Lab02 Report

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AlexNet

In this section of Lab02, AlexNet model was implemented on the CIFAR-10 dataset. It is important to note that under this lab reports, there will be in the total of 4 versions of the AlexNet and they are as follows:

1. AlexNet with Sequential API (AlexNet Sequential)
2. AlexNet with Sequential API with Local-Response Normalization (AlexNet Sequential with LRN)
3. AlexNet with nn.Module (AlexNet nn.Module)
4. AlexNet with nn.Module with Local-Response Normalization (AlexNet nn.Module with LRN)

All 4 variations of AlexNet employed the exact same optimizer as well as the loss functions which are as follows:

- criterion = nn.CrossEntropyLoss()
- optimizer = optim.SGD(model.parameters(), lr=0.001, momentum=0.9)

The number of trainable parameters of each model is as follows:

1. AlexNet Sequential has 58,322,314 trainable parameters
2. AlexNet Sequential with LRN has 58,322,314 trainable parameters
3. AlexNet nn.Module has 57,044,810 trainable parameters
4. AlexNet nn.Module with LRN has 57,044,810 trainable parameter

The models were trained for 10 epochs with the batch size of 4 and the performances at the 10th epoch of each model and the test accuracies are as follows:

- AlexNet Sequential: Train acc = 86.49%, Val acc = 76.64%, Test acc = 77.21%
- AlexNet Sequential with LRN: Train acc = 87.21%, Val acc = 79.69%, Test acc = 79.21%
- AlexNet nn.Module: Train acc = 87.29%, Val acc = 80.19% , Test acc = 80.89%
- AlexNet nn.Module with LRN: Train acc = 85.21%, Val acc = 77.78% , Test acc = 77.99%

NOTE: The comparison between the test set results can be found at the discussion section below

Libaries

In [1]:

```
import torch
import torchvision
from torchvision import datasets, models, transforms
import torch.nn as nn
import torch.optim as optim
import time
import os
import copy
import torch.nn.functional as F
from IPython.display import clear_output
```

1. Prepare Dataset

In [2]:

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

# Download CIFAR-10 and split into training, validation, and test sets

train_dataset = torchvision.datasets.CIFAR10(root='./data', train=True,
                                             download=True, transform=preproc

# Split the training set into training and validation sets randomly.
# CIFAR-10 train contains 50,000 examples, so let's split 80%/20%.

train_dataset, val_dataset = torch.utils.data.random_split(train_dataset, [40

# Download the test set. If you use data augmentation transforms for the trai
# you'll want to use a different transformer here.

test_dataset = torchvision.datasets.CIFAR10(root='./data', train=False,
                                            download=True, transform=preproce
train_dataloader = torch.utils.data.DataLoader(train_dataset, batch_size=4,
                                               shuffle=True, num_workers=2)
val_dataloader = torch.utils.data.DataLoader(val_dataset, batch_size=4,
                                             shuffle=False, num_workers=2)
test_dataloader = torch.utils.data.DataLoader(test_dataset, batch_size=4,
                                              shuffle=False, num_workers=2)
```

```
Files already downloaded and verified
Files already downloaded and verified
```

In [3]:

```
from chosen_gpu import get_freer_gpu
device = torch.device(get_freer_gpu()) if torch.cuda.is_available() else torc
print("Configured device: ", device)
```

```
Configured device:  cuda:1
```

2. Define models

2.1 AlexNet with Sequential API with no LRN

In [4]:

```
# Simple module to flatten a batched feature map tensor into a batched vector

class Flatten(nn.Module):
    def forward(self, x):
        batch_size = x.shape[0]
        return x.view(batch_size, -1)

# AlexNet-like model using the Sequential API

NUM_CLASSES = 10

alexnet_sequential = 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),

    nn.AdaptiveAvgPool2d((6, 6)),   #<<<< do anything to get 6*6 any featrue
    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, NUM_CLASSES)
)
```

2.2 AlexNet with Sequential API with LRN added

In [5]:

```
# AlexNet-like model using the Sequential API

class Flatten(nn.Module):
    def forward(self, x):
        batch_size = x.shape[0]
        return x.view(batch_size, -1)

NUM_CLASSES = 10

alexnet_sequential_LRN = nn.Sequential(

    nn.Conv2d(3, 96, kernel_size=11, stride=4, padding=2),
    nn.ReLU(inplace=True),
    nn.LocalResponseNorm(5, alpha = 0.0001, beta = 0.75, k = 2.0),
    nn.MaxPool2d(kernel_size=3, stride=2),

    nn.Conv2d(96, 256, kernel_size=5, padding=2),
    nn.ReLU(inplace=True),
    nn.LocalResponseNorm(5, alpha = 0.0001, beta = 0.75, k = 2.0),
    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),

    nn.AdaptiveAvgPool2d((6, 6)),   #<<<< do anything to get 6*6 any featrue
    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, NUM_CLASSES)
)
```

2.3 AlexNet with nn.Module

In [6]:

```
class AlexNetModule(nn.Module):
    '''
    An AlexNet-like CNN

    Attributes
    ----------
    num_classes : int
        Number of classes in the final multinomial output layer
    features : Sequential
        The feature extraction portion of the network
    avgpool : AdaptiveAvgPool2d
        Convert the final feature layer to 6x6 feature maps by average poolin
    classifier : Sequential
        Classify the feature maps into num_classes classes
    '''
    def __init__(self, num_classes: int = 10) -> None:
        super().__init__()
        self.num_classes = num_classes
        self.features = nn.Sequential(
            nn.Conv2d(3, 64, kernel_size=11, stride=4, padding=2),
            nn.ReLU(inplace=True),
            nn.LocalResponseNorm(5, alpha = 0.0001, beta = 0.75, k = 2.0),
            nn.MaxPool2d(kernel_size=3, stride=2),
            nn.Conv2d(64, 192, kernel_size=5, padding=2),
            nn.ReLU(inplace=True),
            nn.LocalResponseNorm(5, alpha = 0.0001, beta = 0.75, k = 2.0),
            nn.MaxPool2d(kernel_size=3, stride=2),
            nn.Conv2d(192, 384, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.Conv2d(384, 256, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.Conv2d(256, 256, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=3, stride=2),
        )
        self.avgpool = nn.AdaptiveAvgPool2d((6, 6))
        self.classifier = nn.Sequential(
            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, num_classes),
        )

    def forward(self, x: torch.Tensor) -> torch.Tensor:
        x = self.features(x)
        x = self.avgpool(x)
        x = torch.flatten(x, 1)
        x = self.classifier(x)
        return x
```

2.4 AlexNet with nn.Module with LRN added

In [7]:

```
class AlexNetModule_LRN(nn.Module):
    '''
    An AlexNet-like CNN

    Attributes
    ----------
    num_classes : int
        Number of classes in the final multinomial output layer
    features : Sequential
        The feature extraction portion of the network
    avgpool : AdaptiveAvgPool2d
        Convert the final feature layer to 6x6 feature maps by average poolin
    classifier : Sequential
        Classify the feature maps into num_classes classes
    '''
    def __init__(self, num_classes: int = 10) -> None:
        super().__init__()
        self.num_classes = num_classes
        self.features = nn.Sequential(
            nn.Conv2d(3, 64, kernel_size=11, stride=4, padding=2),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=3, stride=2),
            nn.Conv2d(64, 192, kernel_size=5, padding=2),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=3, stride=2),
            nn.Conv2d(192, 384, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.Conv2d(384, 256, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.Conv2d(256, 256, kernel_size=3, padding=1),
            nn.ReLU(inplace=True),
            nn.MaxPool2d(kernel_size=3, stride=2),
        )
        self.avgpool = nn.AdaptiveAvgPool2d((6, 6))
        self.classifier = nn.Sequential(
            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, num_classes),
        )

    def forward(self, x: torch.Tensor) -> torch.Tensor:
        x = self.features(x)
        x = self.avgpool(x)
        x = torch.flatten(x, 1)
        x = self.classifier(x)
        return x
```

3. Define Train and Evaluation Functions

In [8]:

```
def train_model(model, dataloaders, criterion, optimizer, num_epochs=25, weig
    '''
    train_model function

    Train a PyTorch model for a given number of epochs.

