

Build my own CNN

Practice – CNN

- Run “7.2. MyCNN.ipynb”



Build my own CNN model

```
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
```

Suppose input image size = 64 x 64x 3

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_mode=False)
    (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_mode=False)
  )
  (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

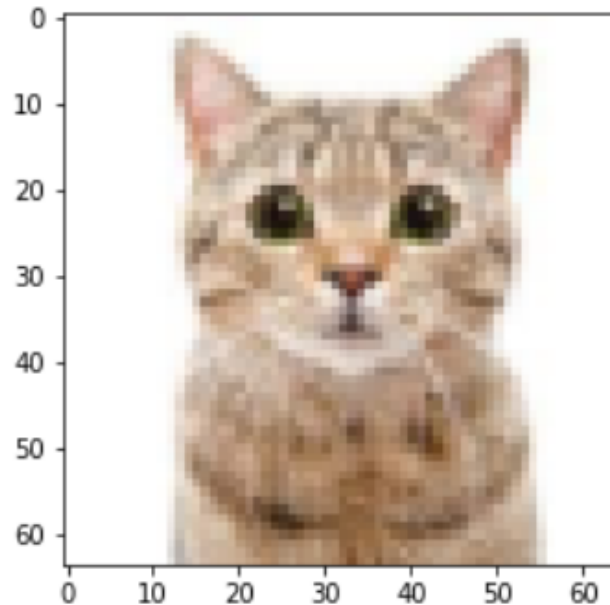
Total params: 10,402
Trainable params: 10,402
Non-trainable params: 0

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()
```

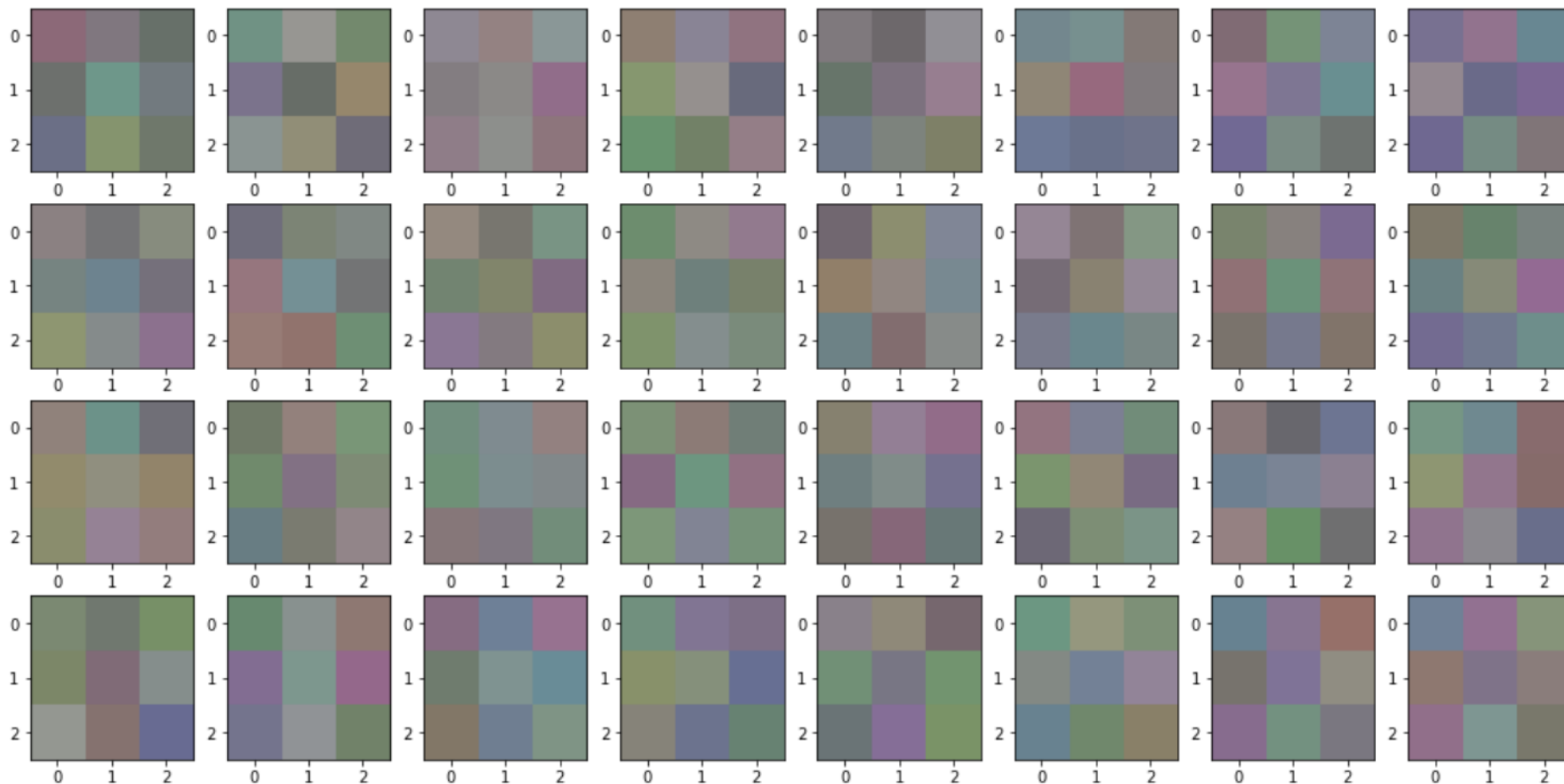
(64, 64, 3) 0.027450978755950928 1.0



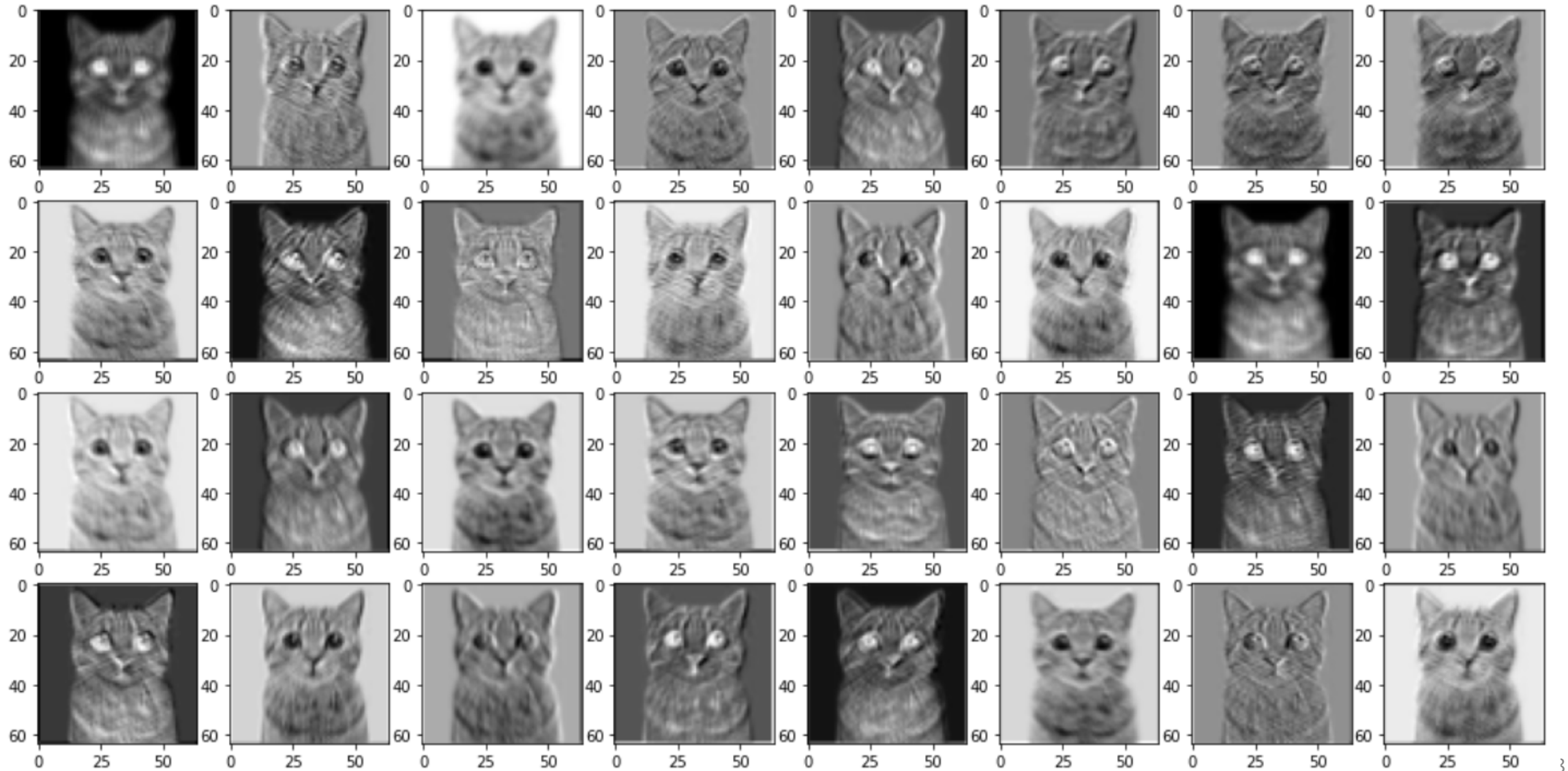
Input image size = 64 x 64x 3

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
```

