Practice – CNN

- Run “7.1. CNN (AlexNet).ipynb"

Load pre-trained image classification models

```
[2]  import torchvision
     model = torchvision.models.alexnet(pretrained=True)
```

Downloading: "https://download.pytorch.org/models

100% 233M/233M

Torchvision - https://pytorch.org/vision/stable/index.html

ImageNet - http://www.image-net.org/

Image Classification - https://machinelearningmastery.com/applications-of-deep-learning-for-computer-vision/

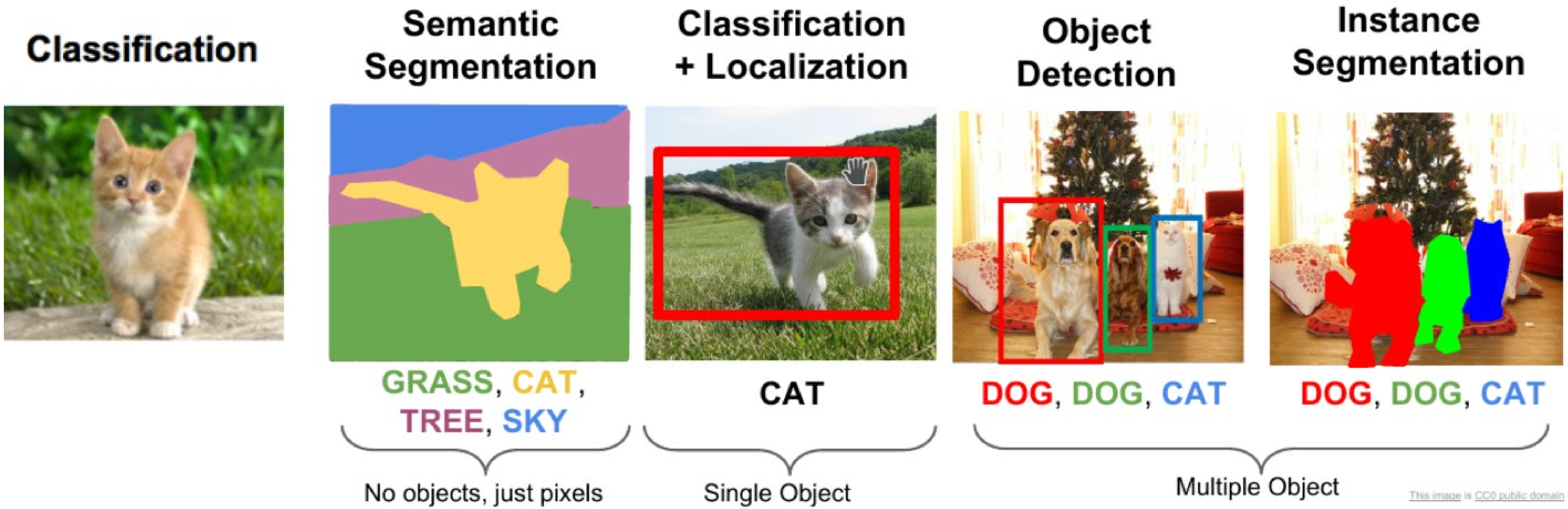
Computer vision tasks

Alex Net
VGG16
Res Net

U Net

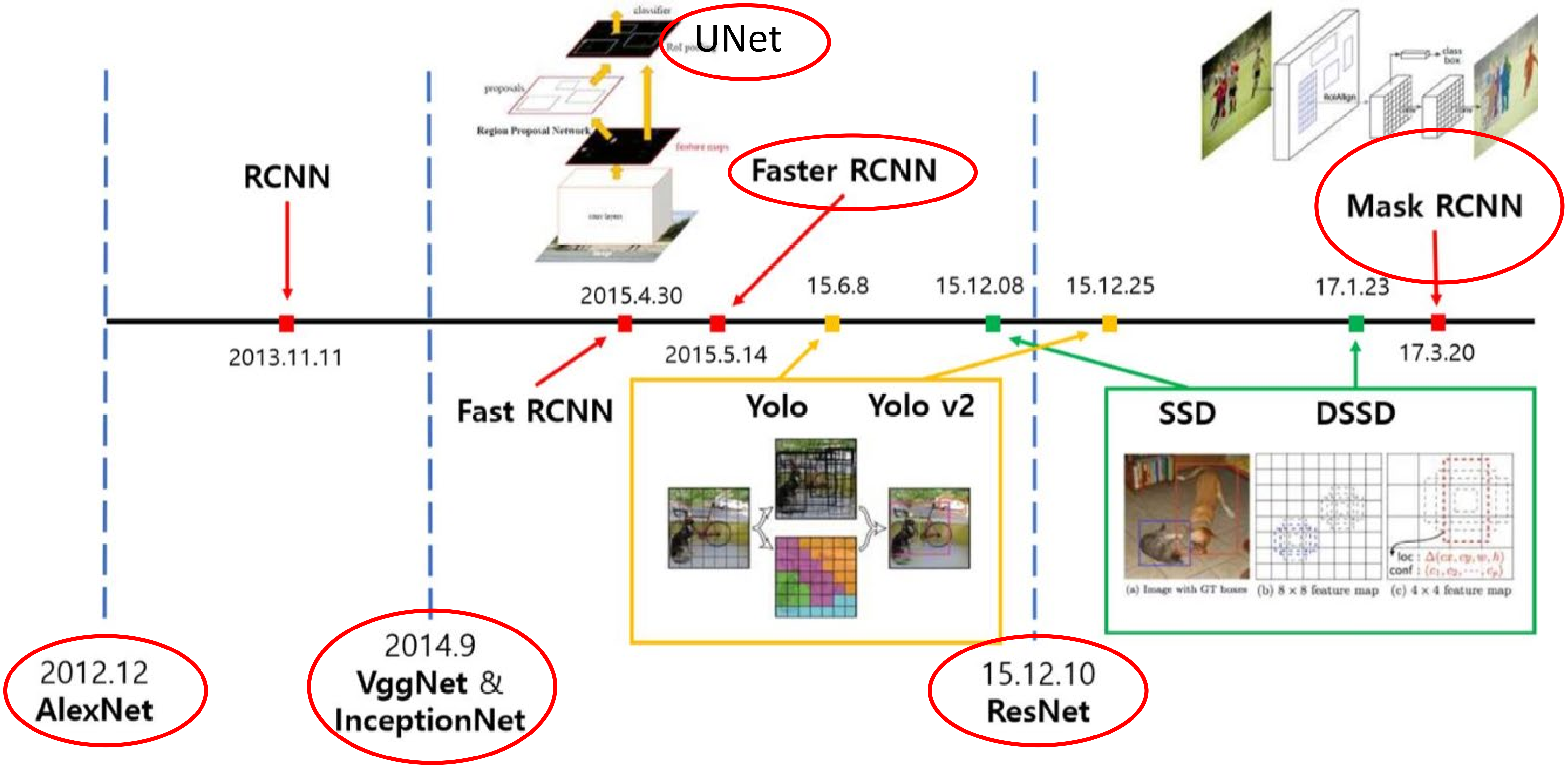
Faster RCNN

Mask RCNN



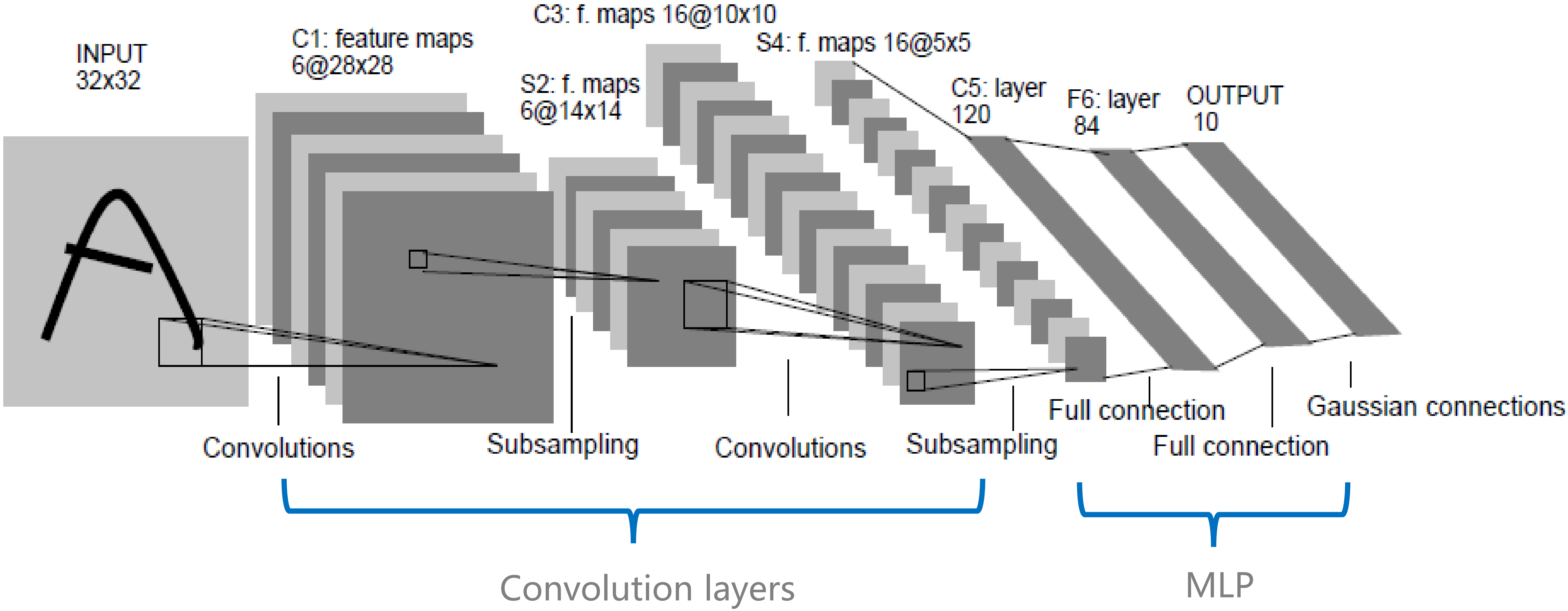
圖片來源: https://kharshit.github.io/blog/2019/08/23/quick-intro-to-instance-segmentation

CNN family



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

LeNet

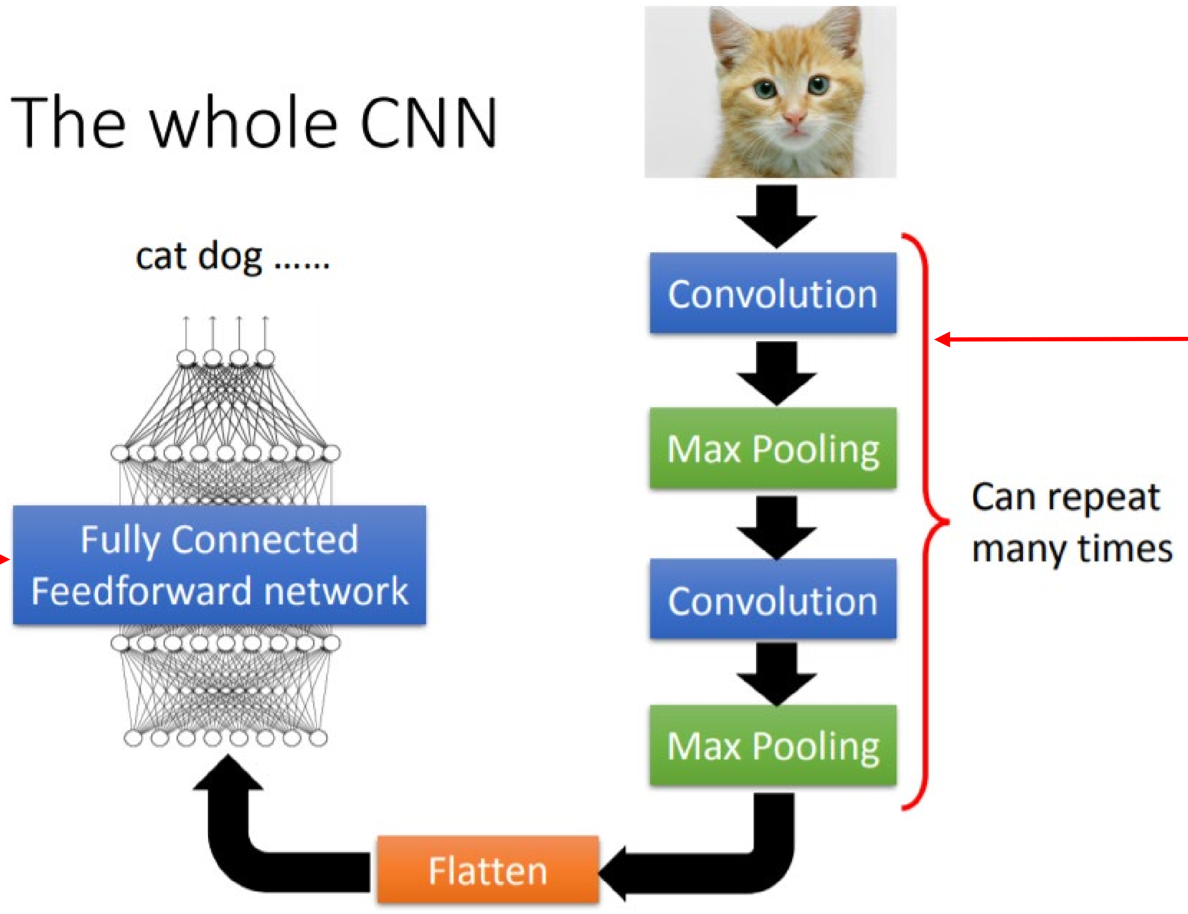


LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86(11), 2278-2324.