            Parameters:
                    model: Pytorch model
```

```
                    dataloaders: dataset
                    criterion: loss function
                    optimizer: update weights function
                    num_epochs: number of epochs
                    weights_name: file name to save weights
                    is_inception: The model is inception net (Google LeNet) o

            Returns:
                    model: Best model from evaluation result
                    val_acc_history: evaluation accuracy history
                    loss_acc_history: loss value history
    '''
    since = 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()

        if (epoch+1) % 5 == 0:
            print('Epoch {}/{}'.format(epoch, num_epochs - 1))
            print('-' * 10)

        # Each epoch has a training and validation phase
        for phase in ['train', 'val']:
            if phase == 'train':
                model.train()  # Set model to training mode
            else:
                model.eval()   # Set model to evaluate mode

            running_loss = 0.0
            running_corrects = 0

            # Iterate over the train/validation dataset according to which ph

            for inputs, labels in dataloaders[phase]:

                # Inputs is one batch of input images, and labels is a corres
                # labeling each image in the batch. First, we move these tens

                inputs = inputs.to(device)
                labels = labels.to(device)

                # Zero out any parameter gradients that have previously been
                # gradients accumulate over as many backward() passes as we l
                # to be zeroed out after each optimizer step.

                optimizer.zero_grad()

                # Instruct PyTorch to track gradients only if this is the tra
                # forward propagation and optionally the backward propagation

                with torch.set_grad_enabled(phase == 'train'):
                    # The inception model is a special case during training b
                    # output used to encourage discriminative representations
                    # We need to calculate loss for both outputs. Otherwise,
                    # calculate the loss on.
                    if is_inception and phase == 'train':
                        # From https://discuss.pytorch.org/t/how-to-optimize-
                        outputs, aux_outputs = model(inputs)
                        loss1 = criterion(outputs, labels)
```

```python
                    loss2 = criterion(aux_outputs, labels)
                    loss = loss1 + 0.4 * loss2
                else:
                    outputs = model(inputs)
                    loss = criterion(outputs, labels)

                _, preds = torch.max(outputs, 1)

                # Backpropagate only if in training phase

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

            # Gather our summary statistics

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

        epoch_loss = running_loss / len(dataloaders[phase].dataset)
        epoch_acc = running_corrects.double() / len(dataloaders[phase].da
        epoch_end = time.time()

        elapsed_epoch = epoch_end - epoch_start

        if (epoch+1) % 5 == 0:
            print('{} Loss: {:.4f} Acc: {:.4f}'.format(phase, epoch_loss,
            print("Epoch time taken: ", elapsed_epoch)

        # If this is the best model on the validation set so far, deep co

        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(), f'AlexNet/{weights_name}.pth')
        if phase == 'val':
            val_acc_history.append(epoch_acc)
        if phase == 'train':
            loss_acc_history.append(epoch_loss)

#         print()

    # Output summary statistics, load the best weight set, and return results

    time_elapsed = time.time() - since
    print('Training complete in {:.0f}m {:.0f}s'.format(time_elapsed // 60, t
    print('Best val Acc: {:4f}'.format(best_acc))
    model.load_state_dict(best_model_wts)
    return model, val_acc_history, loss_acc_history
```

In [9]:

```python
def evaluate(model, iterator, criterion):

    total = 0
    correct = 0
    epoch_loss = 0
    epoch_acc = 0

    predicteds = []
    trues = []

    model.eval()

    with torch.no_grad():
```

```
        for batch, labels in iterator:

            #Move tensors to the configured device
            batch = batch.to(device)
            labels = labels.to(device)

            predictions = model(batch.float())
            loss = criterion(predictions, labels.long())

            predictions = nn.functional.softmax(predictions, dim=1)
            _, predicted = torch.max(predictions.data, 1)  #returns max value

            predicteds.append(predicted)
            trues.append(labels)
            total += labels.size(0)  #keep track of total
            correct += (predicted == labels).sum().item()  #.item() give the
            acc = 100 * (correct / total)

            epoch_loss += loss.item()
            epoch_acc += acc

    return epoch_loss / len(iterator), epoch_acc / len(iterator),predicteds,
```

In [10]:

```
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()
```

4. Train the models

4.1 Define models to train

In [11]:

```
alexnet_sequential = alexnet_sequential
alexnet_sequential_LRN = alexnet_sequential_LRN
alexnet_nn = AlexNetModule(10)
alexnet_nn_LRN = AlexNetModule_LRN(10)

models = [alexnet_sequential, alexnet_sequential_LRN, alexnet_nn, alexnet_nn_
model_names = ['AlexNet Sequential', 'AlexNet Sequential with LRN', 'AlexNet 
# criterion = criterion.to(device)
```

4.1 Loss and Optimizer Functions

In [12]:

```
criterion = nn.CrossEntropyLoss()

optimizers = []
for model in models:
    optimizer = optim.SGD(model.parameters(), lr=0.001, momentum=0.9)
    optimizers.append(optimizer)
```

4.2 Move everything to the configured device

Let's check the availability of GPU...

In [13]:

```
from chosen_gpu import get_freer_gpu
device = torch.device(get_freer_gpu()) if torch.cuda.is_available() else torc
print("Configured device: ", device)
```

```
Configured device:  cuda:3
```

In [14]:

```
for model in models:
    model = model.to(device)

criterion = criterion.to(device)
```

4.3 Count the parameters

In [15]:

```
def count_parameters(model):
    return sum(p.numel() for p in model.parameters() if p.requires_grad)

for i,model in enumerate(models):
    print(f'The model {model_names[i]} has {count_parameters(model):,} trainal
```