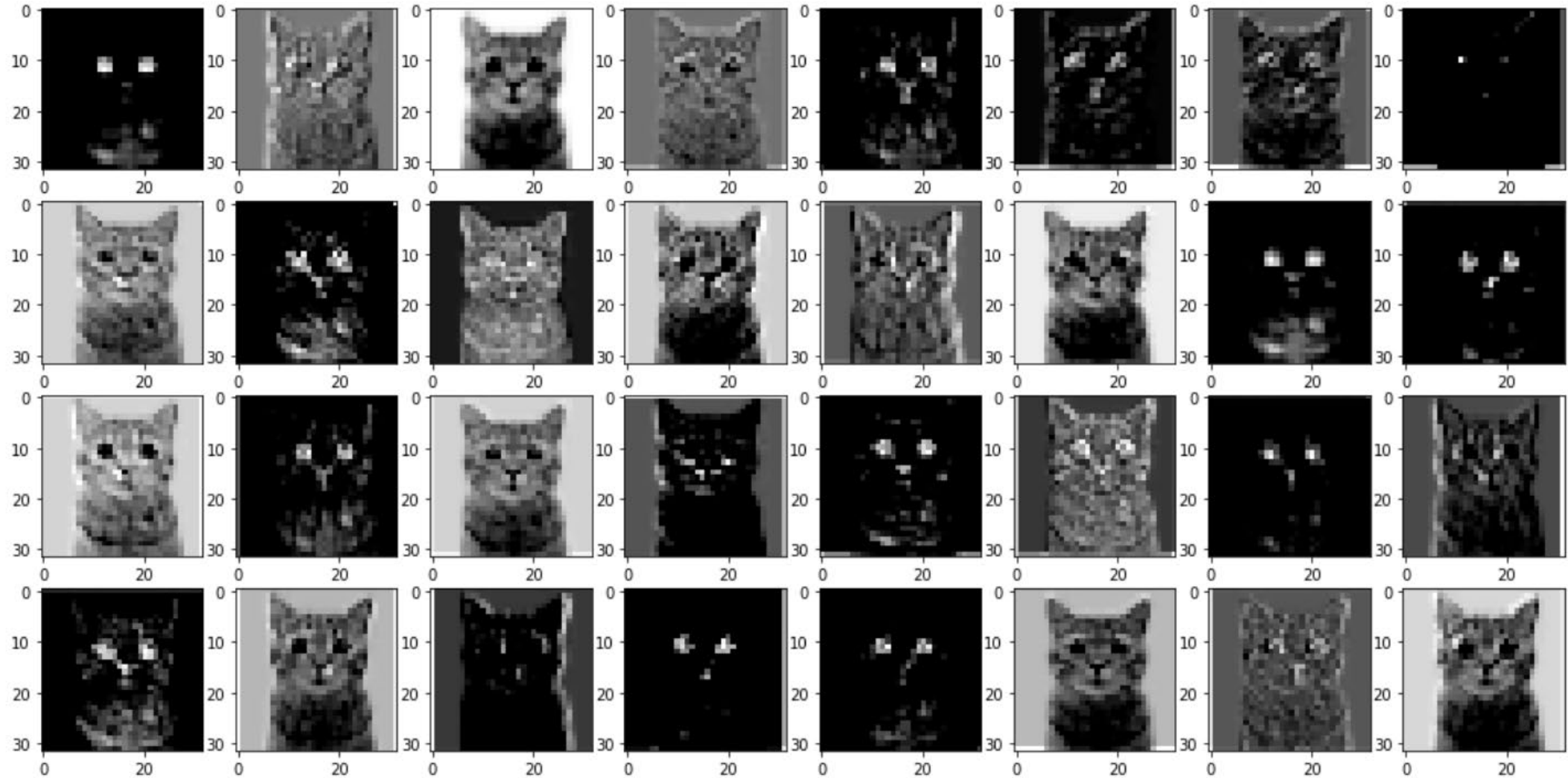


Output feature map, shape = 64x64x32



Feature map after max pooling, shape = 32x32x32

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



Flatten

```
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
```

```
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_mode=False)
    (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_mode=False)
  )
  (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.

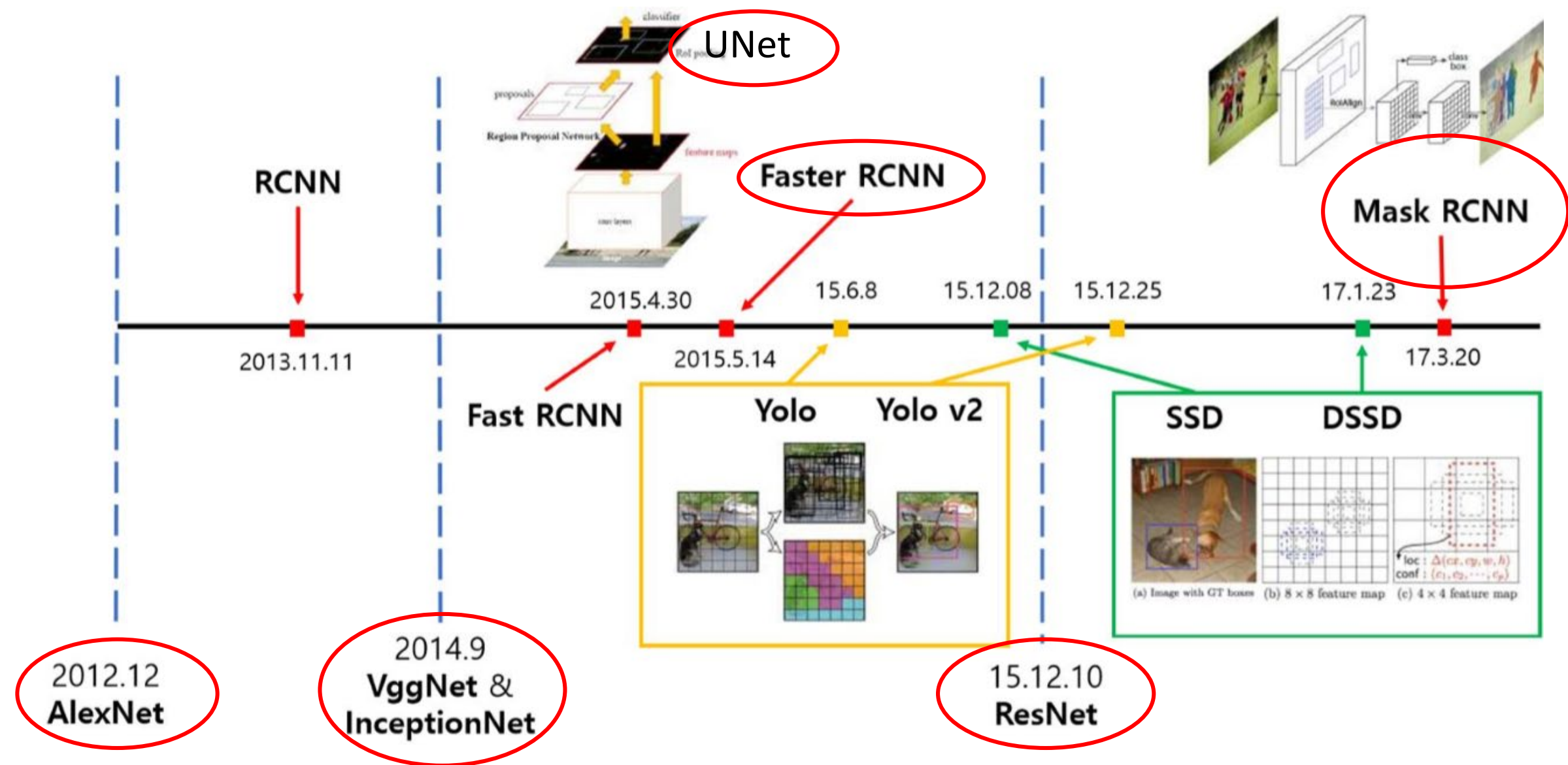
```
class MyCNN(nn.Module):
    def __init__(self):
        super(MyCNN, self).__init__()
        self.features = nn.Sequential(
            #Assume input image H/W=64
            nn.Conv2d(3, 32, 3, 1, 1), #feature map H/W=(64+2*1-3)/1+1 = 64
            nn.ReLU(inplace=True),
            nn.MaxPool2d(2,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

```
[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



Practice – Load ImageNet pre-trained VGG

```
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

The screenshot shows the Kaggle website interface. On the left, a sidebar contains navigation links: Home, Compete, Data (highlighted with a red circle), Code, Communities, Courses, and More. The main content area has a search bar at the top with the text 'Search'. Below it, the word 'Datasets' is