Put model in evaluation mode and in GPU

In [3]:
```
model.eval()
model.to(device)
```

CNN contains two sections: "features" and "classifier"

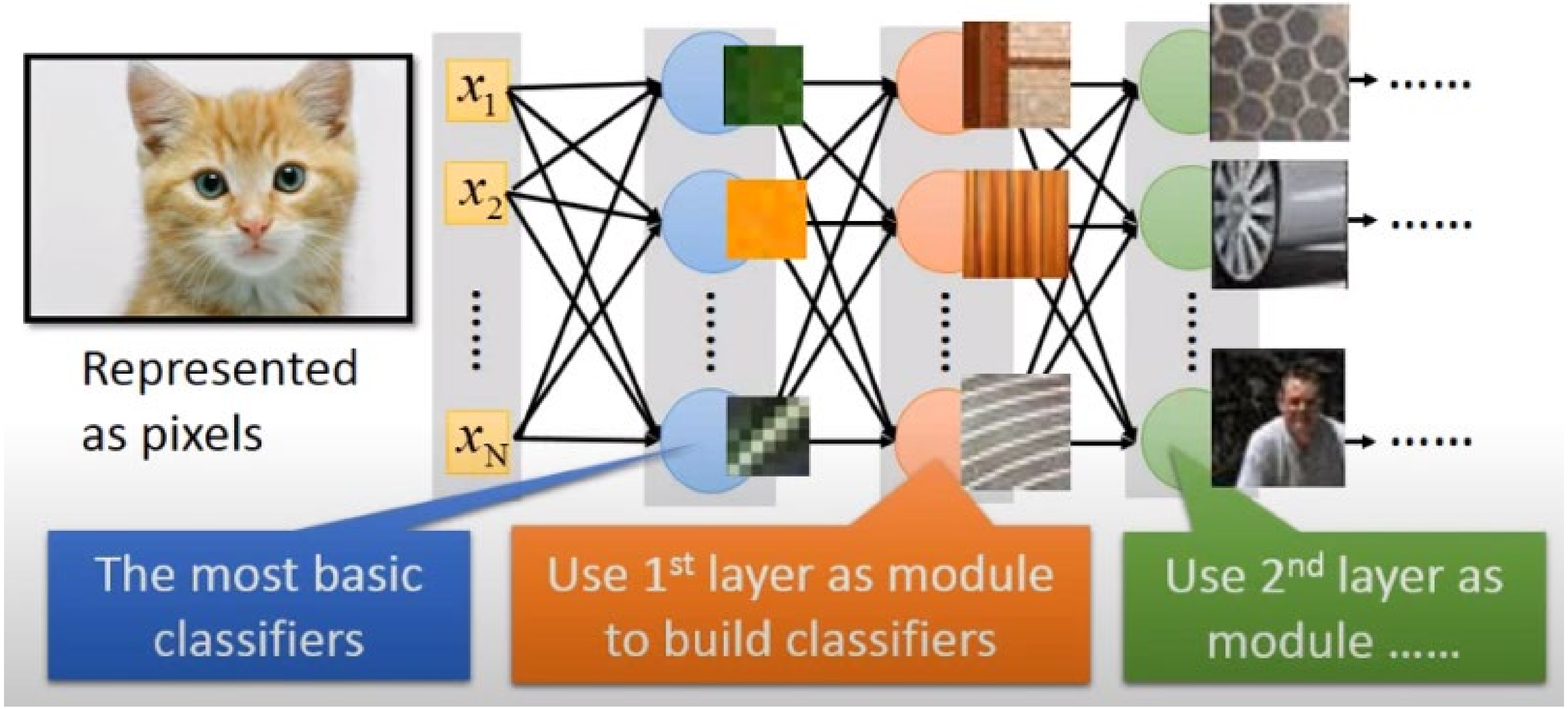


Reference: 李弘毅 ML Lecture 10
https://youtu.be/FrKWiRv254g

```
AlexNet(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(11, 11), stride=(4, 4), paddi
    (1): ReLU(inplace=True)
    (2): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1
    (3): Conv2d(64, 192, kernel_size=(5, 5), stride=(1, 1), paddi
    (4): ReLU(inplace=True)
    (5): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1
    (6): Conv2d(192, 384, kernel_size=(3, 3), stride=(1, 1), padd
    (7): ReLU(inplace=True)
    (8): Conv2d(384, 256, kernel_size=(3, 3), stride=(1, 1), padd
    (9): ReLU(inplace=True)
    (10): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), pad
    (11): ReLU(inplace=True)
    (12): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(6, 6))
  (classifier): Sequential(
    (0): Dropout(p=0.5, inplace=False)
    (1): Linear(in_features=9216, out_features=4096, bias=True)
    (2): ReLU(inplace=True)
    (3): Dropout(p=0.5, inplace=False)
    (4): Linear(in_features=4096, out_features=4096, bias=True)
    (5): ReLU(inplace=True)
    (6): Linear(in_features=4096, out_features=1000, bias=True)
  )
)
```

Why not using MLP to classify images?

If we feed an image to MLP, then each neuron "sees" the whole image's pixels.

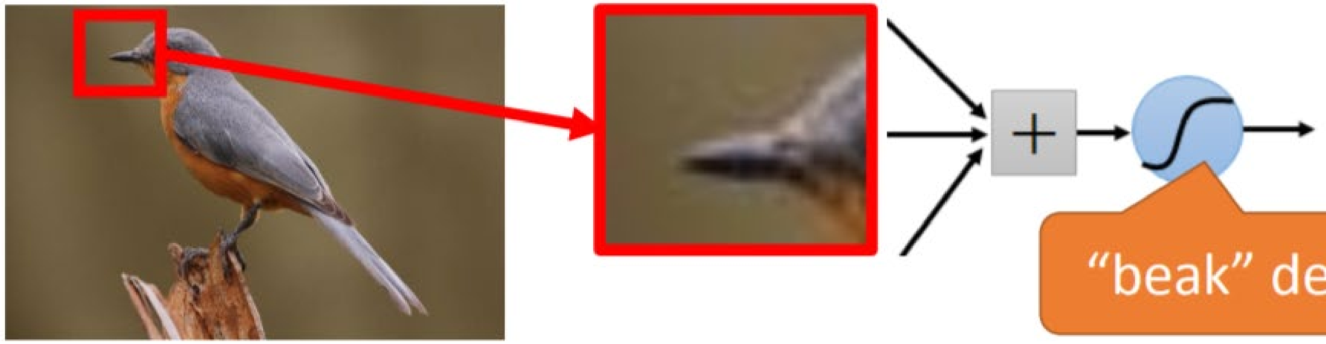


Reference: 李弘毅 ML Lecture 10 https://youtu.be/FrKWiRv254g

Some patterns are much smaller than the whole image

A neuron does not have to see the whole image to discover the pattern.

