Build my own CNN

Practice – CNN

- Run “7.2. MyCNN.ipynb"

Build my own CNN model

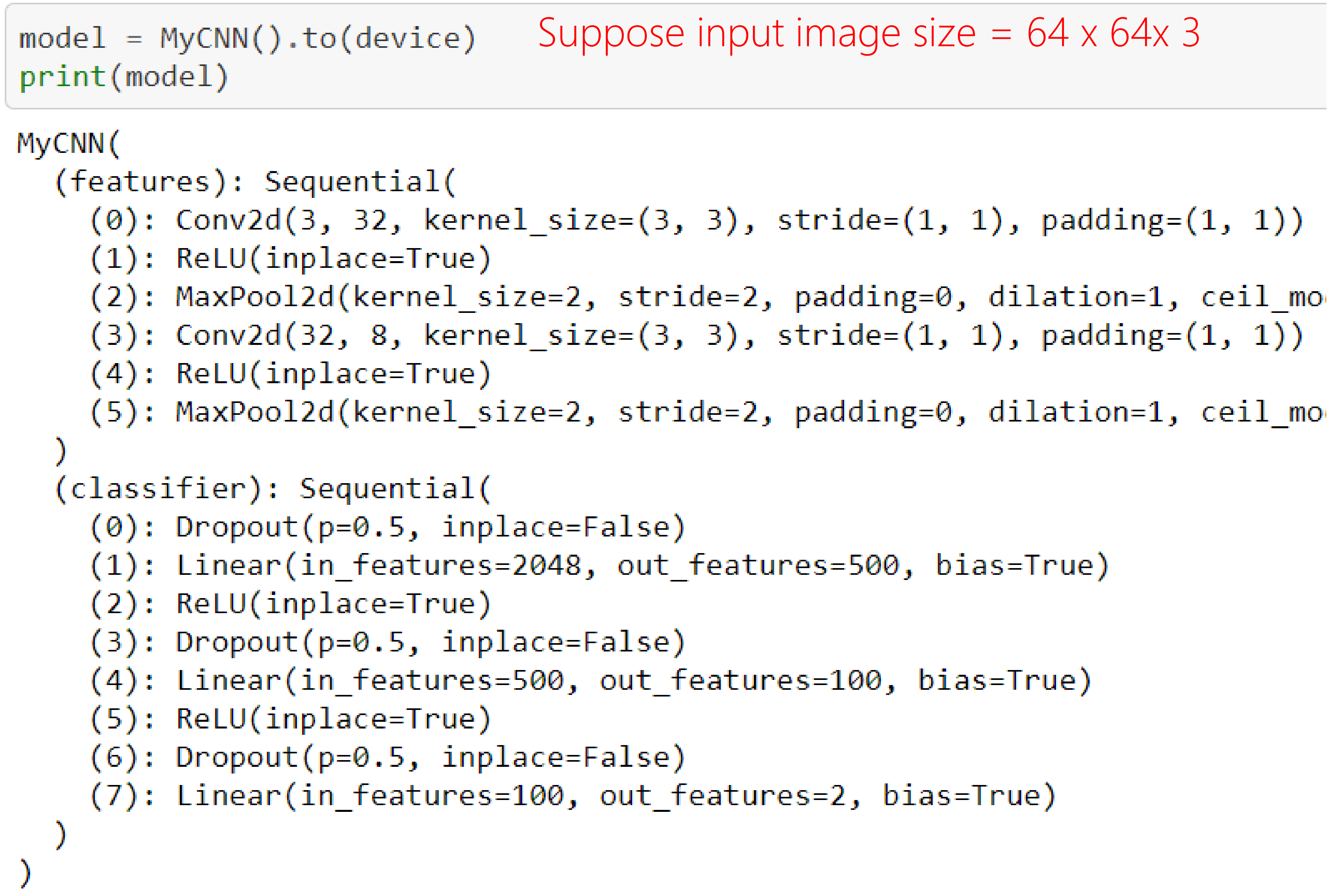
Suppose input image size = 64 x 64x 3

```
class MyCNN(nn.Module):
  def __init__(self):
    super(MyCNN, self).__init__()
    self.features = nn.Sequential(    #Assume input image H/W=64
        nn.Conv2d(3, 32, 3, 1, 1), #feature map H/W=(64+2*1-3)/1+1 = 64
        nn.ReLU(inplace=True),
        nn.MaxPool2d(2, 2, 0),     #H/W=(64+2*0-2)/2+1 = 32
        nn.Conv2d(32, 8, 3, 1, 1), #H/W=(32+2*1-3)/1+1 = 32
        nn.ReLU(inplace=True),
        nn.MaxPool2d(2, 2, 0),     #H/W=(32+2*0-2)/2+1 = 16
    )
    self.classifier = nn.Sequential(
        nn.Dropout(),
        nn.Linear(8 * 16 * 16, 500),
        nn.ReLU(inplace=True),
        nn.Dropout(),
        nn.Linear(500, 100),
        nn.ReLU(inplace=True),
        nn.Dropout(),
        nn.Linear(100, 2),
    )

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

The MLP used in "4.2. Classification with CE loss"

```
MyNet = nn.Sequential(
    nn.Linear(2, 50),
    nn.ReLU(),
    nn.Linear(50, 100),
    nn.ReLU(),
    nn.Linear(100, 50),
    nn.ReLU(),
    nn.Linear(50, 2),
)
MyNet.to(device)
```

Practice: Draw the structure of MyCNN

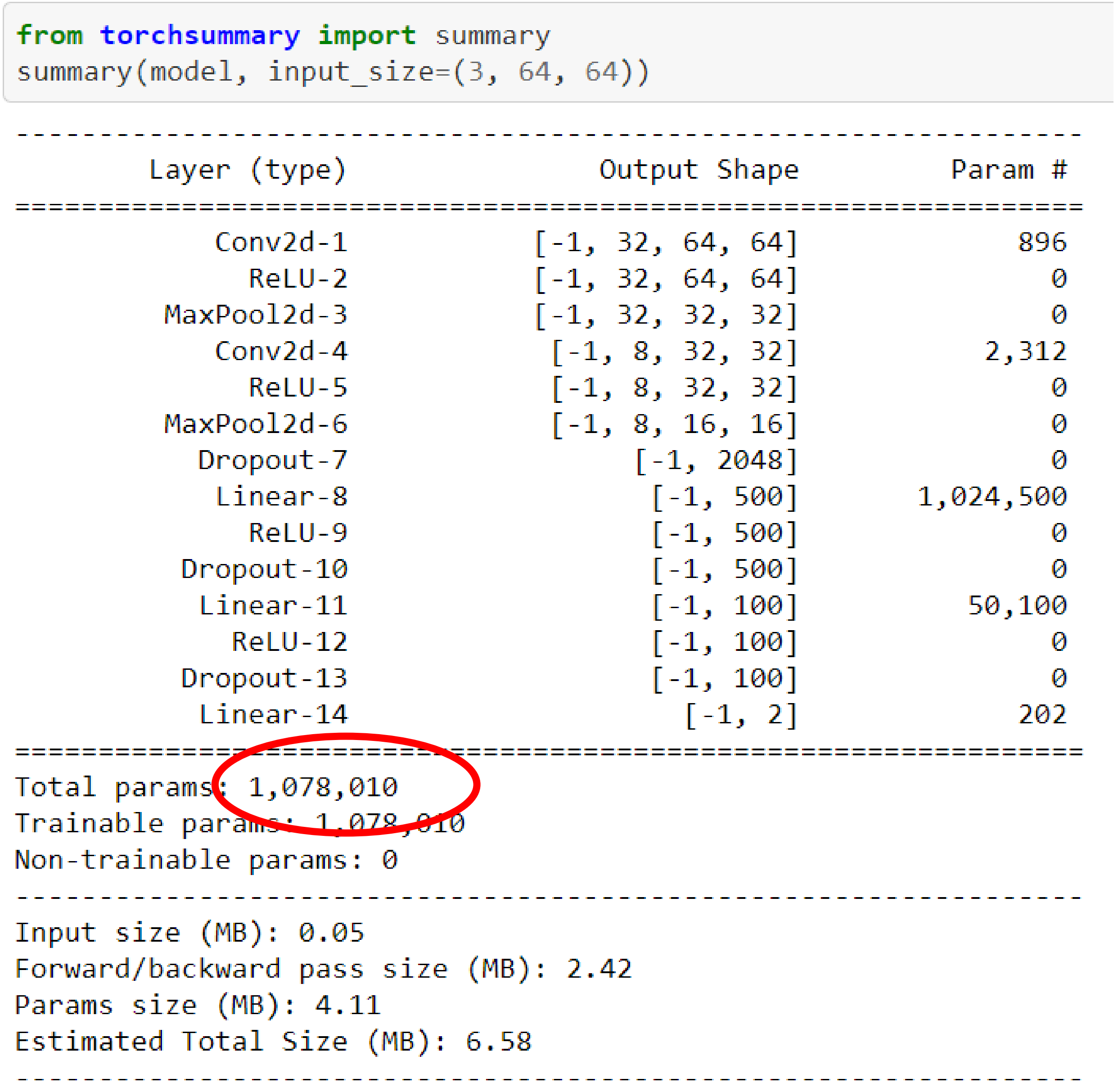


```
model = MyCNN().to(device)
print(model)
```

Suppose input image size = 64 x 64x 3

```
MyCNN(
  (features): Sequential(
    (0): Conv2d(3, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU(inplace=True)
    (2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mo
    (3): Conv2d(32, 8, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (4): ReLU(inplace=True)
    (5): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mo
  )
  (classifier): Sequential(
    (0): Dropout(p=0.5, inplace=False)
    (1): Linear(in_features=2048, out_features=500, bias=True)
    (2): ReLU(inplace=True)
    (3): Dropout(p=0.5, inplace=False)
    (4): Linear(in_features=500, out_features=100, bias=True)
    (5): ReLU(inplace=True)
    (6): Dropout(p=0.5, inplace=False)
    (7): Linear(in_features=100, out_features=2, bias=True)
  )
)
```

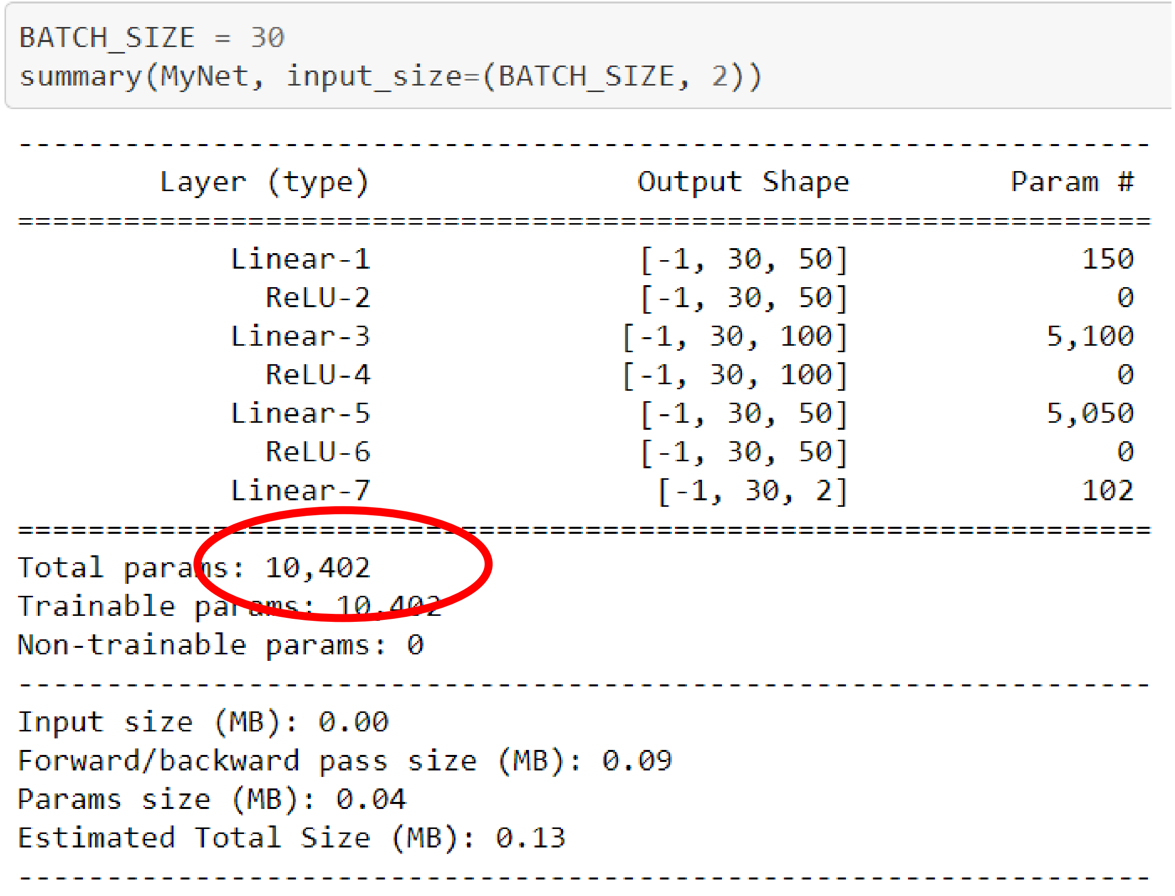
My own CNN



```
from torchsummary import summary
summary(model, input_size=(3, 64, 64))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1           [-1, 32, 64, 64]             896
              ReLU-2           [-1, 32, 64, 64]               0
         MaxPool2d-3           [-1, 32, 32, 32]               0
            Conv2d-4            [-1, 8, 32, 32]           2,312
              ReLU-5            [-1, 8, 32, 32]               0
         MaxPool2d-6            [-1, 8, 16, 16]               0
           Dropout-7                 [-1, 2048]               0
            Linear-8                  [-1, 500]       1,024,500
              ReLU-9                  [-1, 500]               0
          Dropout-10                  [-1, 500]               0
           Linear-11                  [-1, 100]          50,100
             ReLU-12                  [-1, 100]               0
          Dropout-13                  [-1, 100]               0
           Linear-14                    [-1, 2]             202
================================================================
Total params: 1,078,010
Trainable params: 1,078,010
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.05
Forward/backward pass size (MB): 2.42
Params size (MB): 4.11
Estimated Total Size (MB): 6.58
----------------------------------------------------------------
```

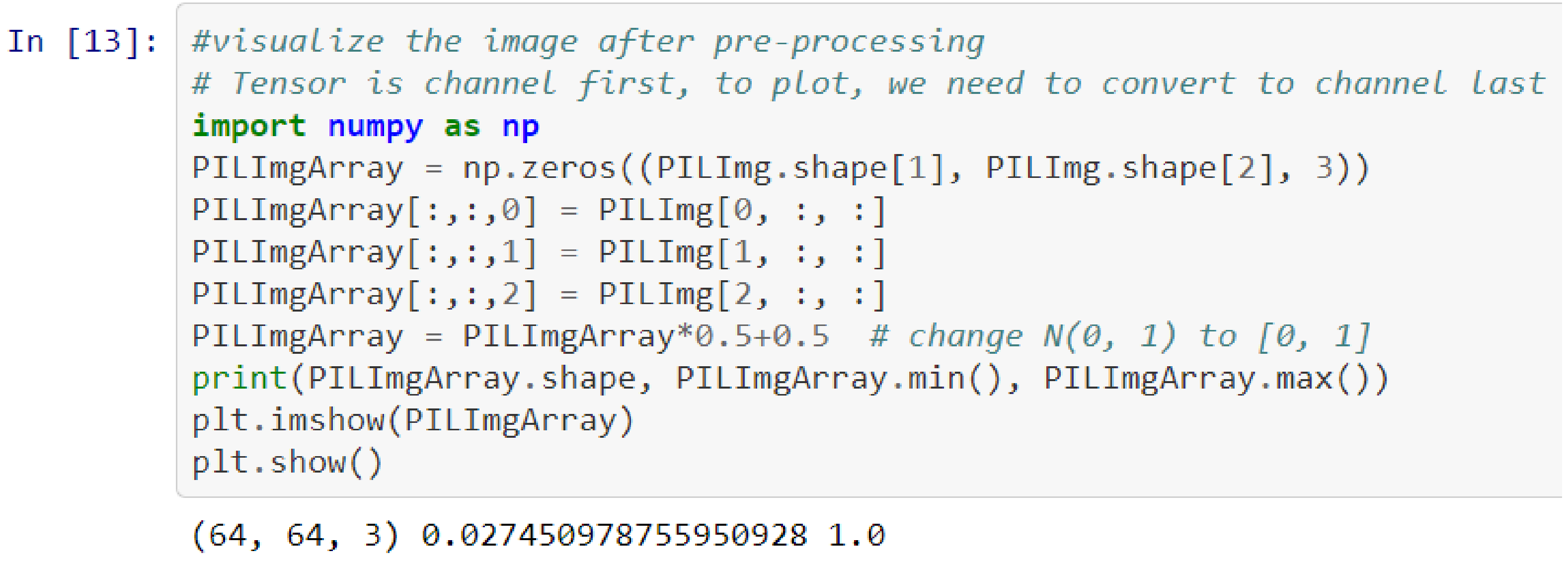
MLP in "4.2. Classification with CE loss"



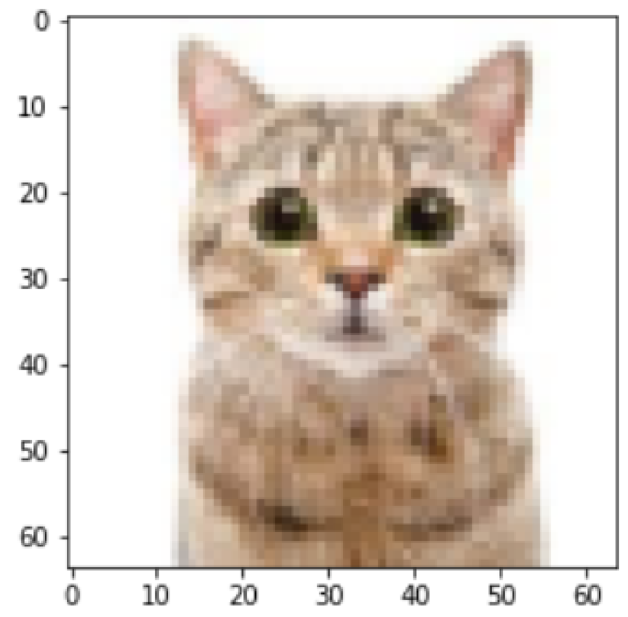
```
BATCH_SIZE = 30
summary(MyNet, input_size=(BATCH_SIZE, 2))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Linear-1               [-1, 30, 50]             150
              ReLU-2               [-1, 30, 50]               0
            Linear-3              [-1, 30, 100]           5,100
              ReLU-4              [-1, 30, 100]               0
            Linear-5               [-1, 30, 50]           5,050
              ReLU-6               [-1, 30, 50]               0
            Linear-7                [-1, 30, 2]             102
================================================================
Total params: 10,402
Trainable params: 10,402
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.00
Forward/backward pass size (MB): 0.09
Params size (MB): 0.04
Estimated Total Size (MB): 0.13
----------------------------------------------------------------
```

Input image after pre-processing

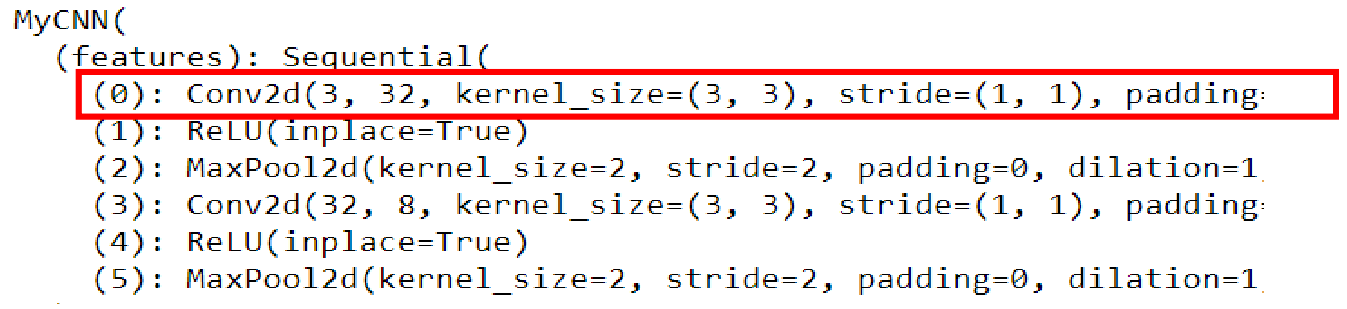


```
In [13]: #visualize the image after pre-processing
         # Tensor is channel first, to plot, we need to convert to channel last
         import numpy as np
         PILImgArray = np.zeros((PILImg.shape[1], PILImg.shape[2], 3))
         PILImgArray[:,:,0] = PILImg[0, :, :]
         PILImgArray[:,:,1] = PILImg[1, :, :]
         PILImgArray[:,:,2] = PILImg[2, :, :]
         PILImgArray = PILImgArray*0.5+0.5  # change N(0, 1) to [0, 1]
         print(PILImgArray.shape, PILImgArray.min(), PILImgArray.max())
         plt.imshow(PILImgArray)
         plt.show()