```
The model AlexNet Sequential has 58,322,314 trainable parameters
The model AlexNet Sequential with LRN has 58,322,314 trainable parameters
The model AlexNet nn.Module has 57,044,810 trainable parameters
The model AlexNet nn.Module with LRN has 57,044,810 trainable parameters
```

4.4 Prepare the dataloader

In [16]:

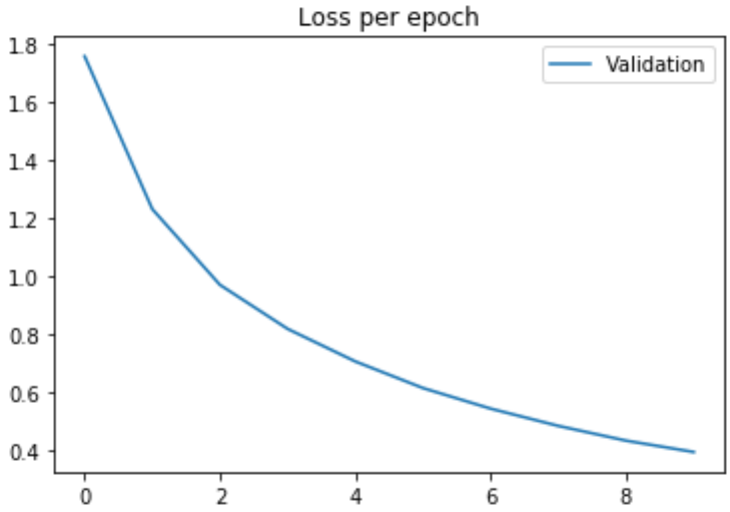
```
dataloaders = { 'train': train_dataloader, 'val': val_dataloader }
```

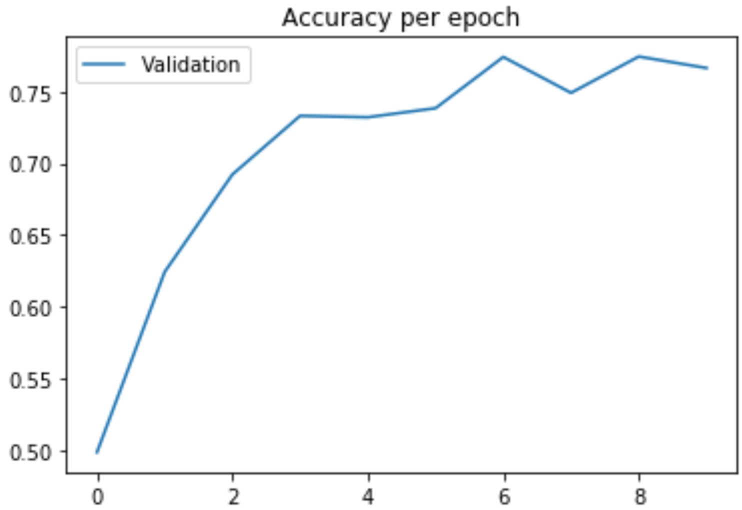
4.5 Train the models

In [17]:

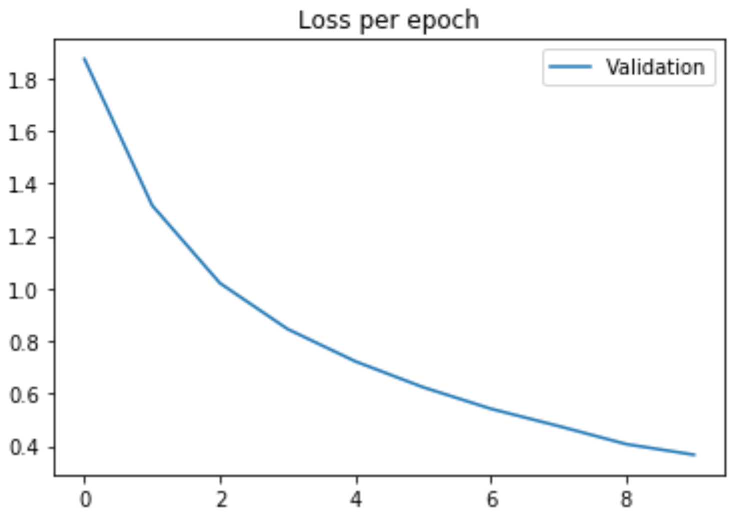
```
# num_epochs = 2
for i, model in enumerate(models):
    print(f'Training: {model_names[i]}')
    best_model, val_acc_history, loss_acc_history = train_model(model, datalo
    plot_data(val_acc_history, loss_acc_history)
    print('='*30)
```

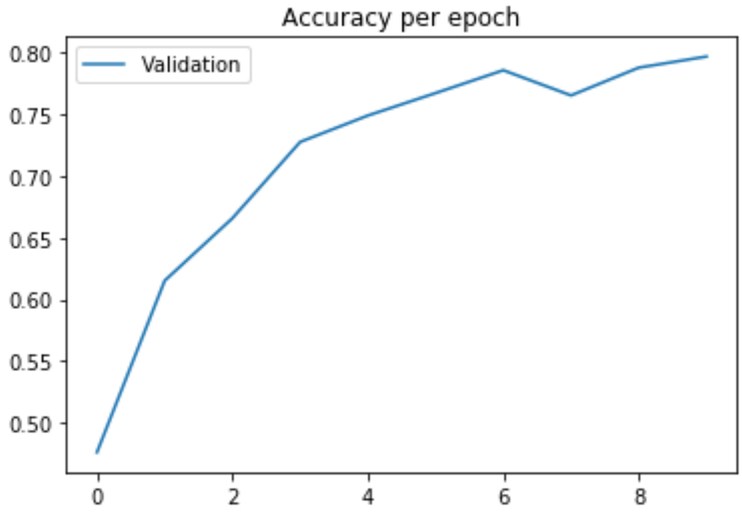
```
Training: AlexNet Sequential
Epoch 4/9
----------
train Loss: 0.7068 Acc: 0.7564
Epoch time taken:  133.41676020622253
val Loss: 0.7907 Acc: 0.7321
Epoch time taken:  147.99698448181152
Epoch 9/9
----------
train Loss: 0.3942 Acc: 0.8649
Epoch time taken:  133.97912788391113
val Loss: 0.7391 Acc: 0.7664
Epoch time taken:  148.03784203529358
Training complete in 25m 3s
Best val Acc: 0.774400
```



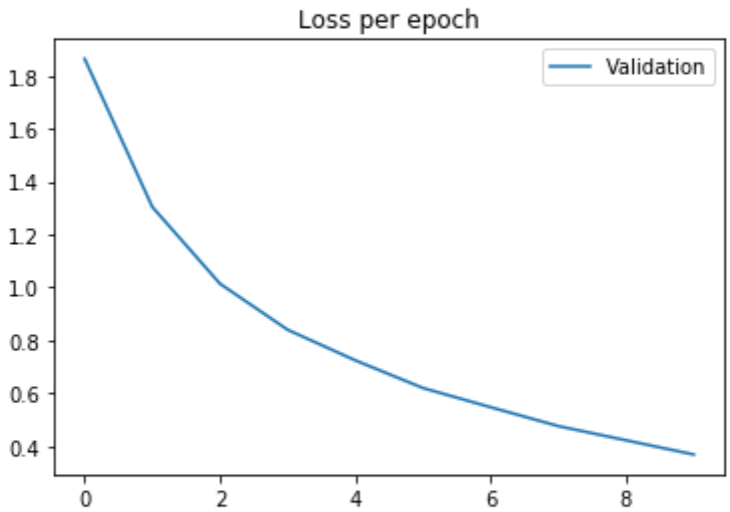


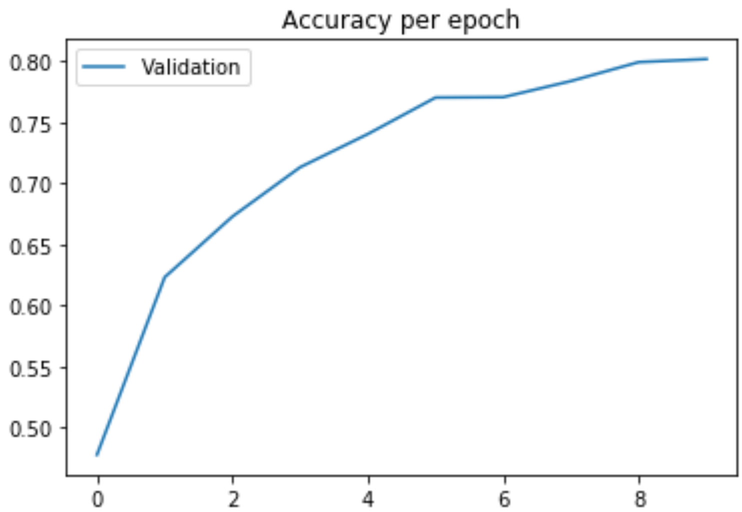

```
==============================
Training: AlexNet Sequential with LRN
Epoch 4/9
----------
train Loss: 0.7223 Acc: 0.7501
Epoch time taken:  160.48420572280884
val Loss: 0.7271 Acc: 0.7491
Epoch time taken:  175.31841039657593
Epoch 9/9
----------
train Loss: 0.3666 Acc: 0.8721
Epoch time taken:  150.73777079582214
val Loss: 0.6074 Acc: 0.7969
Epoch time taken:  165.96219730377197
Training complete in 28m 4s
Best val Acc: 0.796900
```



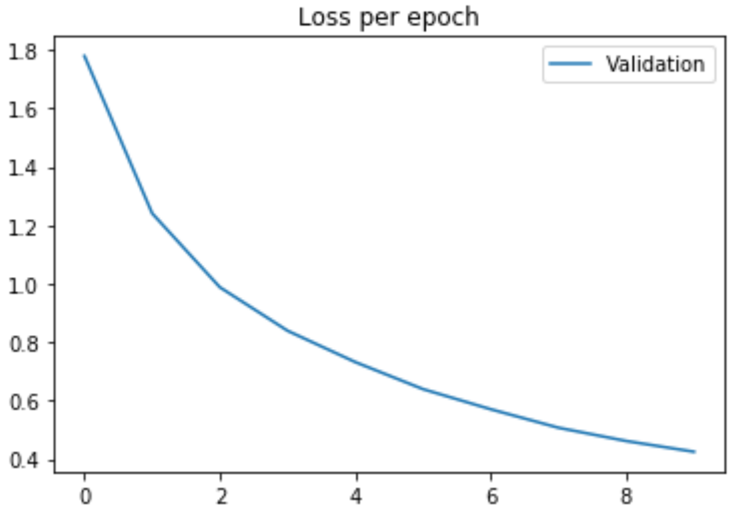


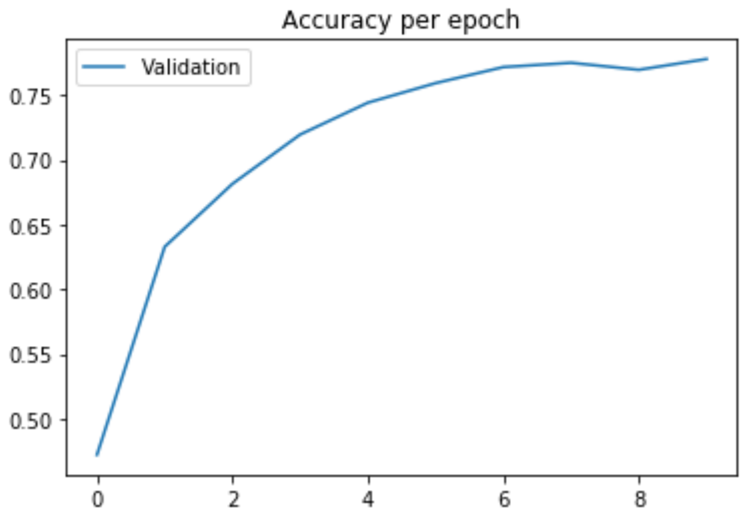

