pytorch-vgg16

September 5, 2021

1 Synopsis

This project aims to build a deep learning model using PyTorch to classify images using convolutional neural networks. The model is trained on the well-known CIFAR-10 dataset (https://www.cs.toronto.edu/~kriz/cifar.html). The techniques of transfer learning (from the VGG16 model with batch normalization) and data augmentation were used to enhance the model's accuracy. A final accuracy of 87.0500 % was obtained on the test set.

2 Setup

Install the torchinfo library to obtain model summaries.

[1]:
```
! pip install torchinfo
```

```
Collecting torchinfo
  Downloading torchinfo-1.5.3-py3-none-any.whl (19 kB)
Installing collected packages: torchinfo
Successfully installed torchinfo-1.5.3
WARNING: Running pip as root will break packages and permissions. You
should install packages reliably by using venv:
https://pip.pypa.io/warnings/venv
```

Import the libraries and methods needed for the project.

[2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import torch
from torch.nn import (
    Sequential,
    Linear,
    ReLU,
    Dropout,
    CrossEntropyLoss
)
from torchvision.transforms import (
    Compose,
```

```
    Resize,
    RandomRotation,
    RandomHorizontalFlip,
    RandomCrop,
    ToTensor,
    Normalize
)
from torchvision.datasets import CIFAR10
from torch.utils.data import (
    random_split,
    DataLoader
)
from torchvision.models import vgg16_bn
from torchinfo import summary
from torch.optim import Adam
from copy import deepcopy
```

3 Preprocessing

Lay out the image size, means and standard deviations expected by the pretrained model.

[3]:
```
pretrained_size = 224
pretrained_means = [0.485, 0.456, 0.406]
pretrained_stds = [0.229, 0.224, 0.225]
```

Define transforms for the training set.

[4]:
```
train_transforms = Compose([
    Resize(size = pretrained_size),
    RandomRotation(degrees = 5),
    RandomHorizontalFlip(p = 0.5),
    RandomCrop(size = pretrained_size,
               padding = 10),
    ToTensor(),
    Normalize(mean = pretrained_means,
              std = pretrained_stds)
])
```

Define transforms for the test set.

[5]:
```
test_transforms = Compose([
    Resize(size = pretrained_size),
    ToTensor(),
    Normalize(mean = pretrained_means,
              std = pretrained_stds)
])
```

4 Load the data

Load the data, performing the predefined transforms.

[6]:
```
ROOT = ".data"

raw_train_data = CIFAR10(root = ROOT,
                         train = True,
                         download = True,
                         transform = train_transforms)

test_data = CIFAR10(root = ROOT,
                    train = False,
                    download = True,
                    transform = test_transforms)
```

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

0it [00:00, ?it/s]

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

5 Data partitioning

Carve out a validation set from the raw training set. 90 % of the raw training set forms the final training set and the other 10 % forms the validation set.

[7]:
```
SPLIT_FRACTION = 0.9

n_train_examples = int(len(raw_train_data) * SPLIT_FRACTION)
n_valid_examples = len(raw_train_data) - n_train_examples

train_data, valid_data = random_split(dataset = raw_train_data,
                                      lengths = [n_train_examples,␣
 ↪n_valid_examples])
```

Ensure that the validation set uses the same transforms as the test set.

[8]:
```
valid_data = deepcopy(x = valid_data)
valid_data.dataset.transform = test_transforms
```

Check the number of examples in each set.

[9]:
```
print(f"Number of examples in the training set: {len(train_data)}")
print(f"Number of examples in the validation set: {len(valid_data)}")
print(f"Number of examples in the test set: {len(test_data)}")
```