displayed in large bold letters. A search bar below 'Datasets' contains the text 'cartoon'. Below the search bar, a filter tag 'Computer Vision' with a close button 'X' is highlighted with a red circle. Underneath, a section titled '4 Datasets' lists two datasets. The first dataset is 'Landscape Pictures' by Arnaud ROUGETET, updated a year ago, with a usability of 8.8, 4319 files, and 620 MB. The second dataset is 'Tom & Jerry Detection' by Vijayakumar, also updated a year ago, with a usability of 7.5, 464 files, and 47 MB. This second dataset is highlighted with a red circle.

≡ kaggle

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Computer Vision X

4 Datasets

 **Landscape Pictures**
Arnaud ROUGETET · Updated a year ago
Usability 8.8 · 4319 Files (other) · 620 MB

 **Tom & Jerry Detection**
Vijayakumar · Updated a year ago
Usability 7.5 · 464 Files (other) · 47 MB

Tom & Jerry

Tom & Jerry Detection | Kaggle

kaggle.com/vijayjoyz/tom-jerry-detection

應用程式 Microsoft Azure N... 免費線上影片轉Gif... YouTube Google 學術搜尋 GitHub Colaboratory 李弘毅 ML 元智大學個人portal 其他書籤

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Dataset



Tom & Jerry Detection

Image Dataset For detecting tom & jerry

 Vijayakumar • updated a year ago (Version 1)

Data

Tasks

Code (2)

Discussion

Activity

Metadata

Download (49 MB)