         (64, 64, 3) 0.027450978755950928 1.0
```

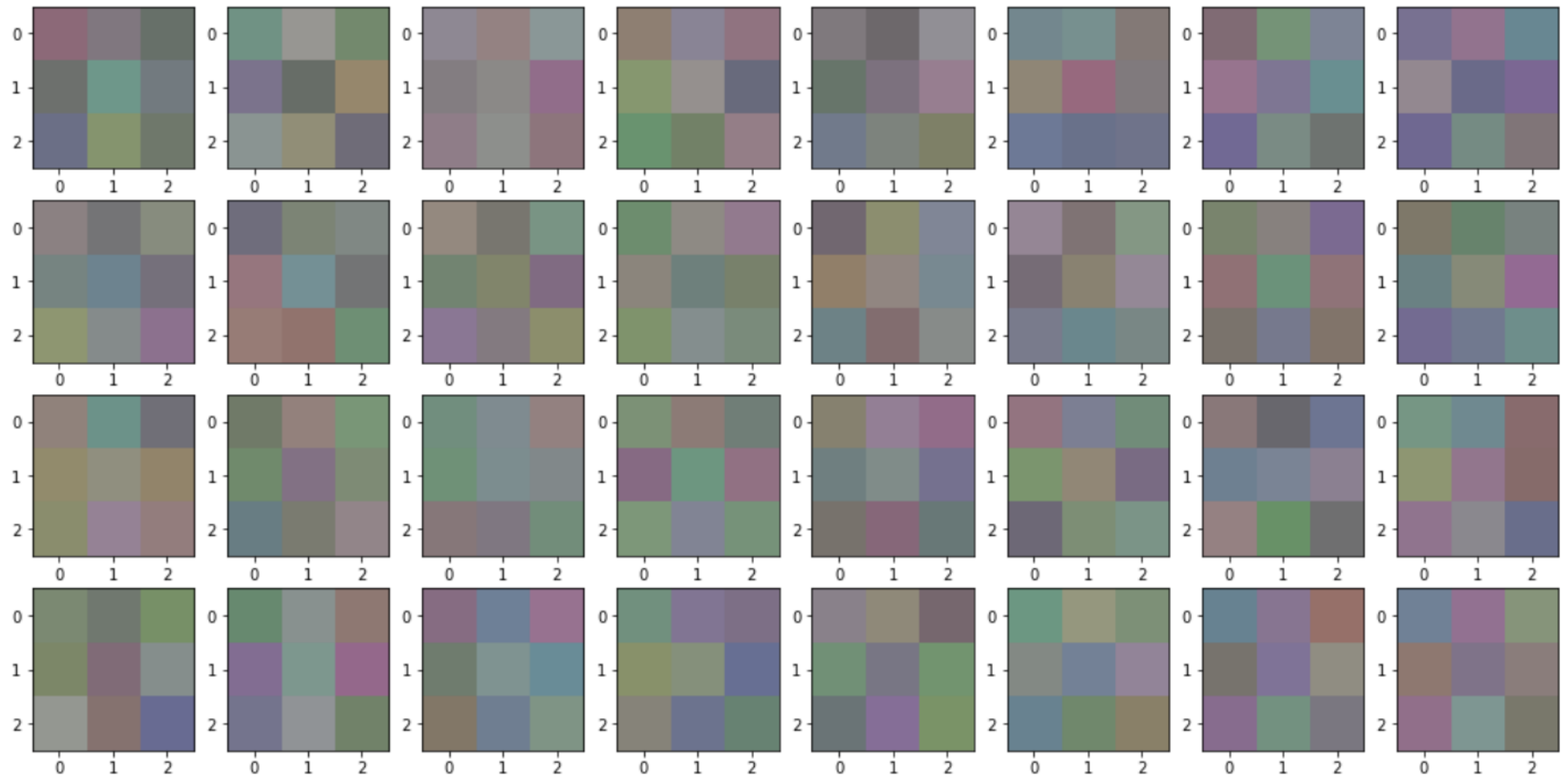


Input image size = 64 x 64x 3

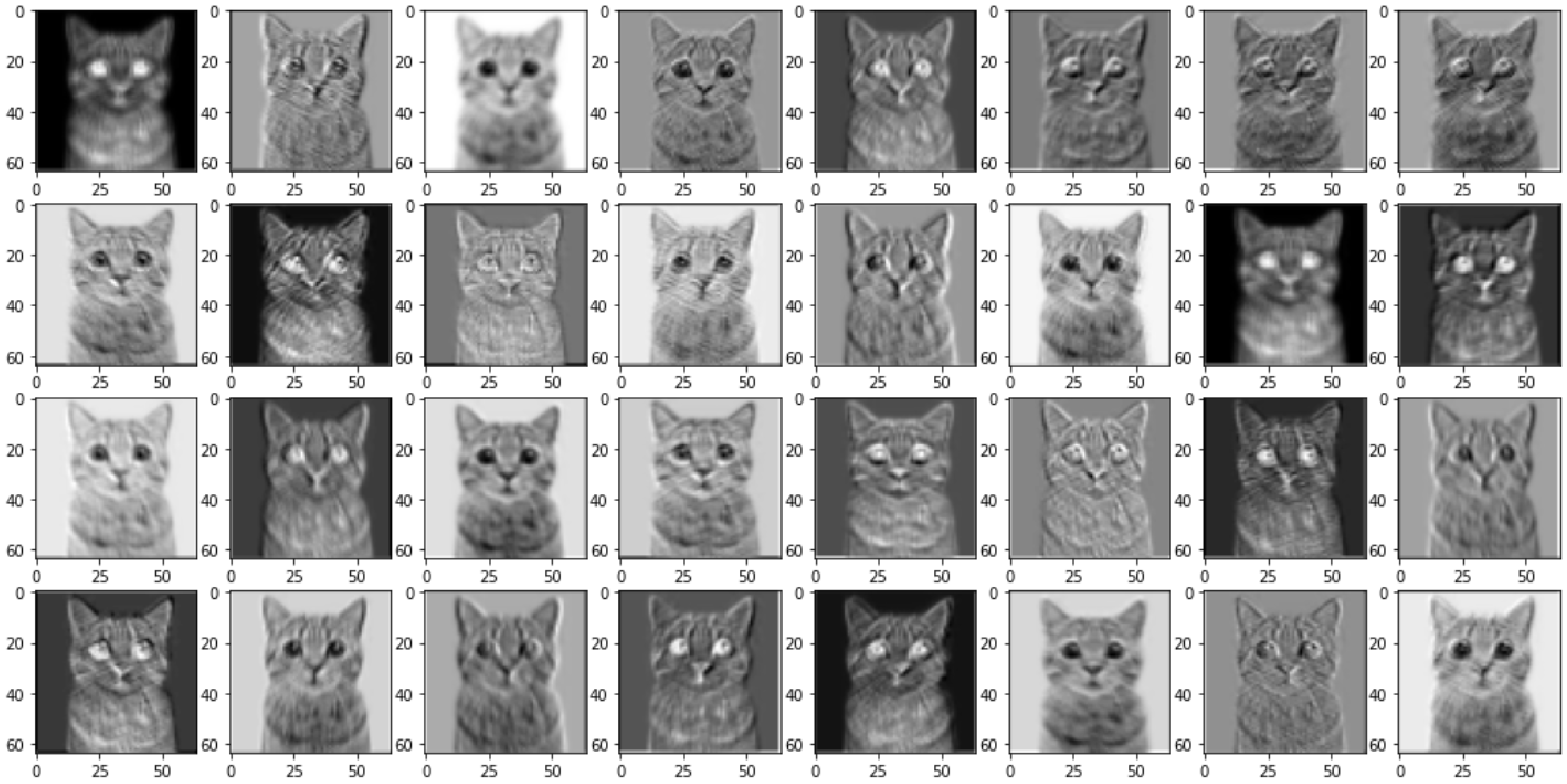
Initial filter weights



```
MyCNN(
  (features): Sequential(
    (0): Conv2d(3, 32, kernel_size=(3, 3), stride=(1, 1), padding
    (1): ReLU(inplace=True)
    (2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1
    (3): Conv2d(32, 8, kernel_size=(3, 3), stride=(1, 1), padding
    (4): ReLU(inplace=True)
    (5): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1
```

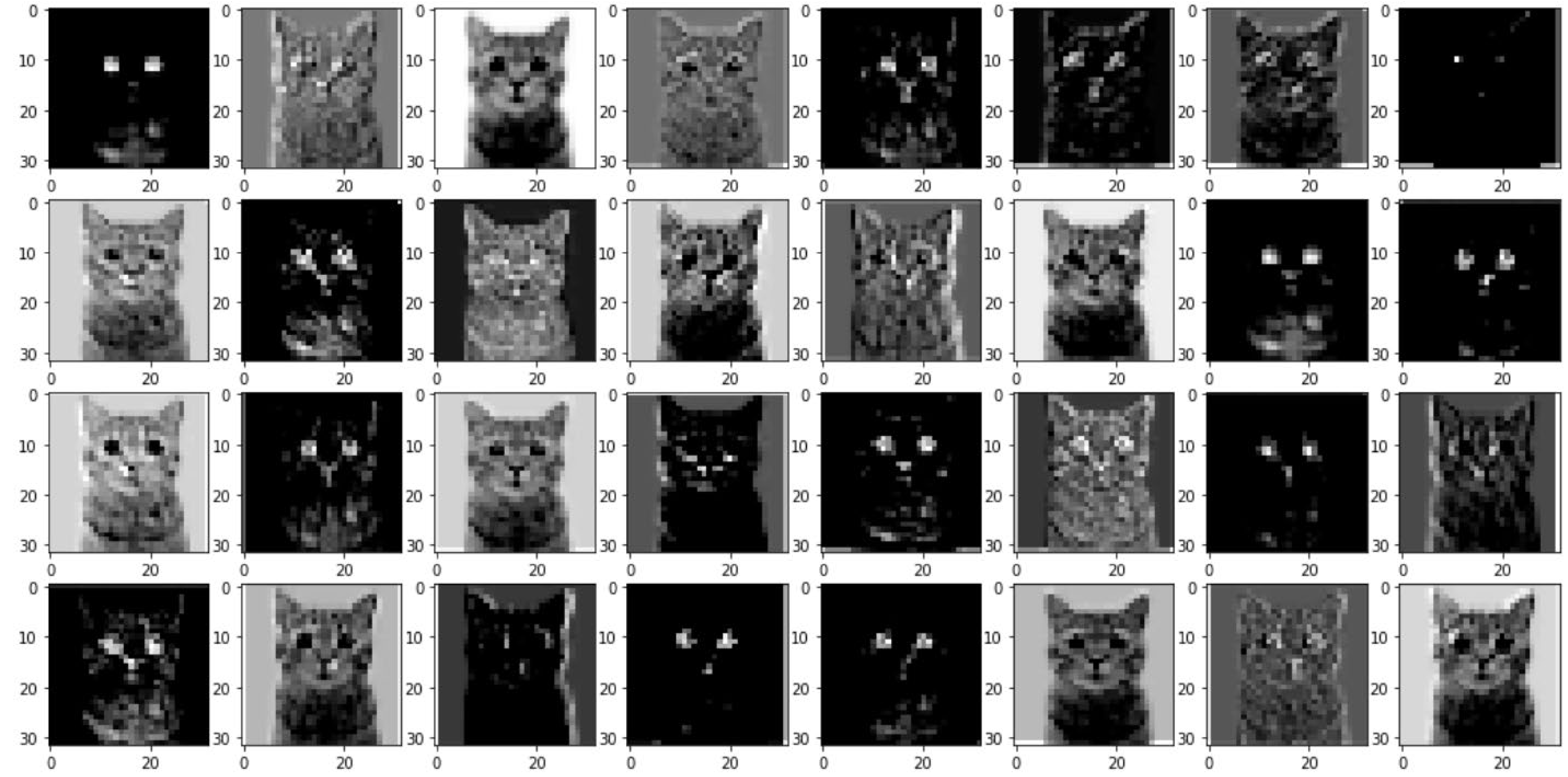


Output feature map, shape = 64x64x32



Feature map after max pooling, shape = 32x32x32

```
torch.Size([1, 32, 32, 32])
```



Flatten

```python
class MyCNN(nn.Module):
  def __init__(self):
    super(MyCNN, self).__init__()
    self.features = nn.Sequential(    #Assume input image H/W=64
        nn.Conv2d(3, 32, 3, 1, 1), #feature map H/W=(64+2*1-3)/1+1 = 64
        nn.ReLU(inplace=True),
        nn.MaxPool2d(2, 2, 0),     #H/W=(64+2*0-2)/2+1 = 32
        nn.Conv2d(32, 8, 3, 1, 1), #H/W=(32+2*1-3)/1+1 = 32
        nn.ReLU(inplace=True),
        nn.MaxPool2d(2, 2, 0),     #H/W=(32+2*0-2)/2+1 = 16
    )
    self.classifier = nn.Sequential(
        nn.Dropout(),
        nn.Linear(8 * 16 * 16, 500),
        nn.ReLU(inplace=True),
        nn.Dropout(),
        nn.Linear(500, 100),
        nn.ReLU(inplace=True),
        nn.Dropout(),
        nn.Linear(100, 2),
    )

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

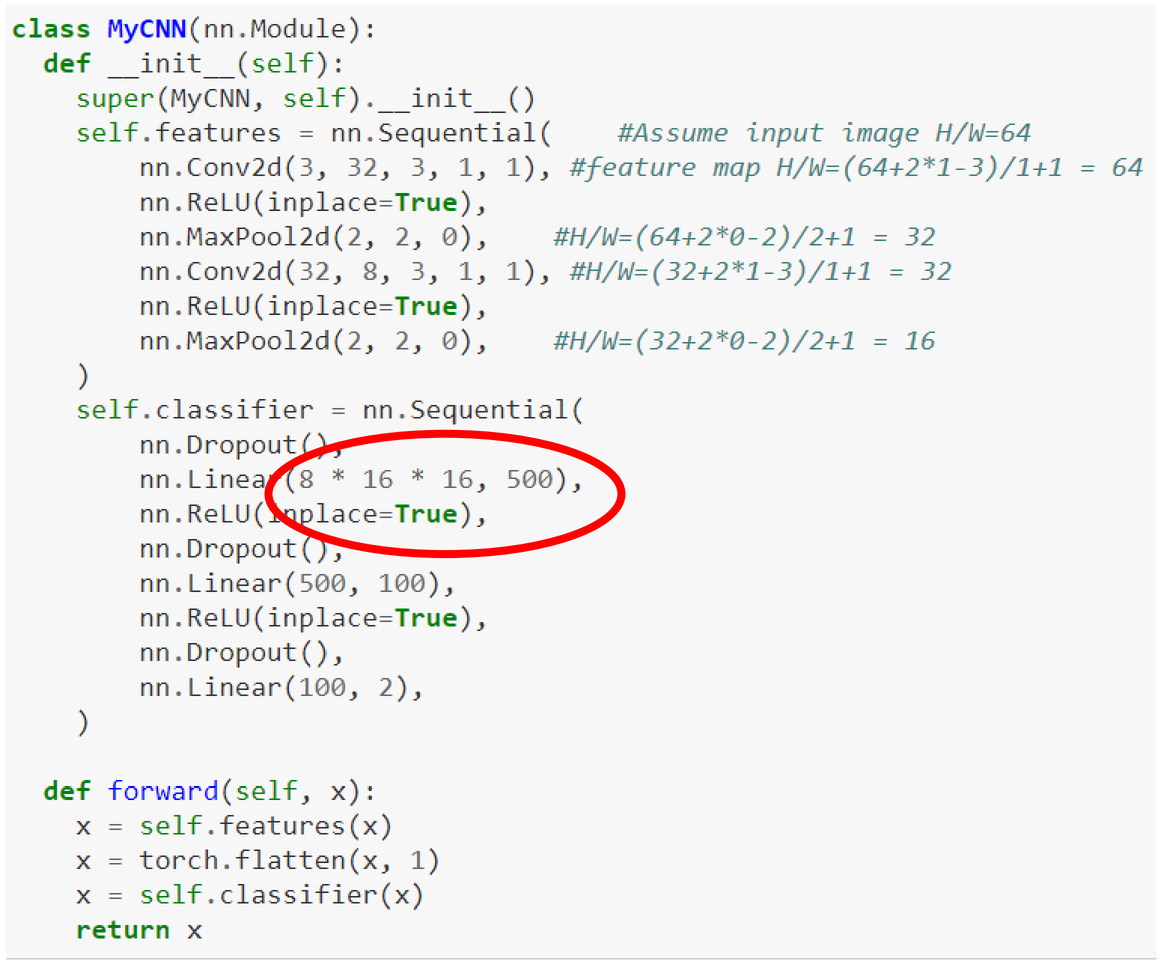
```python
model = MyCNN().to(device)
print(model)
```

```
MyCNN(
  (features): Sequential(
    (0): Conv2d(3, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU(inplace=True)
    (2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mo
    (3): Conv2d(32, 8, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (4): ReLU(inplace=True)
    (5): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mo
  )
  (classifier): Sequential(
    (0): Dropout(p=0.5, inplace=False)
    (1): Linear(in_features=2048, out_features=500, bias=True)
    (2): ReLU(inplace=True)
    (3): Dropout(p=0.5, inplace=False)
    (4): Linear(in_features=500, out_features=100, bias=True)
    (5): ReLU(inplace=True)
    (6): Dropout(p=0.5, inplace=False)
    (7): Linear(in_features=100, out_features=2, bias=True)
  )
)
```

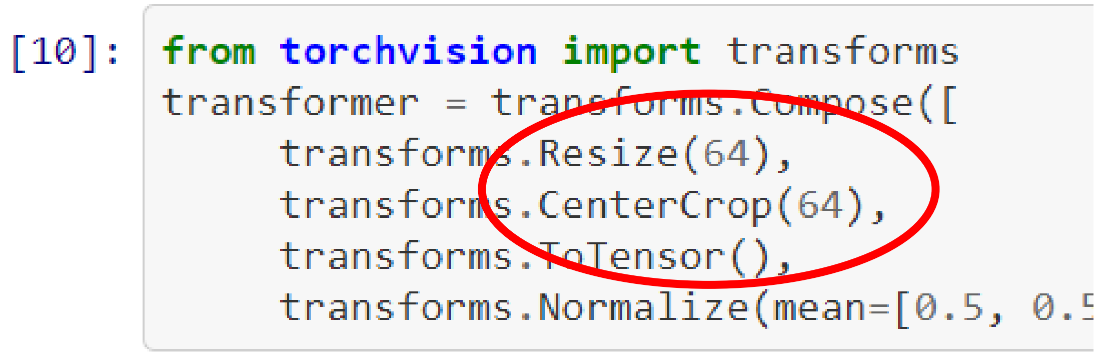
```
In [22]: WholeConvLayers = model.features
         out1 = WholeConvLayers(imageTensor.to(device))
         print(out1.shape)

         torch.Size([1, 8, 16, 16])

In [23]: out2 = torch.flatten(out1, 1)
         print(out2.shape)

         torch.Size([1, 2048])

In [24]: ClassifierMLP = model.classifier
         out = ClassifierMLP(out2)
```

HW5 (1)

- Let the input image size be 224x224x3. Modify your CNN.



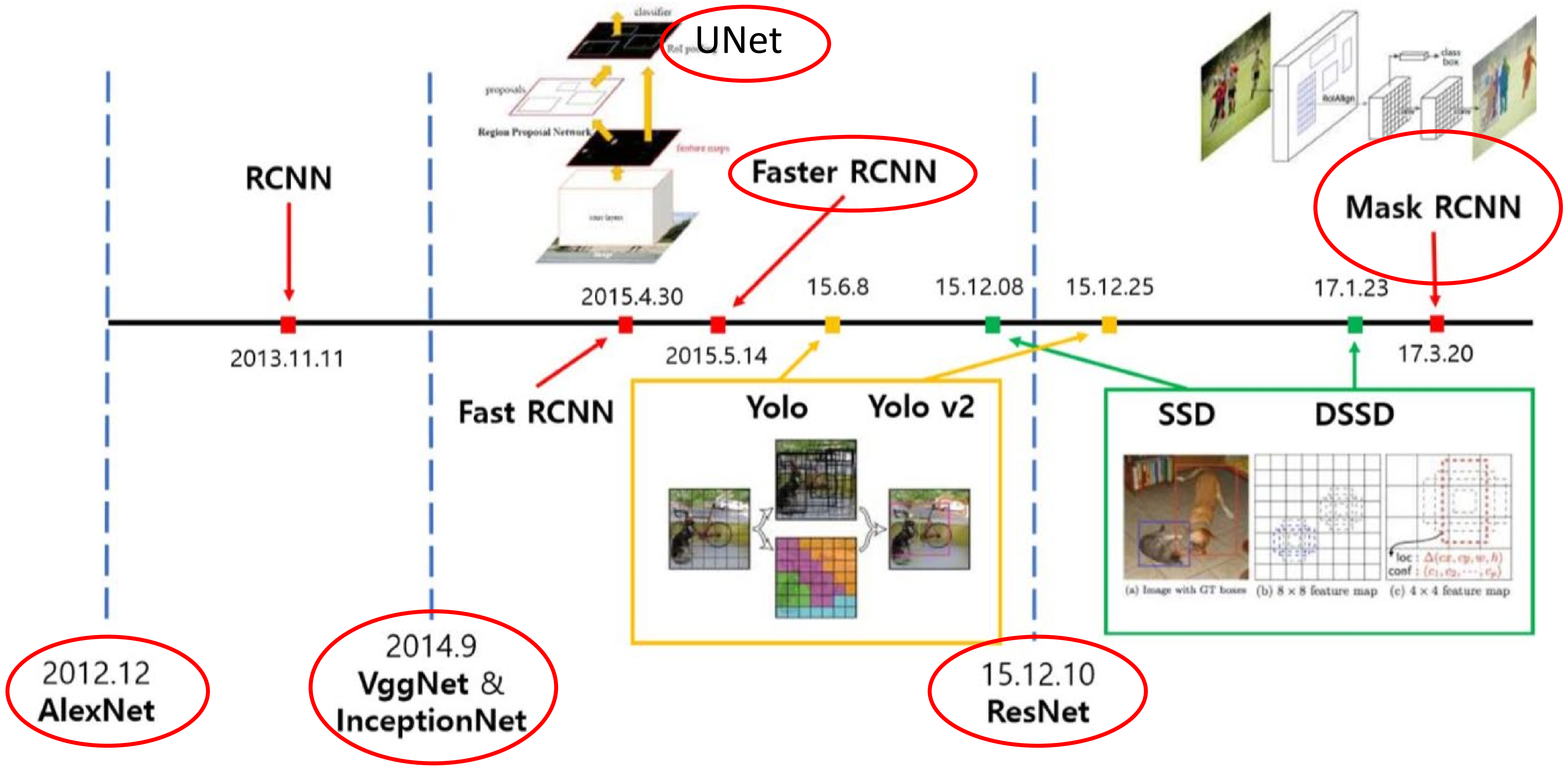
```python
class MyCNN(nn.Module):
  def __init__(self):
    super(MyCNN, self).__init__()
    self.features = nn.Sequential(    #Assume input image H/W=64
        nn.Conv2d(3, 32, 3, 1, 1), #feature map H/W=(64+2*1-3)/1+1 = 64
        nn.ReLU(inplace=True),
        nn.MaxPool2d(2, 2, 0),     #H/W=(64+2*0-2)/2+1 = 32
        nn.Conv2d(32, 8, 3, 1, 1), #H/W=(32+2*1-3)/1+1 = 32
        nn.ReLU(inplace=True),
        nn.MaxPool2d(2, 2, 0),     #H/W=(32+2*0-2)/2+1 = 16
    )
    self.classifier = nn.Sequential(
        nn.Dropout(),
        nn.Linear(8 * 16 * 16, 500),
        nn.ReLU(inplace=True),
        nn.Dropout(),
        nn.Linear(500, 100),
        nn.ReLU(inplace=True),
        nn.Dropout(),
        nn.Linear(100, 2),
    )

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



```python
[10]: from torchvision import transforms
      transformer = transforms.Compose([
            transforms.Resize(64),
            transforms.CenterCrop(64),
            transforms.ToTensor(),
            transforms.Normalize(mean=[0.5, 0.5
```

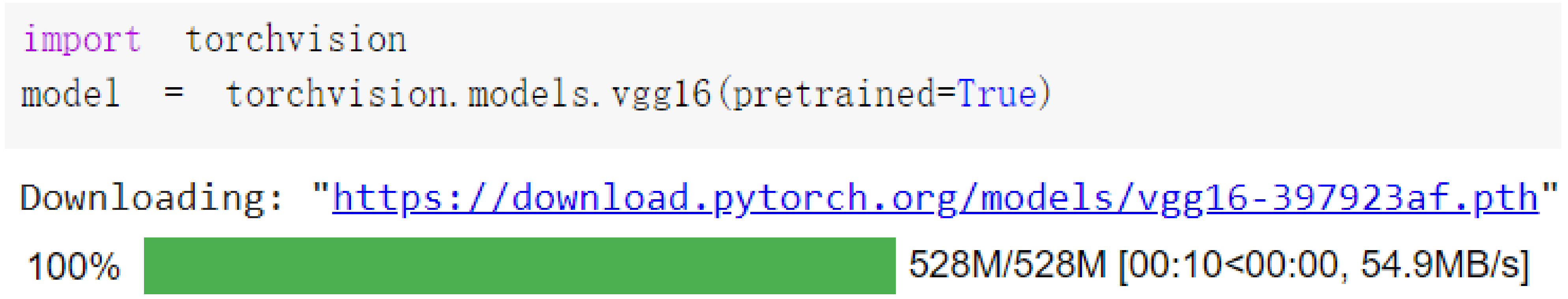
VGG16

CNN family



圖來源: 李春煌 FasterRCNN講義 https://youtu.be/2i9CcmJp2yI

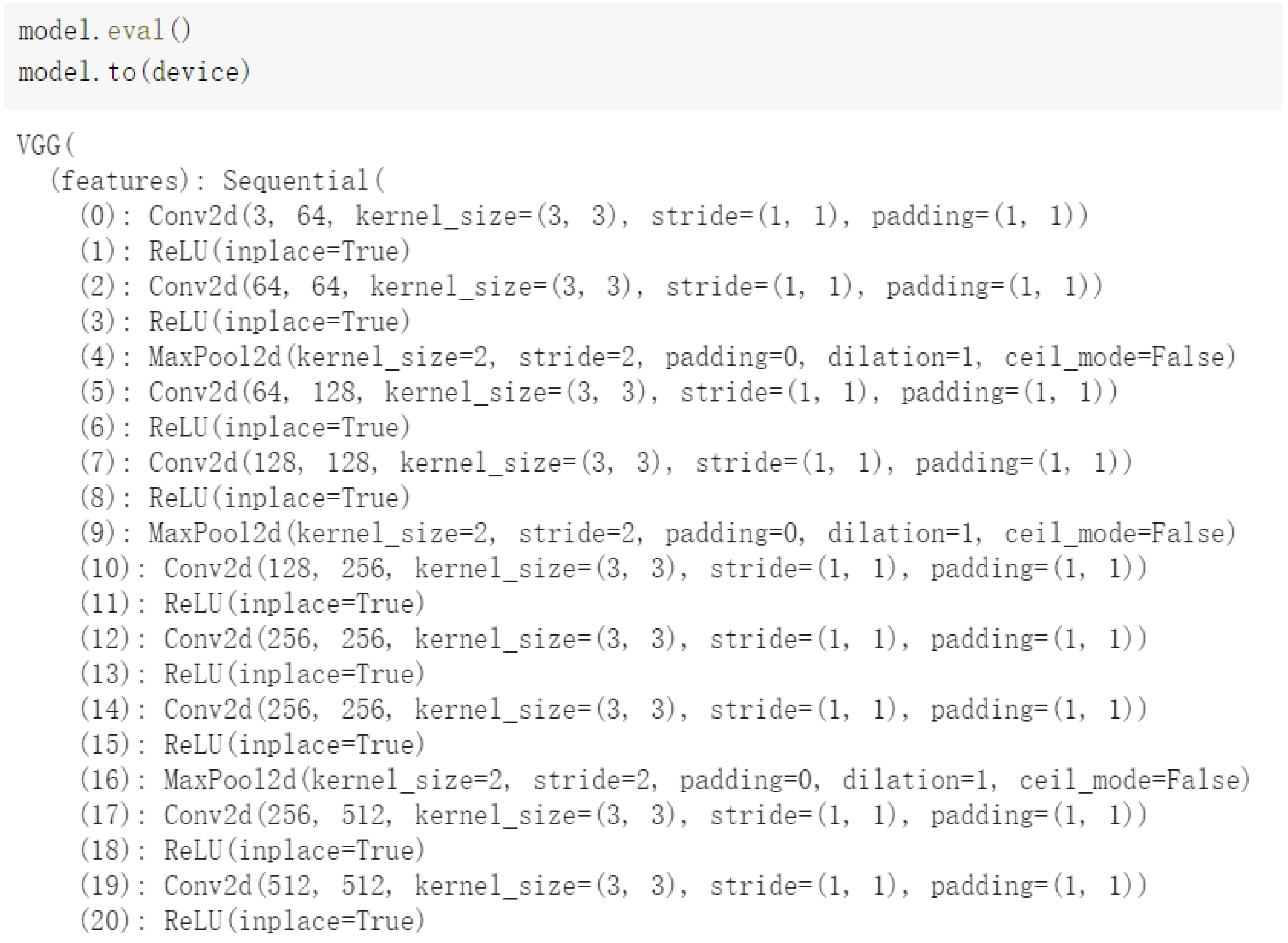
Practice – Load ImageNet pre-trained VGG



