: 0.4933 Acc: 0.8655
Epoch time taken:  200.27890300750732

Epoch 13/14
----------
train Loss: 0.2094 Acc: 0.9763
Epoch time taken:  181.96090602874756
val Loss: 0.4891 Acc: 0.8655
Epoch time taken:  193.4967324733734

Epoch 14/14
----------
train Loss: 0.1830 Acc: 0.9807
Epoch time taken:  186.15909695625305
val Loss: 0.5137 Acc: 0.8614
Epoch time taken:  197.42910432815552

Training complete in 48m 16s
Best val Acc: 0.865500
```

[ ]:

```python
from architecture.custom_layers import LocalResponseNormalize

class AlexNet(nn.Module):
    def __init__(self, n_classes: int = 10):
        super(AlexNet, self).__init__()

        self.feature_extractors = nn.Sequential(
            nn.Conv2d(3, 96, kernel_size=11, stride=4, padding=2),
            nn.ReLU(inplace=True),
            LocalResponseNormalize(size=5, alpha=1e-4, beta=0.75, k=2),
            nn.MaxPool2d(kernel_size=3, stride=2),

            nn.Conv2d(96, 256, kernel_size=5, padding=2),
            nn.ReLU(inplace=True),
            LocalResponseNormalize(size=5, alpha=1e-4, beta=0.75, k=2),
            nn.MaxPool2d(kernel_size=3, stride=2),
```

```
            nn.Conv2d(256, 384, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),

            nn.Conv2d(384, 384, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),

            nn.Conv2d(384, 256, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=3, stride=2),
        )

        self.adaptive_pool = nn.AdaptiveAvgPool2d((6, 6))

        self.classification = nn.Sequential(
            nn.Flatten(),
            nn.Dropout(),
            nn.Linear(256 * 6 * 6, 4096),
            nn.ReLU(inplace=True),
            nn.Dropout(),
            nn.Linear(4096, 4096),
            nn.ReLU(inplace=True),
            nn.Linear(4096, n_classes)
        )

    def forward(self, x):
        x = self.feature_extractors(x)
        x = self.adaptive_pool(x)
        x = self.classification(x)

        return x
```

[ ]:
```
alx = AlexNet().to(device)

params = torch.load('main_alex_module_lr_0.001_best.pth')

alx.load_state_dict(params)

test_model(alx, test_dataloader, device)

# from summary import summary_string
# model_summary, _ = summary_string(alx, input_size=(3, 224, 224))

# with open('alexnet_summary.txt', 'w') as f:
#     f.write(str(model_summary))
```

```
/tmp/ipykernel_994233/2959433572.py:3: FutureWarning: You are using `torch.load`
with `weights_only=False` (the current default value), which uses the default
```

```
pickle module implicitly. It is possible to construct malicious pickle data
which will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-models for
more details). In a future release, the default value for `weights_only` will be
flipped to `True`. This limits the functions that could be executed during
unpickling. Arbitrary objects will no longer be allowed to be loaded via this
mode unless they are explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control of the
loaded file. Please open an issue on GitHub for any issues related to this
experimental feature.
  params = torch.load('main_alex_module_lr_0.001_best.pth')
```

```
Accuracy on the CIFAR-10 test set: 53.60%
```

[ ]:
```python
googlenet = GoogleNet(n_classes=10).to(device)

params = torch.load('main_googlenet_module_lr_0.001_best.pth')

googlenet.load_state_dict(params)

test_model(googlenet, test_dataloader, device)
```

```
/tmp/ipykernel_994233/1979083515.py:3: FutureWarning: You are using `torch.load`
with `weights_only=False` (the current default value), which uses the default
pickle module implicitly. It is possible to construct malicious pickle data
which will execute arbitrary code during unpickling (See
https://github.com/pytorch/pytorch/blob/main/SECURITY.md#untrusted-models for
more details). In a future release, the default value for `weights_only` will be
flipped to `True`. This limits the functions that could be executed during
unpickling. Arbitrary objects will no longer be allowed to be loaded via this
mode unless they are explicitly allowlisted by the user via
`torch.serialization.add_safe_globals`. We recommend you start setting
`weights_only=True` for any use case where you don't have full control of the
loaded file. Please open an issue on GitHub for any issues related to this
experimental feature.
  params = torch.load('main_googlenet_module_lr_0.001_best.pth')
```

```
Accuracy on the CIFAR-10 test set: 71.19%
```

[ ]:
```python
def test_model(model, dataloader, device):
    model.eval()
    correct = 0
    total = 0

    with torch.no_grad():
        for images, labels in dataloader:
            images, labels = images.to(device), labels.to(device)
            outputs = model(images)
```

```
            _, predicted = torch.max(outputs, 1)
            total += labels.size(0)
            correct += (predicted == labels).sum().item()

    accuracy = 100 * correct / total
    print(f"Accuracy on the CIFAR-10 test set: {accuracy:.2f}%")