```
Number of examples in the training set: 45000
Number of examples in the validation set: 5000
Number of examples in the test set: 10000
```

6 Check transforms

Plot 25 sample images to check whether the proposed transforms are sensible.

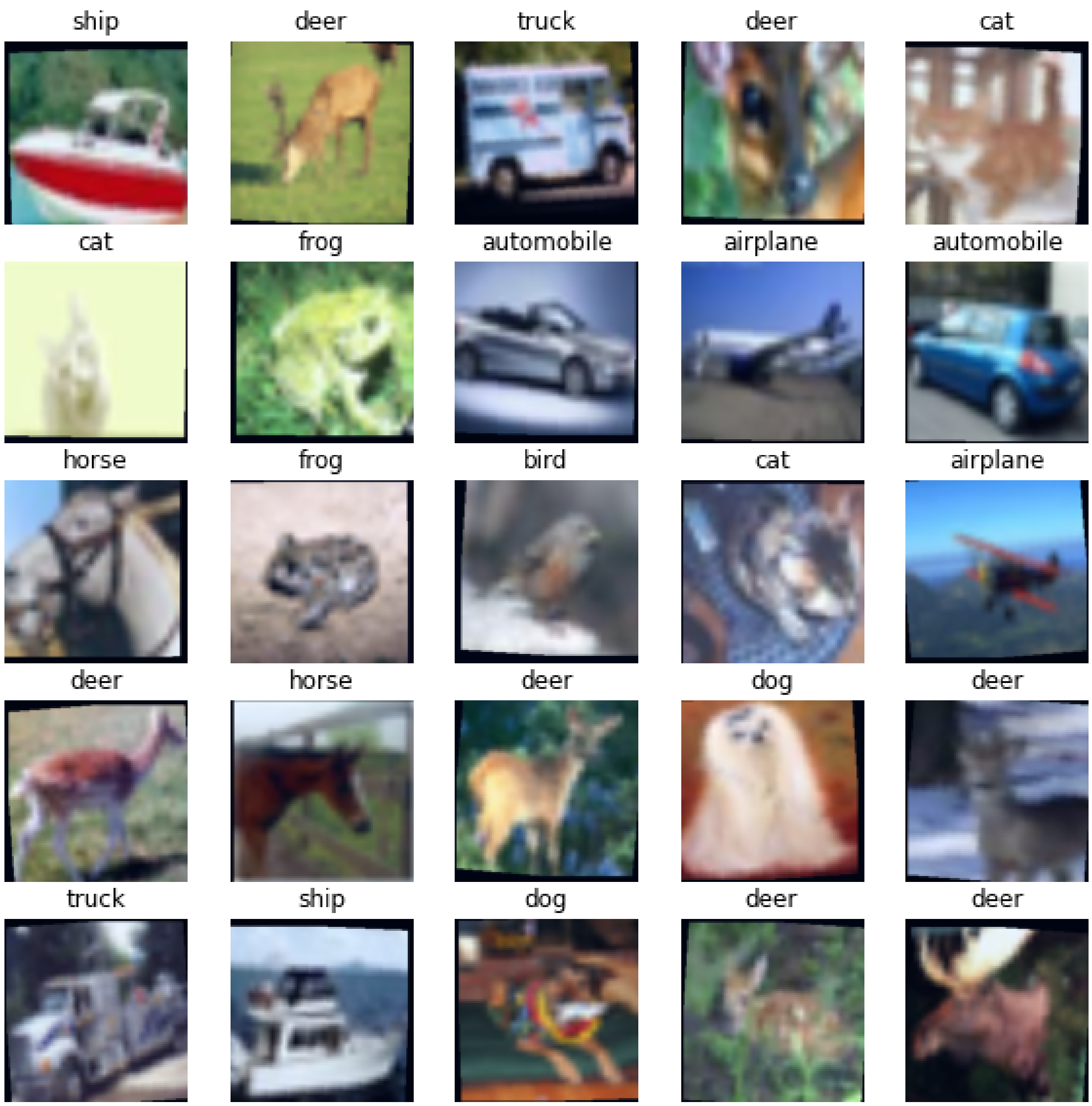
[10]:
```
def normalize_image(image):

    image_min = image.min()
    image_max = image.max()
    image.clamp_(min = image_min,
                 max = image_max)
    image.subtract_(image_min).div_(image_max - image_min + 1e-5)

    return image
```

[11]:
```
def plot_images(images,
                labels,
                classes,
                normalize = True):

    num_images = len(images)

    rows = int(np.sqrt(num_images))
    columns = int(np.sqrt(num_images))

    fig = plt.figure(figsize = [10, 10])

    for i in range(rows * columns):

        ax = fig.add_subplot(rows, columns, (i+1))

        image = images[i]

        if normalize:
            image = normalize_image(image)

        ax.imshow(image.permute(1, 2, 0).cpu().numpy())
        ax.set_title(classes[labels[i]])
        ax.axis("off")
```

[12]:
```
N_IMAGES = 25
```

[13]:
```
images, labels = zip(*[(image, label) for (image, label) in
                       [train_data[i] for i in range(N_IMAGES)]])
```

```
classes = test_data.classes

plot_images(images, labels, classes)
```



7 Form data iterators

Form iterators for the training, validation and test sets using a desired batch size.

[14]:
```
BATCH_SIZE = 128
```

[15]:
```
train_iterator = DataLoader(dataset = train_data,
                            shuffle = True,
                            batch_size = BATCH_SIZE)

valid_iterator = DataLoader(dataset = valid_data,
                            batch_size = BATCH_SIZE)

test_iterator = DataLoader(dataset = test_data,
                           batch_size = BATCH_SIZE)
```

8 Define the model

Import a pretrained VGG16 model with batch normalization.

[16]:
```
model = vgg16_bn(pretrained = True)
```

```
Downloading: "https://download.pytorch.org/models/vgg16_bn-6c64b313.pth" to
/root/.cache/torch/hub/checkpoints/vgg16_bn-6c64b313.pth
```