```python
import torchvision
model = torchvision.models.vgg16(pretrained=True)
```

```
Downloading: "https://download.pytorch.org/models/vgg16-397923af.pth"
100%  528M/528M [00:10<00:00, 54.9MB/s]
```

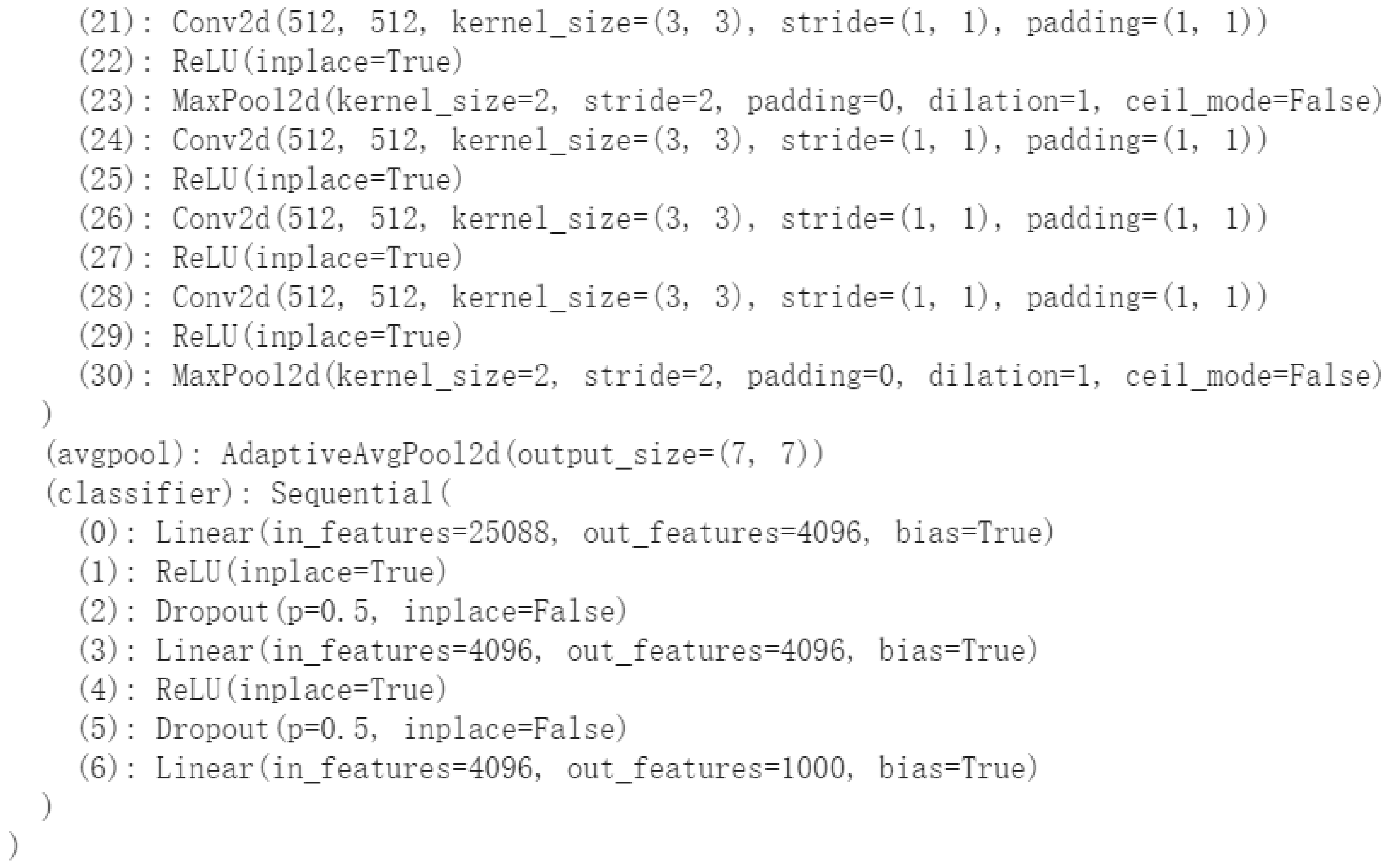
Practice: Draw the structure of VGG16



```
model.eval()
model.to(device)
```

```
VGG(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (1): ReLU(inplace=True)
    (2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (3): ReLU(inplace=True)
    (4): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (5): Conv2d(64, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (6): ReLU(inplace=True)
    (7): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (8): ReLU(inplace=True)
    (9): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (10): Conv2d(128, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (11): ReLU(inplace=True)
    (12): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (13): ReLU(inplace=True)
    (14): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (15): ReLU(inplace=True)
    (16): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (17): Conv2d(256, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (18): ReLU(inplace=True)
    (19): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (20): ReLU(inplace=True)
```

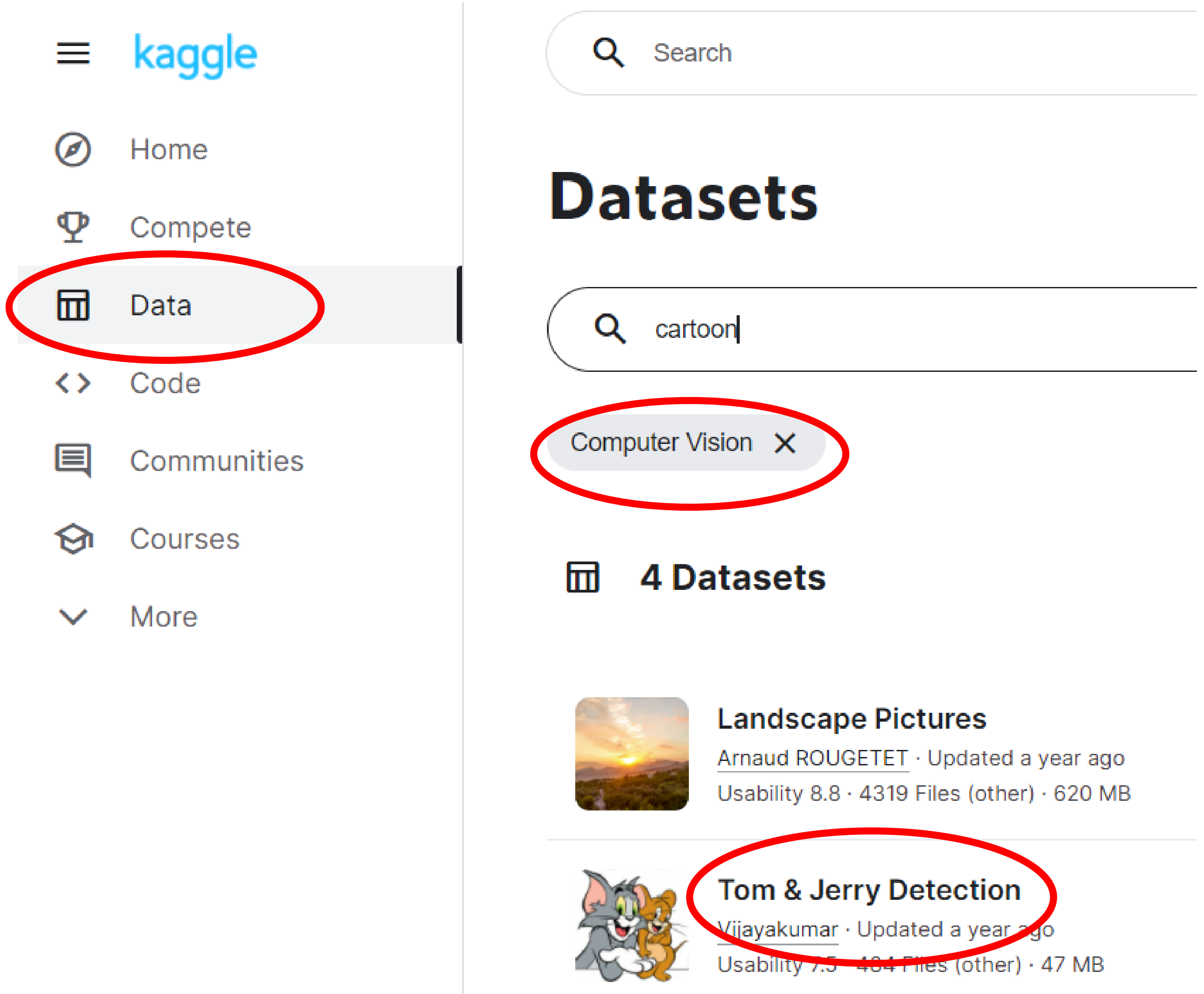
Practice: Draw the structure of VGG16



```
    (21): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (22): ReLU(inplace=True)
    (23): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
    (24): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (25): ReLU(inplace=True)
    (26): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (27): ReLU(inplace=True)
    (28): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (29): ReLU(inplace=True)
    (30): 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)
  )
)
```

Transfer learning

Download images from Kaggle



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Arnaud ROUGETET · Updated a year ago
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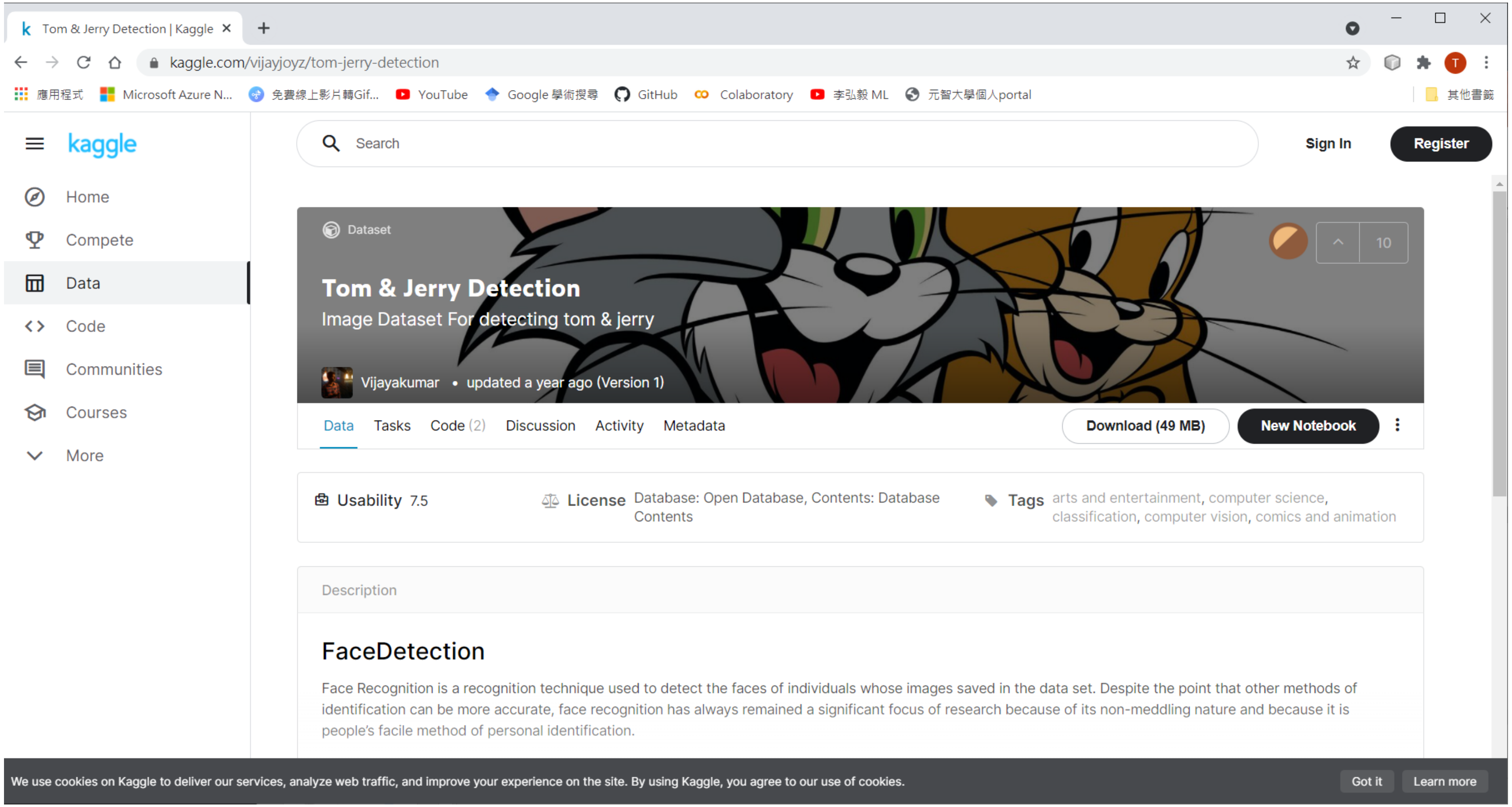
Vijayakumar · Updated a year ago
Usability 7.5 · 404 Files (other) · 47 MB

Tom & Jerry



Tom & Jerry Detection | Kaggle

kaggle.com/vijayjoyz/tom-jerry-detection

Tom & Jerry Detection

Image Dataset For detecting tom & jerry

Vijayakumar • updated a year ago (Version 1)

Usability 7.5

License Database: Open Database, Contents: Database Contents

Tags arts and entertainment, computer science, classification, computer vision, comics and animation

Description

FaceDetection

Face Recognition is a recognition technique used to detect the faces of individuals whose images saved in the data set. Despite the point that other methods of identification can be more accurate, face recognition has always remained a significant focus of research because of its non-meddling nature and because it is people's facile method of personal identification.

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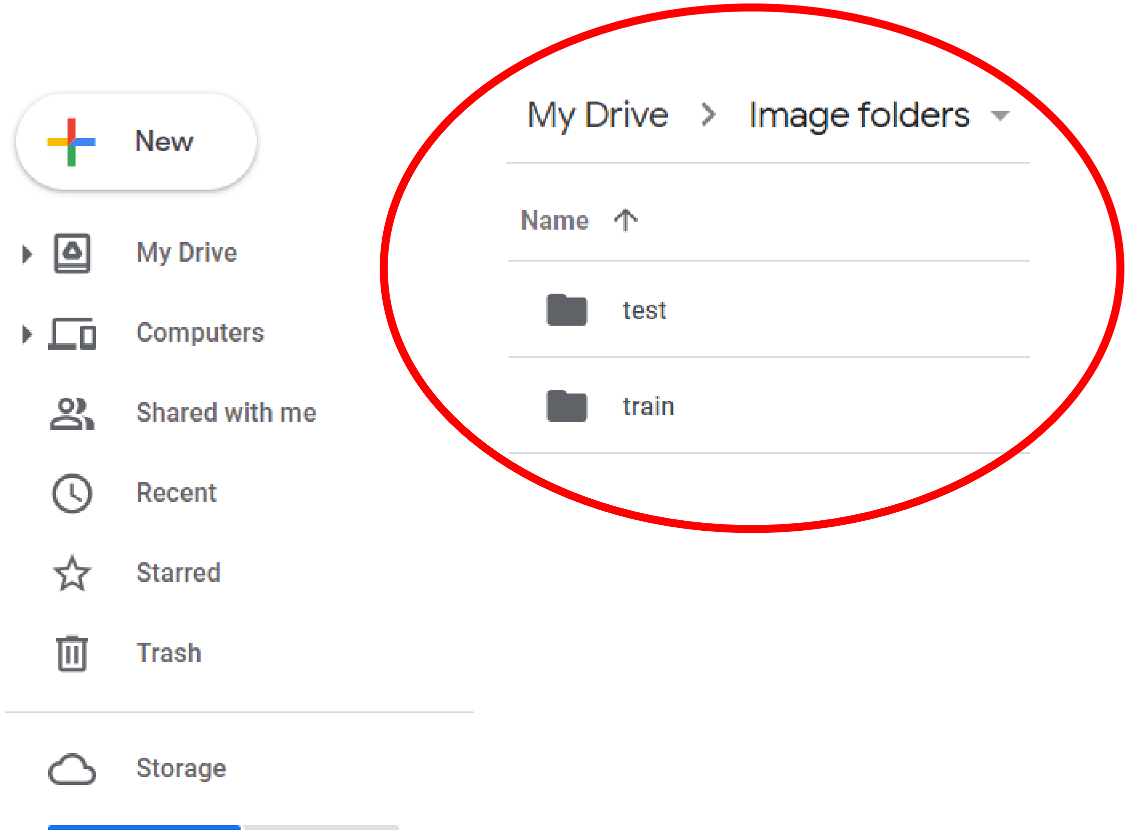
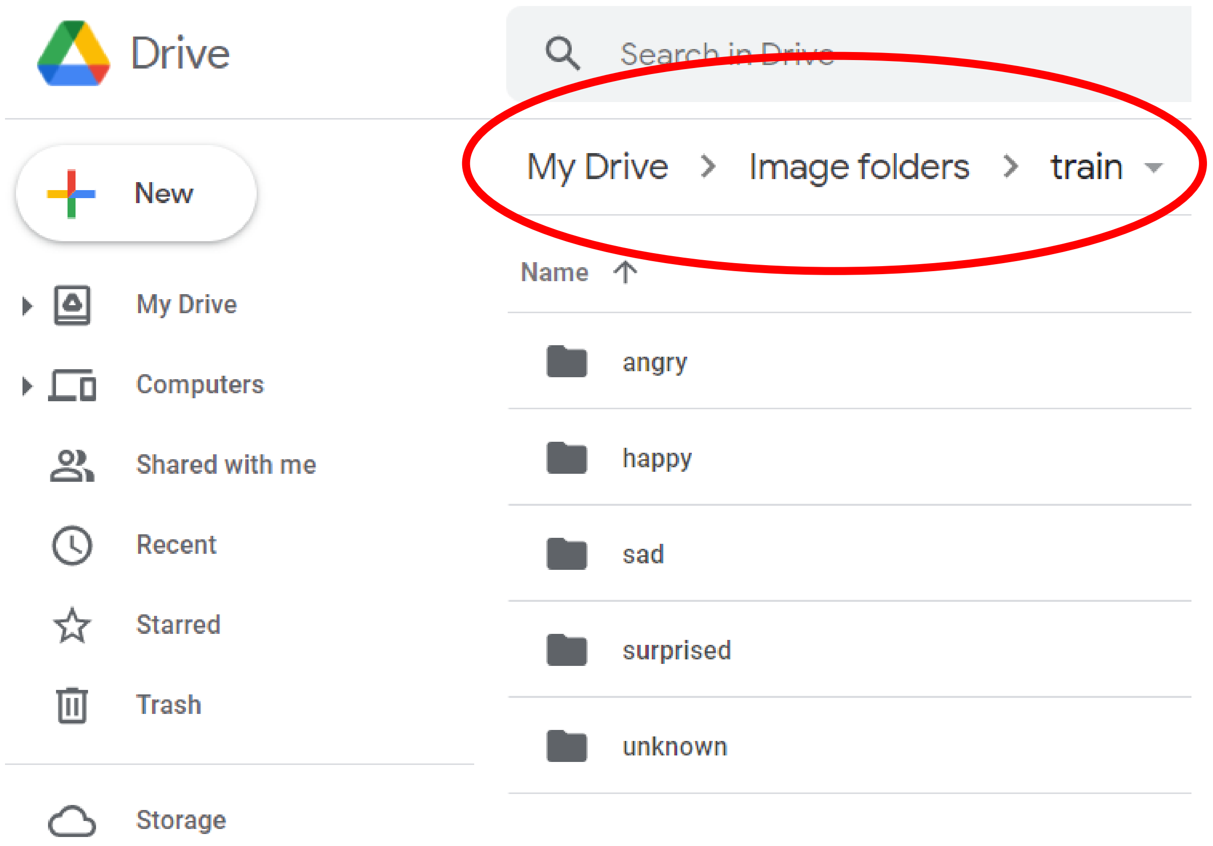
Save images in your Google drive



My Drive > Image folders

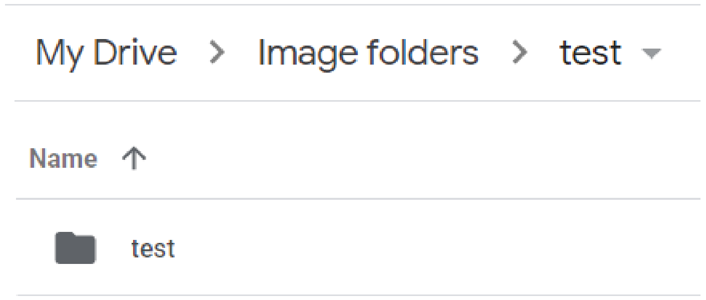
Name ↑
test
train



My Drive > Image folders > train

Name ↑
angry
happy
sad
surprised
unknown

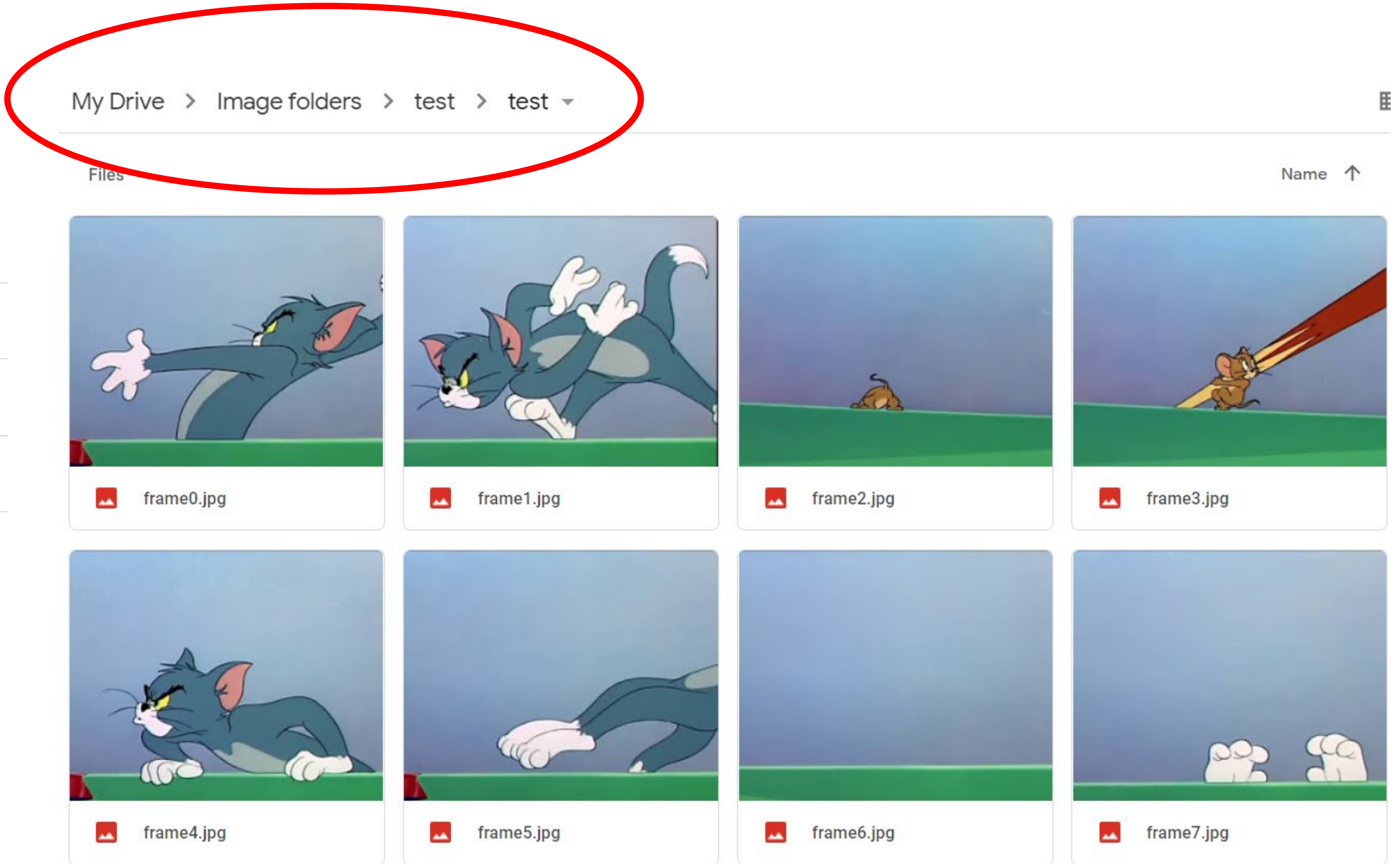
Save images in your Google drive



My Drive > Image folders > test

Name ↑

test



My Drive > Image folders > test > test

Files

Name ↑

frame0.jpg

frame1.jpg

frame2.jpg

frame3.jpg

frame4.jpg

frame5.jpg

frame6.jpg

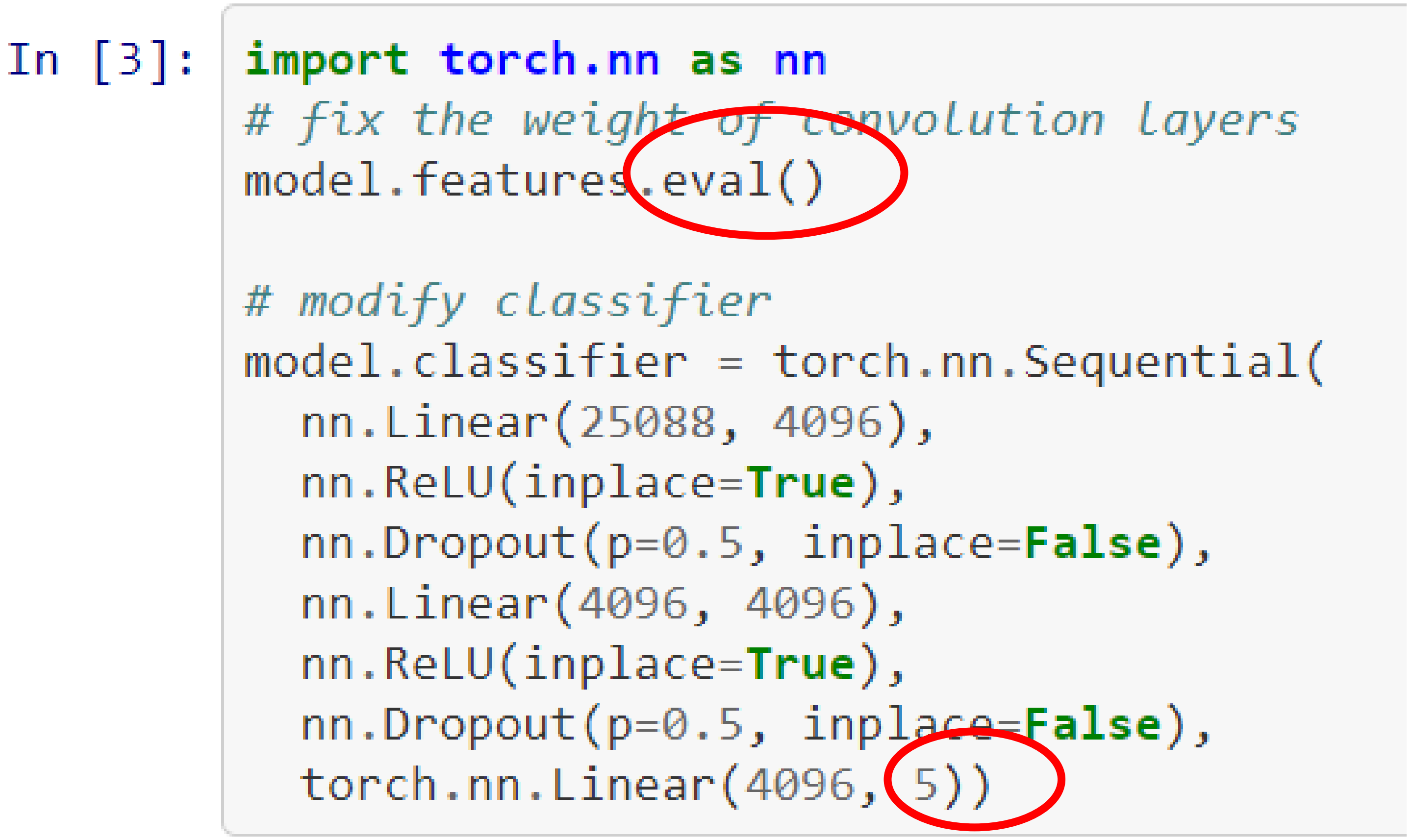
frame7.jpg

Practice

- Run “7.3. Transfer learning.ipynb"

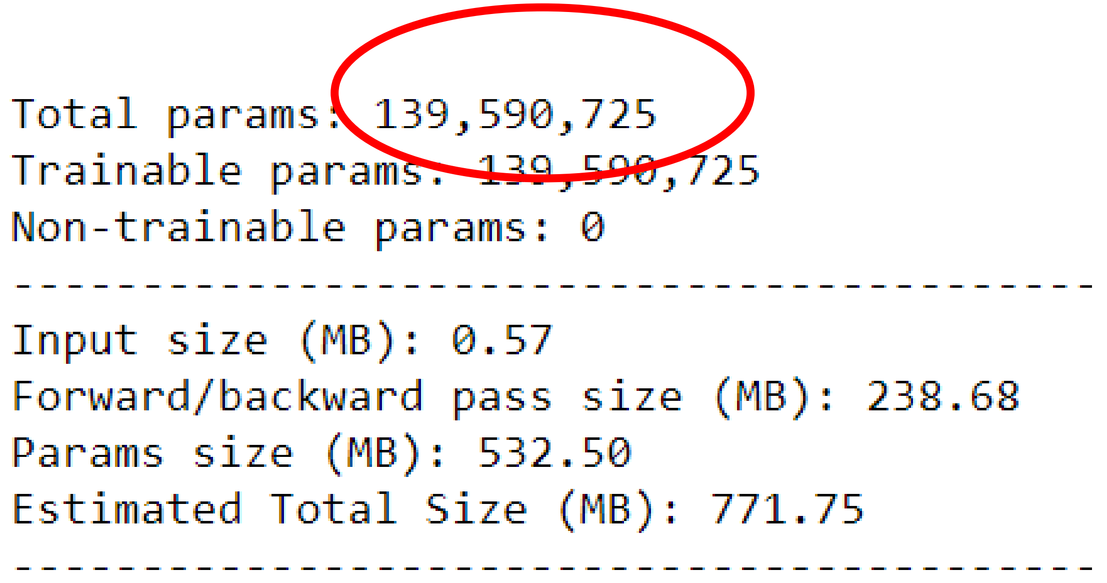
Build our own image classifier

- Suppose input image size = (224, 224, 3)
- Output has 5 classes: Angry, Happy, Sad, Surprised, Unknown



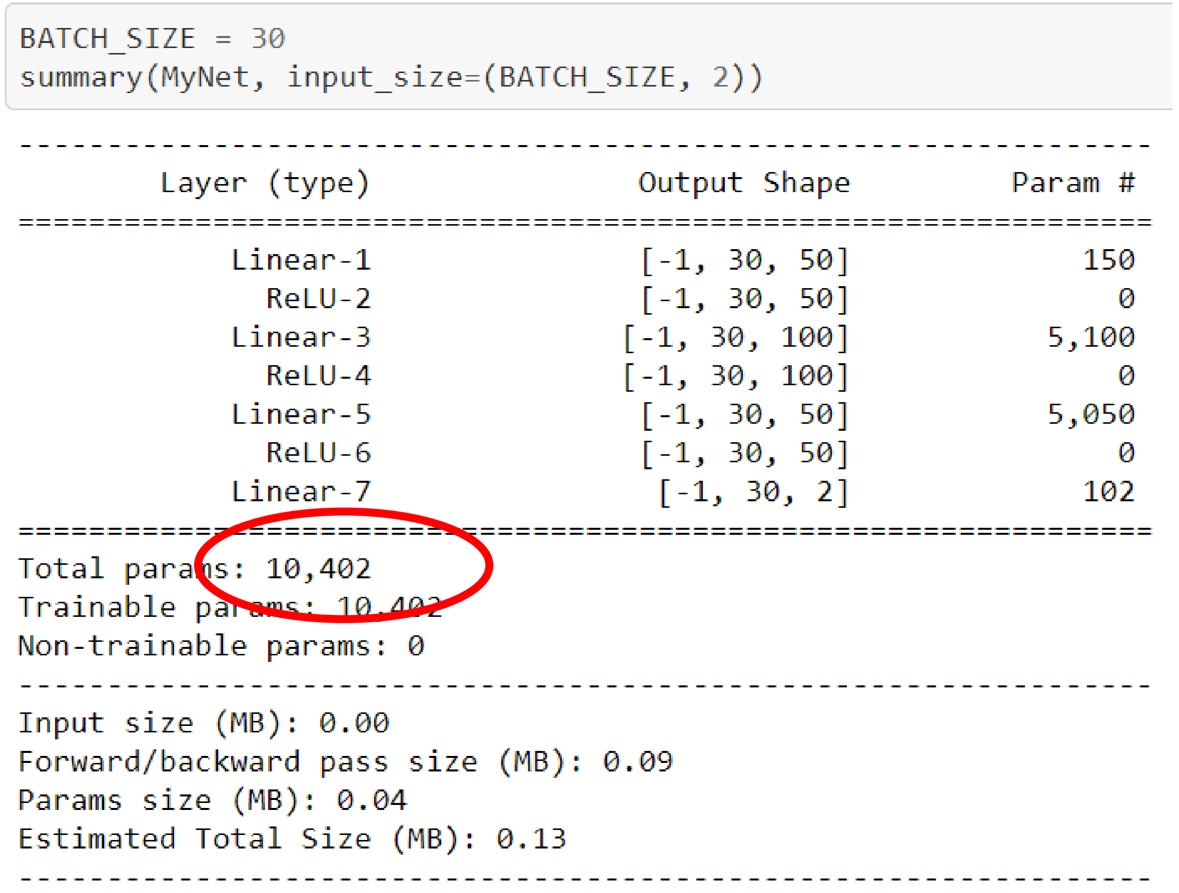
```
In [3]: import torch.nn as nn
        # fix the weight of convolution layers
        model.features.eval()