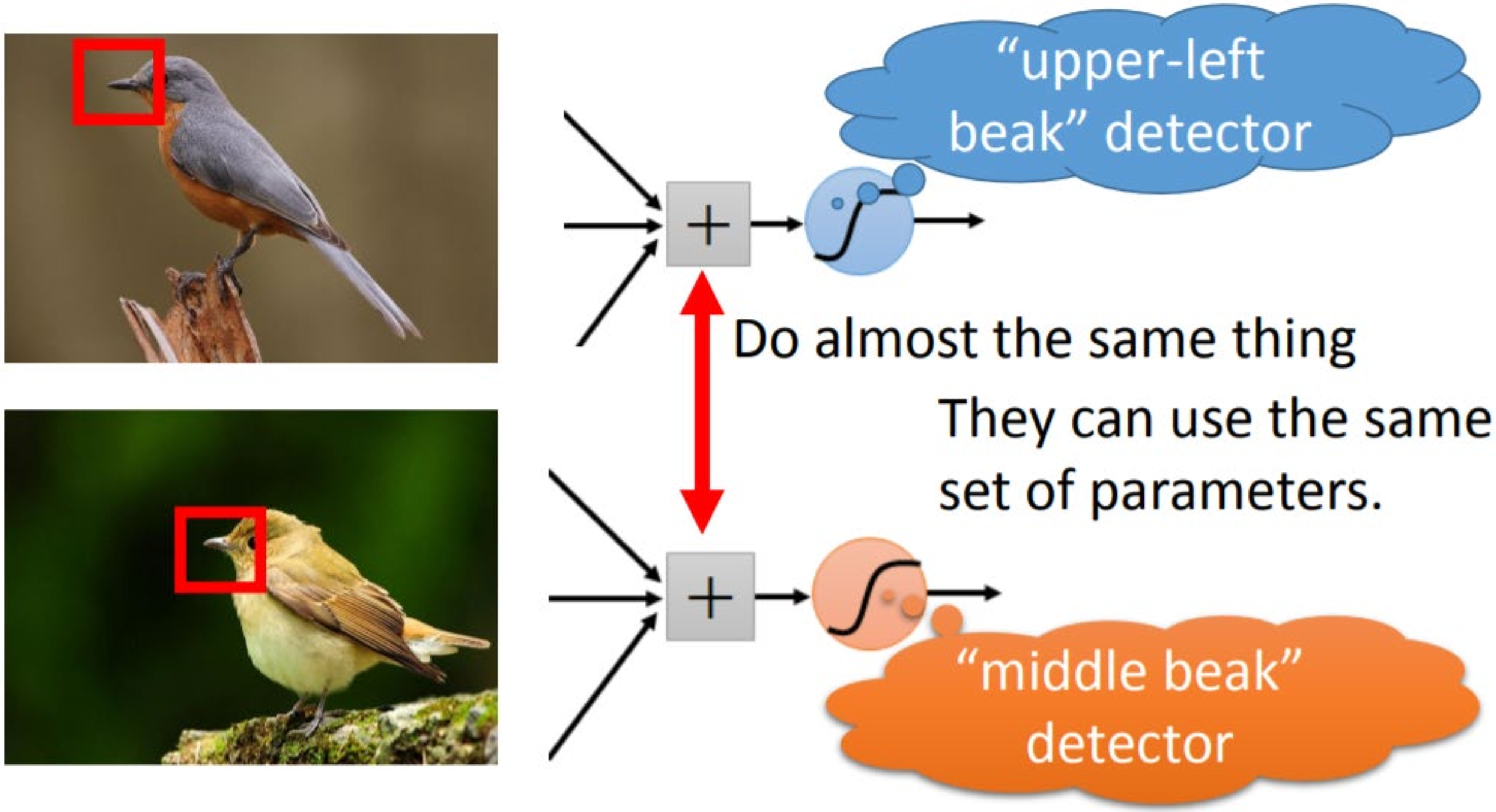
Connecting to small region with less parameters



"beak" detector

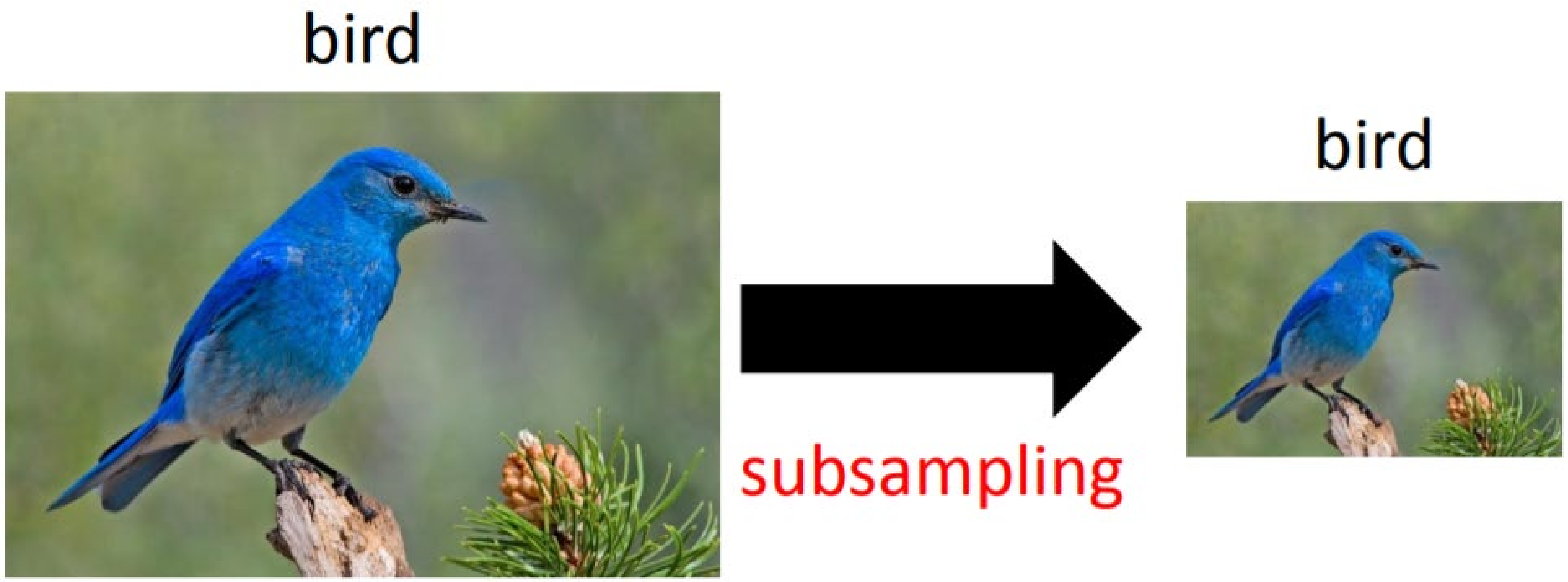
Reference: 李弘毅 ML Lecture 10 https://youtu.be/FrKWiRv254g