```
  0%|          | 0.00/528M [00:00<?, ?B/s]
```

Inspect the layers present in the model.

[17]:
```
model
```

[17]:
```
VGG(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (2): ReLU(inplace=True)
    (3): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (4): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (5): ReLU(inplace=True)
    (6): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (7): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (8): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (9): ReLU(inplace=True)
    (10): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (11): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (12): ReLU(inplace=True)
    (13): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (14): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
```

```
    (15): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (16): ReLU(inplace=True)
    (17): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (18): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (19): ReLU(inplace=True)
    (20): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (21): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (22): ReLU(inplace=True)
    (23): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (24): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (25): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (26): ReLU(inplace=True)
    (27): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (28): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (29): ReLU(inplace=True)
    (30): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (31): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (32): ReLU(inplace=True)
    (33): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (34): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (35): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (36): ReLU(inplace=True)
    (37): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (38): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (39): ReLU(inplace=True)
    (40): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (41): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (42): ReLU(inplace=True)
    (43): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(7, 7))
  (classifier): Sequential(
    (0): Linear(in_features=25088, out_features=4096, bias=True)
    (1): ReLU(inplace=True)
    (2): Dropout(p=0.5, inplace=False)
```

```
    (3): Linear(in_features=4096, out_features=4096, bias=True)
    (4): ReLU(inplace=True)
    (5): Dropout(p=0.5, inplace=False)
    (6): Linear(in_features=4096, out_features=1000, bias=True)
  )
)
```

Ensure that the convolutional feature-extracting base is frozen and the classifier head is unfrozen. Setting requires_grad to False freezes the corresponding layer and setting it to True unfreezes it. The adaptive average pooling layer contains no parameters.

[18]:
```
for param in model.features.parameters():
    param.requires_grad = False
```

[19]:
```
for param in model.classifier.parameters():
    param.requires_grad = True
```

The pretrained model was trained on the ImageNet dataset, which had 1000 classes. Hence, the final layer in the classifier has 1000 output features. Inspect this last layer.

[20]:
```
model.classifier[-1]
```

[20]:
```
Linear(in_features=4096, out_features=1000, bias=True)
```

Since I am currently building a model on the CIFAR-10 dataset, which has 10 classes, I want this final layer to have 10 output features. Replace the final layer with a linear layer which has 10 output features. The newly added layer will have requires_grad set to True and will be trainable.

[21]:
```
N_CLASSES = 10
IN_FEATURES = model.classifier[-1].in_features
```

[22]:
```
final_layer = Linear(in_features = IN_FEATURES,
                     out_features = N_CLASSES)
```

[23]:
```
model.classifier[-1] = final_layer
```

Check that the modified classifier does have 10 output features.

[24]:
```
model.classifier
```

[24]:
```
Sequential(
  (0): Linear(in_features=25088, out_features=4096, bias=True)
  (1): ReLU(inplace=True)
  (2): Dropout(p=0.5, inplace=False)
  (3): Linear(in_features=4096, out_features=4096, bias=True)
  (4): ReLU(inplace=True)
  (5): Dropout(p=0.5, inplace=False)
  (6): Linear(in_features=4096, out_features=10, bias=True)
```

```
)
```

Summarize the final overall model.

[25]:
```python
summary(model,
        input_size = [BATCH_SIZE, 3, 224, 224],
        device = "cuda")
```

[25]:
```
================================================================================
==========
Layer (type:depth-idx)                   Output Shape              Param #
================================================================================
==========
VGG                                      --                        --
 Sequential: 1-1                         [128, 512, 7, 7]          --
     Conv2d: 2-1                         [128, 64, 224, 224]       (1,792)
     BatchNorm2d: 2-2                    [128, 64, 224, 224]       (128)
     ReLU: 2-3                           [128, 64, 224, 224]       --
     Conv2d: 2-4                         [128, 64, 224, 224]       (36,928)
     BatchNorm2d: 2-5                    [128, 64, 224, 224]       (128)
     ReLU: 2-6                           [128, 64, 224, 224]       --
     MaxPool2d: 2-7                      [128, 64, 112, 112]       --
     Conv2d: 2-8                         [128, 128, 112, 112]      (73,856)
     BatchNorm2d: 2-9                    [128, 128, 112, 112]      (256)
     ReLU: 2-10                          [128, 128, 112, 112]      --
     Conv2d: 2-11                        [128, 128, 112, 112]      (147,584)
     BatchNorm2d: 2-12                   [128, 128, 112, 112]      (256)
     ReLU: 2-13                          [128, 128, 112, 112]      --
     MaxPool2d: 2-14                     [128, 128, 56, 56]        --
     Conv2d: 2-15                        [128, 256, 56, 56]        (295,168)
     BatchNorm2d: 2-16                   [128, 256, 56, 56]        (512)
     ReLU: 2-17                          [128, 256, 56, 56]        --
     Conv2d: 2-18                        [128, 256, 56, 56]        (590,080)
     BatchNorm2d: 2-19                   [128, 256, 56, 56]        (512)
     ReLU: 2-20                          [128, 256, 56, 56]        --
     Conv2d: 2-21                        [128, 256, 56, 56]        (590,080)
     BatchNorm2d: 2-22                   [128, 256, 56, 56]        (512)
     ReLU: 2-23                          [128, 256, 56, 56]        --
     MaxPool2d: 2-24                     [128, 256, 28, 28]        --
     Conv2d: 2-25                        [128, 512, 28, 28]        (1,180,160)
     BatchNorm2d: 2-26                   [128, 512, 28, 28]        (1,024)
     ReLU: 2-27                          [128, 512, 28, 28]        --
     Conv2d: 2-28                        [128, 512, 28, 28]        (2,359,808)
     BatchNorm2d: 2-29                   [128, 512, 28, 28]        (1,024)
     ReLU: 2-30                          [128, 512, 28, 28]        --
     Conv2d: 2-31                        [128, 512, 28, 28]        (2,359,808)
     BatchNorm2d: 2-32                   [128, 512, 28, 28]        (1,024)
```