New Notebook

Usability 7.5

License Database: Open Database, Contents: Database Contents

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

Description

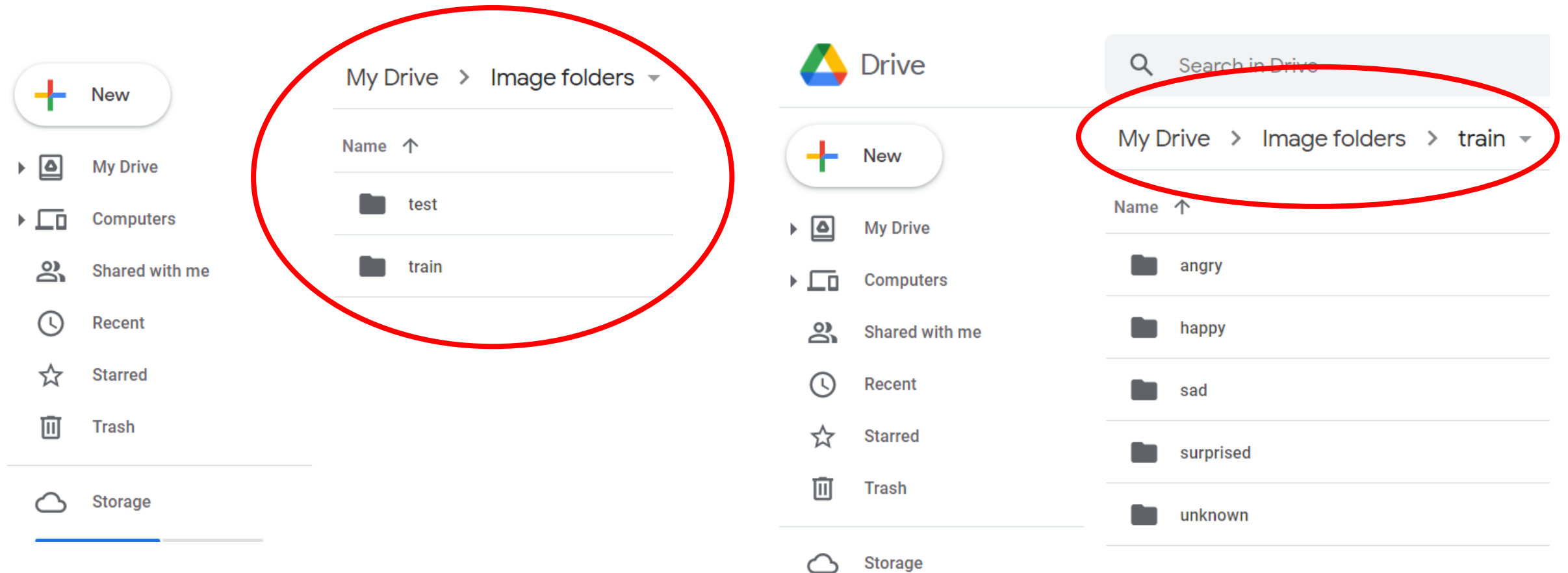
FaceDetection

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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Name ↑

test

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」

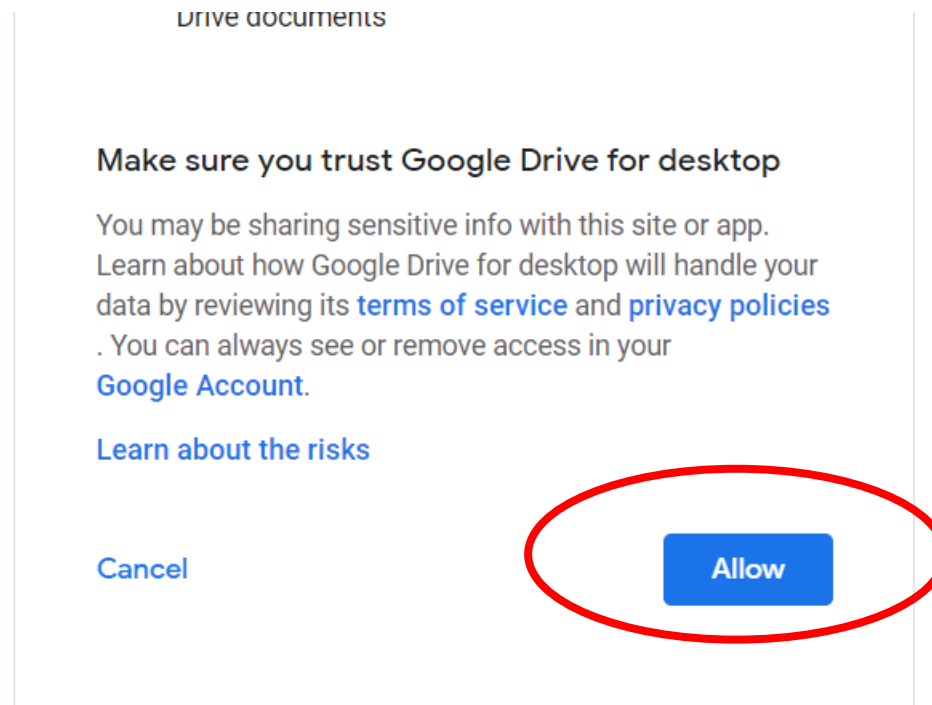
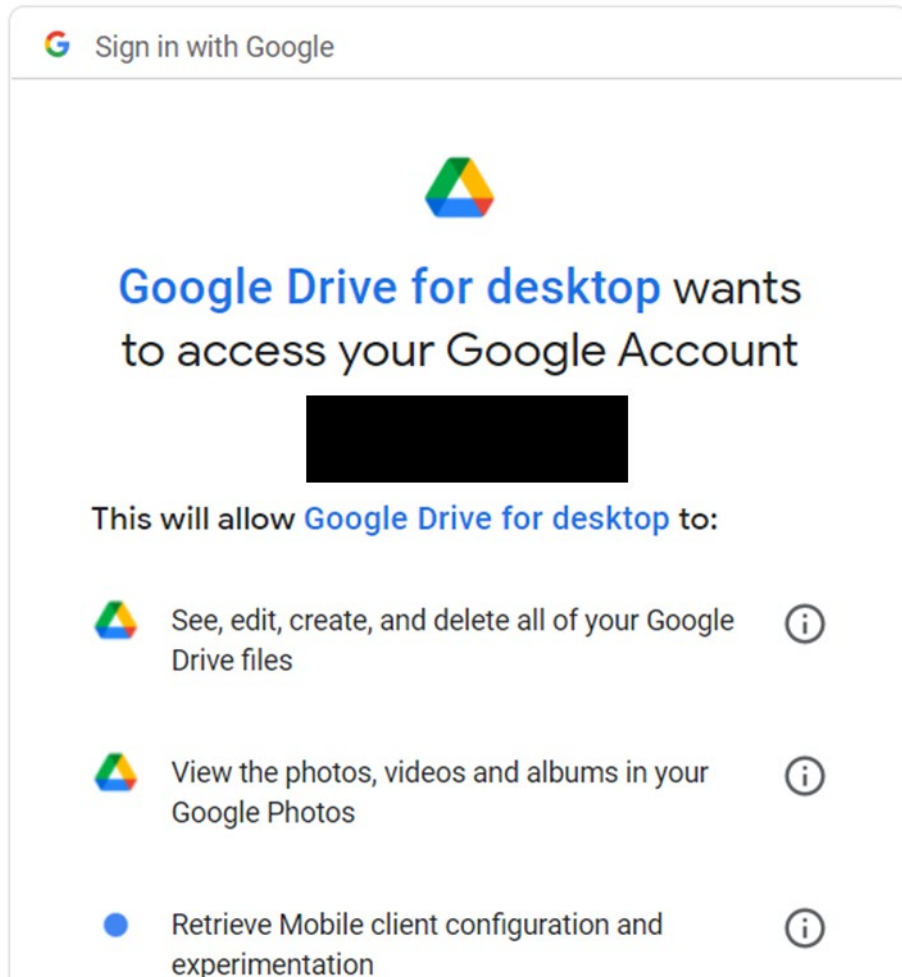
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繁體中文 ▼