# classification_models = torchvision.models.list_models(module=torchvision.
↪models)
```

[ ]:
```
from torchvision.models import alexnet, googlenet
import numpy as np

device = torch.device("cuda:0")

model_alexnet = alexnet(pretrained=True)
model_alexnet.classifier[6] = nn.Linear(4096, 10)

criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam([
    {'params': model_alexnet.features.parameters(), 'lr': 0.0001},
    {'params': model_alexnet.classifier.parameters(), 'lr': 0.001}
])

model_alexnet = model_alexnet.to(device)

epochs = 3
print("TRAIN")
for epoch in range(epochs):
    model_alexnet.train()
    running_loss = 0.0
    for images, labels in train_dataloader:
        images, labels = images.to(device), labels.to(device)

        optimizer.zero_grad()

        outputs = model_alexnet(images)
        loss = criterion(outputs, labels)

        loss.backward()
        optimizer.step()

        running_loss += loss.item()

    print(f"Epoch [{epoch+1}/{epochs}], Loss: {running_loss/
↪len(train_dataloader):.4f}")
```

```
test_model(model_alexnet, test_dataloader, device)

# gnet = googlenet(pretrained=True).to(device)
# gnet.fc = nn.Linear(1024, 10)

# test_model(gnet, test_dataloader, device)
```

```
TRAIN
Epoch [1/3], Loss: 0.9054
Epoch [2/3], Loss: 0.6230
Epoch [3/3], Loss: 0.4961
Accuracy on the CIFAR-10 test set: 67.80%
```

[ ]:
```
model_googlenet = googlenet(pretrained=True, aux_logits=True)

model_googlenet.fc = nn.Linear(1024, 10)

if model_googlenet.aux_logits:
    model_googlenet.aux1.fc2 = nn.Linear(1024, 10)
    model_googlenet.aux2.fc2 = nn.Linear(1024, 10)
model_googlenet = model_googlenet.to(device)

criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam([
    {'params': model_googlenet.parameters(), 'lr': 0.001},
])

epochs = 3
for epoch in range(epochs):
    model_googlenet.train()
    running_loss = 0.0
    for images, labels in train_dataloader:
        images, labels = images.to(device), labels.to(device)

        optimizer.zero_grad()

        outputs, aux1, aux2 = model_googlenet(images)
        loss_main = criterion(outputs, labels)
        loss_aux1 = criterion(aux1, labels)
        loss_aux2 = criterion(aux2, labels)

        loss = loss_main + 0.3 * (loss_aux1 + loss_aux2)

        loss.backward()
        optimizer.step()

        running_loss += loss.item()
```

```
    print(f"Epoch [{epoch+1}/{epochs}], Loss: {running_loss/
 ↪len(train_dataloader):.4f}")


test_model(model_googlenet, test_dataloader, device)
```

```
Epoch [1/3], Loss: 1.4780
Epoch [2/3], Loss: 0.9664
Epoch [3/3], Loss: 0.7703
Accuracy on the CIFAR-10 test set: 74.42%
```

0.1 Exercises

1. Create these three networks. Be sure to properly define your Python classes, with one class per file and a main module that sets up your objects, runs the training process, and saves the necessary data. - done
2. Note that the AlexNet implementation here does not have the local response normalization feature described in the paper. Take a look at the PyTorch implementation of LRN and incorporate it into your AlexNet implementation as it is described in the paper. Compare your test set results with and without LRN.
3. Note that the backbone of the GoogLeNet implemented thus far does not correspond exactly to the description. Modify the architecture to
   1. Use the same backbone (input image size, convolutions, etc.) before the first Inception module
   2. Add the two side classifiers
4. Compare your GoogLeNet and AlexNet implementations on CIFAR-10. Comment on the number of parameters, speed of training, and accuracy of the two models on this dataset when trained from scratch.
5. Experiment with the pretrained GoogLeNet and AlexNet from the torchvision repository. Does it give better results on CIFAR-10 similar to what we found with AlexNet? Comment on what we can glean from the results about the capacity and generalization ability of these two models.

0.2 The report

1. I created each network in the folder architecture - to run training - python main.py

Models	Epochs	Number of Params	Training time	Accuracy (validation set)	Accuracy (test set)
AlexNet	10	58,322,314	10m 1s	0.782500	0.512
AlexNet with LRN	10	58,322,314	10m 58s	0.752600	0.536
GoogleNet with AUX CLASS	10	6,281,258	48m 16s	0.865500	0.7119

Models	Epochs	Number of Params	Training time	Accuracy (validation set)	Accuracy (test set)
AlexNet (from torchvision)	3	58,322,314	-	-	0.678
GoogleNet (from torchvision)	3	6,281,258	-	-	0.7442