```
     ReLU: 2-33                       [128, 512, 28, 28]       --
     MaxPool2d: 2-34                  [128, 512, 14, 14]       --
     Conv2d: 2-35                     [128, 512, 14, 14]       (2,359,808)
     BatchNorm2d: 2-36                [128, 512, 14, 14]       (1,024)
     ReLU: 2-37                       [128, 512, 14, 14]       --
     Conv2d: 2-38                     [128, 512, 14, 14]       (2,359,808)
     BatchNorm2d: 2-39                [128, 512, 14, 14]       (1,024)
     ReLU: 2-40                       [128, 512, 14, 14]       --
     Conv2d: 2-41                     [128, 512, 14, 14]       (2,359,808)
     BatchNorm2d: 2-42                [128, 512, 14, 14]       (1,024)
     ReLU: 2-43                       [128, 512, 14, 14]       --
     MaxPool2d: 2-44                  [128, 512, 7, 7]         --
 AdaptiveAvgPool2d: 1-2               [128, 512, 7, 7]         --
 Sequential: 1-3                      [128, 10]                --
     Linear: 2-45                     [128, 4096]              102,764,544
     ReLU: 2-46                       [128, 4096]              --
     Dropout: 2-47                    [128, 4096]              --
     Linear: 2-48                     [128, 4096]              16,781,312
     ReLU: 2-49                       [128, 4096]              --
     Dropout: 2-50                    [128, 4096]              --
     Linear: 2-51                     [128, 10]                40,970
================================================================================
==========
Total params: 134,309,962
Trainable params: 119,586,826
Non-trainable params: 14,723,136
Total mult-adds (T): 1.98
================================================================================
==========
Input size (MB): 77.07
Forward/backward pass size (MB): 27753.72
Params size (MB): 537.24
Estimated Total Size (MB): 28368.03
================================================================================
==========
```

9 Loss function and optimizer

Define the loss function and the optimizer to be used.

[26]:
```
loss_fn = CrossEntropyLoss()
optimizer = Adam(params = model.parameters(),
                 lr = 0.001)
```

10 Copy the model to the GPU

[27]:
```
if torch.cuda.is_available():
    device = torch.device("cuda")
else:
    device = torch.device("cpu")
```

[28]:
```
print(f"Using {device} device")
```

```
Using cuda device
```

[29]:
```
model.to(device)
```

[29]:
```
VGG(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (2): ReLU(inplace=True)
    (3): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (4): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (5): ReLU(inplace=True)
    (6): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (7): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (8): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (9): ReLU(inplace=True)
    (10): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (11): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (12): ReLU(inplace=True)
    (13): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (14): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (15): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (16): ReLU(inplace=True)
    (17): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (18): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (19): ReLU(inplace=True)
    (20): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (21): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (22): ReLU(inplace=True)
```

```
    (23): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (24): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (25): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (26): ReLU(inplace=True)
    (27): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (28): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (29): ReLU(inplace=True)
    (30): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (31): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (32): ReLU(inplace=True)
    (33): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
    (34): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (35): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (36): ReLU(inplace=True)
    (37): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (38): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (39): ReLU(inplace=True)
    (40): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (41): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    (42): ReLU(inplace=True)
    (43): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(7, 7))
  (classifier): Sequential(
    (0): Linear(in_features=25088, out_features=4096, bias=True)
    (1): ReLU(inplace=True)
    (2): Dropout(p=0.5, inplace=False)
    (3): Linear(in_features=4096, out_features=4096, bias=True)
    (4): ReLU(inplace=True)
    (5): Dropout(p=0.5, inplace=False)
    (6): Linear(in_features=4096, out_features=10, bias=True)
  )
)
```

11 Define the training function

Define a function to train the model and simultaneously validate it, across a desired number of epochs.

[30]:
```
def train(train_iterator,
          valid_iterator,
          model,
          loss_fn,
          optimizer,
          device,
          n_epochs = 5):