The same patterns appear in different regions



Reference: 李弘毅 ML Lecture 10 https://youtu.be/FrKWiRv254g

Subsampling the pixels will not change the object

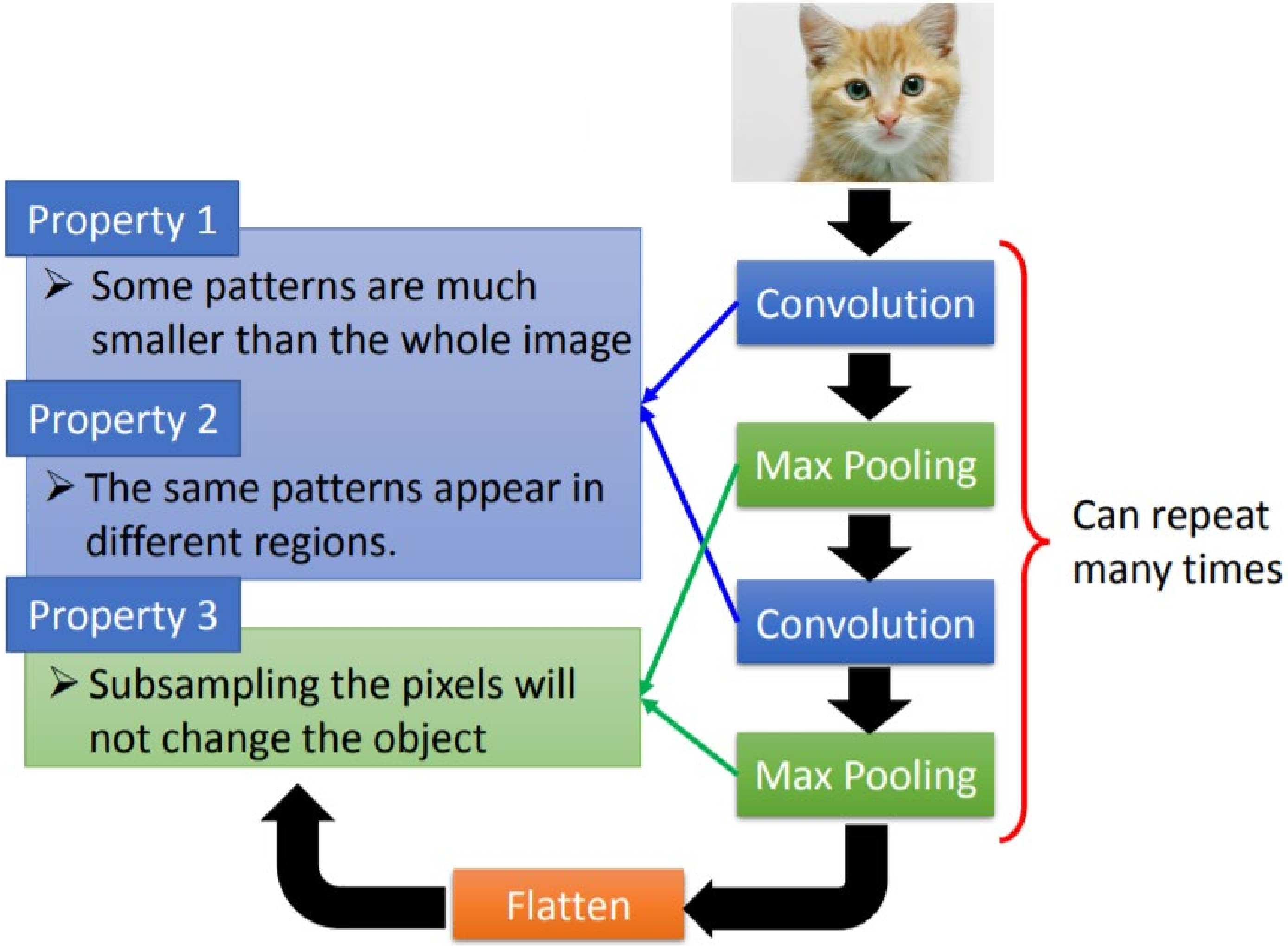


We can subsample the pixels to make image smaller

→ Less parameters for the network to process the image

Reference: 李弘毅 ML Lecture 10 https://youtu.be/FrKWiRv254g

Use convolution and pooling operations to extract important features from input image



Reference: 李弘毅 ML Lecture 10 https://youtu.be/FrKWiRv254g

Use CV to read image file

In [6]:
```
import cv2
import matplotlib.pyplot as plt
image = cv2.imread(fname)
image = cv2.cvtColor(image,cv2.COLOR_BGR2RGB)
plt.imshow(image)
plt.show()
```

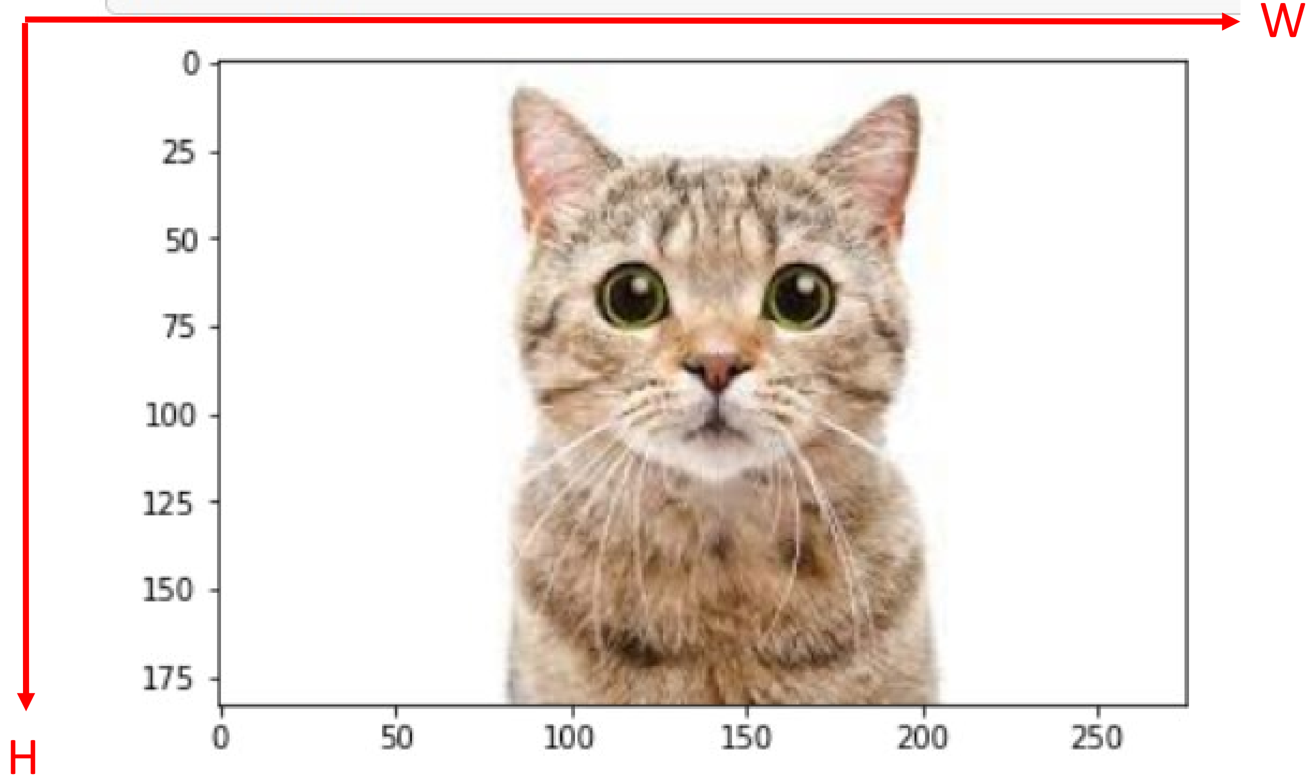


Image pre-processing

- Image width and height – resize, center crop
- Pixel values – Standardized to [0, 1], normalized to N(0, 1)

```
In [7]: from torchvision import transforms
        transformer = transforms.Compose([
             transforms.Resize(224),
             transforms.CenterCrop(224),
             transforms.ToTensor(),
             transforms.Normalize(mean=[0.5, 0.5, 0.5], std=[0.5, 0.5, 0.5] )])
```

```
In [8]: from PIL import Image
        PILImg= Image.fromarray(image.astype('uint8')).convert('RGB')
        PILImg = transformer(PILImg)
        PILImg.shape

Out[8]: torch.Size([3, 224, 224])
```

Prepare input format

Input to CNN

```
In [9]:  imageTensor = torch.unsqueeze(PILImg, 0)
         imageTensor.shape

Out[9]:  torch.Size([1, 3, 224, 224])
```

Input to MLP

```
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])
```

1st convolution

```
AlexNet(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(11, 11), stride=(4, 4), paddi
    (1): ReLU(inplace=True)
    (2): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1
    (3): Conv2d(64, 192, kernel_size=(5, 5), stride=(1, 1), paddi
    (4): ReLU(inplace=True)
    (5): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1
    (6): Conv2d(192, 384, kernel_size=(3, 3), stride=(1, 1), padd
    (7): ReLU(inplace=True)
    (8): Conv2d(384, 256, kernel_size=(3, 3), stride=(1, 1), padd
    (9): ReLU(inplace=True)
    (10): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), pad
    (11): ReLU(inplace=True)
    (12): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=
  )
```

In [10]:
```
conv1 = model.features[0]
print(conv1)
#InChannel=3(RGB),OutChannel=64, filter size=11, stride=4, padding=2
```

```
Conv2d(3, 64, kernel_size=(11, 11), stride=(4, 4), padding=(2, 2))
```

Filter searches patterns in a small region

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

Those are the network parameters to be learned.