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Connect to Google drive



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

4/1AY0e-

g4roX6ceHqek0M4JnYfPrHwEJCdrz8DP6nsD5y1m7Uu7B



```
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)
```

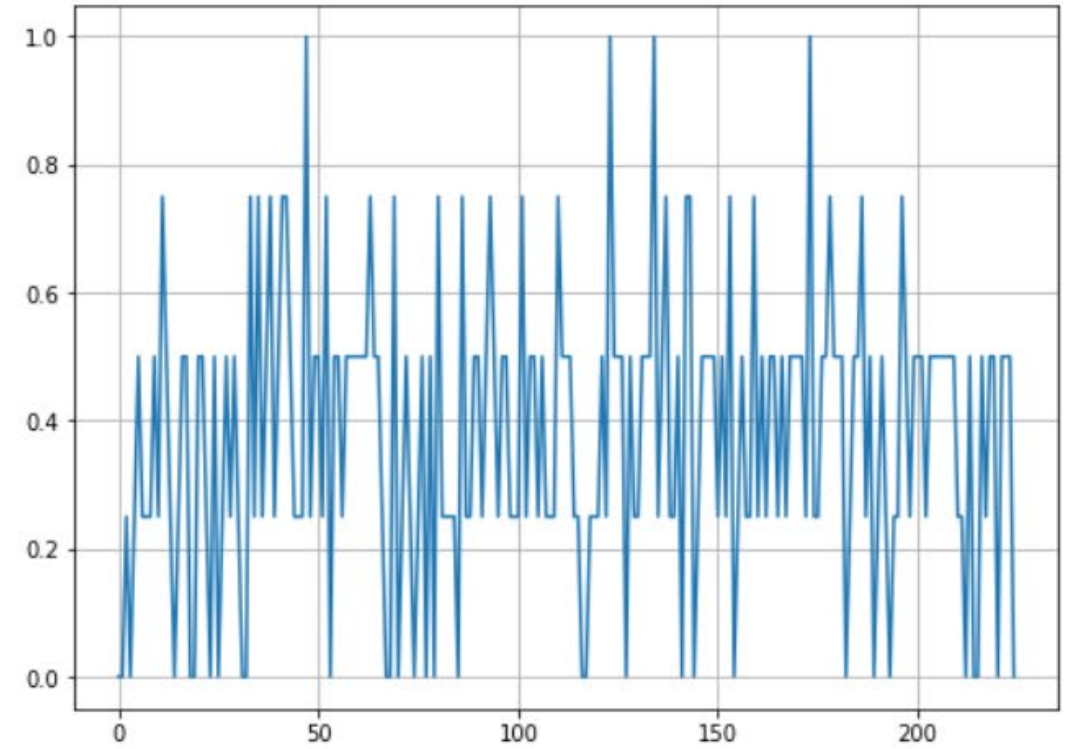
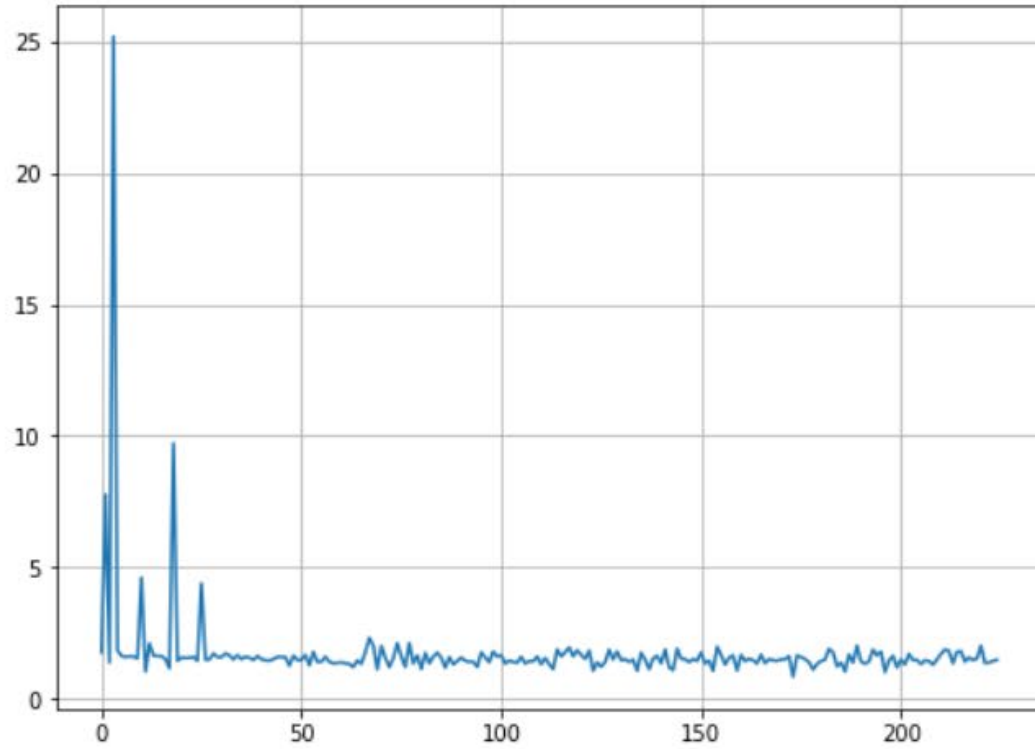
```
epoch = 1, batch: 0, 5, 10, 15, 20, 25, 30, 35, 40, 45,
epoch = 2, batch: 0, 5, 10, 15, 20, 25, 30, 35, 40, 45,
epoch = 3, batch: 0, 5, 10, 15, 20, 25, 30, 35, 40, 45,
```

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 good?