```
==============================
Training: AlexNet nn.Module
Epoch 4/9
----------
train Loss: 0.7238 Acc: 0.7490
Epoch time taken:  142.521098613739
val Loss: 0.7544 Acc: 0.7405
Epoch time taken:  158.08226442337036
Epoch 9/9
----------
train Loss: 0.3680 Acc: 0.8729
Epoch time taken:  145.70187330245972
val Loss: 0.6012 Acc: 0.8019
Epoch time taken:  161.06147384643555
Training complete in 27m 6s
Best val Acc: 0.801900
```





```
==============================
Training: AlexNet nn.Module with LRN
Epoch 4/9
----------
train Loss: 0.7319 Acc: 0.7483
Epoch time taken:  127.8905234336853
val Loss: 0.7403 Acc: 0.7440
Epoch time taken:  142.82484364509583
Epoch 9/9
----------
train Loss: 0.4253 Acc: 0.8521
Epoch time taken:  128.883371591568
val Loss: 0.6581 Acc: 0.7777
Epoch time taken:  143.47376585006714
Training complete in 24m 9s
Best val Acc: 0.777700
```






```
==============================
```

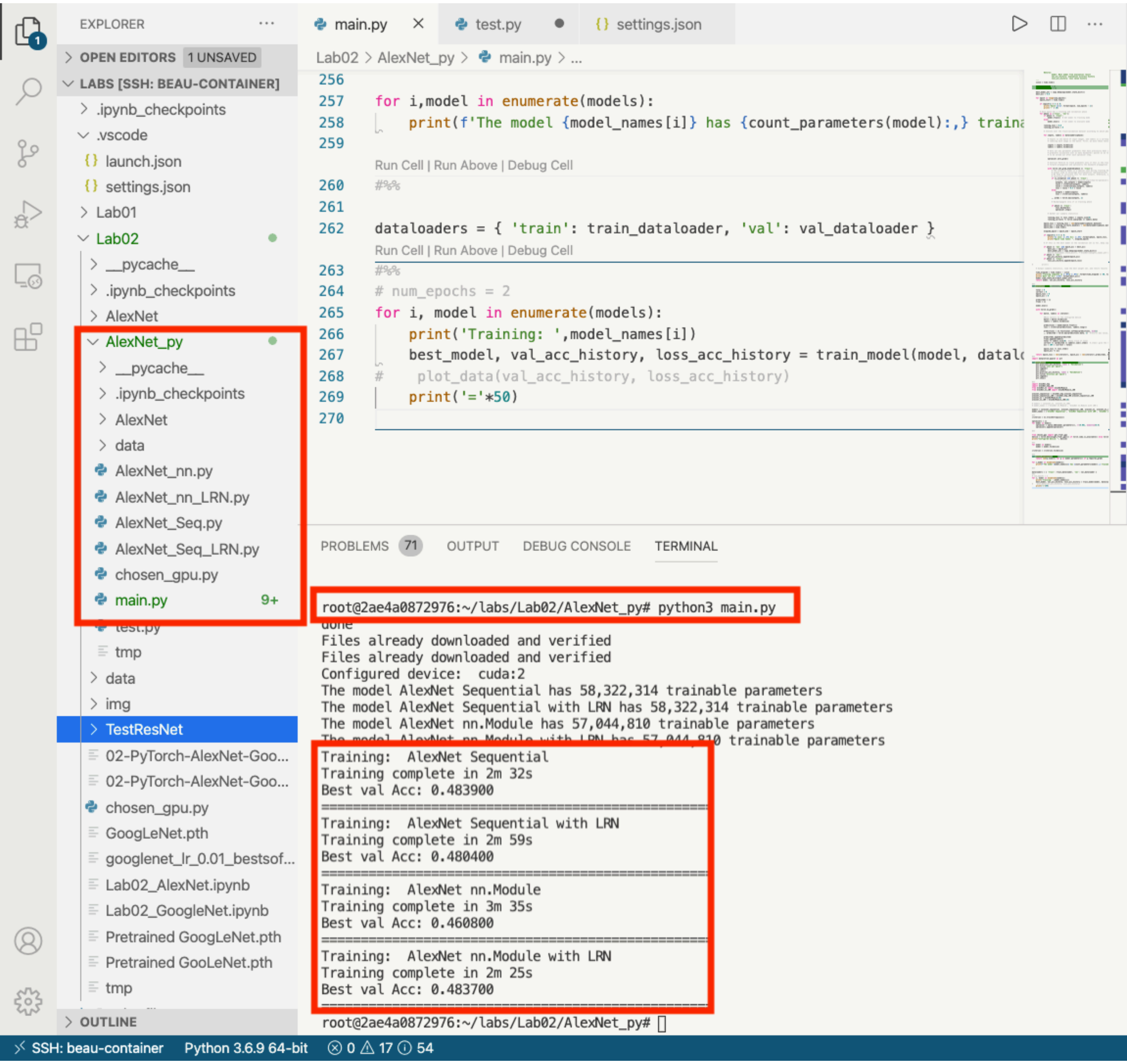
5. Results

In [19]:

```
for i, model in enumerate(models):
    print(f'Model: {model_names[i]}')
    model.load_state_dict(torch.load(f'AlexNet/{model_names[i]}.pth'))
    test_loss, test_acc, test_pred_label, test_true_label  = evaluate(model,
    print(f'Test Loss: {test_loss:.3f} | Test Acc: {test_acc:.2f}%')
```

```
Model: AlexNet Sequential
Test Loss: 0.687 | Test Acc: 77.21%
Model: AlexNet Sequential with LRN
Test Loss: 0.611 | Test Acc: 79.54%
Model: AlexNet nn.Module
Test Loss: 0.600 | Test Acc: 80.89%
```