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

Matrix

-1	1	-1
-1	1	-1
-1	1	-1

Filter 2

Matrix

⋮

Property 1

Each filter detects a small pattern (3 x 3).

Property 1

- Some patterns are much smaller than the whole image

A neuron does not have to see the whole image to discover the pattern.

Connecting to small region with less parameters

Filter searches a particular pattern in different regions

Use Excel to verify!

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

stride=1

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

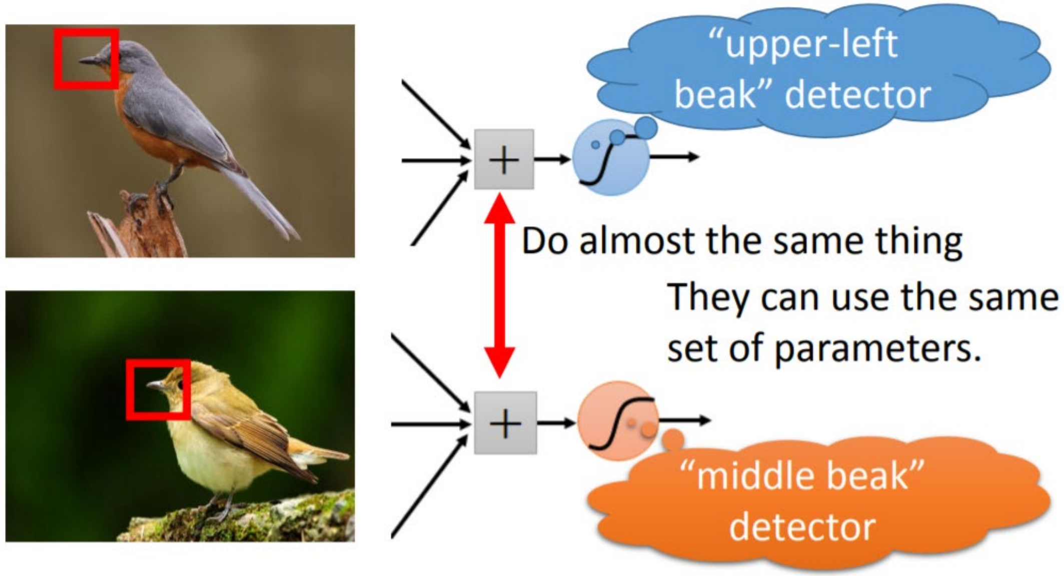
6 x 6 image

3	-1	-3	-1
-3	1	0	-3
-3	-3	0	1
3	-2	-2	-1

Property 2

Property 2

- The same patterns appear in different regions.



Stride determines how filter shifts

1	-1	-1
-1	1	-1
-1	-1	1

stride=1

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

3 -1

1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

If stride=2

1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

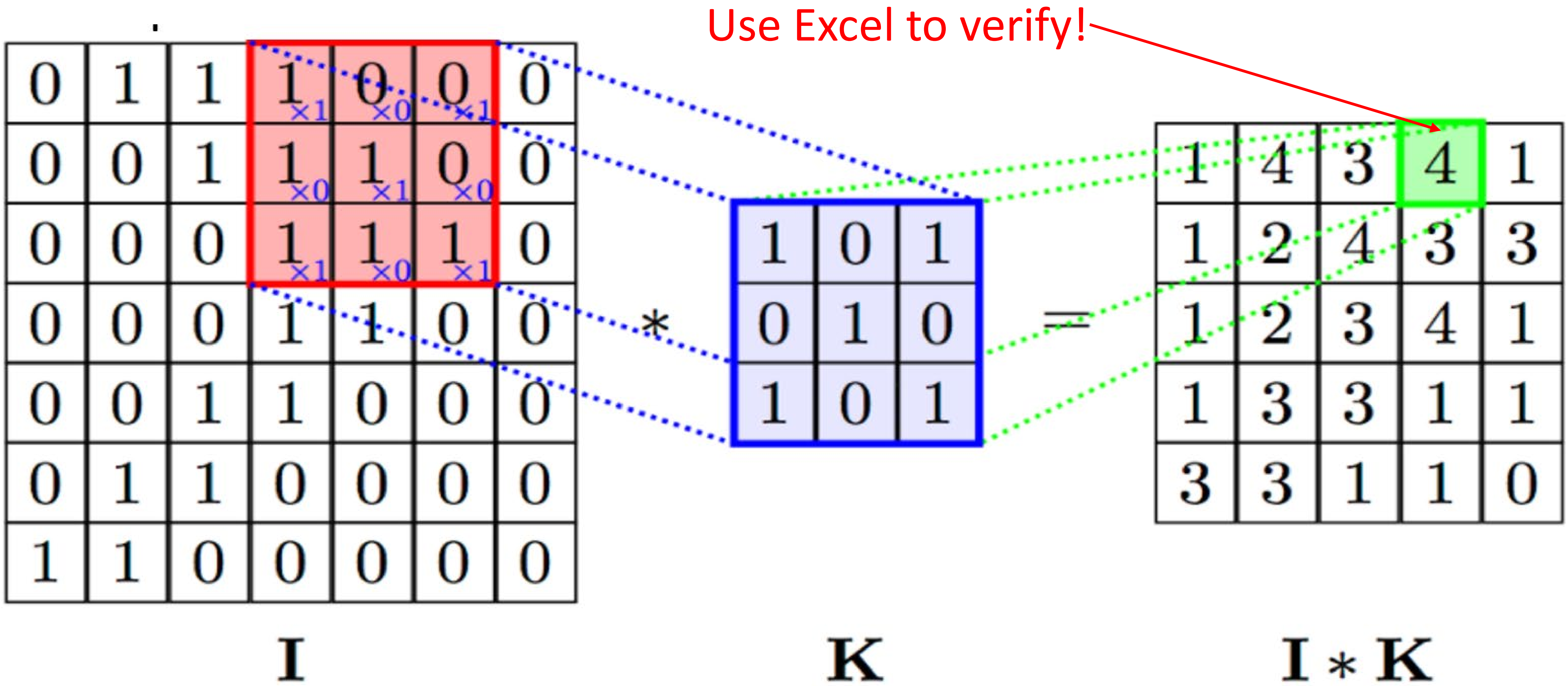
3 -3

We set stride=1 below

Use Excel to verify!

Reference: 李弘毅 ML Lecture 10 https://youtu.be/FrKWiRv254g

Filter searches a particular pattern in different regions



*Visualization of a convolution operation. I is the input to the network, k represents the vector and i*k represents the matrix multiplication resulting of sliding the kernel through the input. Reference (Veličković, 2016)*

Filter searches a particular pattern in different regions

INPUT

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

FILTER

1	0	1
0	1	0
1	0	1

CONVOLVED FEATURE

4		

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

1	0	1
0	1	0
1	0	1

4		
2		

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

1	0	1
0	1	0
1	0	1

4	3	
2		

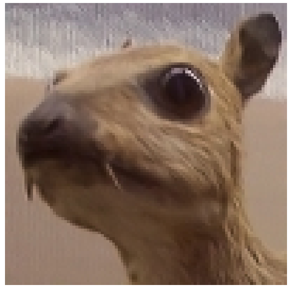
Use Excel to verify!