        # modify classifier
        model.classifier = torch.nn.Sequential(
          nn.Linear(25088, 4096),
          nn.ReLU(inplace=True),
          nn.Dropout(p=0.5, inplace=False),
          nn.Linear(4096, 4096),
          nn.ReLU(inplace=True),
          nn.Dropout(p=0.5, inplace=False),
          torch.nn.Linear(4096, 5))
```

Summary of parameters



```
Total params: 139,590,725
Trainable params: 139,590,725
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.57
Forward/backward pass size (MB): 238.68
Params size (MB): 532.50
Estimated Total Size (MB): 771.75
----------------------------------------------------------------
```

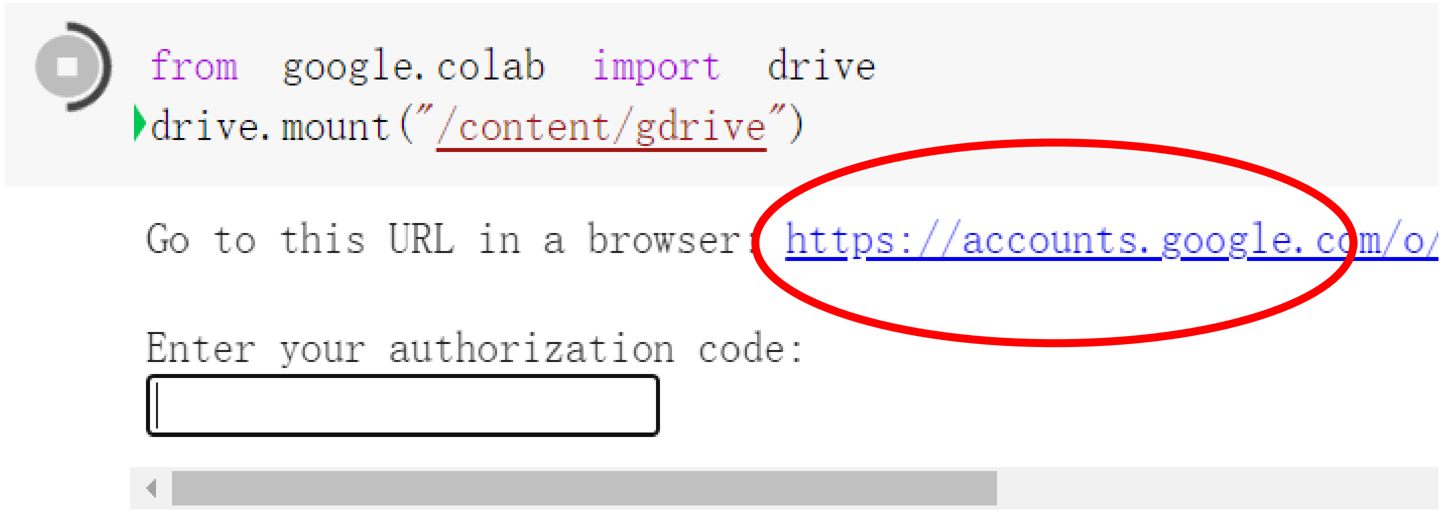
MLP in "4.2. Classification with CE loss"



```
BATCH_SIZE = 30
summary(MyNet, input_size=(BATCH_SIZE, 2))
```

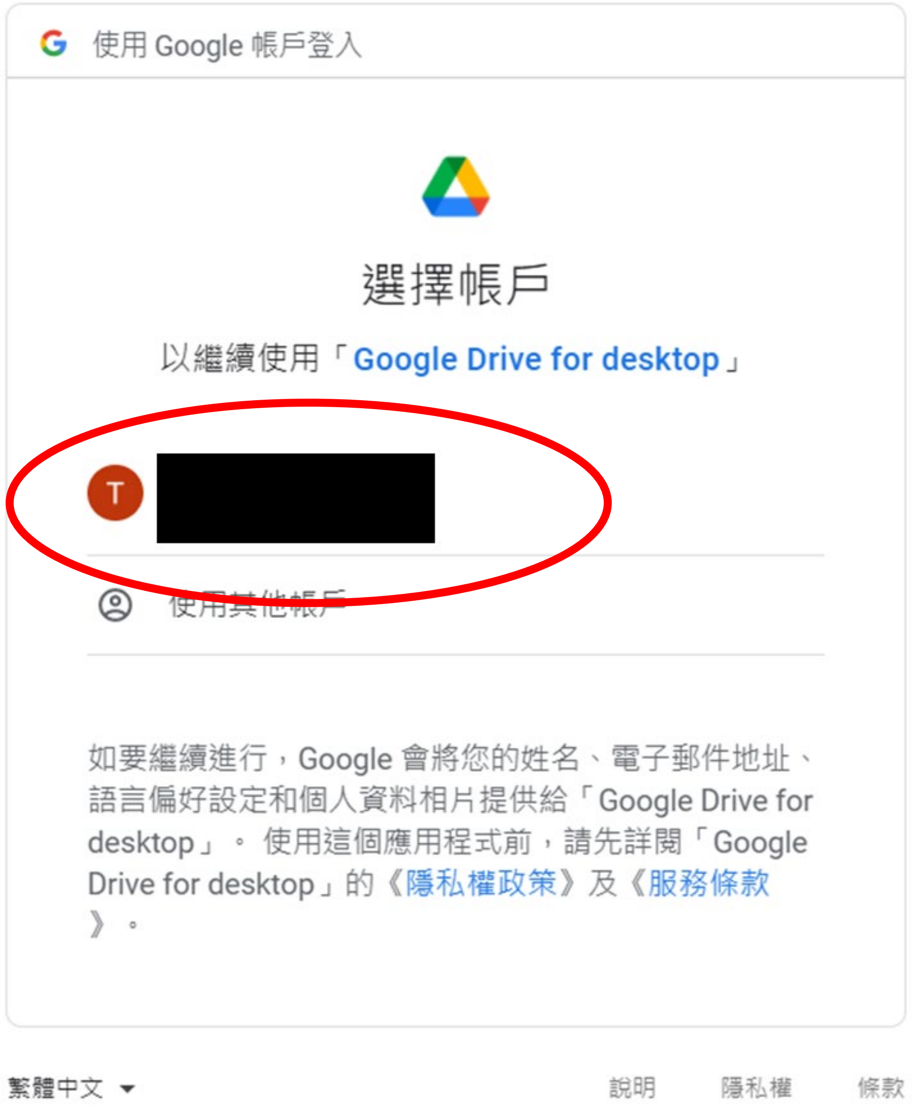
```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Linear-1               [-1, 30, 50]             150
              ReLU-2               [-1, 30, 50]               0
            Linear-3              [-1, 30, 100]           5,100
              ReLU-4              [-1, 30, 100]               0
            Linear-5               [-1, 30, 50]           5,050
              ReLU-6               [-1, 30, 50]               0
            Linear-7                [-1, 30, 2]             102
================================================================
Total params: 10,402
Trainable params: 10,402
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.00
Forward/backward pass size (MB): 0.09
Params size (MB): 0.04
Estimated Total Size (MB): 0.13
----------------------------------------------------------------
```

Connect to Google drive



```
from google.colab import drive
drive.mount("/content/gdrive")
```

```
Go to this URL in a browser: https://accounts.google.com/o/

Enter your authorization code:
```



使用 Google 帳戶登入

選擇帳戶

以繼續使用「Google Drive for desktop」

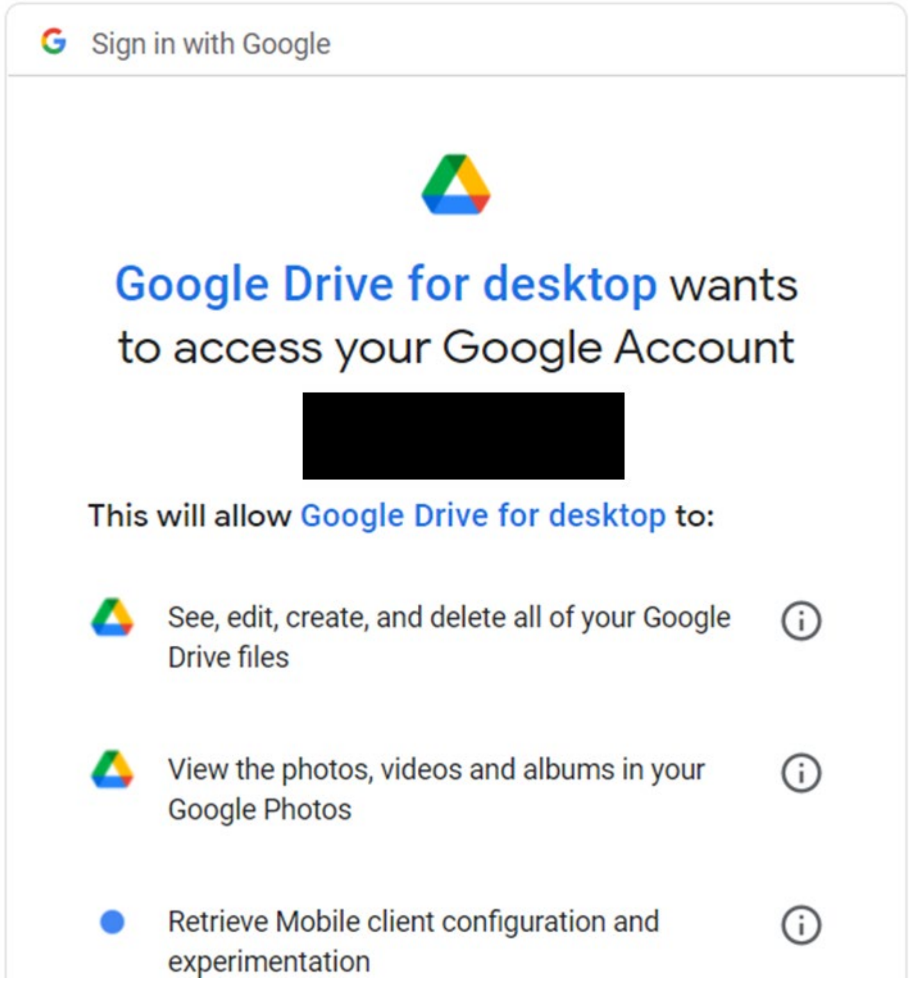
[redacted]

使用其他帳戶

如要繼續進行，Google 會將您的姓名、電子郵件地址、語言偏好設定和個人資料相片提供給「Google Drive for desktop」。 使用這個應用程式前，請先詳閱「Google Drive for desktop」的《隱私權政策》及《服務條款》。

繁體中文 說明 隱私權 條款

Connect to Google drive



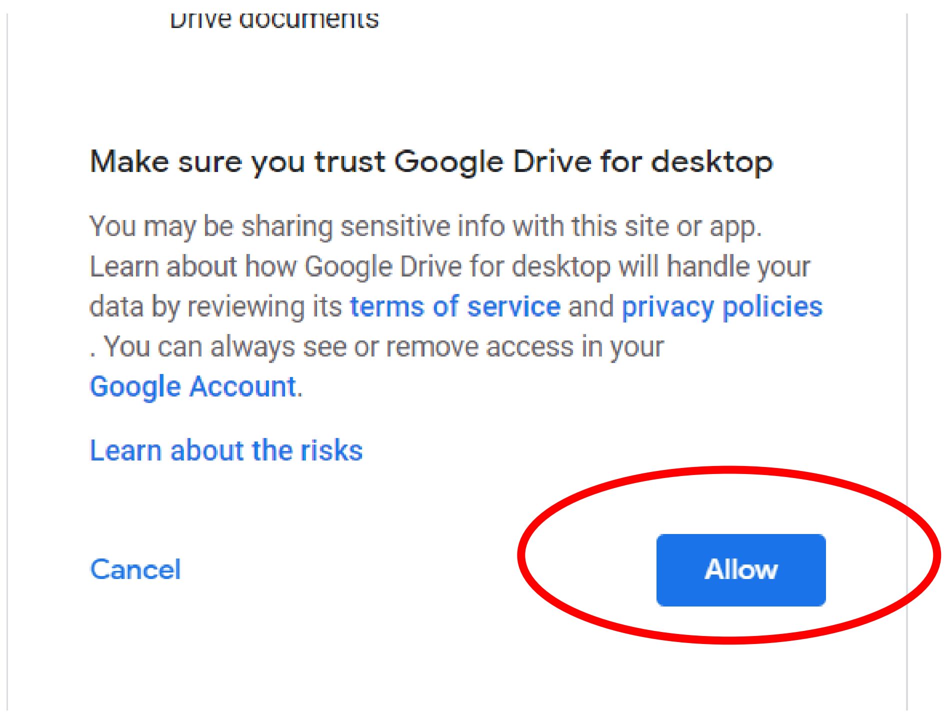
Sign in with Google

Google Drive for desktop wants to access your Google Account

[redacted]

This will allow Google Drive for desktop to:

- See, edit, create, and delete all of your Google Drive files
- View the photos, videos and albums in your Google Photos
- Retrieve Mobile client configuration and experimentation



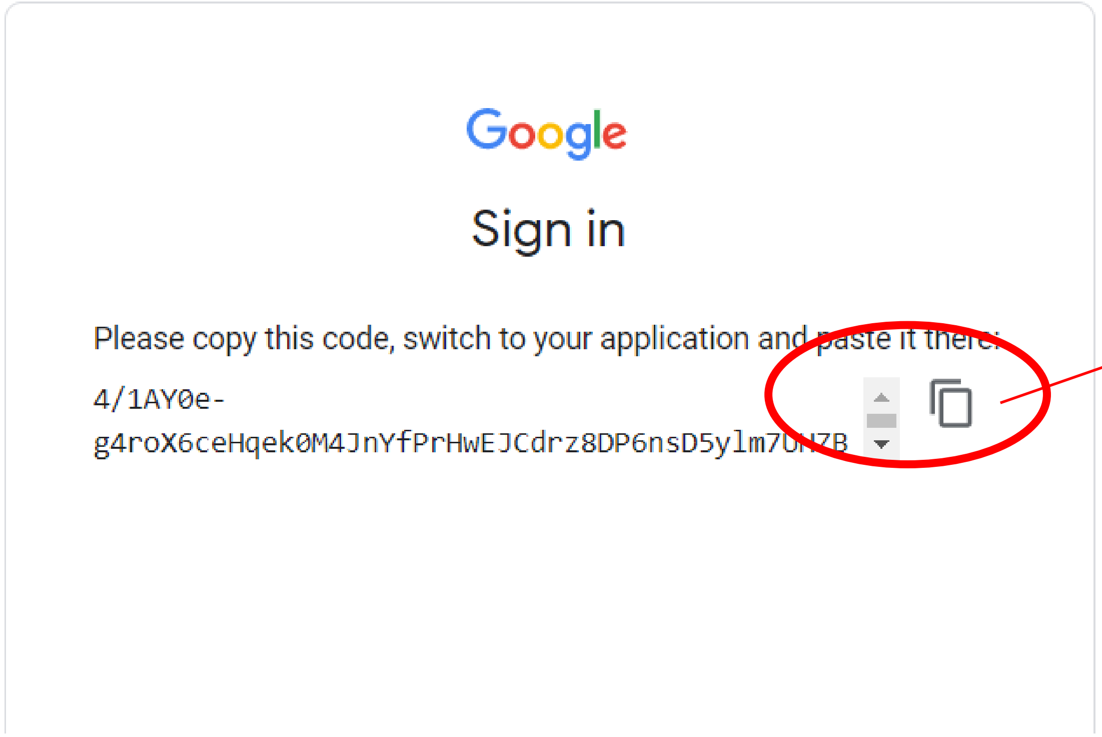
Drive documents

Make sure you trust Google Drive for desktop

You may be sharing sensitive info with this site or app. Learn about how Google Drive for desktop will handle your data by reviewing its terms of service and privacy policies . You can always see or remove access in your Google Account.

Learn about the risks

Connect to Google drive

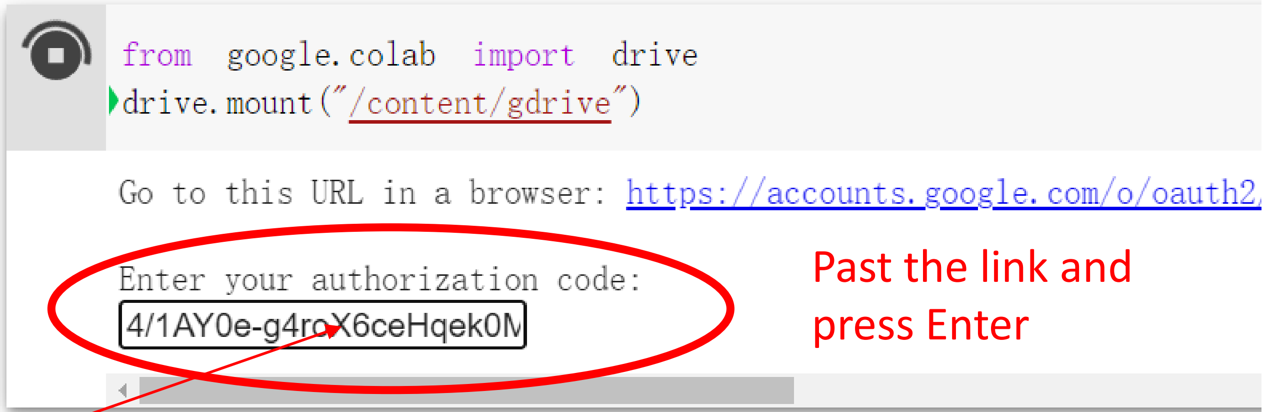


Google

Sign in

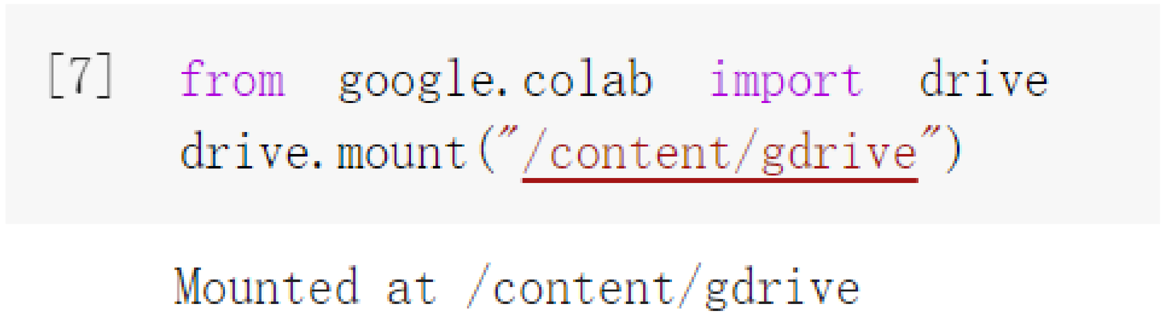
Please copy this code, switch to your application and paste it there:

```
4/1AY0e-
g4roX6ceHqek0M4JnYfPrHwEJCdrz8DP6nsD5ylm7UNZB
```



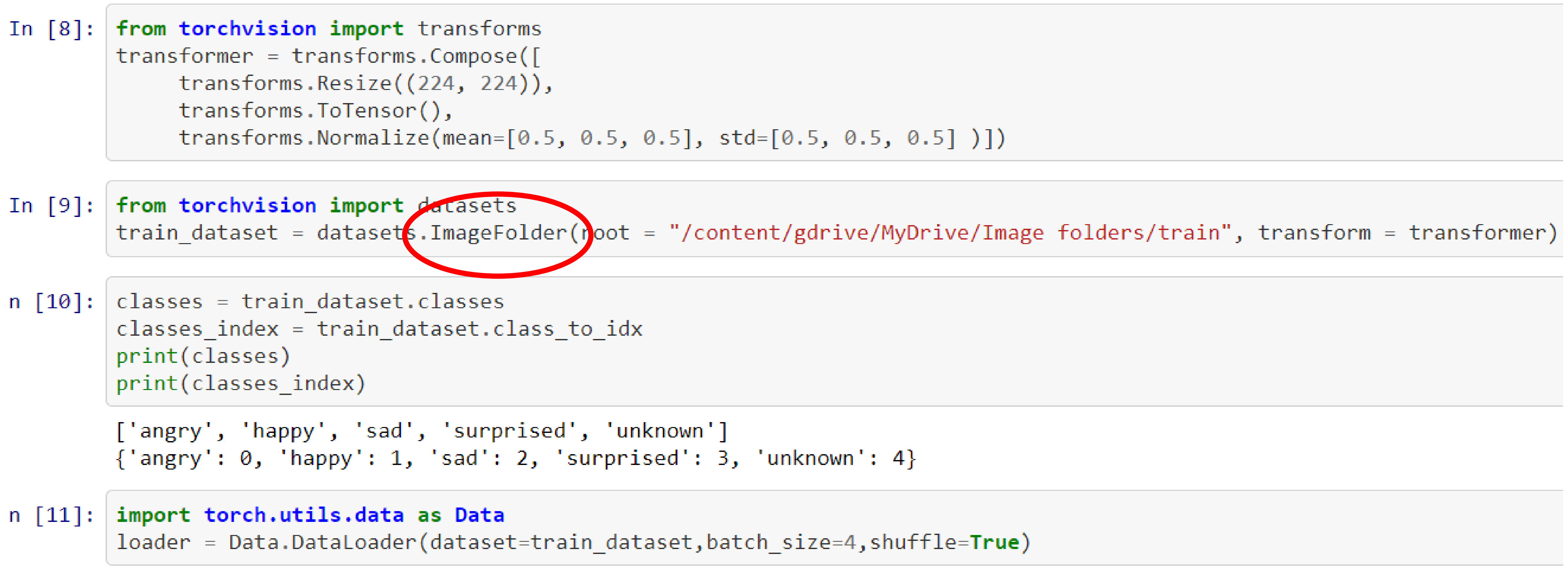
```
from google.colab import drive
drive.mount("/content/gdrive")

Go to this URL in a browser: https://accounts.google.com/o/oauth2

Enter your authorization code:
4/1AY0e-g4roX6ceHqek0M
```

Past the link and press Enter



```
[7] from google.colab import drive
    drive.mount("/content/gdrive")

Mounted at /content/gdrive
```

Batch training using Image Folder



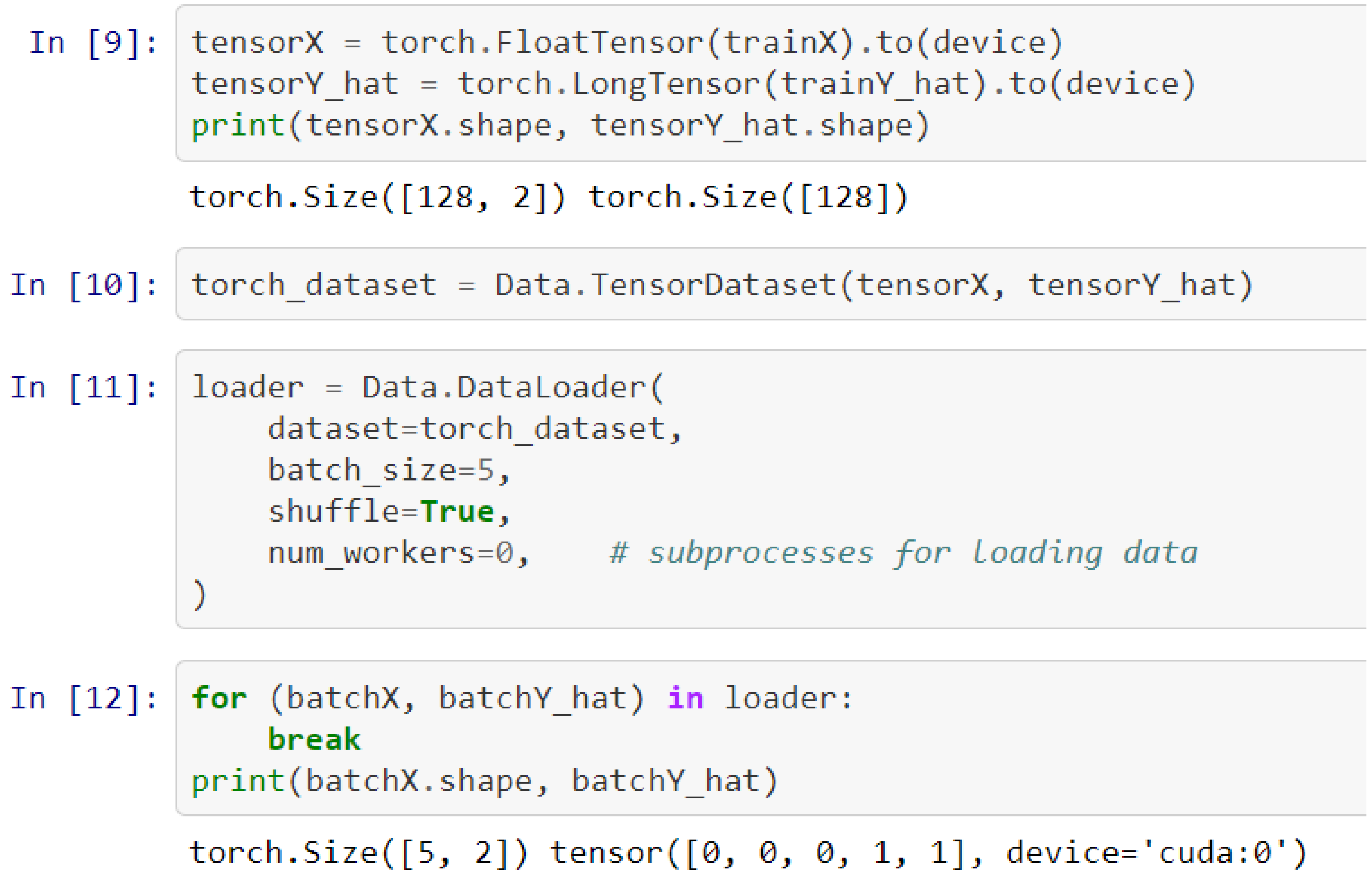
```
In [8]: from torchvision import transforms
        transformer = transforms.Compose([
             transforms.Resize((224, 224)),
             transforms.ToTensor(),
             transforms.Normalize(mean=[0.5, 0.5, 0.5], std=[0.5, 0.5, 0.5] )])
```

```
In [9]: from torchvision import datasets
        train_dataset = datasets.ImageFolder(root = "/content/gdrive/MyDrive/Image folders/train", transform = transformer)
```

```
n [10]: classes = train_dataset.classes
        classes_index = train_dataset.class_to_idx
        print(classes)
        print(classes_index)

        ['angry', 'happy', 'sad', 'surprised', 'unknown']
        {'angry': 0, 'happy': 1, 'sad': 2, 'surprised': 3, 'unknown': 4}
```

```
n [11]: import torch.utils.data as Data
        loader = Data.DataLoader(dataset=train_dataset,batch_size=4,shuffle=True)
```

Batch training using data in RAM



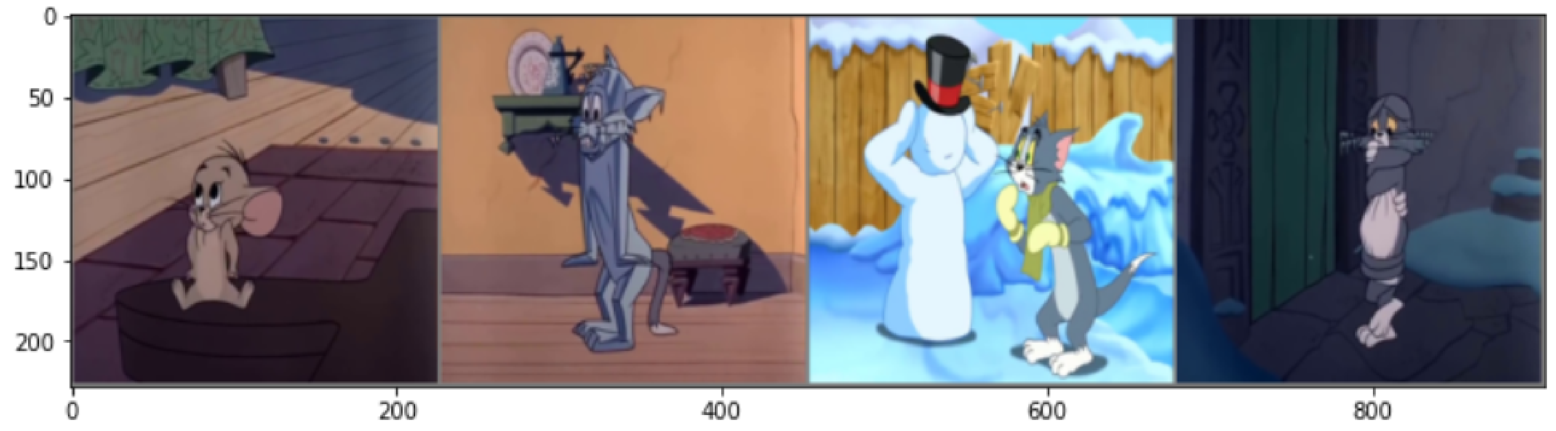
```
In [9]:  tensorX = torch.FloatTensor(trainX).to(device)
         tensorY_hat = torch.LongTensor(trainY_hat).to(device)
         print(tensorX.shape, tensorY_hat.shape)

         torch.Size([128, 2]) torch.Size([128])

In [10]: torch_dataset = Data.TensorDataset(tensorX, tensorY_hat)

In [11]: loader = Data.DataLoader(
             dataset=torch_dataset,
             batch_size=5,
             shuffle=True,
             num_workers=0,    # subprocesses for loading data
         )

In [12]: for (batchX, batchY_hat) in loader:
             break
         print(batchX.shape, batchY_hat)

         torch.Size([5, 2]) tensor([0, 0, 0, 1, 1], device='cuda:0')
```

One batch has 4 images

```
[12]: for batchX, batchY_hat in loader:
        break;
      print(batchX.shape, batchY_hat.shape, batchY_hat)
```

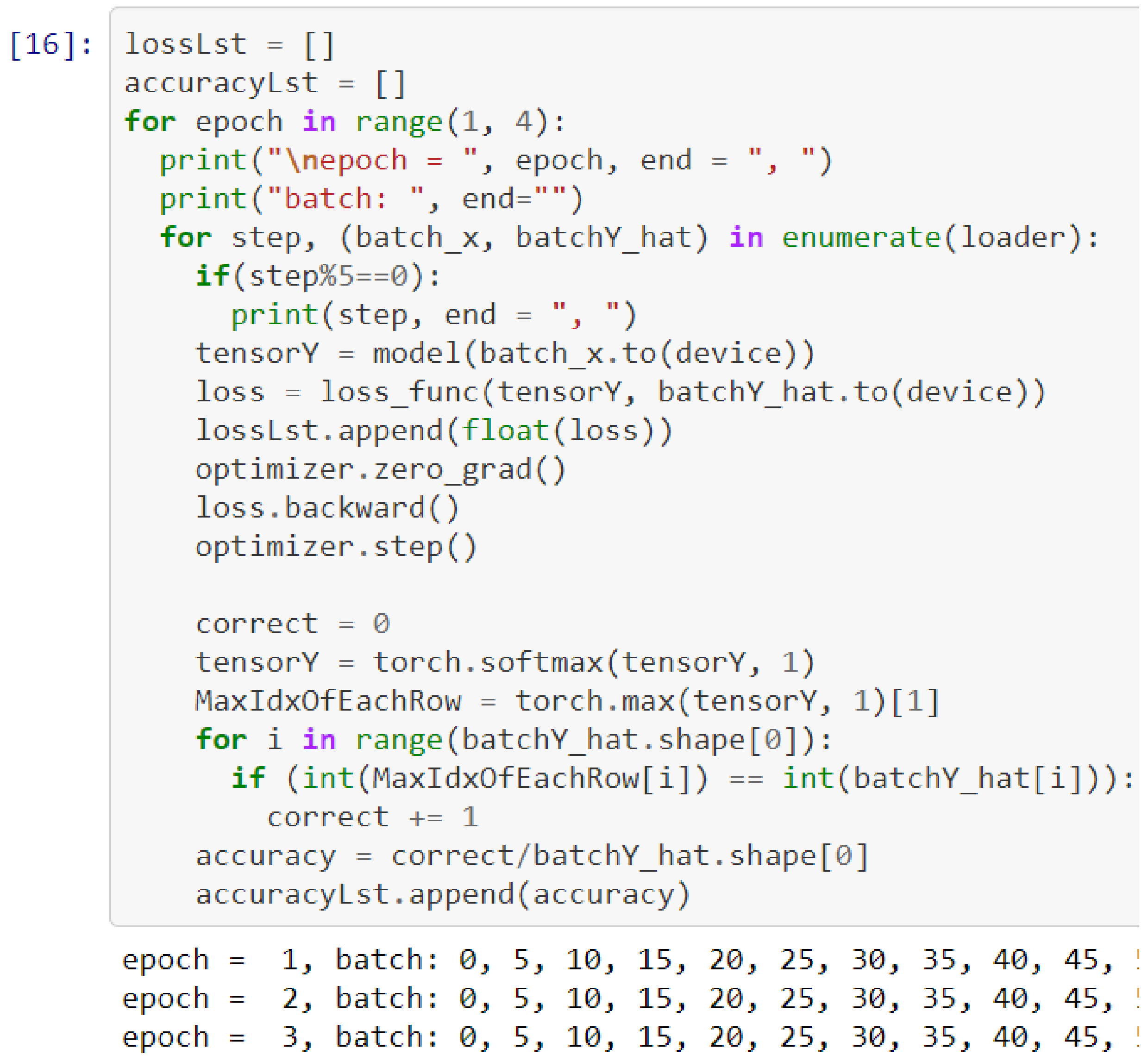
```
torch.Size([4, 3, 224, 224]) torch.Size([4]) tensor([3, 2, 3, 2])
```

```
[13]: import numpy as np
      import matplotlib.pyplot as plt
      imgTensor = torchvision.utils.make_grid(batchX)
      imgArray = imgTensor.numpy()
      imgArray1 = np.zeros((imgArray.shape[1], imgArray.shape[2], 3))
      imgArray1[:,:,0] = imgArray[0, :, :]
      imgArray1[:,:,1] = imgArray[1, :, :]
      imgArray1[:,:,2] = imgArray[2, :, :]
      imgArray1 = imgArray1*0.5+0.5
      plt.figure(figsize=(12, 6))
      plt.imshow(imgArray1)
      plt.show()
      print([classes[i] for i in batchY_hat])
```



```
['surprised', 'sad', 'surprised', 'sad']
```

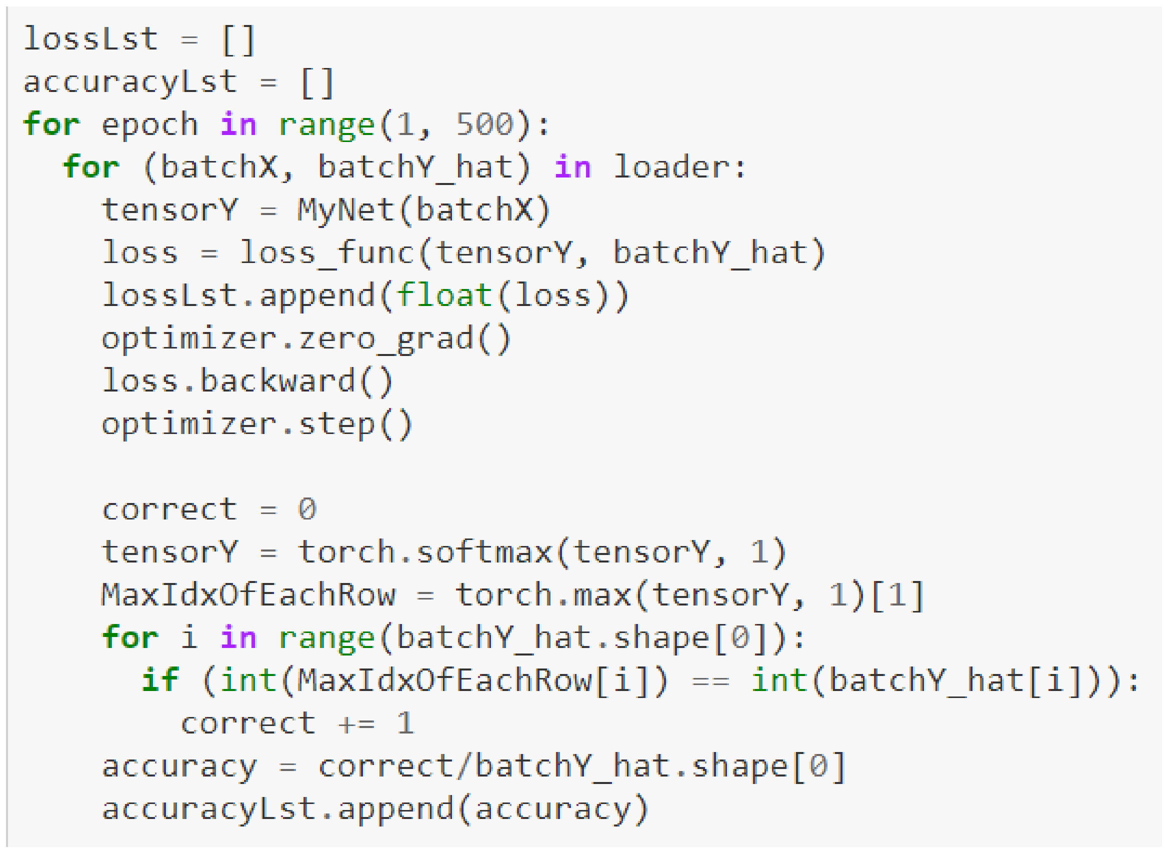
Batch training loop