```
Model: AlexNet nn.Module with LRN
Test Loss: 0.669 | Test Acc: 77.99%
```


EXPLORER
OPEN EDITORS 1 UNSAVED
LABS [SSH: BEAU-CONTAINER]
.ipynb_checkpoints
.vscode
launch.json
settings.json
Lab01
Lab02
__pycache__
.ipynb_checkpoints
AlexNet
AlexNet_py
__pycache__
.ipynb_checkpoints
AlexNet
data
AlexNet_nn.py
AlexNet_nn_LRN.py
AlexNet_Seq.py
AlexNet_Seq_LRN.py
chosen_gpu.py
main.py 9+
tmp
data
img
TestResNet
02-PyTorch-AlexNet-Goo...
02-PyTorch-AlexNet-Goo...
chosen_gpu.py
GoogLeNet.pth
googlenet_lr_0.01_bestsof...
Lab02_AlexNet.ipynb
Lab02_GoogleNet.ipynb
Pretrained GoogLeNet.pth
Pretrained GooLeNet.pth
tmp
OUTLINE
main.py
test.py
settings.json
Lab02 > AlexNet_py > main.py > ...
for i,model in enumerate(models):
print(f'The model {model_names[i]} has {count_parameters(model):,} traina
Run Cell | Run Above | Debug Cell
#%%
dataloaders = { 'train': train_dataloader, 'val': val_dataloader }
Run Cell | Run Above | Debug Cell
#%%
# num_epochs = 2
for i, model in enumerate(models):
print('Training: ',model_names[i])
best_model, val_acc_history, loss_acc_history = train_model(model, datalo
# plot_data(val_acc_history, loss_acc_history)
print('='*50)
PROBLEMS 71
OUTPUT
DEBUG CONSOLE
TERMINAL
root@2ae4a0872976:~/labs/Lab02/AlexNet_py# python3 main.py
Files already downloaded and verified
Files already downloaded and verified
Configured device: cuda:2
The model AlexNet Sequential has 58,322,314 trainable parameters
The model AlexNet Sequential with LRN has 58,322,314 trainable parameters
The model AlexNet nn.Module has 57,044,810 trainable parameters
Training: AlexNet Sequential
Training complete in 2m 32s
Best val Acc: 0.483900
Training: AlexNet Sequential with LRN
Training complete in 2m 59s
Best val Acc: 0.480400
Training: AlexNet nn.Module
Training complete in 3m 35s
Best val Acc: 0.460800
Training: AlexNet nn.Module with LRN
Training complete in 2m 25s
Best val Acc: 0.483700
root@2ae4a0872976:~/labs/Lab02/AlexNet_py#
SSH: beau-container
Python 3.6.9 64-bit
0 17 54

GoogLeNet

In this section of Lab02, GoogLeNet model was implemented on the CIFAR-10 dataset. With the same data set, 2 versions of GoogLeNet were employed namely,

1. GoogLeNet from scratch (GoogLeNet)
2. Pretrained GoogLeNet

Since the given architechture of GoogLeNet was not the same as what can be found on the original paper and also does not suit out problem (a 10-class classification problem), the modification of the architechture was necessary. The modification includes:

e.g.

- The number of output (from 1000 to 10 classes)
- The input image size
- The addition of a convolutional layer at pre_layers
- The padding
- Replacement of BatchNorm2d to Local-Response Normalization
- The addition of the two auxiliary layers
- The losses of auxiliary layers
- etc.

The two versions were impleneted with the exact same optimizer as well as the loss functions and they are as follows:

- criterion = nn.CrossEntropyLoss()
- optimizer = optim.SGD(model.parameters(), lr=0.001, momentum=0.9)

The number of trainable parameters of each model are as follows:

1. GoogLeNet has 10,635,134 trainable parameters
2. Pretrained GooLeNet has 6,624,904 trainable parameters

The models were both trained for 10 epochs with the batch size of 4 and their performace at the 10th epoch are:

- GoogLeNet: Train acc = 91.58% , Val acc = 96.62% , Test acc = 86.77%
- Pretrained GoogLeNet: Train acc = 97.98% , Val acc = 99.40% , Test acc = 93.60%

NOTE: The comparison between GoogLeNet and AlexNet on CIFAR-10 and the comparison between GoogLeNet and Pretrained GoogLeNet can be found in the discussion section

TASK: 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

Libaries

In [23]:
```
import torch
import torchvision
from torchvision import datasets, models, transforms
import torch.nn as nn
import torch.optim as optim
import time
import os
import copy
import torch.nn.functional as F
```

1. Prepare data set

In [24]:
```
# Preprocess inputs to 3x32x32 with CIFAR-specific normalization parameters

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

# Download CIFAR-10 and set up train, validation, and test datasets with new

train_dataset = torchvision.datasets.CIFAR10(root='./data', train=True,
                                            download=True, transform=preproce

train_datset, val_dataset = torch.utils.data.random_split(train_dataset, [400

test_dataset = torchvision.datasets.CIFAR10(root='./data', train=False,
                                            download=True, transform=preproce

# Create DataLoaders

batch_size = 4

train_dataloader = torch.utils.data.DataLoader(train_dataset, batch_size=batc
                                               shuffle=True, num_workers=2)
val_dataloader = torch.utils.data.DataLoader(val_dataset, batch_size=batch_si
                                             shuffle=True, num_workers=2)
test_dataloader = torch.utils.data.DataLoader(test_dataset, batch_size=batch_
                                              shuffle=False, num_workers=2)
```

```
Files already downloaded and verified
Files already downloaded and verified
```

2. Define Models

2.1 Inception Block

In [25]:
```
class Inception(nn.Module):
    '''
    Inception block for a GoogLeNet-like CNN

    Attributes
    ----------
    in_planes : int
        Number of input feature maps
    n1x1 : int
        Number of direct 1x1 convolutions
    n3x3red : int
        Number of 1x1 reductions before the 3x3 convolutions
    n3x3 : int
        Number of 3x3 convolutions
```

```
    n5x5red : int
        Number of 1x1 reductions before the 5x5 convolutions
    n5x5 : int
        Number of 5x5 convolutions
    pool_planes : int
        Number of 1x1 convolutions after 3x3 max pooling
    b1 : Sequential
        First branch (direct 1x1 convolutions)
    b2 : Sequential
        Second branch (reduction then 3x3 convolutions)
    b3 : Sequential
        Third branch (reduction then 5x5 convolutions)
    b4 : Sequential
        Fourth branch (max pooling then reduction)
    '''

    def __init__(self, in_planes, n1x1, n3x3red, n3x3, n5x5red, n5x5, pool_pl
        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(True),
        )

        # 1x1 conv -> 3x3 conv branch
        self.b2 = nn.Sequential(
            nn.Conv2d(in_planes, n3x3red, kernel_size=1),
            nn.BatchNorm2d(n3x3red),
            nn.ReLU(True),
            nn.Conv2d(n3x3red, n3x3, kernel_size=3, padding=1),
            nn.BatchNorm2d(n3x3),
            nn.ReLU(True),
        )

        # 1x1 conv -> 5x5 conv branch
        self.b3 = nn.Sequential(
            nn.Conv2d(in_planes, n5x5red, kernel_size=1),
            nn.BatchNorm2d(n5x5red),
            nn.ReLU(True),
            nn.Conv2d(n5x5red, n5x5, kernel_size=3, padding=1),
            nn.BatchNorm2d(n5x5),
            nn.ReLU(True),
            nn.Conv2d(n5x5, n5x5, kernel_size=3, padding=1),
            nn.BatchNorm2d(n5x5),
            nn.ReLU(True),
        )

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

2.2 Auxiliary Layers

In [26]:

```
class Aux_layer(nn.Module):
    def __init__(self, position):
        super(Aux_layer, self).__init__()

        self.avgpool = nn.AvgPool2d(5, stride=3)
        self.position = position

        if self.position == 'a4':
            self.conv = nn.Sequential(nn.Conv2d(512,128,kernel_size = 1,strid
        else:
            self.conv = nn.Sequential(nn.Conv2d(528,128,kernel_size = 1,strid

        self.fc1 = nn.Sequential(nn.Linear(2048, 1024), nn.ReLU(True), nn.Dro
        self.fc2 = nn.Linear(1024, 10)

    def forward(self,x):
        aux = self.avgpool(x)
        aux = self.conv(aux)
#         print(f'aux conv: {aux.shape}')
        aux = aux.flatten(start_dim = 1)
#         print(f'aux: {aux.shape}')
        aux = self.fc1(aux)
        aux = self.fc2(aux)
        return aux
```

2.3 GoogLeNet

In [27]:

```
class GoogLeNet(nn.Module):
    '''
    GoogLeNet-like CNN

    Attributes
    ----------
    pre_layers : Sequential
        Initial convolutional layer
    a3 : Inception
        First inception block
    b3 : Inception
        Second inception block
    maxpool : MaxPool2d
        Pooling layer after second inception block
    a4 : Inception
        Third inception block
    b4 : Inception
        Fourth inception block
    c4 : Inception
        Fifth inception block
    d4 : Inception
        Sixth inception block
    e4 : Inception
        Seventh inception block
    a5 : Inception
        Eighth inception block
```

```
    b5 : Inception
        Ninth inception block
    avgpool : AvgPool2d
        Average pool layer after final inception block
    linear : Linear
        Fully connected layer
    '''

    def __init__(self):
        super(GoogLeNet, self).__init__()

        self.is_debug = False

        self.pre_layers = nn.Sequential(
            nn.Conv2d(3,64, kernel_size=7, stride =2, padding =3),
            nn.ReLU(True),
            nn.MaxPool2d(3, stride =2, padding = 1),
            nn.LocalResponseNorm(5, alpha = 0.0001, beta = 0.75, k = 2.0),
            nn.Conv2d(64, 64, kernel_size=1),
            nn.ReLU(True),
            nn.Conv2d(64, 192, kernel_size=3, stride = 1, padding=1),
            nn.ReLU(True),
            nn.LocalResponseNorm(5, alpha = 0.0001, beta = 0.75, k = 2.0),
            nn.MaxPool2d(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(3, stride=2, padding=1)

        self.a4 = Inception(480, 192,  96, 208, 16,  48,  64)
        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)
        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(7, stride=1) ## orig = 8
        self.dropout = nn.Dropout(0.4)
        self.linear = nn.Linear(1024, 10)

        self.aux_a4 = Aux_layer('a4')
        self.aux_d4 = Aux_layer('d4')

    def forward(self, x):
        out = self.pre_layers(x)

        if self.is_debug : print(f'pre-layer: {out.shape}')

        out = self.a3(out)
        if self.is_debug : print(f'a3: {out.shape}')

        out = self.b3(out)
        if self.is_debug : print(f'b3 :{out.shape}')

        out = self.maxpool(out)
        if self.is_debug : print(f'maxpool: {out.shape}')

        out = self.a4(out)
        if self.is_debug : print(f'a4: {out.shape}')

        aux_a4 = self.aux_a4(out)
```

```
        out = self.b4(out)
        if self.is_debug : print(f'b4 : {out.shape}')

        out = self.c4(out)
        if self.is_debug : print(f'c4 : {out.shape}')

        out = self.d4(out)
        if self.is_debug : print(f'd4 : {out.shape}')

        aux_d4 = self.aux_d4(out)
        out = self.e4(out)
        if self.is_debug : print(f'e4 : {out.shape}')

        out = self.maxpool(out)
        if self.is_debug : print(f'maxpool : {out.shape}')

        out = self.a5(out)
        if self.is_debug : print(f'a5 : {out.shape}')

        out = self.b5(out)
        if self.is_debug : print(f'b5 : {out.shape}')

        out = self.avgpool(out)
        if self.is_debug : print(f'avgpool : {out.shape}')

        out = self.dropout(out)
        out = out.view(out.size(0), -1)
        out = self.linear(out)

        if self.training == True:
            return out, aux_a4, aux_d4
        else:
            return out
```