    # Initialize the history list which will contain all losses and metrics

    history_list = []

    for i in range(n_epochs):

        # Start setting up the training procedure

        print(f"Epoch {i+1}")
        print("-------------------------------")

        train_size = len(train_iterator.dataset)
        n_train_batches = len(train_iterator)
        train_loss = 0
        average_train_loss = 0
        train_n_correct = 0
        train_accuracy = 0

        # Set the model to training mode

        model.train()

        for train_batch, (X, y) in enumerate(train_iterator):

            # Copy the tensors to the GPU

            X = X.to(device)
            y = y.to(device)

            # Reset the gradients of the model parameters to zero

            optimizer.zero_grad()

            # Obtain the model prediction and loss

            pred = model(X)
            loss = loss_fn(pred, y)

            # Backpropagate the loss and deposit each gradient in place
```

```
            loss.backward()

            # Adjust the parameters using the gradients collected in the␣
↪backward pass

            optimizer.step()

            # Increment the validation loss and the number of correctly labeled␣
↪instances
            # Build up these aggregate values instance by instance

            train_loss += loss.item()
            train_n_correct += (pred.argmax(1) == y).type(torch.float).sum().
↪item()

            # Display the training loss after every hundredth batch is trained

            if train_batch % 100 == 0:
                loss = loss.item()
                current_instance = train_batch * len(X)
                print(f"Loss: {loss:.6f} [{current_instance:5f} / {train_size:
↪5f}]")

        # Obtain average training loss and accuracy for the entire epoch

        average_train_loss = train_loss / n_train_batches
        train_accuracy = train_n_correct / train_size

        # After training is finished, start validation

        valid_size = len(valid_iterator.dataset)
        n_valid_batches = len(valid_iterator)
        valid_loss = 0
        average_valid_loss = 0
        valid_n_correct = 0
        valid_accuracy = 0

        with torch.no_grad():

            # Set the model to evaluation mode

            model.eval()

            for X, y in valid_iterator:

                # Copy the tensors to the GPU
```

```
                X = X.to(device)
                y = y.to(device)

                # Obtain the model prediction and loss

                pred = model(X)
                loss = loss_fn(pred, y)

                # Increment the validation loss and the number of correctly␣
↪labeled instances
                # Build up aggregate values instance by instance

                valid_loss += loss.item()
                valid_n_correct += (pred.argmax(1) == y).type(torch.float).
↪sum().item()

        # Obtain average validation loss and accuracy for the entire epoch

        average_valid_loss = valid_loss / n_valid_batches
        valid_accuracy = valid_n_correct / valid_size

        print("Validation error:")
        print(f"Accuracy: {valid_accuracy:.6f}, Average loss:␣
↪{average_valid_loss:.6f}")
        print()

        history_list.append([average_train_loss, average_valid_loss,␣
↪train_accuracy, valid_accuracy])

    # Display a message indicating training has finished

    print()
    print("Done!")

    # Create a data frame containing the entire training and validation history

    history = pd.DataFrame(data = history_list,
                           columns = ["average_train_loss",␣
↪"average_valid_loss",
                                      "train_accuracy", "valid_accuracy"])

    return model, history
```

12 Train the model

Pick a suitable number of epochs.

[31]:
```
n_epochs = 20
```

Run the training function.

[32]:
```
model, history = train(train_iterator = train_iterator,
                       valid_iterator = valid_iterator,
                       model = model,
                       loss_fn = loss_fn,
                       optimizer = optimizer,
                       device = device,
                       n_epochs = n_epochs)
```

```
Epoch 1
-------------------------------
Loss: 2.434332 [0.000000 / 45000.000000]
Loss: 0.868250 [12800.000000 / 45000.000000]
Loss: 0.799944 [25600.000000 / 45000.000000]
Loss: 0.652485 [38400.000000 / 45000.000000]
Validation error:
Accuracy: 0.809000, Average loss: 0.566040

Epoch 2
-------------------------------
Loss: 0.769252 [0.000000 / 45000.000000]
Loss: 0.766743 [12800.000000 / 45000.000000]
Loss: 0.738539 [25600.000000 / 45000.000000]
Loss: 0.375083 [38400.000000 / 45000.000000]
Validation error:
Accuracy: 0.848000, Average loss: 0.470199

Epoch 3
-------------------------------
Loss: 0.465486 [0.000000 / 45000.000000]
Loss: 0.500572 [12800.000000 / 45000.000000]
Loss: 0.381555 [25600.000000 / 45000.000000]
Loss: 0.553747 [38400.000000 / 45000.000000]
Validation error:
Accuracy: 0.841200, Average loss: 0.481155