```
[16]: lossLst = []
      accuracyLst = []
      for epoch in range(1, 4):
        print("\nepoch = ", epoch, end = ", ")
        print("batch: ", end="")
        for step, (batch_x, batchY_hat) in enumerate(loader):
          if(step%5==0):
            print(step, end = ", ")
          tensorY = model(batch_x.to(device))
          loss = loss_func(tensorY, batchY_hat.to(device))
          lossLst.append(float(loss))
          optimizer.zero_grad()
          loss.backward()
          optimizer.step()

          correct = 0
          tensorY = torch.softmax(tensorY, 1)
          MaxIdxOfEachRow = torch.max(tensorY, 1)[1]
          for i in range(batchY_hat.shape[0]):
            if (int(MaxIdxOfEachRow[i]) == int(batchY_hat[i])):
              correct += 1
          accuracy = correct/batchY_hat.shape[0]
          accuracyLst.append(accuracy)
```

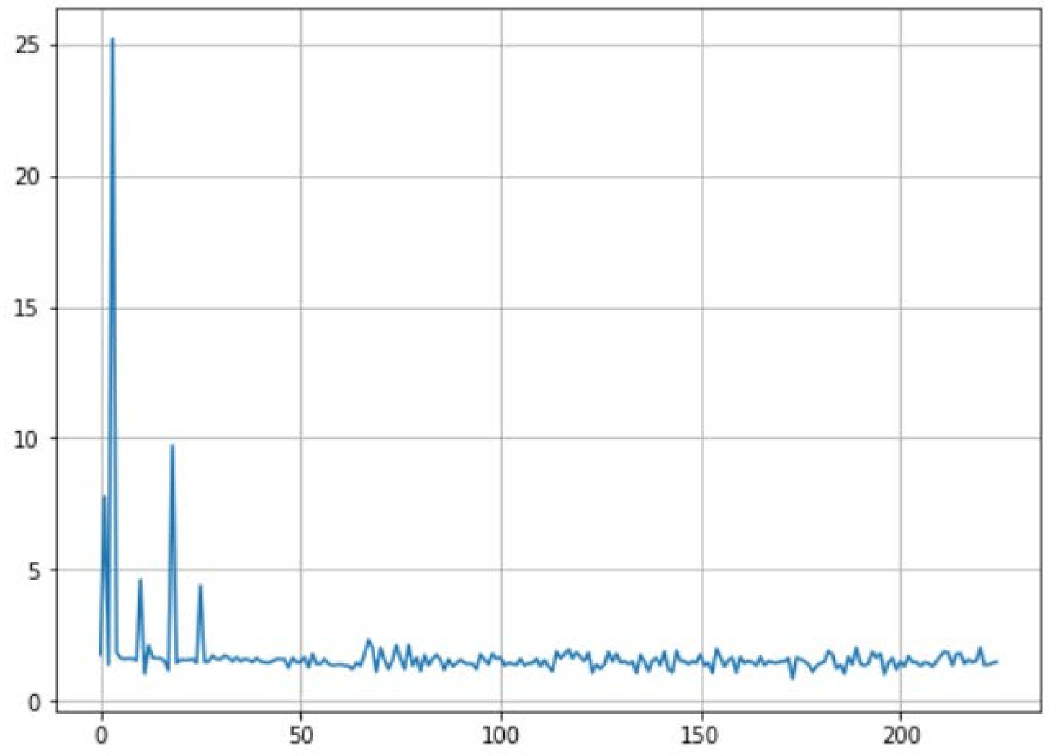
```
epoch =  1, batch: 0, 5, 10, 15, 20, 25, 30, 35, 40, 45,
epoch =  2, batch: 0, 5, 10, 15, 20, 25, 30, 35, 40, 45,
epoch =  3, batch: 0, 5, 10, 15, 20, 25, 30, 35, 40, 45,
```

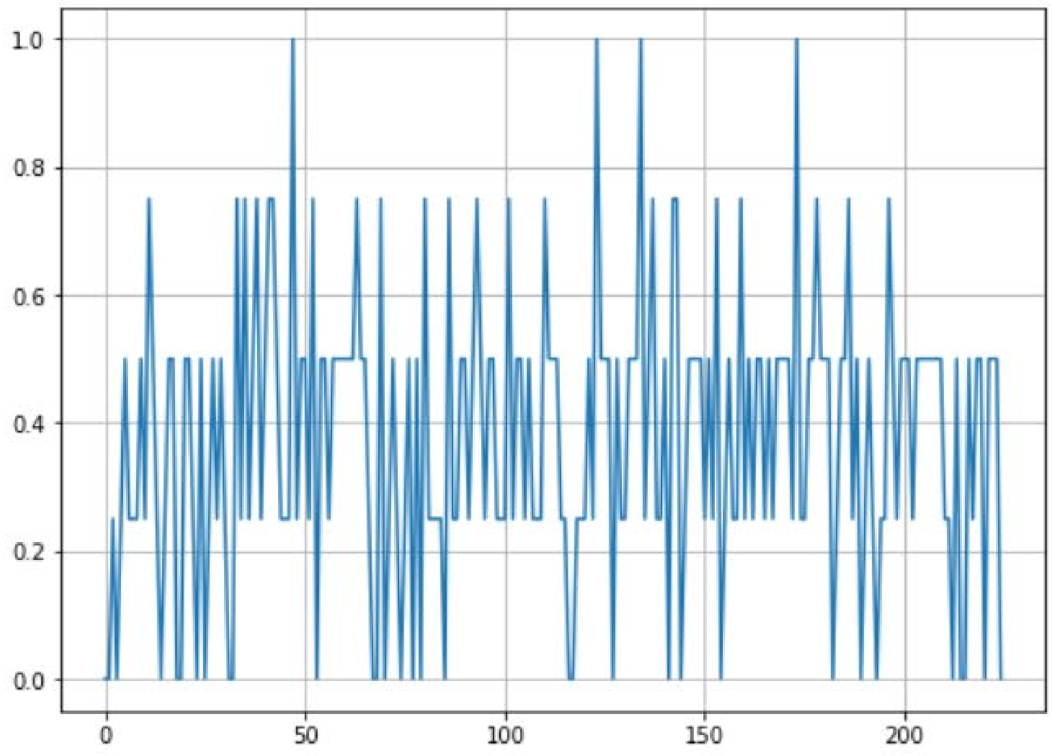
MLP in “4.2. Classification with CE loss”



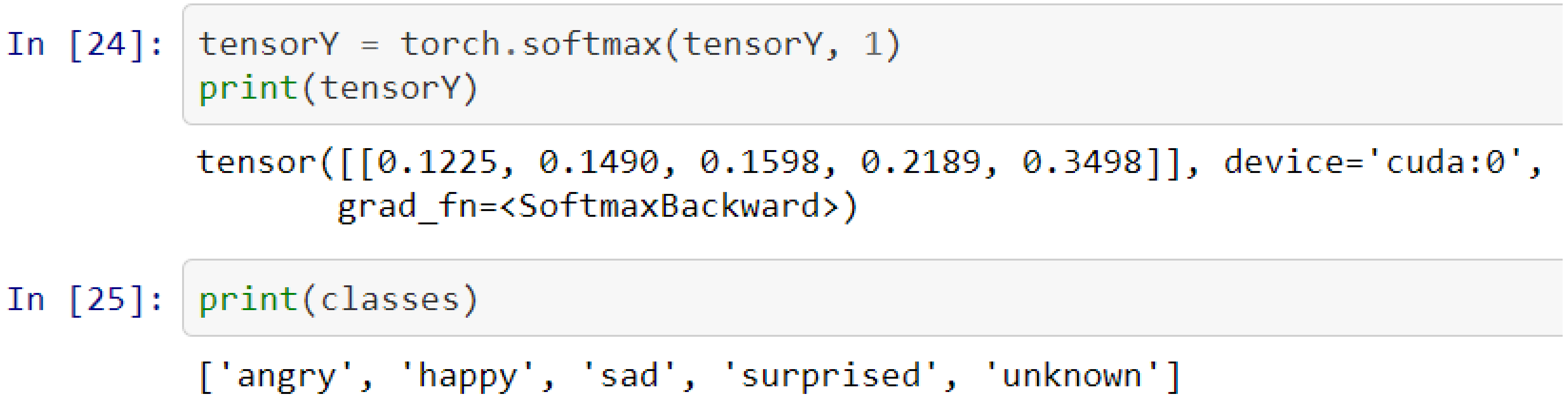
```
lossLst = []
accuracyLst = []
for epoch in range(1, 500):
  for (batchX, batchY_hat) in loader:
    tensorY = MyNet(batchX)
    loss = loss_func(tensorY, batchY_hat)
    lossLst.append(float(loss))
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()

    correct = 0
    tensorY = torch.softmax(tensorY, 1)
    MaxIdxOfEachRow = torch.max(tensorY, 1)[1]
    for i in range(batchY_hat.shape[0]):
      if (int(MaxIdxOfEachRow[i]) == int(batchY_hat[i])):
        correct += 1
    accuracy = correct/batchY_hat.shape[0]
    accuracyLst.append(accuracy)
```

Why training is not successful?





Biased prediction

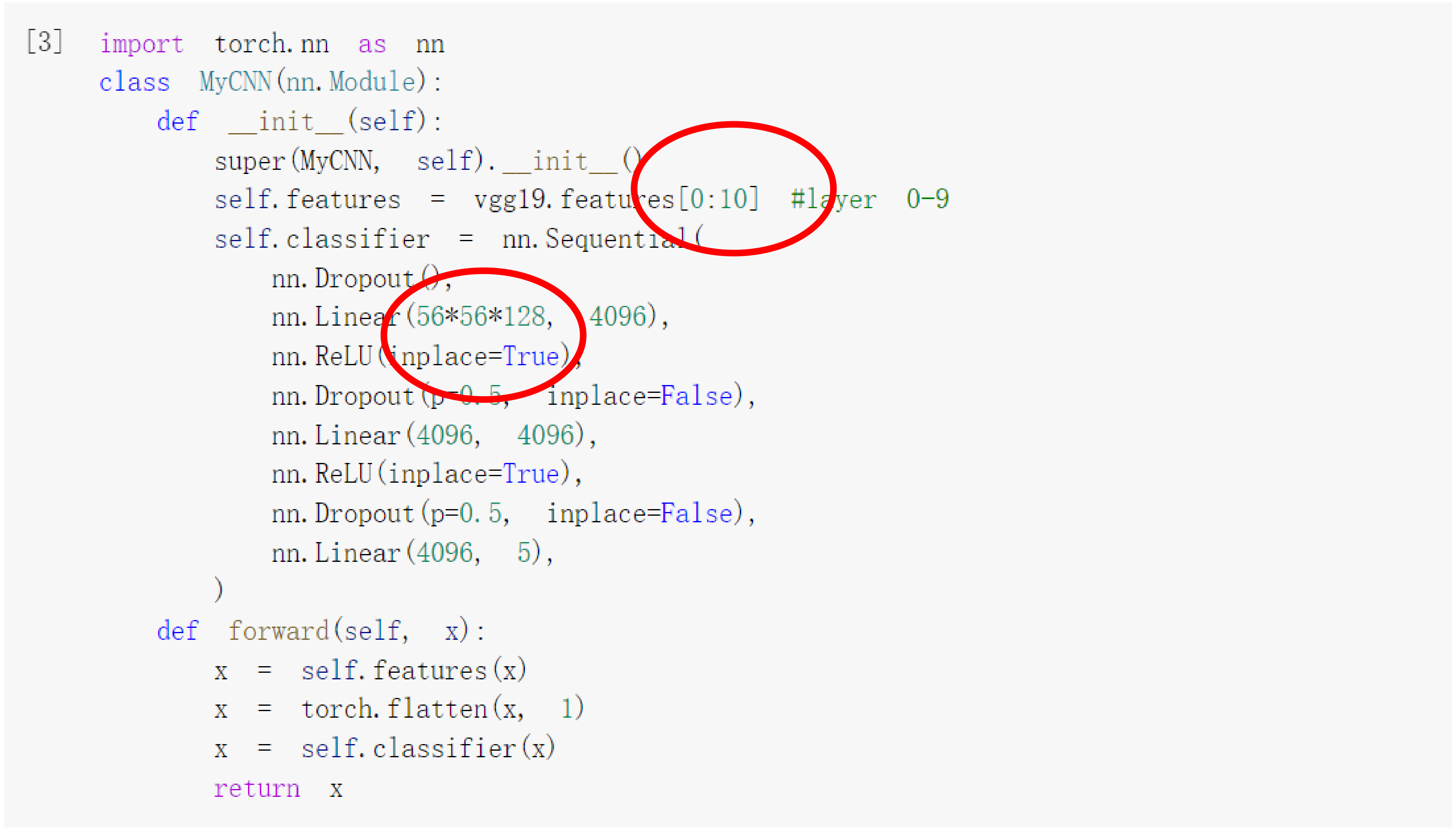


```
In [24]: tensorY = torch.softmax(tensorY, 1)
         print(tensorY)

         tensor([[0.1225, 0.1490, 0.1598, 0.2189, 0.3498]], device='cuda:0',
                grad_fn=<SoftmaxBackward>)

In [25]: print(classes)

         ['angry', 'happy', 'sad', 'surprised', 'unknown']
```

Transfer learning design 2

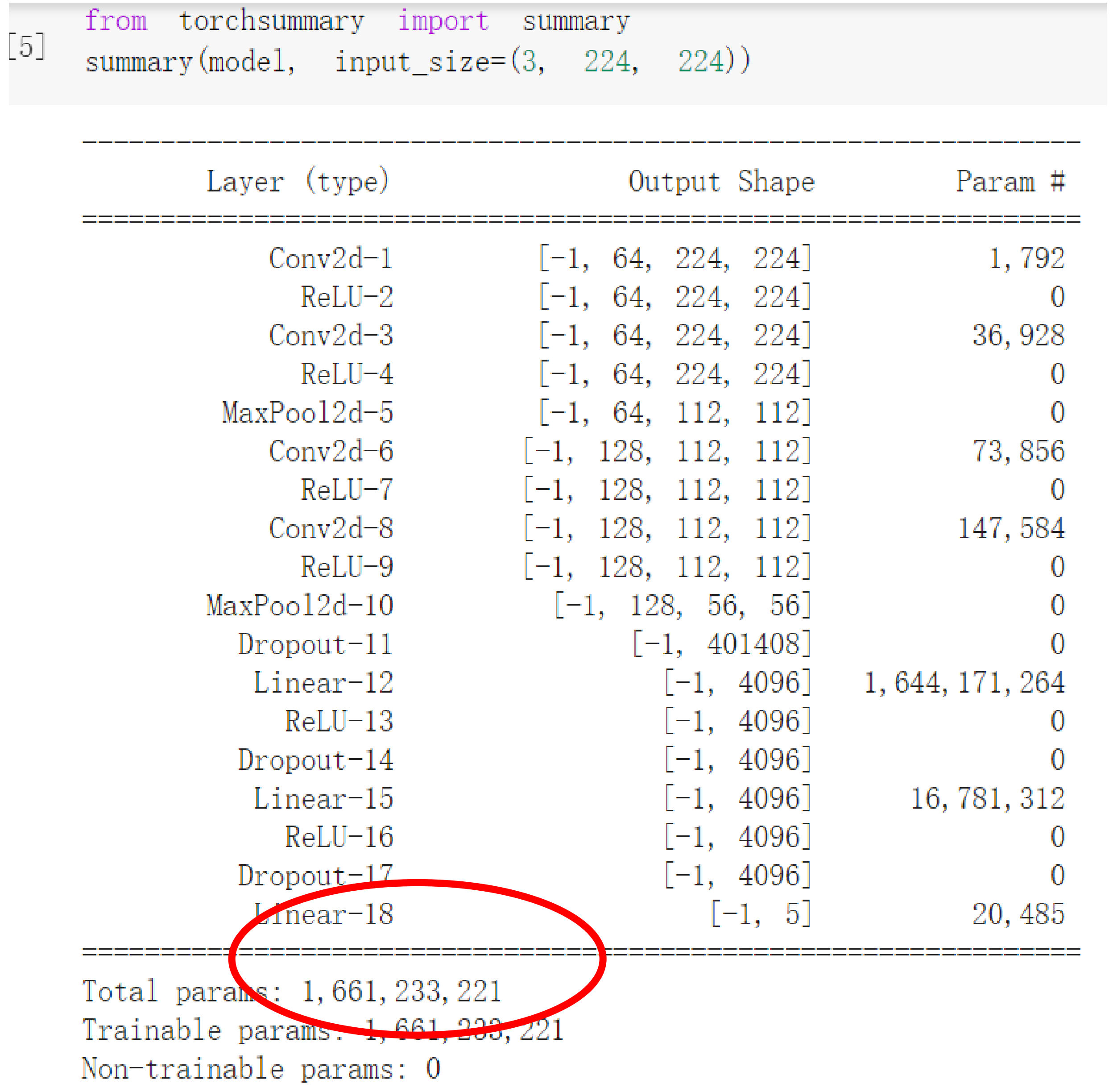
Use first 10 layers in convolution section

Let input image size = (224, 224, 3), Output has 5 classes: Angry, Happy, Sad, Surprised, Unknown



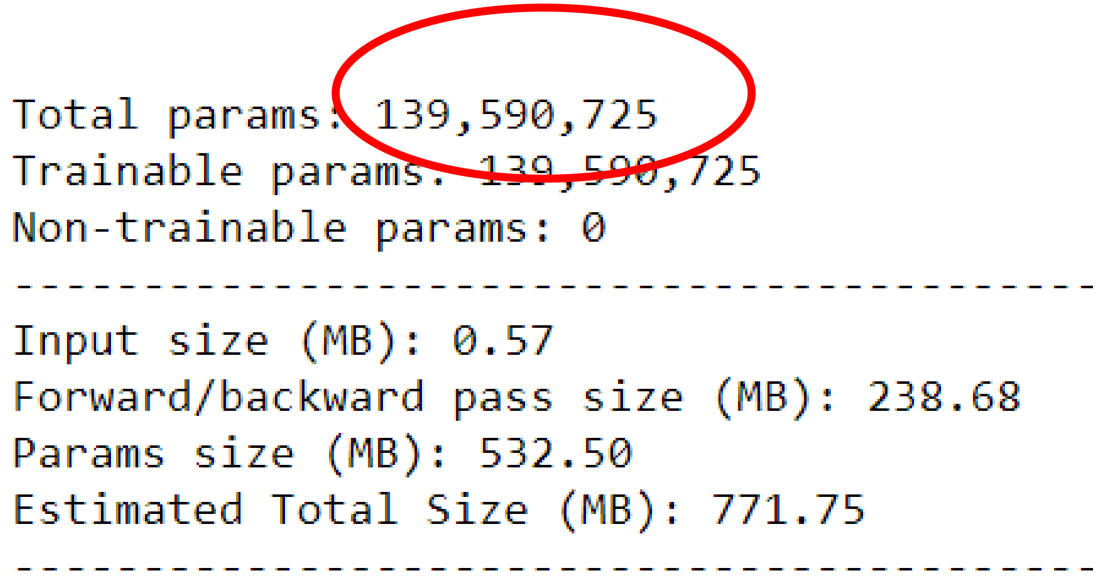
```
[3] import torch.nn as nn
    class MyCNN(nn.Module):
        def __init__(self):
            super(MyCNN, self).__init__()
            self.features = vgg19.features[0:10] #layer 0-9
            self.classifier = nn.Sequential(
                nn.Dropout(),
                nn.Linear(56*56*128, 4096),
                nn.ReLU(inplace=True),
                nn.Dropout(p=0.5, inplace=False),
                nn.Linear(4096, 4096),
                nn.ReLU(inplace=True),
                nn.Dropout(p=0.5, inplace=False),
                nn.Linear(4096, 5),
            )
        def forward(self, x):
            x = self.features(x)
            x = torch.flatten(x, 1)
            x = self.classifier(x)
            return x
```

1,661M parameters !



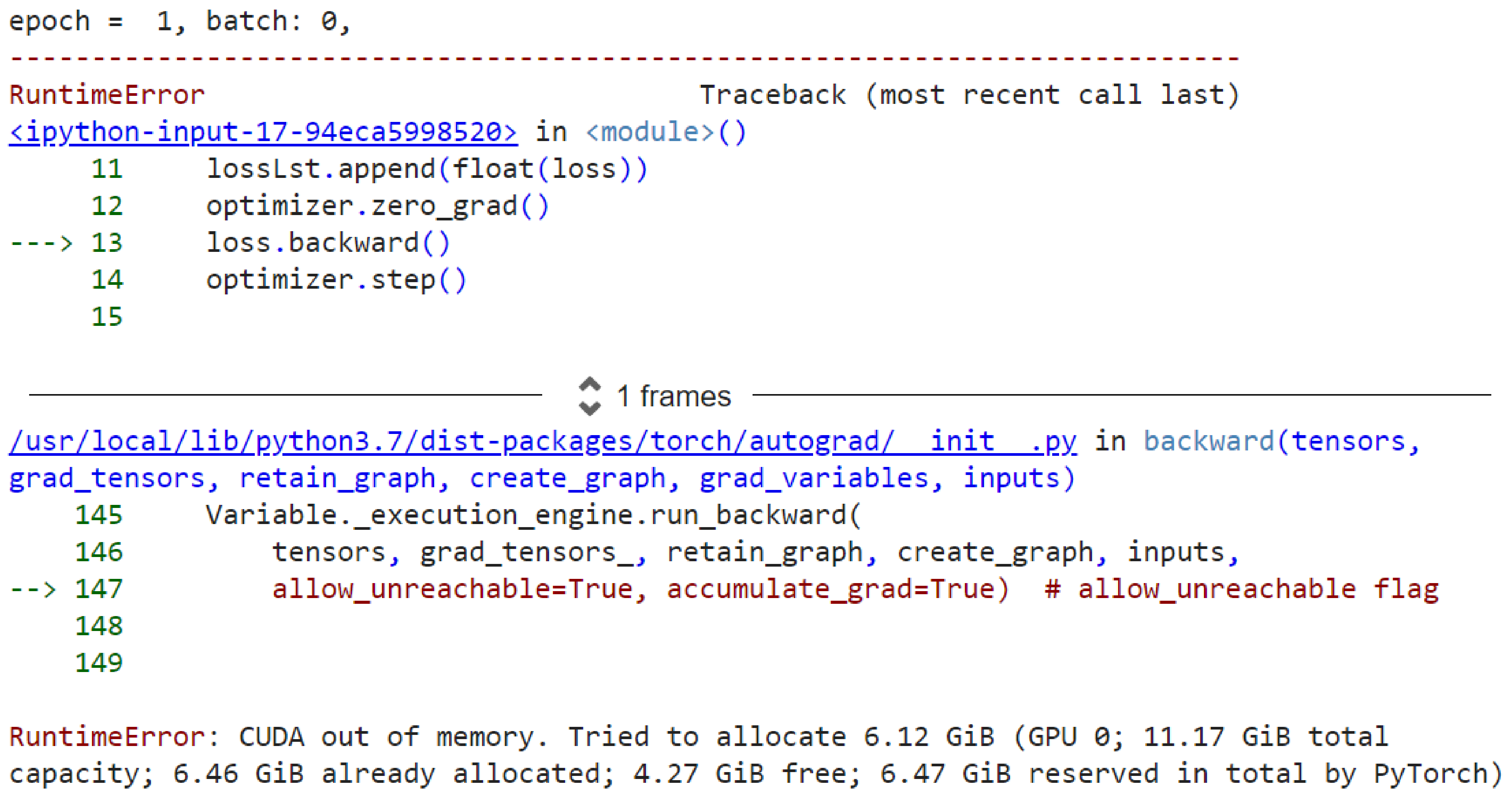
```
[5]  from torchsummary import summary
     summary(model, input_size=(3, 224, 224))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1         [-1, 64, 224, 224]           1,792
              ReLU-2         [-1, 64, 224, 224]               0
            Conv2d-3         [-1, 64, 224, 224]          36,928
              ReLU-4         [-1, 64, 224, 224]               0
         MaxPool2d-5         [-1, 64, 112, 112]               0
            Conv2d-6        [-1, 128, 112, 112]          73,856
              ReLU-7        [-1, 128, 112, 112]               0
            Conv2d-8        [-1, 128, 112, 112]         147,584
              ReLU-9        [-1, 128, 112, 112]               0
        MaxPool2d-10          [-1, 128, 56, 56]               0
          Dropout-11              [-1, 401408]               0
           Linear-12                [-1, 4096]   1,644,171,264
             ReLU-13                [-1, 4096]               0
          Dropout-14                [-1, 4096]               0
           Linear-15                [-1, 4096]      16,781,312
             ReLU-16                [-1, 4096]               0
          Dropout-17                [-1, 4096]               0
           Linear-18                   [-1, 5]          20,485
================================================================
Total params: 1,661,233,221
Trainable params: 1,661,233,221
Non-trainable params: 0
```