3. Define Train and Evaluation Functions

In [28]:

```
def train_model(model, dataloaders, criterion, optimizer, num_epochs=25, weig
    '''
    train_model function

    Train a PyTorch model for a given number of epochs.

            Parameters:
                    model: Pytorch model
                    dataloaders: dataset
                    criterion: loss function
                    optimizer: update weights function
                    num_epochs: number of epochs
                    weights_name: file name to save weights
                    is_inception: The model is inception net (Google LeNet) o

            Returns:
                    model: Best model from evaluation result
                    val_acc_history: evaluation accuracy history
                    loss_acc_history: loss value history
    '''
    since = 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()

    if (epoch+1) % 5 == 0:
        print('Epoch {}/{}'.format(epoch, num_epochs - 1))
        print('-' * 10)

    # Each epoch has a training and validation phase
    for phase in ['train', 'val']:
        if phase == 'train':
            model.train()  # Set model to training mode
        else:
            model.eval()   # Set model to evaluate mode

        running_loss = 0.0
        running_corrects = 0

        # Iterate over the train/validation dataset according to which ph

        for inputs, labels in dataloaders[phase]:

            # Inputs is one batch of input images, and labels is a corres
            # labeling each image in the batch. First, we move these tens

            inputs = inputs.to(device)
            labels = labels.to(device)

            # Zero out any parameter gradients that have previously been 
            # gradients accumulate over as many backward() passes as we l
            # to be zeroed out after each optimizer step.

            optimizer.zero_grad()

            # Instruct PyTorch to track gradients only if this is the tra
            # forward propagation and optionally the backward propagation

            with torch.set_grad_enabled(phase == 'train'):
                # The inception model is a special case during training b
                # output used to encourage discriminative representations
                # We need to calculate loss for both outputs. Otherwise, 
                # calculate the loss on.

                if is_inception and phase == 'train':
                    # From https://discuss.pytorch.org/t/how-to-optimize-
                    outputs, aux_a4, aux_d4 = model(inputs)
                    loss1 = criterion(outputs, labels)
                    loss2 = criterion(aux_a4, labels)
                    loss3 = criterion(aux_d4, labels)
                    loss = loss1 + 0.3*(loss2+loss3)
#                 elif is_inception and weights_name == 'GoogLeNet' and p
#                     outputs, _, _ = model(inputs) #,_,_ or in the forwa
#                     loss = criterion(outputs, labels)
                else:
                    outputs = model(inputs) #,_,_ or in the forward()
                    loss = criterion(outputs, labels)

                outputs = nn.functional.softmax(outputs, dim=1)
                _, preds = torch.max(outputs, 1)

                # Backpropagate only if in training phase

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

```
                # Gather our summary statistics

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

            epoch_loss = running_loss / len(dataloaders[phase].dataset)
            epoch_acc = running_corrects.double() / len(dataloaders[phase].da
            epoch_end = time.time()

            elapsed_epoch = epoch_end - epoch_start

            if (epoch+1) % 5 == 0:
                print('{} Loss: {:.4f} Acc: {:.4f}'.format(phase, epoch_loss,
                print("Epoch time taken: ", elapsed_epoch)

            # If this is the best model on the validation set so far, deep co

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

#          print()

    # Output summary statistics, load the best weight set, and return results

    time_elapsed = time.time() - since
    print('Training complete in {:.0f}m {:.0f}s'.format(time_elapsed // 60, t
    print('Best val Acc: {:4f}'.format(best_acc))
    model.load_state_dict(best_model_wts)
    return model, val_acc_history, loss_acc_history
```

In [29]:

```
def evaluate(model, iterator, criterion,model_name):

    total = 0
    correct = 0
    epoch_loss = 0
    epoch_acc = 0

    predicteds = []
    trues = []

    model.eval()

    with torch.no_grad():

        for batch, labels in iterator:

            #Move tensors to the configured device
            batch = batch.to(device)
            labels = labels.to(device)

            predictions = model(batch.float())

            loss = criterion(predictions, labels.long())

            predictions = nn.functional.softmax(predictions, dim=1)
            _, predicted = torch.max(predictions.data, 1)  #returns max value
```

```
            predicteds.append(predicted)
            trues.append(labels)
            total += labels.size(0)  #keep track of total
            correct += (predicted == labels).sum().item()   #.item() give the 
            acc = 100 * (correct / total)

            epoch_loss += loss.item()
            epoch_acc += acc

    return epoch_loss / len(iterator), epoch_acc / len(iterator),predicteds, 
```

In [30]:

```
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()
```

4. Train the models

4.1 Define models to train

In [43]:

```
googlenet = GoogLeNet()
googlenet_pre = torch.hub.load('pytorch/vision:v0.6.0', 'googlenet', pretrain
#change the last output to be 10 classes
googlenet_pre.fc = nn.Linear(1024,10)
models = [googlenet, googlenet_pre]
model_names = ['GoogLeNet', 'Pretrained GoogLeNet']
# models = [googlenet_pre]
# model_names = ['Pretrained GoogLeNet']
```

```
Using cache found in /root/.cache/torch/hub/pytorch_vision_v0.6.0
```

4.2 Loss and Optimizer Functions

In [44]:

```
criterion = nn.CrossEntropyLoss()

optimizers = []
for model in models:
    optimizer = optim.SGD(model.parameters(), lr=0.001, momentum=0.9)
    optimizers.append(optimizer)
```

4.2 Move everything to the configured device

Let's check the availability of GPU...

In [45]:

```
from chosen_gpu import get_freer_gpu
device = torch.device(get_freer_gpu()) if torch.cuda.is_available() else torc
print("Configured device: ", device)
```

```
Configured device:  cuda:1
```

In [46]:

```
for model in models:
    model = model.to(device)
```

```
criterion = criterion.to(device)
```

4.3 Count the parameters

In [47]:

```
def count_parameters(model):
    return sum(p.numel() for p in model.parameters() if p.requires_grad)

for i,model in enumerate(models):
    print(f'The model {model_names[i]} has {count_parameters(model):,} trainal
```