Epoch 4
-------------------------------
Loss: 0.626594 [0.000000 / 45000.000000]
Loss: 0.496887 [12800.000000 / 45000.000000]
Loss: 0.688359 [25600.000000 / 45000.000000]
```

```
Loss: 0.550530 [38400.000000 / 45000.000000]
Validation error:
Accuracy: 0.841600, Average loss: 0.471855

Epoch 5
-------------------------------
Loss: 0.551628 [0.000000 / 45000.000000]
Loss: 0.501269 [12800.000000 / 45000.000000]
Loss: 0.413113 [25600.000000 / 45000.000000]
Loss: 0.639579 [38400.000000 / 45000.000000]
Validation error:
Accuracy: 0.853600, Average loss: 0.442192

Epoch 6
-------------------------------
Loss: 0.459690 [0.000000 / 45000.000000]
Loss: 0.502496 [12800.000000 / 45000.000000]
Loss: 0.466987 [25600.000000 / 45000.000000]
Loss: 0.356123 [38400.000000 / 45000.000000]
Validation error:
Accuracy: 0.857800, Average loss: 0.433987

Epoch 7
-------------------------------
Loss: 0.498197 [0.000000 / 45000.000000]
Loss: 0.612914 [12800.000000 / 45000.000000]
Loss: 0.407371 [25600.000000 / 45000.000000]
Loss: 0.655261 [38400.000000 / 45000.000000]
Validation error:
Accuracy: 0.856000, Average loss: 0.457914

Epoch 8
-------------------------------
Loss: 0.586647 [0.000000 / 45000.000000]
Loss: 0.644281 [12800.000000 / 45000.000000]
Loss: 0.515462 [25600.000000 / 45000.000000]
Loss: 0.527976 [38400.000000 / 45000.000000]
Validation error:
Accuracy: 0.863800, Average loss: 0.424889

Epoch 9
-------------------------------
Loss: 0.436477 [0.000000 / 45000.000000]
Loss: 0.361601 [12800.000000 / 45000.000000]
Loss: 0.528743 [25600.000000 / 45000.000000]
Loss: 0.603855 [38400.000000 / 45000.000000]
Validation error:
Accuracy: 0.867200, Average loss: 0.401357
```

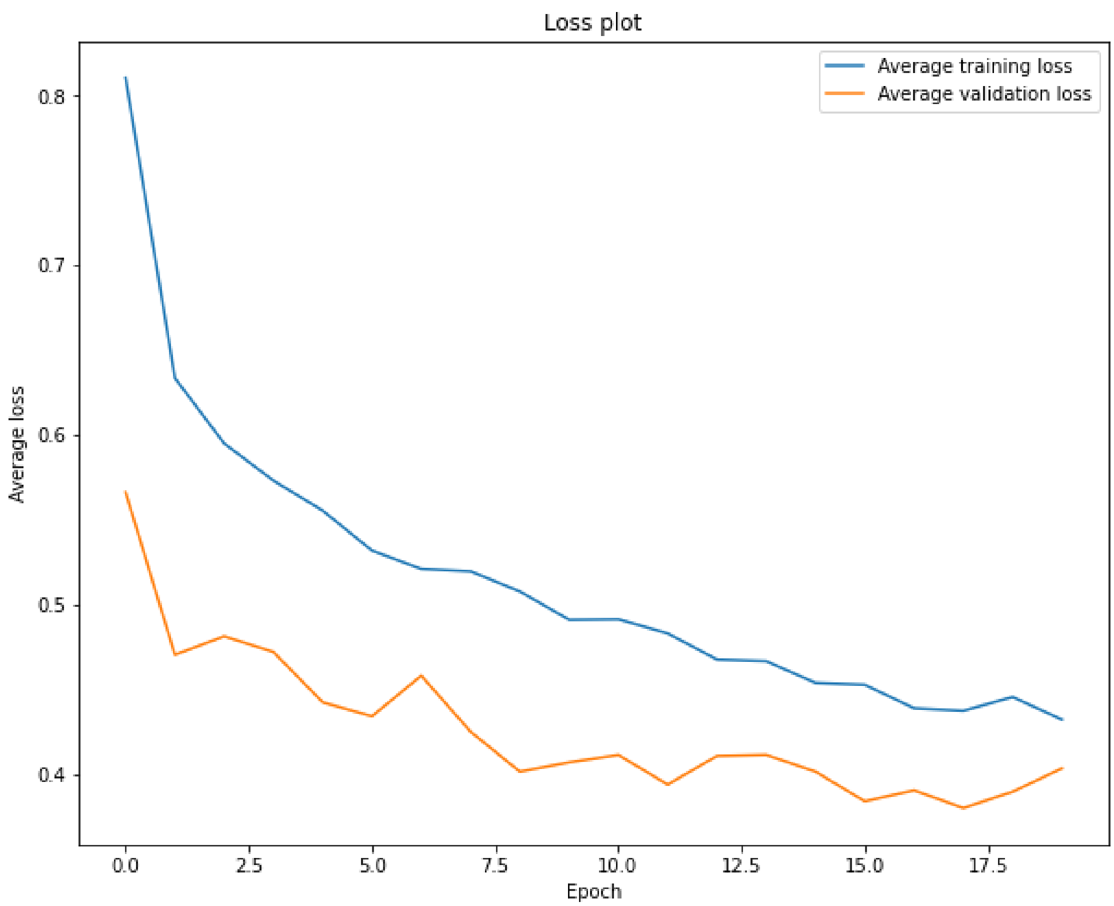
```
Epoch 10
-------------------------------
Loss: 0.509597 [0.000000 / 45000.000000]
Loss: 0.440453 [12800.000000 / 45000.000000]
Loss: 0.512997 [25600.000000 / 45000.000000]
Loss: 0.469684 [38400.000000 / 45000.000000]
Validation error:
Accuracy: 0.870000, Average loss: 0.406826