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

1	0	1
0	1	0
1	0	1

4	3	4
2	4	3
2	3	4

Input image



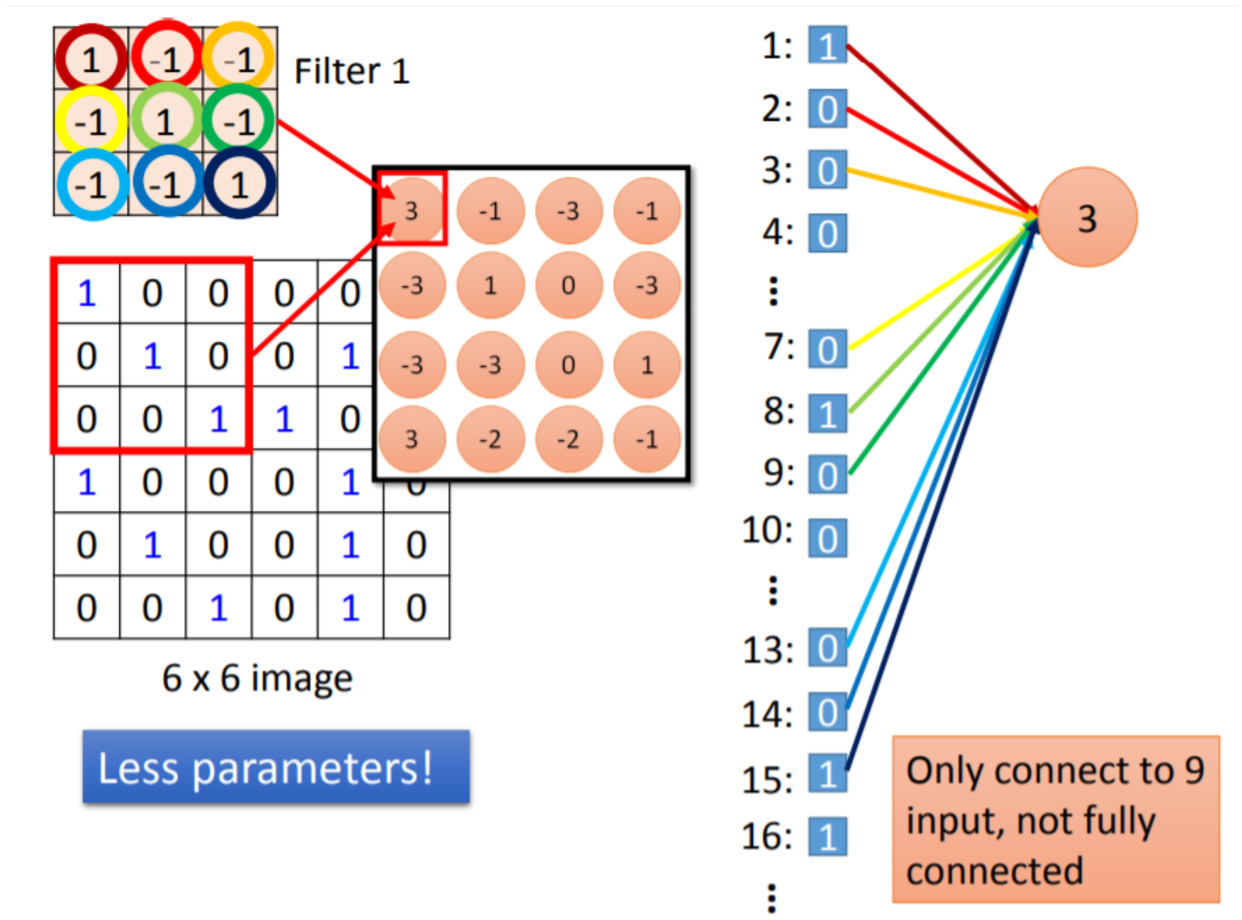
Convolution Kernel

$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

Feature map

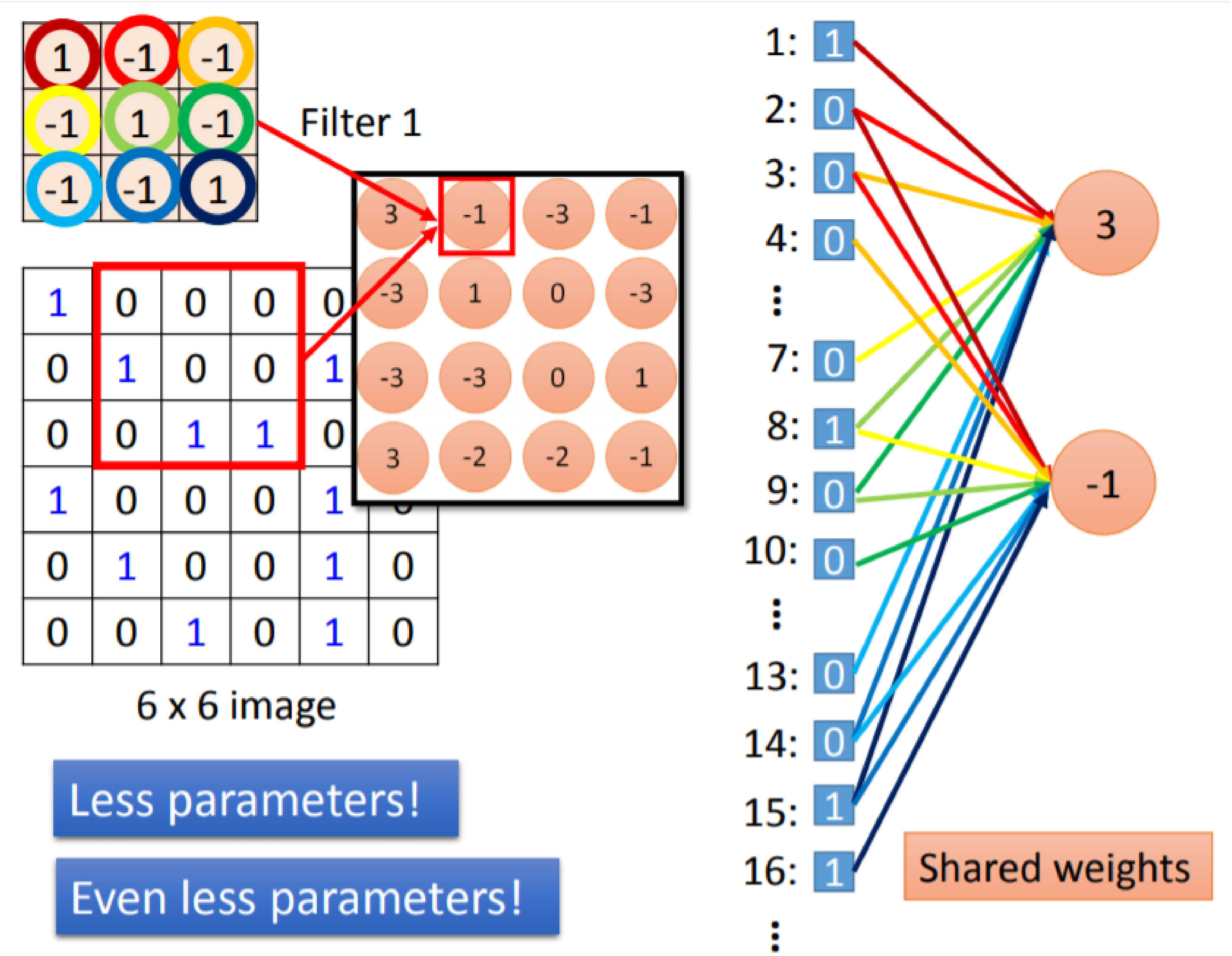
圖來源: https://developer.nvidia.com/discover/convolution

Convolution can be represented as partially connected NN, which has less parameters and is less complicated than the fully connected NN.