Biased prediction, why?

```
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 happy and angry faces.

Can we recognize faces of healthy vs dementia people?


<https://www.memoryhealth.com/blogs/the-brain-blog/the-faces-of-alzheimers-disease-and-dementia>



HW5 (2) – Some idea

Results by searching "dementia" in Kaggle

3 Results Sort by: Relevancy




Dataset

Dataset_Alzheimer

by Yasir Hussein Shakir

3 months ago • 34 MB • ^ 7

Alzheimer's treatments cannot stop Alzheimer's from progressing, they




Dataset

Alzheimer_binaryclassification

by Smiti14

2 months ago • 33 MB • ^ 0



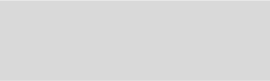
Dataset

combo01

by SHIYONA DASH

2 months ago • 94 MB • ^ 0

Alzheimer_s Dataset



名稱

- test
- train

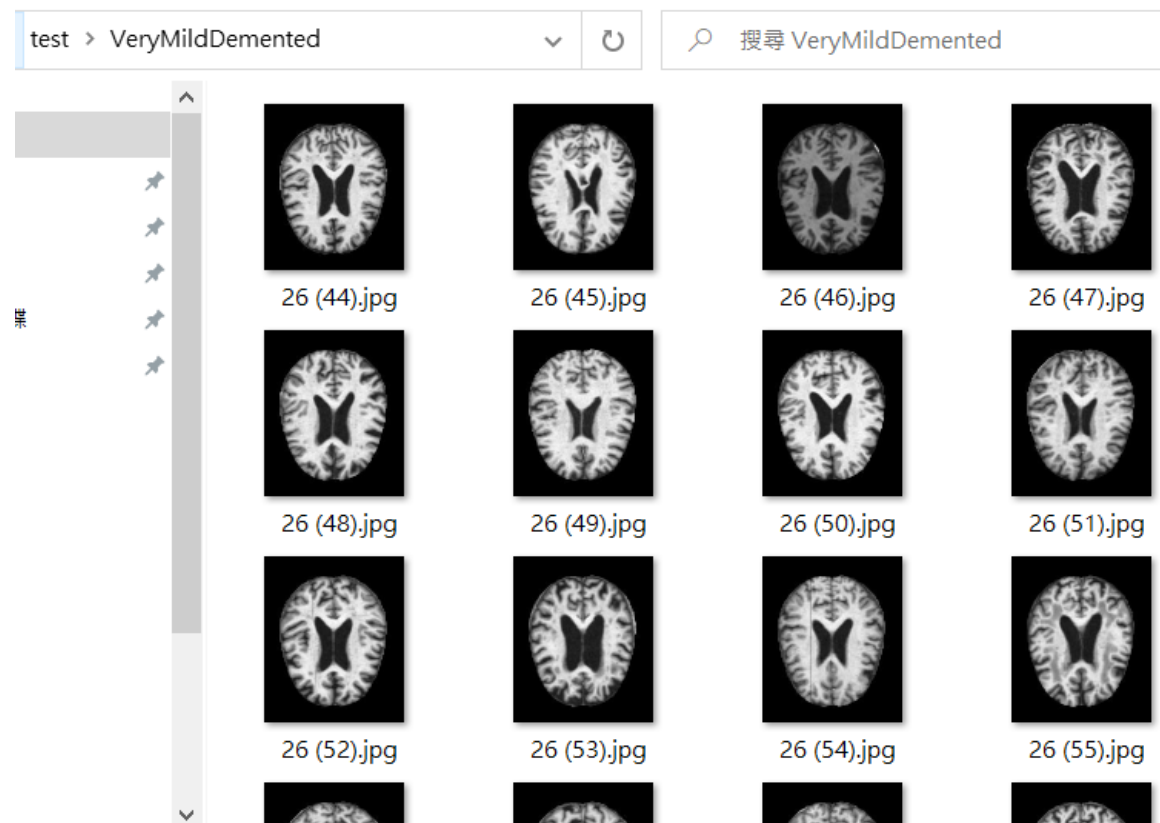
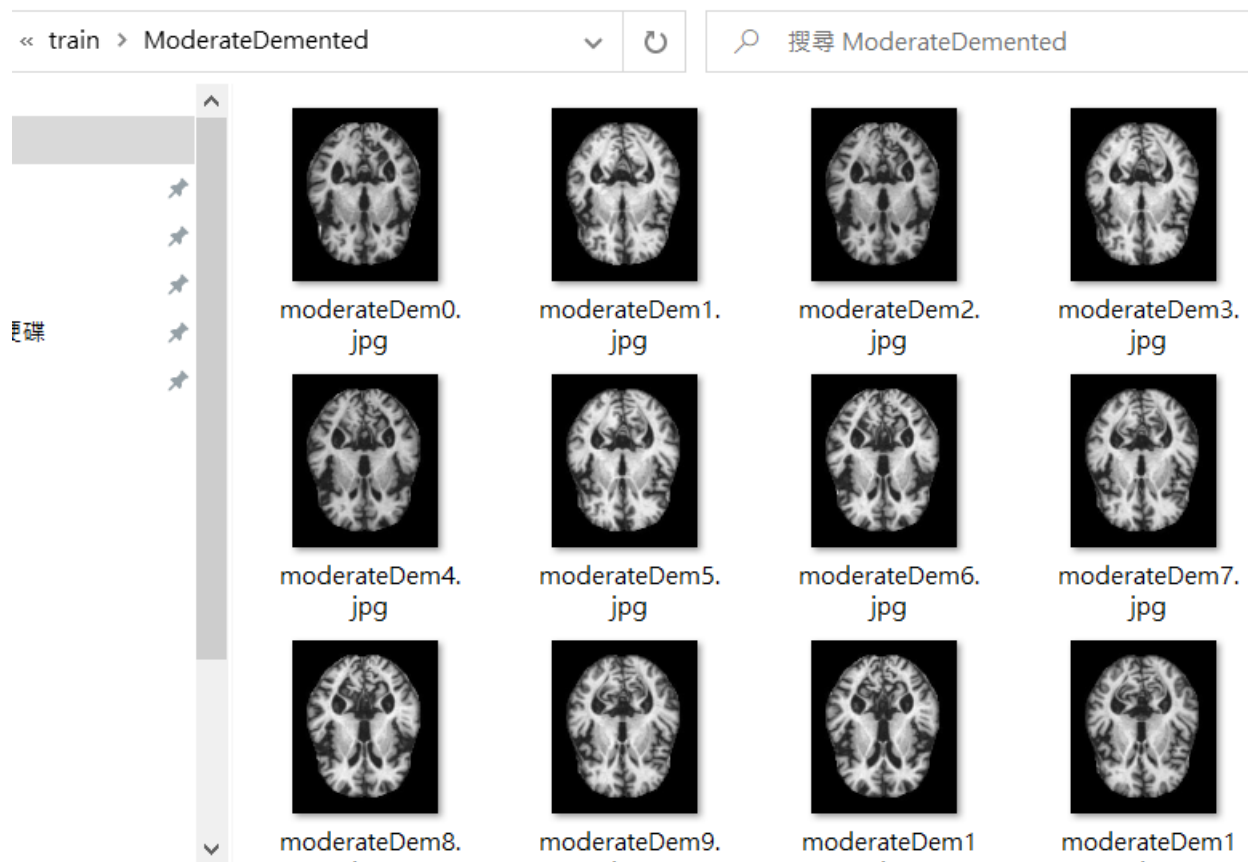