Epoch 11
-------------------------------
Loss: 0.554744 [0.000000 / 45000.000000]
Loss: 0.581503 [12800.000000 / 45000.000000]
Loss: 0.681727 [25600.000000 / 45000.000000]
Loss: 0.562679 [38400.000000 / 45000.000000]
Validation error:
Accuracy: 0.863600, Average loss: 0.411188

Epoch 12
-------------------------------
Loss: 0.319590 [0.000000 / 45000.000000]
Loss: 0.393904 [12800.000000 / 45000.000000]
Loss: 0.621188 [25600.000000 / 45000.000000]
Loss: 0.588325 [38400.000000 / 45000.000000]
Validation error:
Accuracy: 0.876800, Average loss: 0.393733

Epoch 13
-------------------------------
Loss: 0.408933 [0.000000 / 45000.000000]
Loss: 0.375278 [12800.000000 / 45000.000000]
Loss: 0.544092 [25600.000000 / 45000.000000]
Loss: 0.406210 [38400.000000 / 45000.000000]
Validation error:
Accuracy: 0.870200, Average loss: 0.410596

Epoch 14
-------------------------------
Loss: 0.621815 [0.000000 / 45000.000000]
Loss: 0.611037 [12800.000000 / 45000.000000]
Loss: 0.346763 [25600.000000 / 45000.000000]
Loss: 0.618866 [38400.000000 / 45000.000000]
Validation error:
Accuracy: 0.868800, Average loss: 0.411225

Epoch 15
-------------------------------
```

```
Loss: 0.479597 [0.000000 / 45000.000000]
Loss: 0.372814 [12800.000000 / 45000.000000]
Loss: 0.460519 [25600.000000 / 45000.000000]
Loss: 0.394958 [38400.000000 / 45000.000000]
Validation error:
Accuracy: 0.868400, Average loss: 0.401347

Epoch 16
-------------------------------
Loss: 0.375869 [0.000000 / 45000.000000]
Loss: 0.609816 [12800.000000 / 45000.000000]
Loss: 0.515159 [25600.000000 / 45000.000000]
Loss: 0.592108 [38400.000000 / 45000.000000]
Validation error:
Accuracy: 0.878200, Average loss: 0.383860

Epoch 17
-------------------------------
Loss: 0.353972 [0.000000 / 45000.000000]
Loss: 0.320062 [12800.000000 / 45000.000000]
Loss: 0.620991 [25600.000000 / 45000.000000]
Loss: 0.385208 [38400.000000 / 45000.000000]
Validation error:
Accuracy: 0.873400, Average loss: 0.390292

Epoch 18
-------------------------------
Loss: 0.347028 [0.000000 / 45000.000000]
Loss: 0.397949 [12800.000000 / 45000.000000]
Loss: 0.398912 [25600.000000 / 45000.000000]
Loss: 0.421690 [38400.000000 / 45000.000000]
Validation error:
Accuracy: 0.873600, Average loss: 0.379931

Epoch 19
-------------------------------
Loss: 0.501018 [0.000000 / 45000.000000]
Loss: 0.479010 [12800.000000 / 45000.000000]
Loss: 0.477444 [25600.000000 / 45000.000000]
Loss: 0.430662 [38400.000000 / 45000.000000]
Validation error:
Accuracy: 0.869400, Average loss: 0.389478

Epoch 20
-------------------------------
Loss: 0.368026 [0.000000 / 45000.000000]
Loss: 0.495289 [12800.000000 / 45000.000000]
Loss: 0.384818 [25600.000000 / 45000.000000]
```

```
Loss: 0.506044 [38400.000000 / 45000.000000]
Validation error:
Accuracy: 0.868200, Average loss: 0.403250