```
Total params: 139,590,725
Trainable params: 139,590,725
Non-trainable params: 0
------------------------------------------
Input size (MB): 0.57
Forward/backward pass size (MB): 238.68
Params size (MB): 532.50
Estimated Total Size (MB): 771.75
------------------------------------------
```

CUDA out of memory!



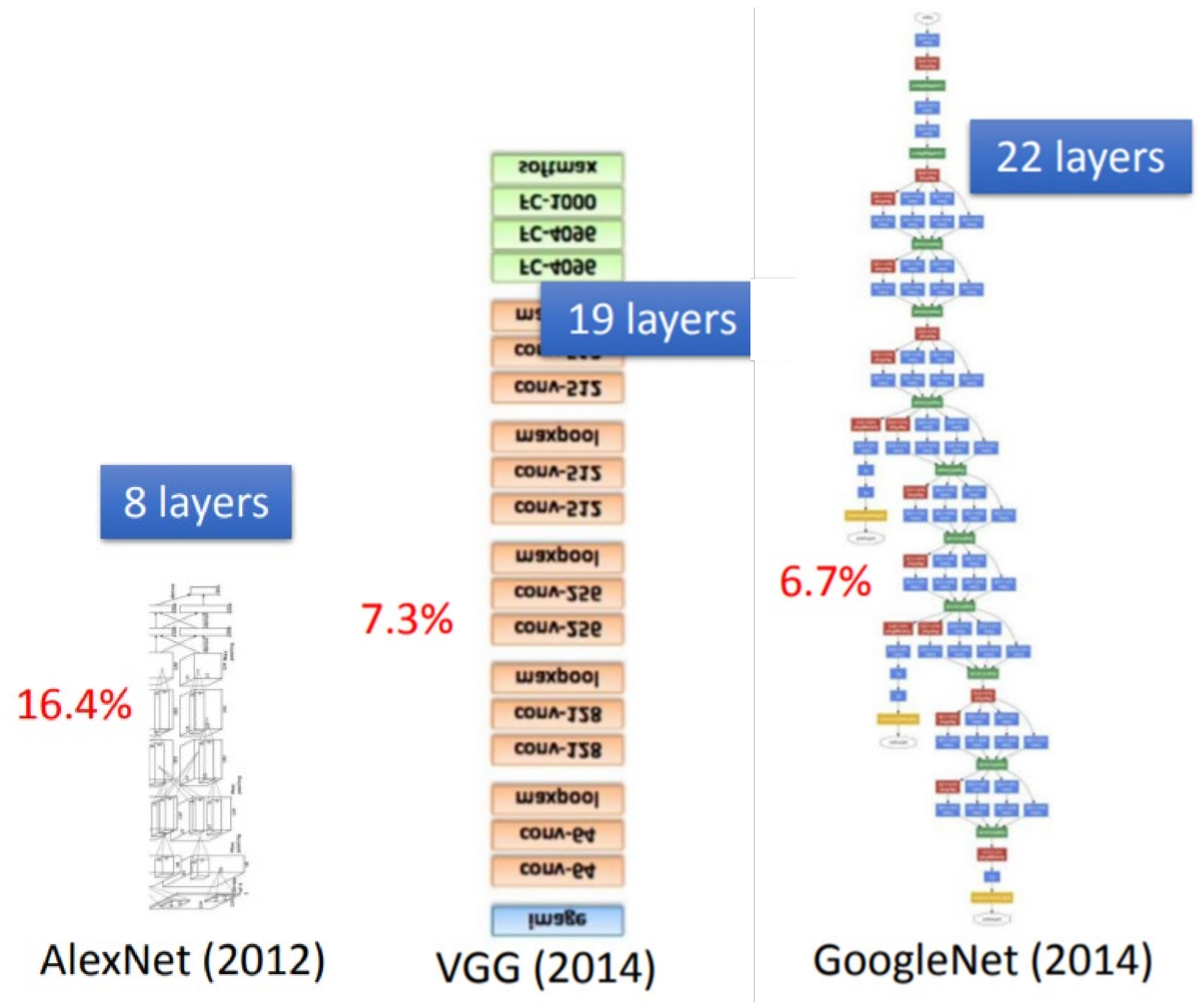
```
epoch =  1, batch: 0,
---------------------------------------------------------------------------
RuntimeError                              Traceback (most recent call last)
<ipython-input-17-94eca5998520> in <module>()
     11     lossLst.append(float(loss))
     12     optimizer.zero_grad()
---> 13     loss.backward()
     14     optimizer.step()
     15

                          1 frames
/usr/local/lib/python3.7/dist-packages/torch/autograd/__init__.py in backward(tensors,
grad_tensors, retain_graph, create_graph, grad_variables, inputs)
    145     Variable._execution_engine.run_backward(
    146         tensors, grad_tensors_, retain_graph, create_graph, inputs,
--> 147         allow_unreachable=True, accumulate_grad=True)  # allow_unreachable flag
    148
    149

RuntimeError: CUDA out of memory. Tried to allocate 6.12 GiB (GPU 0; 11.17 GiB total
capacity; 6.46 GiB already allocated; 4.27 GiB free; 6.47 GiB reserved in total by PyTorch)
```

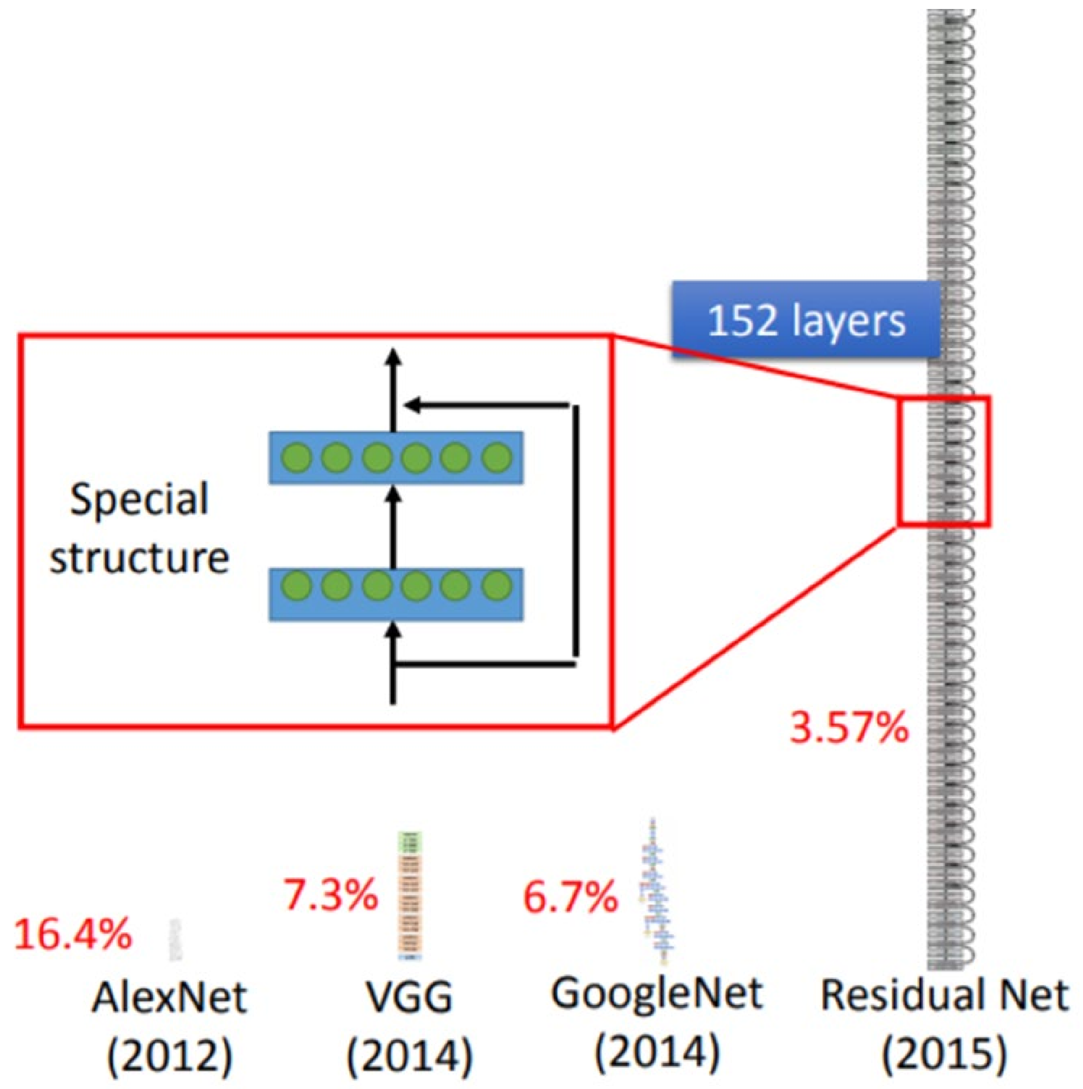
HW5 (2)

- Use transfer learning to train an image classifier to recognize healthy vs dementia from faces.

ResNet

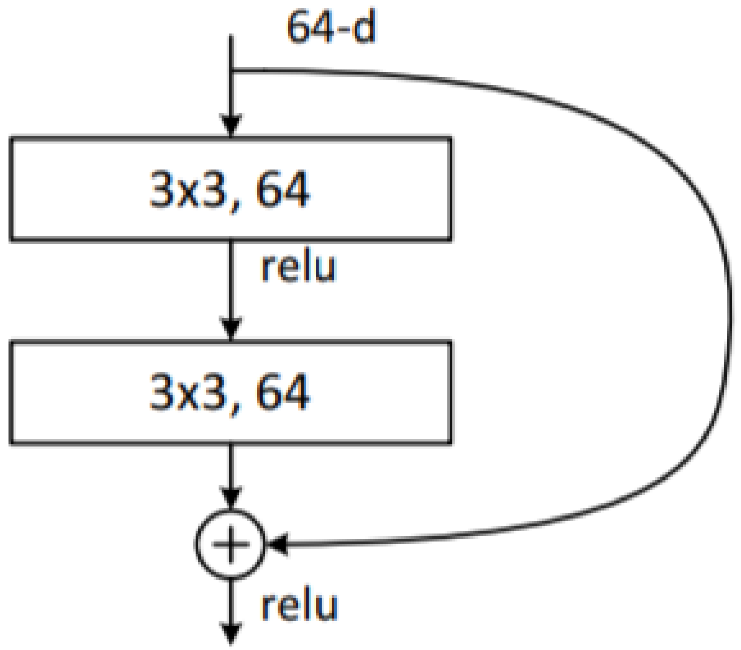
Going deeper and deeper…



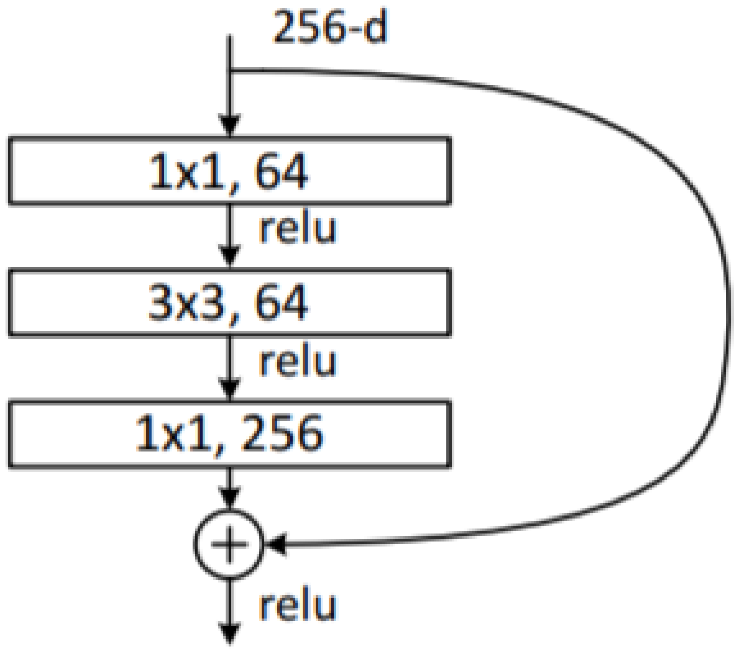


Reference: 李弘毅 ML Lecture 6 https://youtu.be/Dr-WRlEFefw

ResNet



Basic block



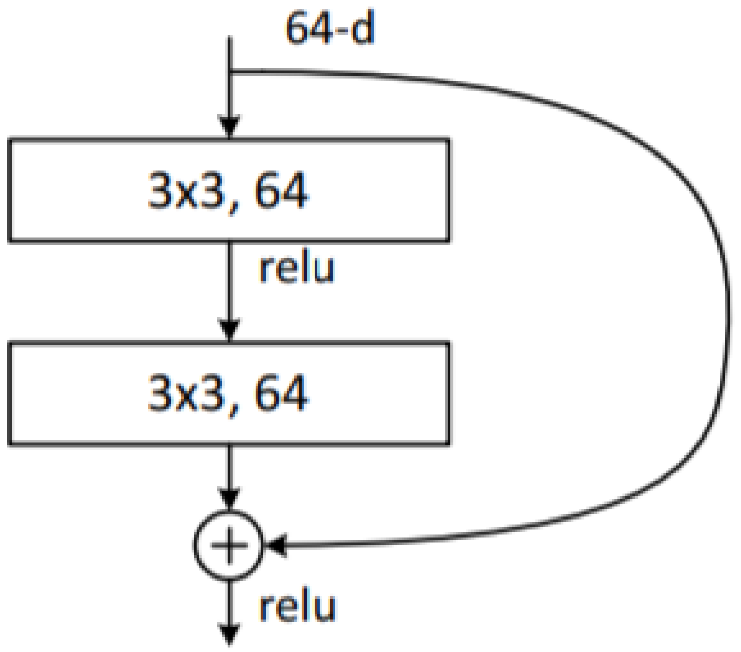
Bottleneck block

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).

Practice

- Run “7.4. Build ResNet from scratch.ipynb"

Basic loop



```
class BasicBlock(nn.Module):
  expansion = 1
  def __init__(self, inplanes, planes, stride=1, downsample=None,):
    super(BasicBlock, self).__init__()
    self.conv1=conv3x3(inplanes,planes,stride)
    self.bn1=nn.BatchNorm2d(planes)
    self.relu=nn.ReLU(inplace=True)
    self.conv2=conv3x3(planes,planes)
    self.bn2=nn.BatchNorm2d(planes)
    self.downsample=downsample
    self.stride=stride

    if(stride!=1 or inplanes!=planes*self.expansion):
      self.downsample=nn.Sequential(
        nn.Conv2d(inplanes,planes*self.expansion,kernel_size=1,stride
        nn.BatchNorm2d(planes*self.expansion),
      )

  def forward(self, x):
    residual = x
    out = self.conv1(x)
    out = self.bn1(out)
    out = self.relu(out)
    out = self.conv2(out)
    out = self.bn2(out)

    # Downsample:feature Map size/2 || Channel increase
    if (self.downsample is not None):
      residual = self.downsample(x)
    print("out= ", out.shape, "residual= ", residual.shape)
    out+=residual
    out=self.relu(out)
    return out
```

Batch Normalization

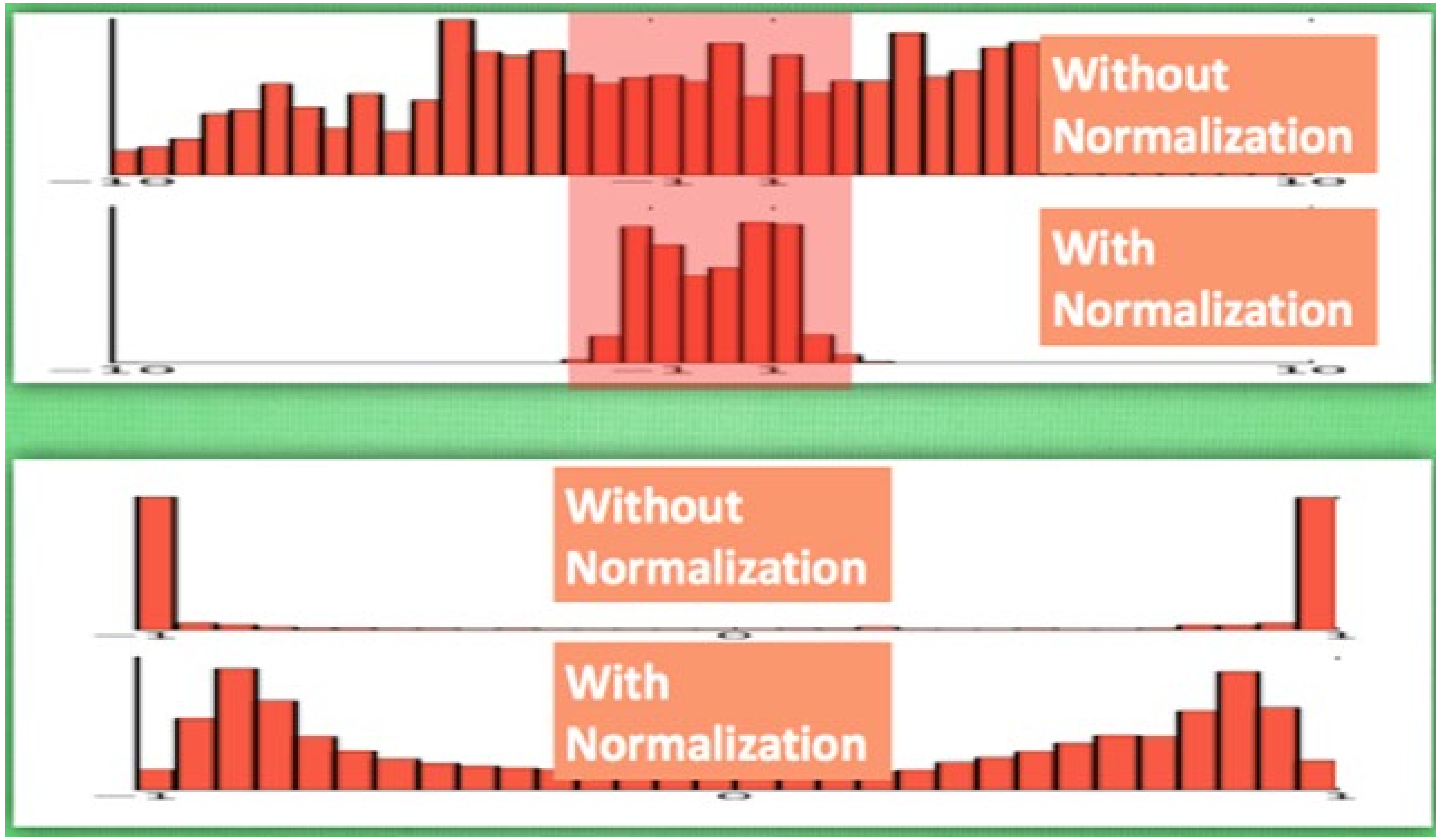
Applies Batch Normalization over a 4D input (a mini-batch of 2D inputs with additional channel dimension) as described in the paper Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift .

$$y = \frac{x - \mathrm{E}[x]}{\sqrt{\mathrm{Var}[x] + \epsilon}} * \gamma + \beta$$

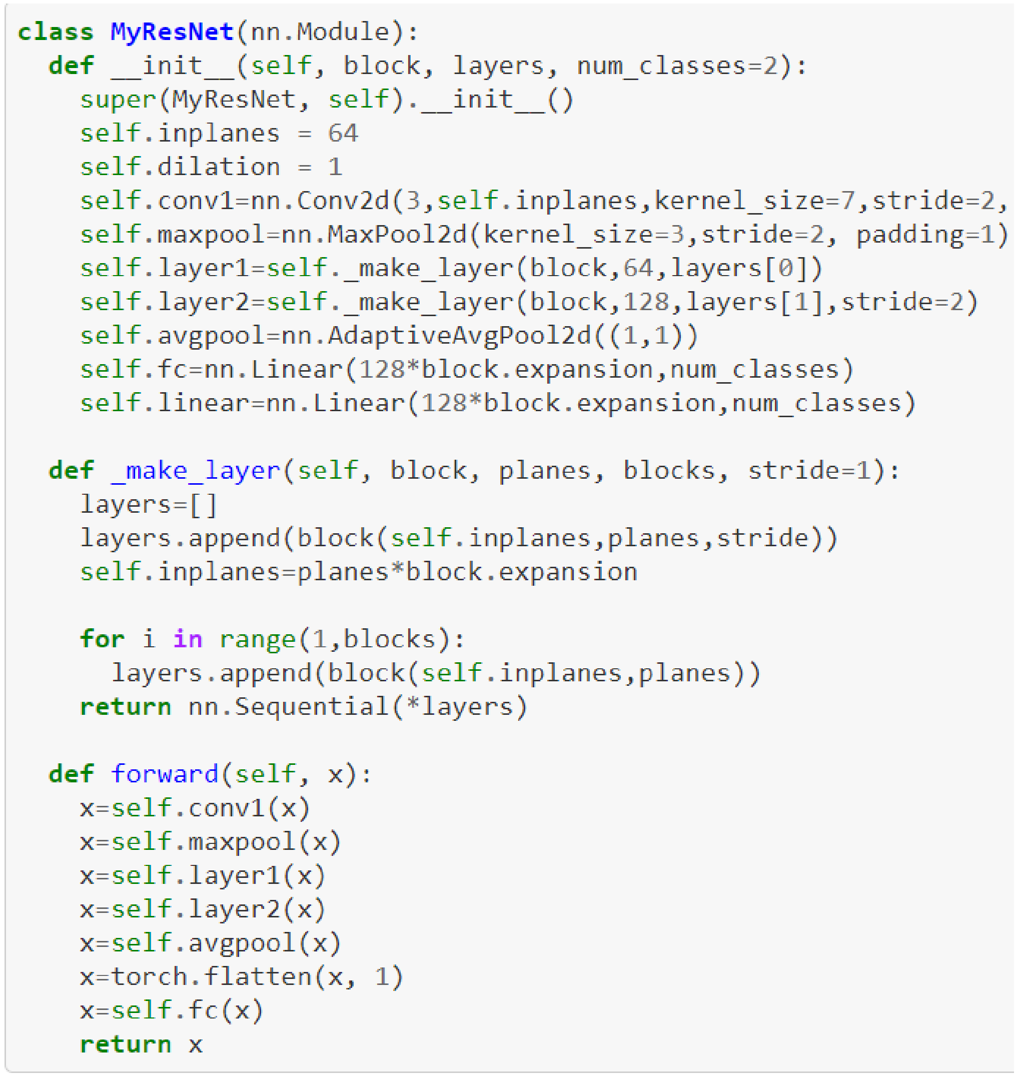
- The mean and standard-deviation are calculated per-dimension over the mini-batches.
- By default, the elements of γare set to 1 and the elements of β are set to 0.

https://pytorch.org/docs/stable/generated/torch.nn.BatchNorm2d.html

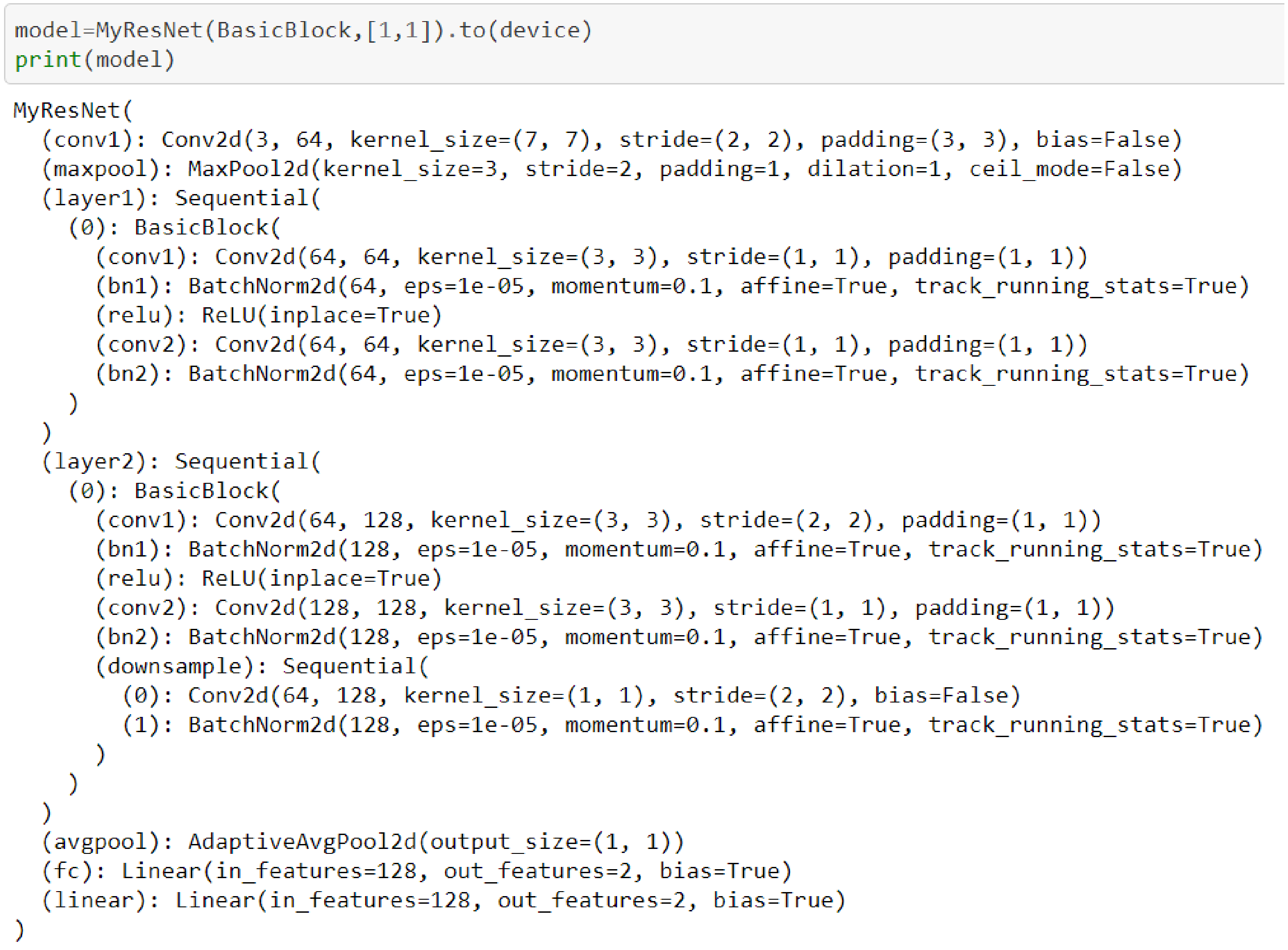
Batch Normalization



https://medium.com/ching-i/batch-normalization-%E4%BB%8B%E7%B4%B9-135a24928f12



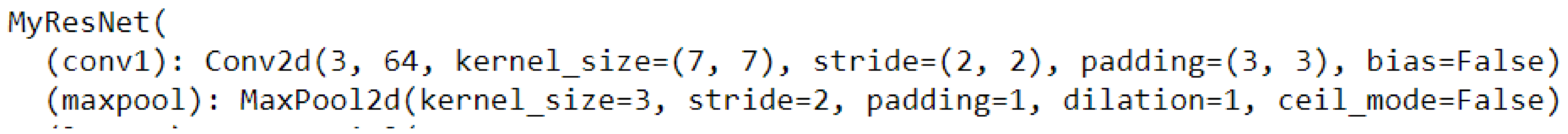
```python
class MyResNet(nn.Module):
  def __init__(self, block, layers, num_classes=2):
    super(MyResNet, self).__init__()
    self.inplanes = 64
    self.dilation = 1
    self.conv1=nn.Conv2d(3,self.inplanes,kernel_size=7,stride=2,
    self.maxpool=nn.MaxPool2d(kernel_size=3,stride=2, padding=1)
    self.layer1=self._make_layer(block,64,layers[0])
    self.layer2=self._make_layer(block,128,layers[1],stride=2)
    self.avgpool=nn.AdaptiveAvgPool2d((1,1))
    self.fc=nn.Linear(128*block.expansion,num_classes)
    self.linear=nn.Linear(128*block.expansion,num_classes)