Alzheimer_s Dataset > train

名稱

- MildDemented
- ModerateDemented
- NonDemented
- VeryMildDemented

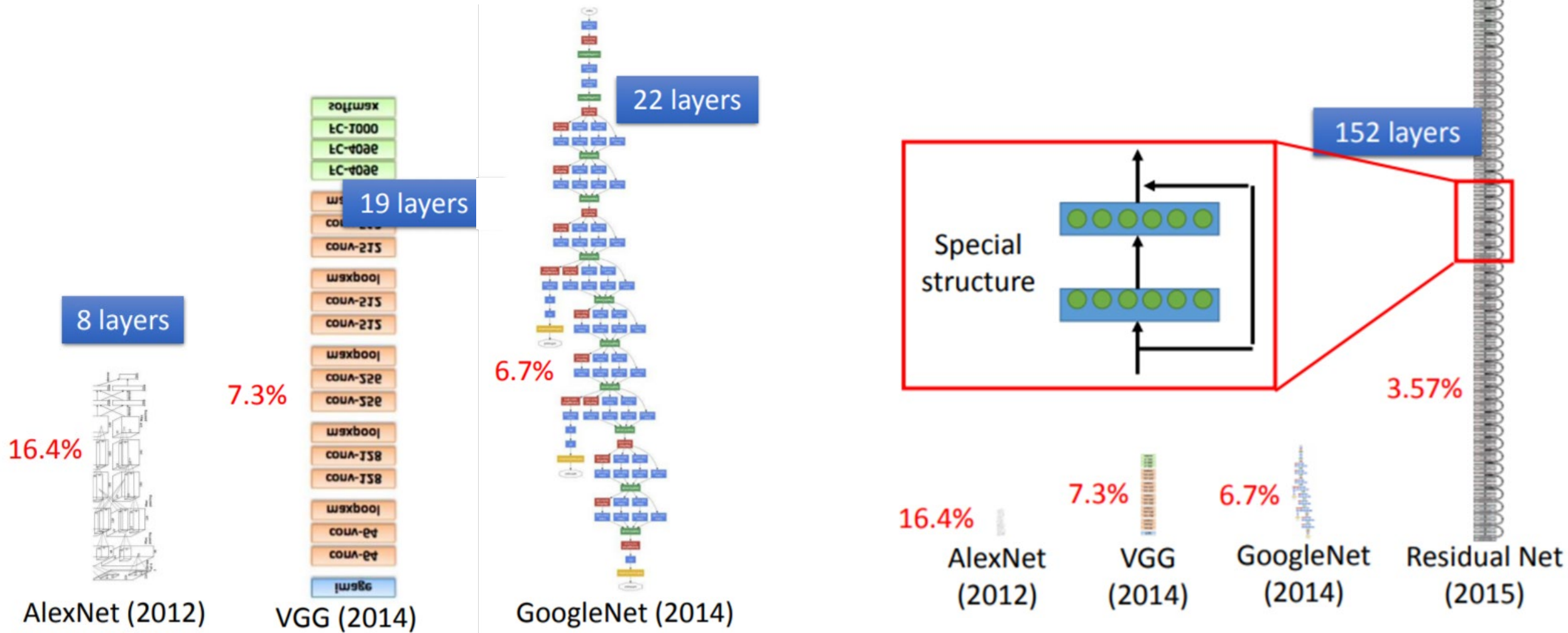
端硬碟

HW5 (2) – Some idea

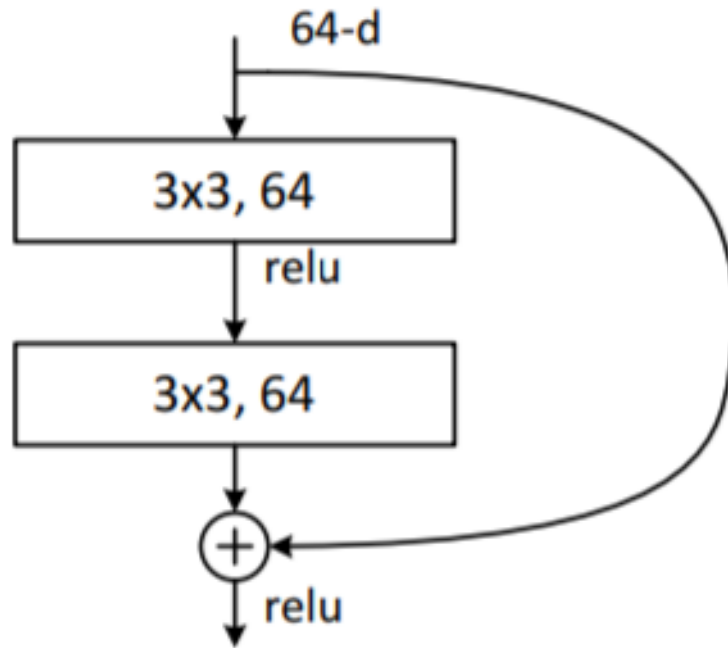


ResNet

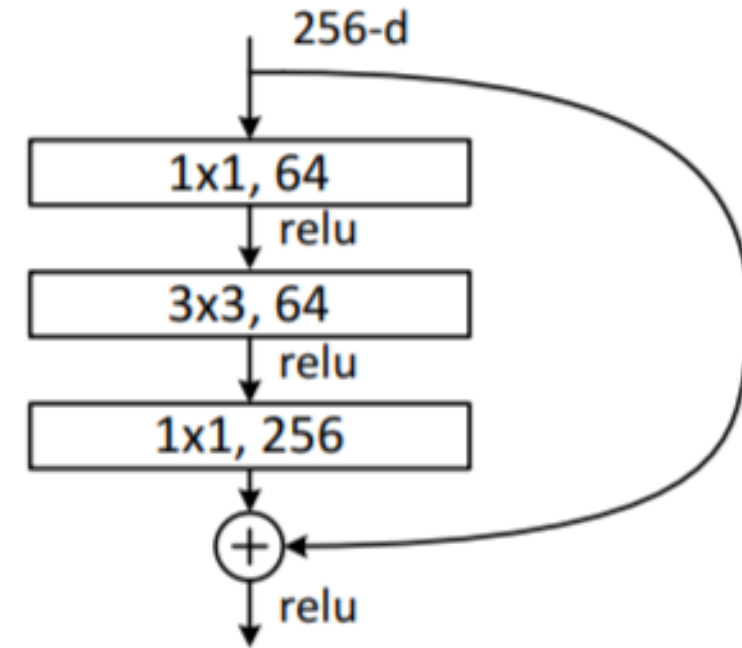
Going deeper and deeper...



ResNet



Basic block



Bottleneck block

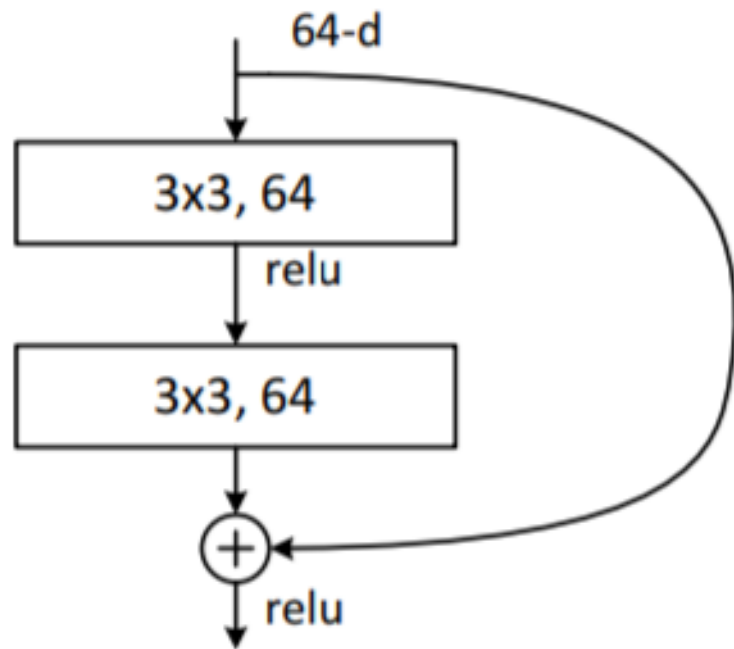
He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).

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

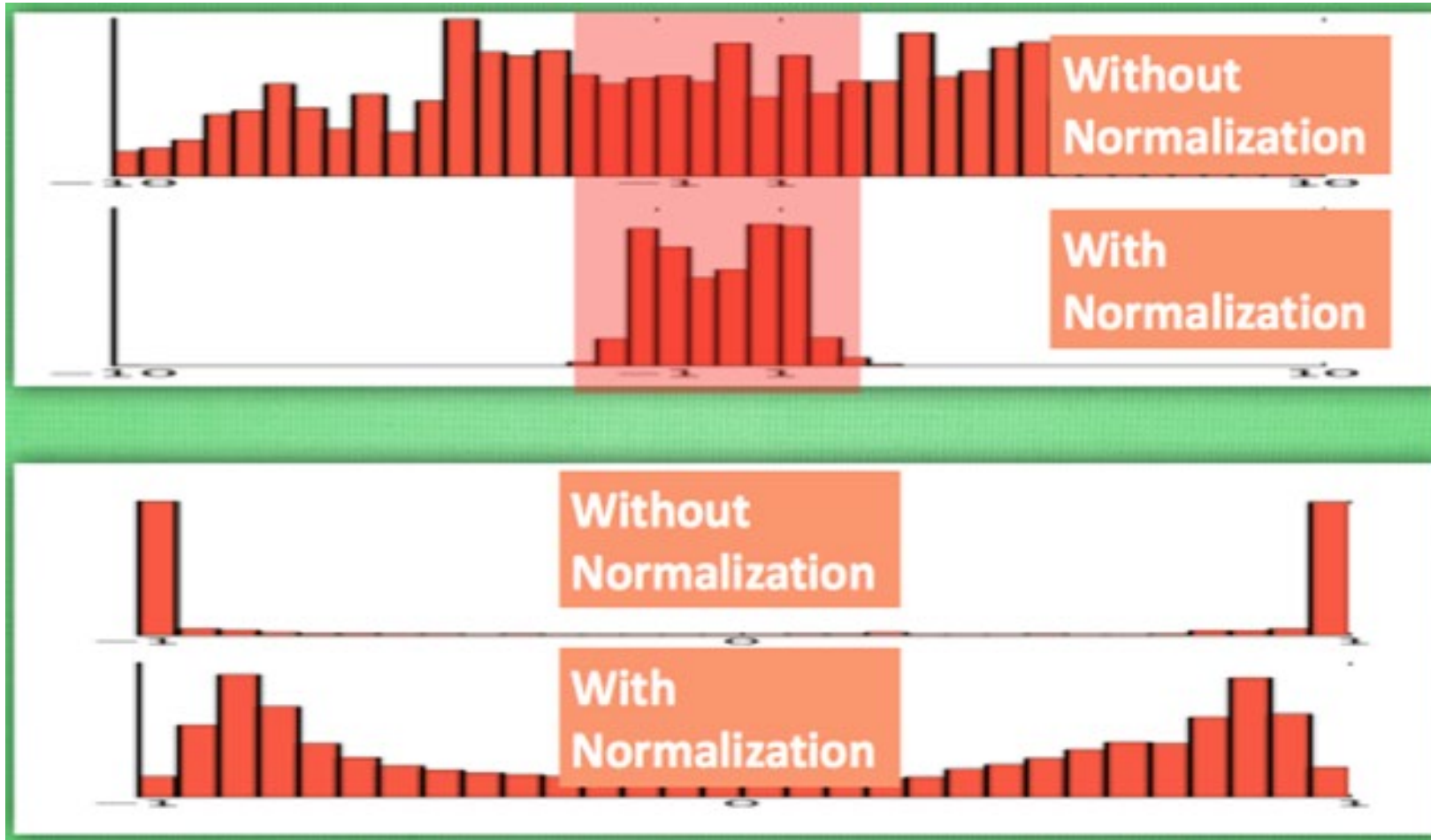
Applies Batch Normalization over a 4D input (a mini-batch of 2D inputs with additional channel dimension) as described in the paper [Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift](#).

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

- The mean and standard-deviation are calculated per-dimension over the mini-batches.
- By default, the elements of γ are 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>

```

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

```

```

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 the structure of MyResNet

```
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 the structure of MyResNet

```
(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 the structure of MyResNet

```
(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 the structure of MyResNet

```
(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 pre-trained ResNet

In [2]: `import torchvision`

`model = torchvision.models.resnet18(pretrained=True)`

Downloading: "<https://download.pytorch.org/models/resnet18-5c106cde.pth>" to

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)
  )
)
```