Done!
```

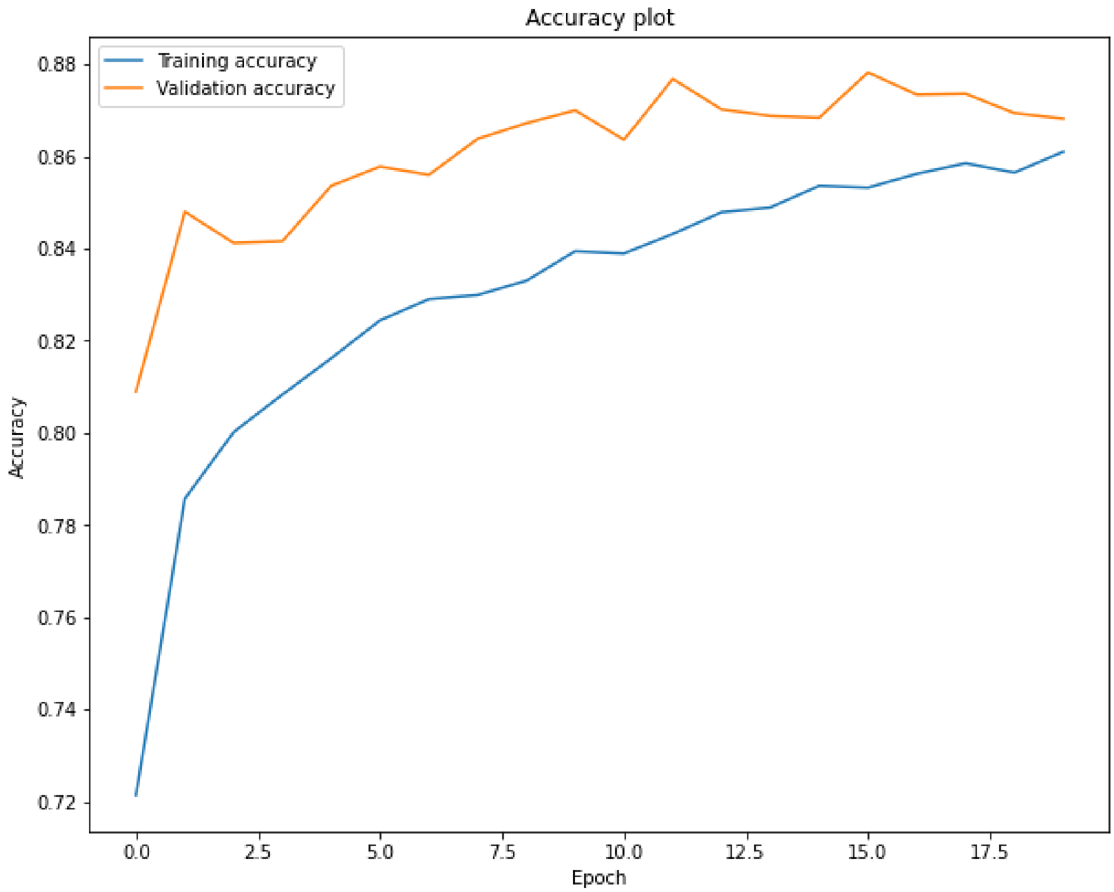
Plot the training and validation loss.

[33]:
```
plt.figure(figsize = [10, 8])
plt.plot(history["average_train_loss"],
         label = "Average training loss")
plt.plot(history["average_valid_loss"],
         label = "Average validation loss")
plt.legend()
plt.xlabel("Epoch")
plt.ylabel("Average loss")
plt.title("Loss plot")
plt.show()
```



Plot the training and validation accuracy.

[34]:
```
plt.figure(figsize = [10, 8])
plt.plot(history["train_accuracy"],
         label = "Training accuracy")
plt.plot(history["valid_accuracy"],
         label = "Validation accuracy")
plt.legend()
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.title("Accuracy plot")
plt.show()
```



13 Evaluate the model

Perform a final evaluation of the model on the test set. First, define a function to carry out the same.

[35]:
```
def evaluate(test_iterator,
             model,
             loss_fn,
             device):

    size = len(test_iterator.dataset)
    num_batches = len(test_iterator)
    test_loss = 0
    correct = 0

    with torch.no_grad():
        for X, y in test_iterator:
            X = X.to(device)
            y = y.to(device)
            pred = model(X)
            test_loss += loss_fn(pred, y).item()
            correct += (pred.argmax(1) == y).type(torch.float).sum().item()

    average_loss = test_loss / num_batches
    accuracy = correct / size

    print("Test error:")
    print(f"Accuracy: {accuracy:.6f}, Average loss: {average_loss:.6f}")
```

Then, run the function on the model which has just been trained.

[36]:
```
evaluate(test_iterator = test_iterator,
         model = model,
         loss_fn = loss_fn,
         device = device)
```

```
Test error:
Accuracy: 0.870500, Average loss: 0.395295
```

14 Save the model

Save the model to disk.

[37]:
```
torch.save(model, "pytorch-vgg16-cifar-10-model.pth")
```