```
The model GoogLeNet has 10,635,134 trainable parameters
The model Pretrained GoogLeNet has 11,990,138 trainable parameters
```

4.4 Prepare the dataloader

In [36]:

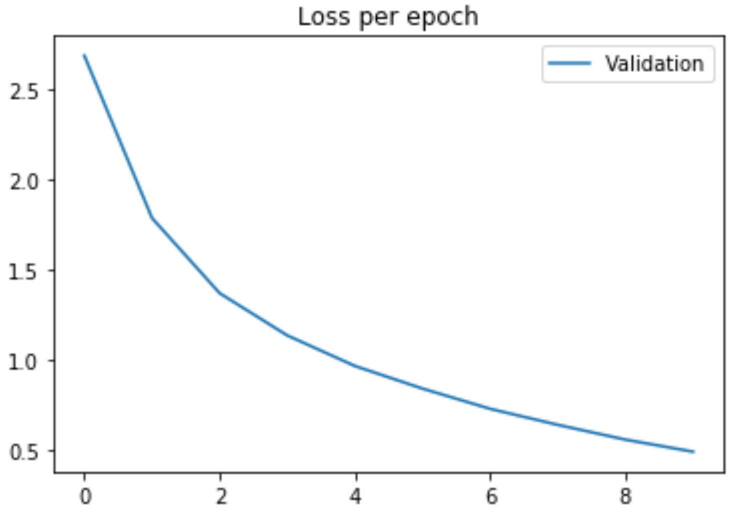
```
dataloaders = { 'train': train_dataloader, 'val': val_dataloader }
```

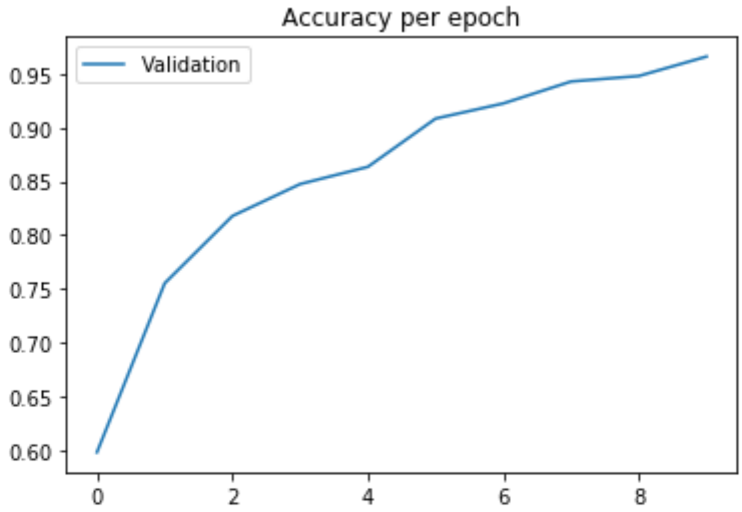
4.5 Train the models

In [20]:

```
print(f'Training: {model_names[0]}')
best_model, val_acc_history, loss_acc_history = train_model(models[0], datalo
plot_data(val_acc_history, loss_acc_history)
```

```
Training: GoogLeNet
Epoch 4/9
----------
train Loss: 0.9656 Acc: 0.8094
Epoch time taken:  1312.412663936615
val Loss: 0.3936 Acc: 0.8636
Epoch time taken:  1387.3063054084778
Epoch 9/9
----------
train Loss: 0.4886 Acc: 0.9158
Epoch time taken:  1246.7739770412445
val Loss: 0.1084 Acc: 0.9662
Epoch time taken:  1339.1904847621918
Training complete in 228m 49s
Best val Acc: 0.966200
```

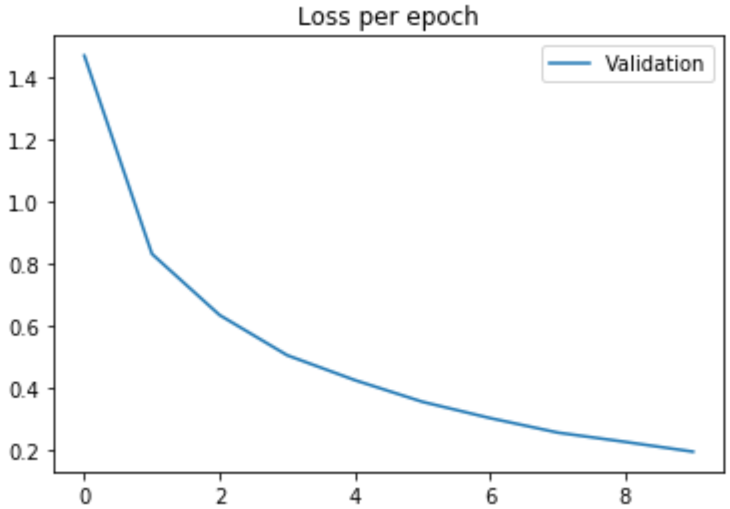


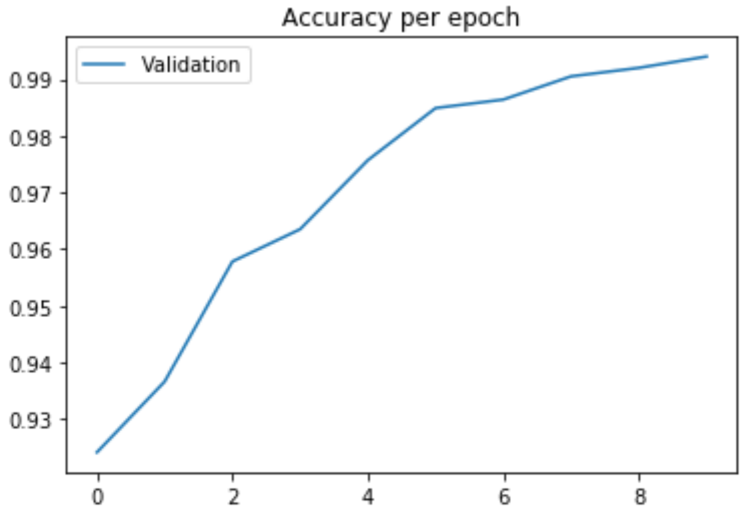


In [38]:

```
print(f'Training: {model_names[1]}')
best_model, val_acc_history, loss_acc_history = train_model(models[1], datalo
plot_data(val_acc_history, loss_acc_history)
```

```
Training: Pretrained GoogLeNet
Epoch 4/9
----------
train Loss: 0.4255 Acc: 0.9400
Epoch time taken:  1023.3844466209412
val Loss: 0.0772 Acc: 0.9757
Epoch time taken:  1086.9910814762115
Epoch 9/9
----------
train Loss: 0.1957 Acc: 0.9798
Epoch time taken:  1048.2613151073456
val Loss: 0.0192 Acc: 0.9940
Epoch time taken:  1116.5802915096283
Training complete in 179m 42s
Best val Acc: 0.994000
```



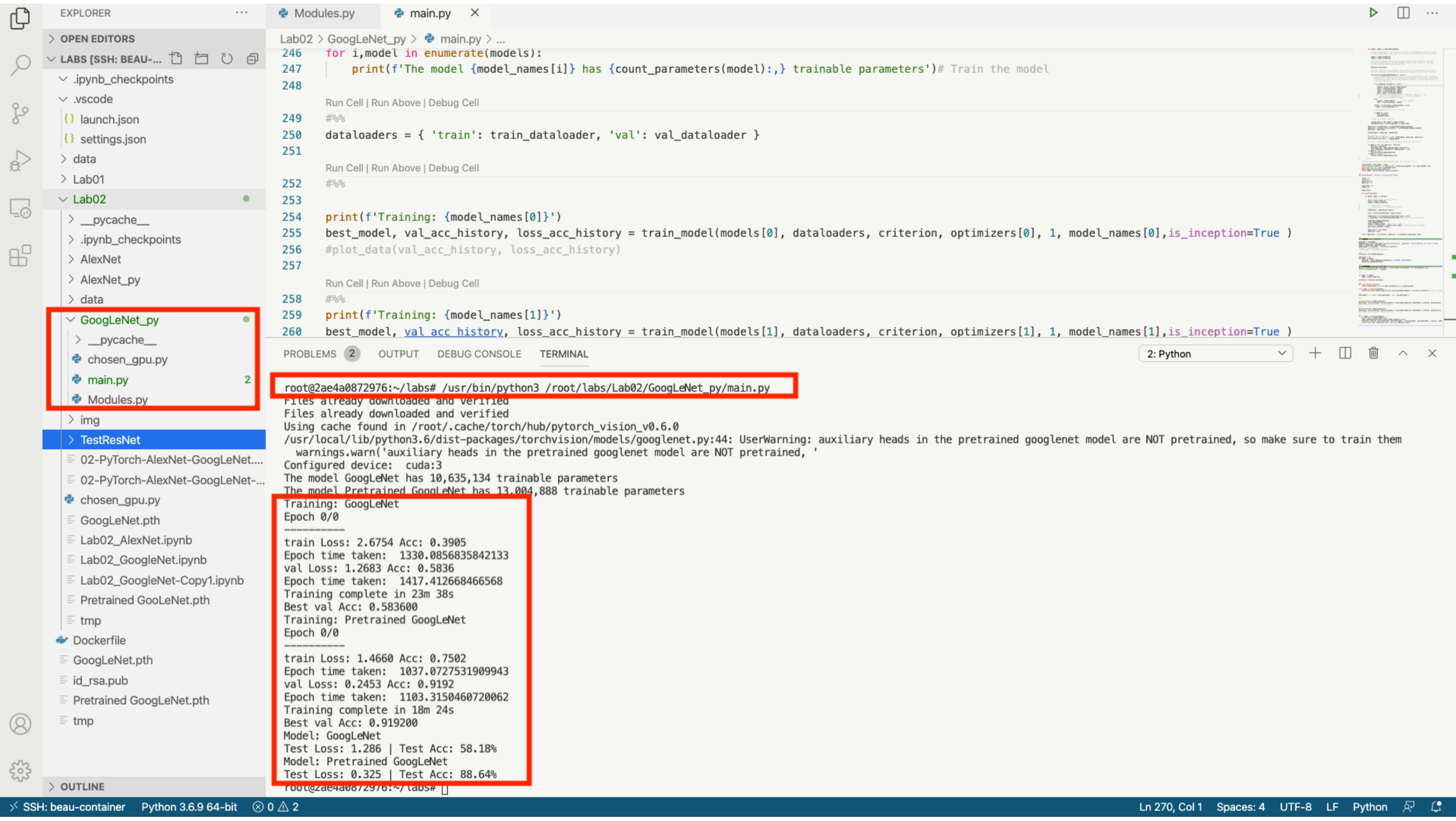


5. Results

In [39]:

```
for i, model in enumerate(models):
    print(f'Model: {model_names[i]}')
    model.load_state_dict(torch.load(f'{model_names[i]}.pth'))
    test_loss, test_acc, test_pred_label, test_true_label  = evaluate(model, 
    print(f'Test Loss: {test_loss:.3f} | Test Acc: {test_acc:.2f}%')
```

```
Model: GoogLeNet
Test Loss: 0.408 | Test Acc: 86.77%
Model: Pretrained GoogLeNet
Test Loss: 0.238 | Test Acc: 93.60%
```


EXPLORER
OPEN EDITORS
LABS [SSH: BEAU-...
.ipynb_checkpoints
.vscode
launch.json
settings.json
data
Lab01
Lab02
__pycache__
.ipynb_checkpoints
AlexNet
AlexNet_py
data
GoogLeNet_py
__pycache__
chosen_gpu.py
main.py
Modules.py
img
TestResNet
02-PyTorch-AlexNet-GoogLeNet....
02-PyTorch-AlexNet-GoogLeNet-...
chosen_gpu.py
GoogLeNet.pth
Lab02_AlexNet.ipynb
Lab02_GoogleNet.ipynb
Lab02_GoogleNet-Copy1.ipynb
Pretrained GooLeNet.pth
tmp
Dockerfile
GoogLeNet.pth
id_rsa.pub
Pretrained GoogLeNet.pth
tmp
OUTLINE
Modules.py
main.py
Lab02 > GoogLeNet_py > main.py > ...
for i,model in enumerate(models):
print(f'The model {model_names[i]} has {count_parameters(model):,} trainable parameters')# Train the model
Run Cell | Run Above | Debug Cell
#%%
dataloaders = { 'train': train_dataloader, 'val': val_dataloader }
Run Cell | Run Above | Debug Cell
#%%
print(f'Training: {model_names[0]}')
best_model, val_acc_history, loss_acc_history = train_model(models[0], dataloaders, criterion, optimizers[0], 1, model_names[0],is_inception=True)
#plot_data(val_acc_history, loss_acc_history)
Run Cell | Run Above | Debug Cell
#%%
print(f'Training: {model_names[1]}')
best_model, val_acc_history, loss_acc_history = train_model(models[1], dataloaders, criterion, optimizers[1], 1, model_names[1],is_inception=True)
PROBLEMS 2
OUTPUT
DEBUG CONSOLE
TERMINAL
2: Python
root@2ae4a0872976:~/labs# /usr/bin/python3 /root/labs/Lab02/GoogLeNet_py/main.py
Files already downloaded and verified
Files already downloaded and verified
Using cache found in /root/.cache/torch/hub/pytorch_vision_v0.6.0
/usr/local/lib/python3.6/dist-packages/torchvision/models/googlenet.py:44: UserWarning: auxiliary heads in the pretrained googlenet model are NOT pretrained, so make sure to train them
warnings.warn('auxiliary heads in the pretrained googlenet model are NOT pretrained, '
Configured device: cuda:3
The model GoogLeNet has 10,635,134 trainable parameters
The model Pretrained GoogLeNet has 13,004,888 trainable parameters
Training: GoogLeNet
Epoch 0/0
----
train Loss: 2.6754 Acc: 0.3905
Epoch time taken: 1330.0856835842133
val Loss: 1.2683 Acc: 0.5836
Epoch time taken: 1417.412668466568
Training complete in 23m 38s
Best val Acc: 0.583600
Training: Pretrained GoogLeNet
Epoch 0/0
----
train Loss: 1.4660 Acc: 0.7502
Epoch time taken: 1037.0727531909943
val Loss: 0.2453 Acc: 0.9192
Epoch time taken: 1103.3150460720062
Training complete in 18m 24s
Best val Acc: 0.919200
Model: GoogLeNet
Test Loss: 1.286 | Test Acc: 58.18%
Model: Pretrained GoogLeNet
Test Loss: 0.325 | Test Acc: 88.64%
root@2ae4a0872976:~/labs#
SSH: beau-container
Python 3.6.9 64-bit
Ln 270, Col 1
Spaces: 4
UTF-8
LF
Python

Discussion

1. Create VSCode projects for each of 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.

The screenshot proves which show that i got my vscode working are at the end of the respective section.

1. 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.

See the implementation under AlexNet section.

- AlexNet Sequential: Train acc = 86.49%, Val acc = 76.64%, Test acc = 77.21%, Epoch time: 140s
- AlexNet Sequential with LRN: Train acc = 87.21%, Val acc = 79.69%, Test acc = 79.21%, Epoch time: 170s
- AlexNet nn.Module: Train acc = 87.29%, Val acc = 80.19% , Test acc = 80.86%, Epoch time: 159s
- AlexNet nn.Module with LRN: Train acc = 85.21%, Val acc = 77.78% , Test acc = 77.99%, Epoch time: 143s

When comparing the results of AlexNet Sequential model and those of AlexNet Sequential with LRN model, AlexNet Sequential with LRN model outperforms AlexNet Sequential without LRN model by around 2%, however it takes longer to complete training. The results also align to what is described in the paper. Moreover, the plots of AlexNet with LRN implemented are also smoother.

1. Note that the backbone of the GoogLeNet implemented thus far does not correspond exactly to the description. Modify the architecture to
    A. Use the same backbone (input image size, convolutions, etc.) before the first Inception module
    B. Add the two side classifiers

See the implementation under GoogLeNet section.

1. 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.

- AlexNet Sequential with LRN:
    Train acc = 87.21%,
    Val acc = 79.69%,
    Test acc = 79.21%

Epoch Time = 2m 50s,
Number of trainable parameters = 58,322,314

Note: there are 4 different versions of AlexNet model experimented in this lab, however the best performing AlexNet model version was selected for this section.

- GoogLeNet:
  Train acc = 91.58 %,
  Val acc = 96.62%,
  Test acc = 86.77%,
  Epoch Time = 22m 43s,
  Number of trainable parameters = 10,635,134

As shown abovem GoogLeNet could achieve a considerably higher accuracies while having the number of trainable parameters lower. However, GoogLeNet seems to require a lot more training time and takes more time to converge when compared to AlexNet.

1. Experiment with the pretrained GoogLeNet from the torchvision repository. Does it give better results on CIFAR-10 similar to what we found with AlexNet last week? Comment on what we can glean from the results about the capacity and generalization ability of these two models.

- Pretrained AlexNet:
  Train acc = 97.63%,
  Val acc = 89.22%,
  Test acc = 88.18%,
  Epoch Time = 2m 1s,
  Number of trainable parameters = 44,428,106

- Pretrained GoogLeNet:
  Train acc = 97.98%,
  Val acc = 99.40%,
  Test acc = 93.60%,
  Epoch Time = 21m 31s,
  Number of trainable parameters = 11,990,138

The pretrained version of both models perform better than that of the from-scratch version. Both versions of GoogLeNet achieve higher accuracies on Cifar-10 while having less the number of trainable parameters. However, they seem to require a lot more training time.