  def _make_layer(self, block, planes, blocks, stride=1):
    layers=[]
    layers.append(block(self.inplanes,planes,stride))
    self.inplanes=planes*block.expansion

    for i in range(1,blocks):
      layers.append(block(self.inplanes,planes))
    return nn.Sequential(*layers)

  def forward(self, x):
    x=self.conv1(x)
    x=self.maxpool(x)
    x=self.layer1(x)
    x=self.layer2(x)
    x=self.avgpool(x)
    x=torch.flatten(x, 1)
    x=self.fc(x)
    return x
```



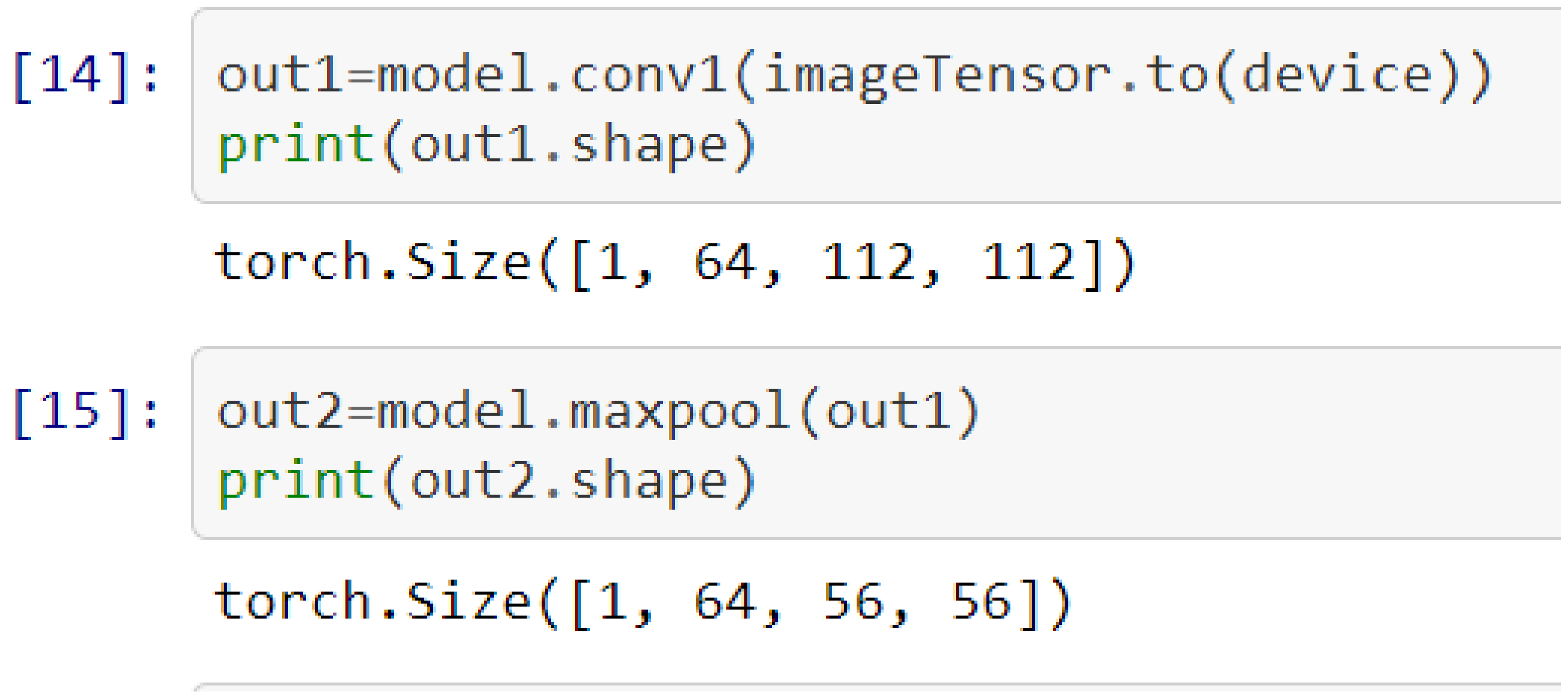
```python
model=MyResNet(BasicBlock,[1,1]).to(device)
print(model)
```

```
MyResNet(
  (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
  (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
  (layer1): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (layer2): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1))
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (downsample): Sequential(
        (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
        (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      )
    )
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(1, 1))
  (fc): Linear(in_features=128, out_features=2, bias=True)
  (linear): Linear(in_features=128, out_features=2, bias=True)
)
```

Practice – Draw filters, blocks and feature maps

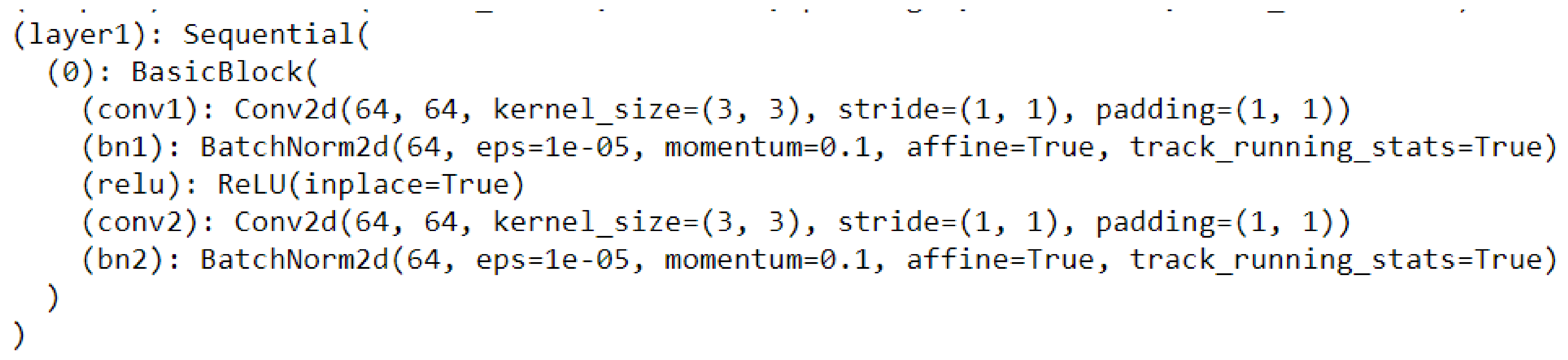


```
MyResNet(
  (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
  (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
```

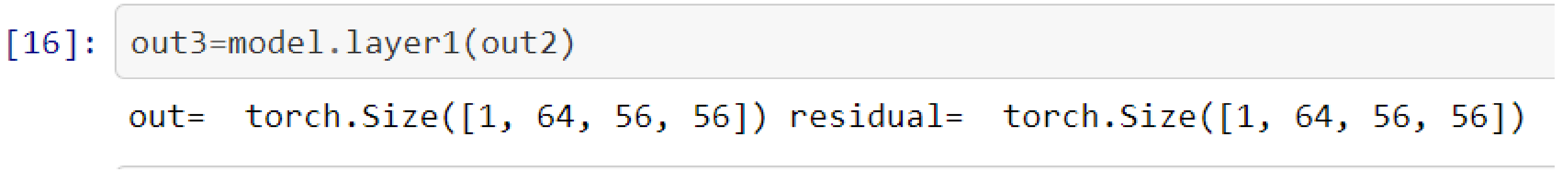


```
[14]: out1=model.conv1(imageTensor.to(device))
      print(out1.shape)

      torch.Size([1, 64, 112, 112])

[15]: out2=model.maxpool(out1)
      print(out2.shape)

      torch.Size([1, 64, 56, 56])
```

Practice – Draw filters, blocks and feature maps

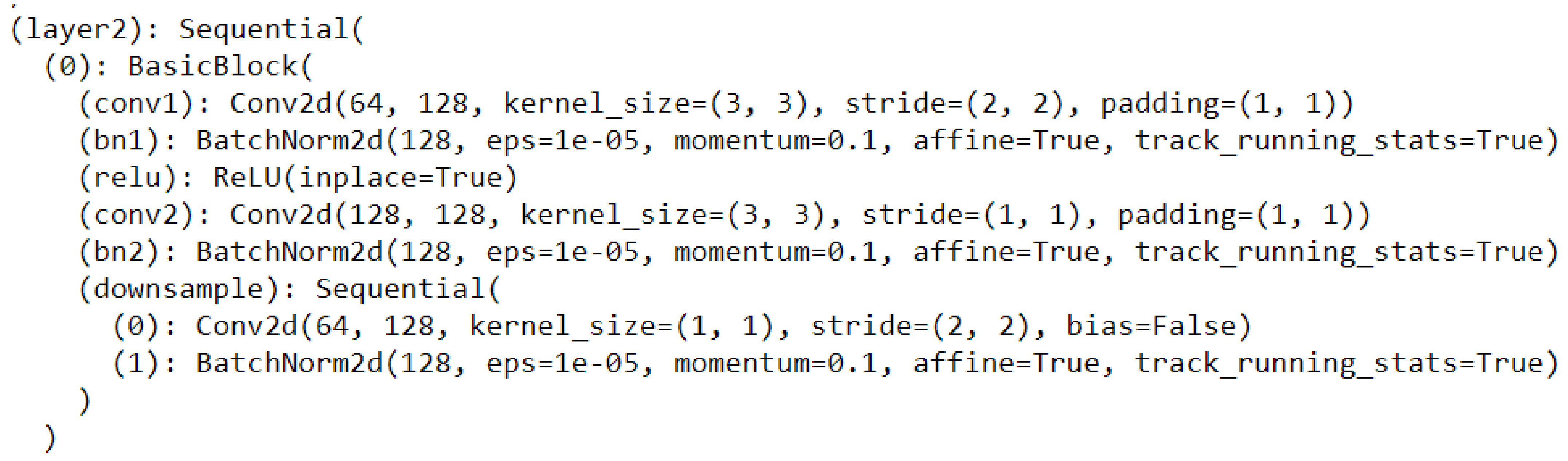


```
(layer1): Sequential(
  (0): BasicBlock(
    (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace=True)
    (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  )
)
```

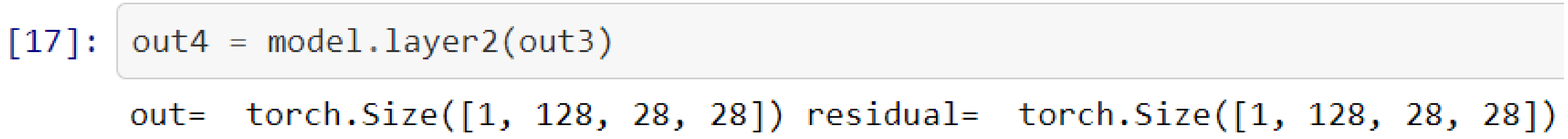


```
[16]: out3=model.layer1(out2)

      out=  torch.Size([1, 64, 56, 56]) residual=  torch.Size([1, 64, 56, 56])
```

Practice – Draw filters, blocks and feature maps

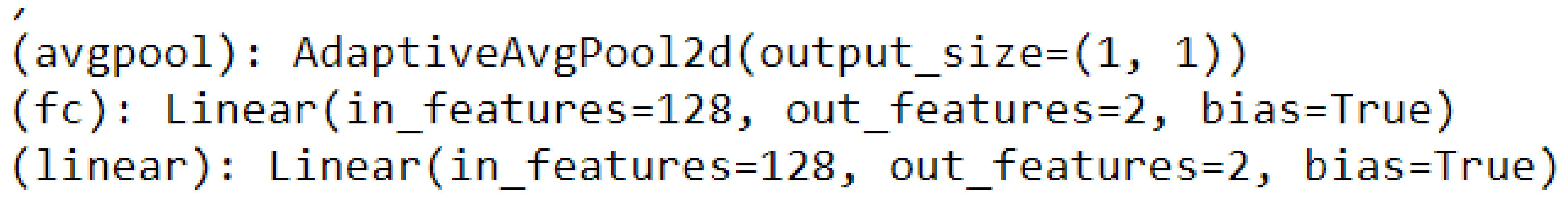


```
(layer2): Sequential(
  (0): BasicBlock(
    (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1))
    (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace=True)
    (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
    (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (downsample): Sequential(
      (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
      (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
```

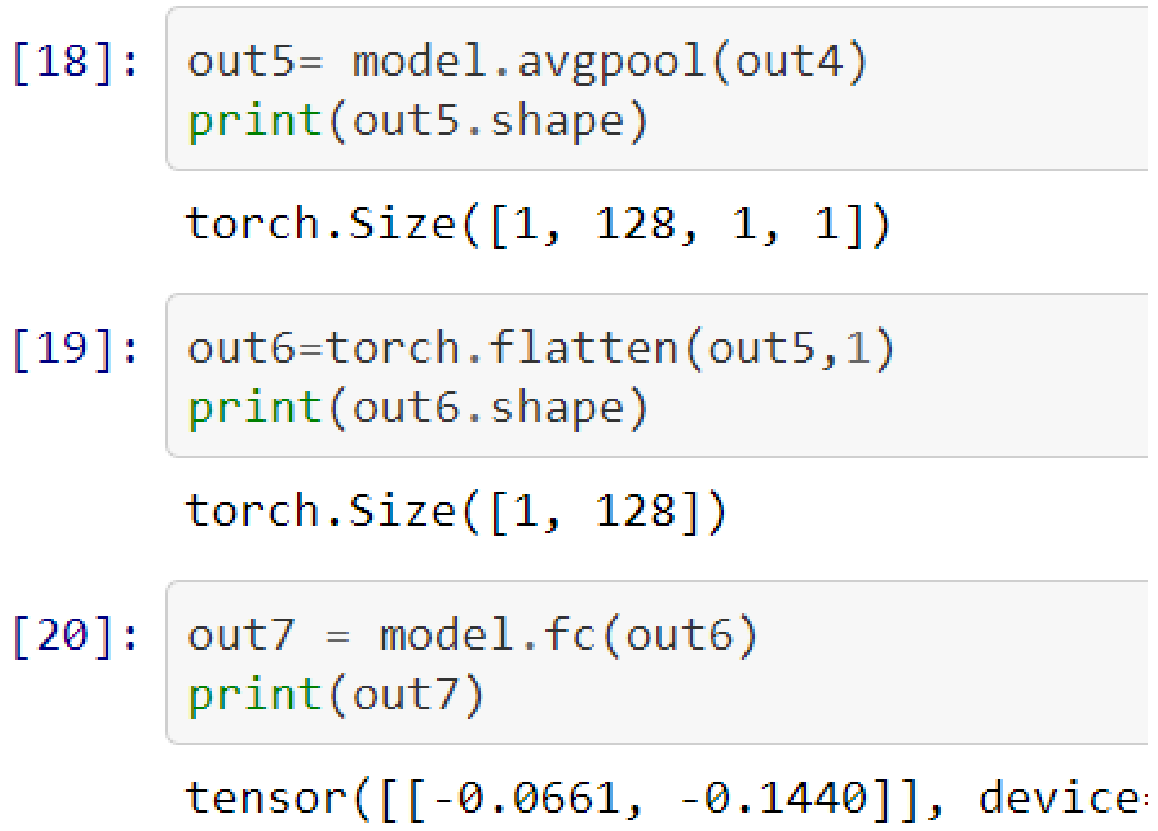


```
[17]: out4 = model.layer2(out3)

      out=  torch.Size([1, 128, 28, 28]) residual=  torch.Size([1, 128, 28, 28])
```

Practice – Draw filters, blocks and feature maps

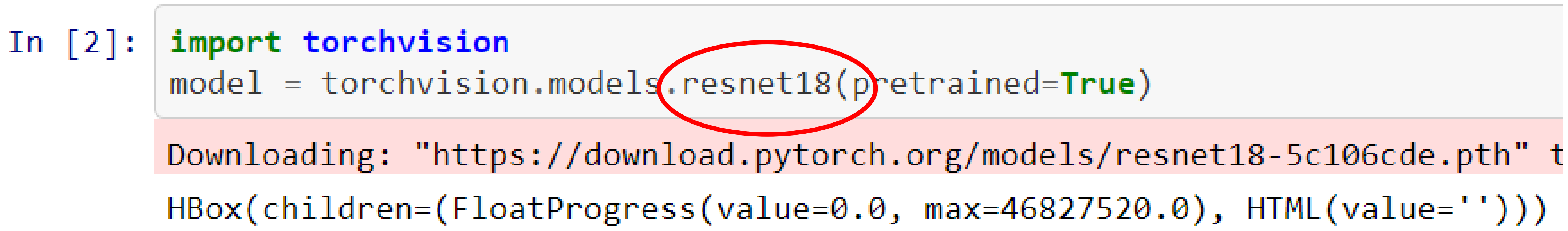


```
,
(avgpool): AdaptiveAvgPool2d(output_size=(1, 1))
(fc): Linear(in_features=128, out_features=2, bias=True)
(linear): Linear(in_features=128, out_features=2, bias=True)
```



```
[18]: out5= model.avgpool(out4)
      print(out5.shape)

      torch.Size([1, 128, 1, 1])

[19]: out6=torch.flatten(out5,1)
      print(out6.shape)

      torch.Size([1, 128])

[20]: out7 = model.fc(out6)
      print(out7)

      tensor([[-0.0661, -0.1440]], device
```

Practice – Load ImageNet pre-trained ResNet

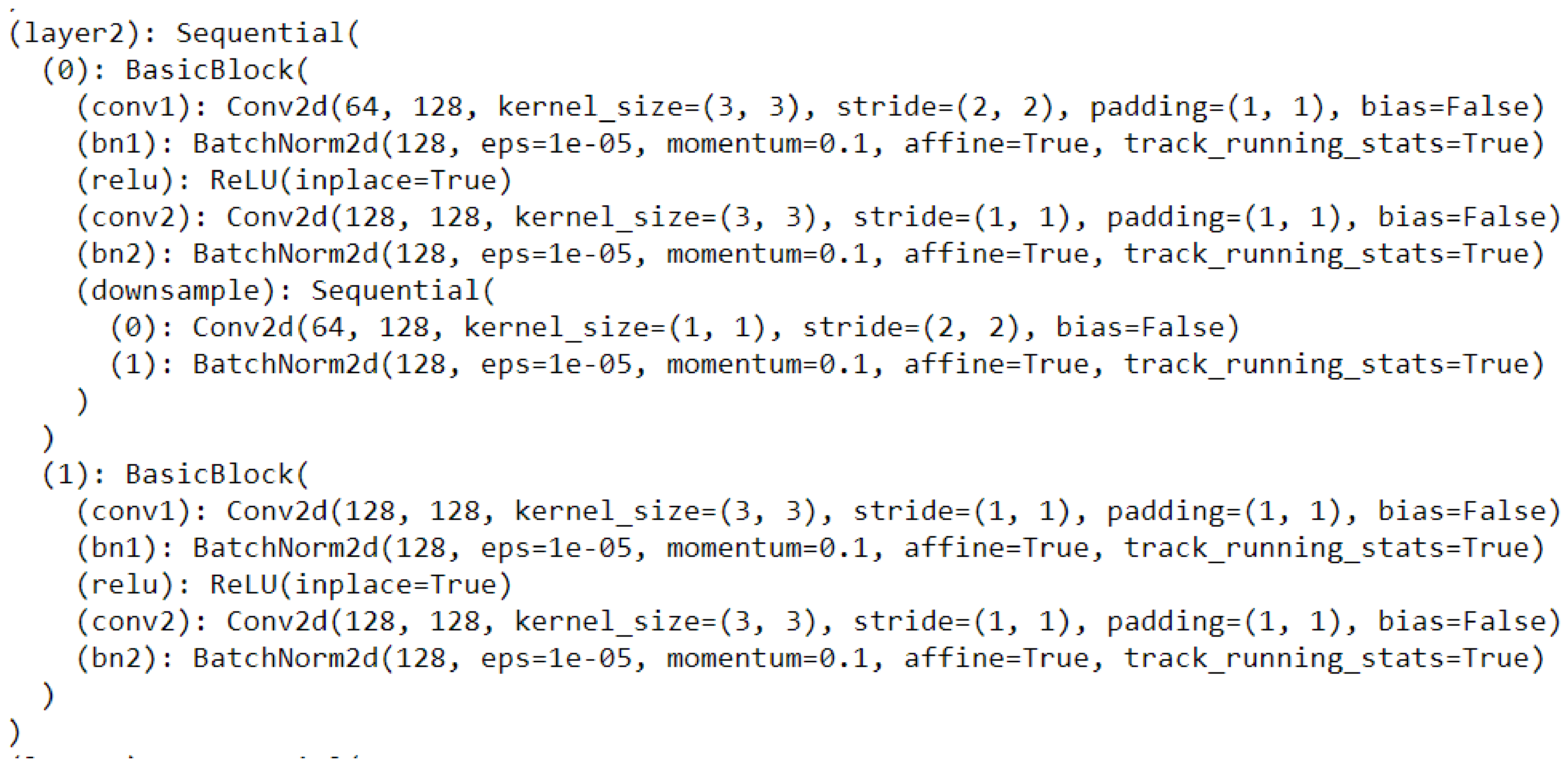


```
In [2]: import torchvision
        model = torchvision.models.resnet18(pretrained=True)

        Downloading: "https://download.pytorch.org/models/resnet18-5c106cde.pth" t

        HBox(children=(FloatProgress(value=0.0, max=46827520.0), HTML(value='')))
```

ResNet

```
ResNet(
  (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2), padding=(3, 3), bias=False)
  (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (relu): ReLU(inplace=True)
  (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1, ceil_mode=False)
  (layer1): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
    (1): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
```

ResNet



```
(layer2): Sequential(
  (0): BasicBlock(
    (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2), padding=(1, 1), bias=False)
    (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace=True)
    (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (downsample): Sequential(
      (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2), bias=False)
      (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    )
  )
  (1): BasicBlock(
    (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
    (relu): ReLU(inplace=True)
    (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1), bias=False)
    (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  )
)
```