Reference: 李弘毅 ML Lecture 10 https://youtu.be/FrKWiRv254g

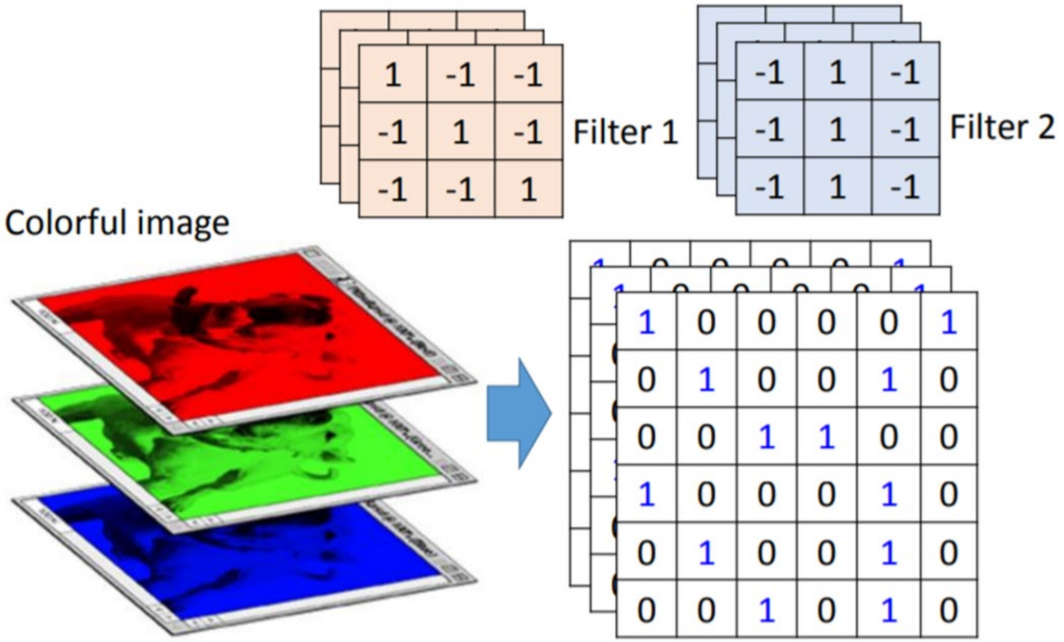
Partially connected NN with shared weights and hence with even less parameters.



Reference: 李弘毅 ML Lecture 10 https://youtu.be/FrKWiRv254g

Filter has depth

If input image has 3 channels, then each convolution filter also has 3 channels




```
[10] conv1 = model.features[0]
     print(conv1)
     #InChannel=3(RGB),OutChannel=64, filter size=11,

     Conv2d(3, 64, kernel_size=(11, 11), stride=(4, 4),
```

```
[11] weight1 = conv1.weight.data.cpu().numpy()
     print(weight1.shape)
     #64 filters, depth=3, size =11 by 11

     (64, 3, 11, 11)
```

Reference: 李弘毅 ML Lecture 10 https://youtu.be/FrKWiRv254g

Take a look at the learned filter weights of 1st convolution

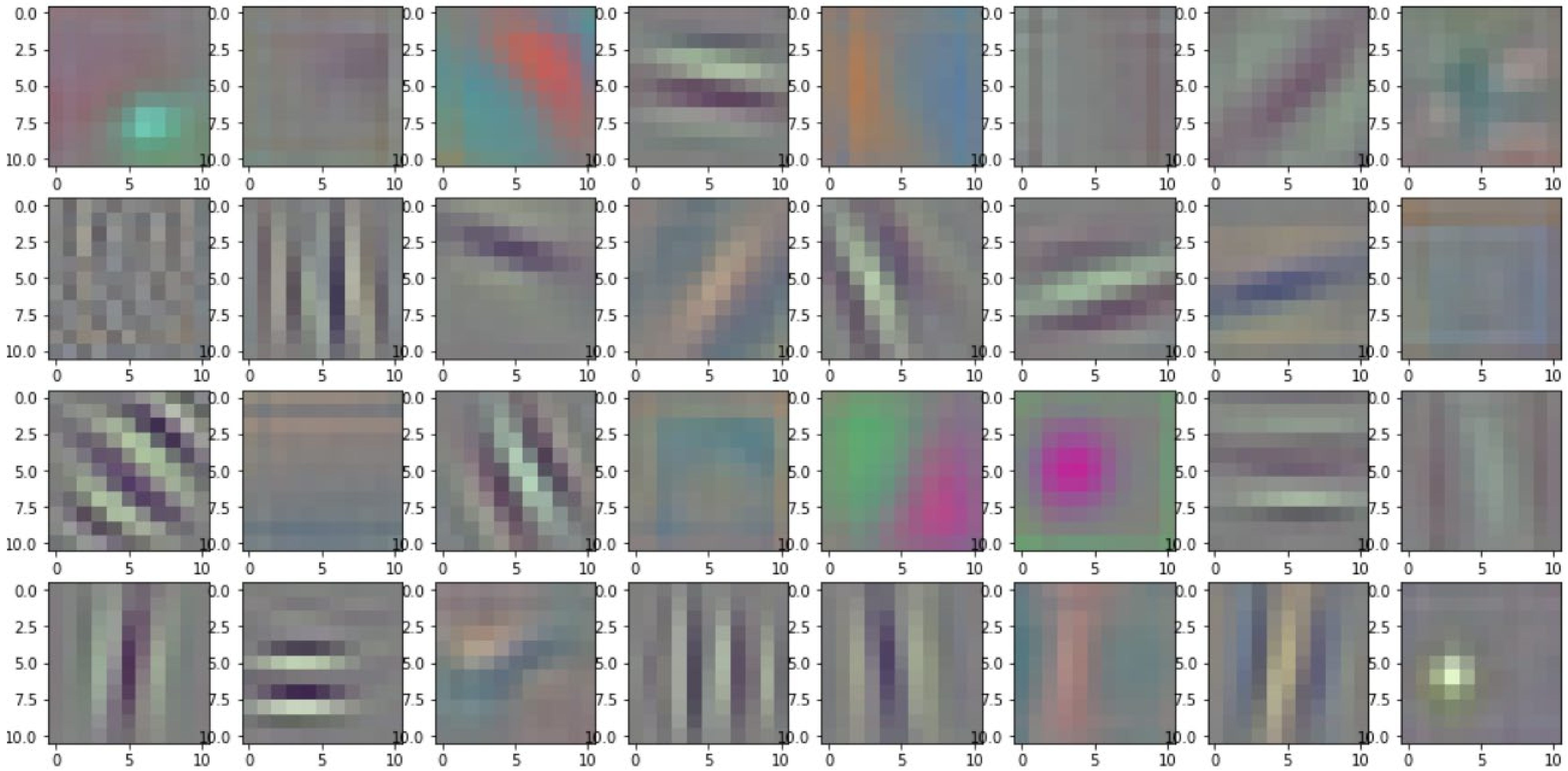
```
[11] weight1 = conv1.weight.data.cpu().numpy()
     print(weight1.shape)
     #64 filters, depth=3, size =11 by 11
```

```
(64, 3, 11, 11)
```

Visualize filters in the 1st convolution layer

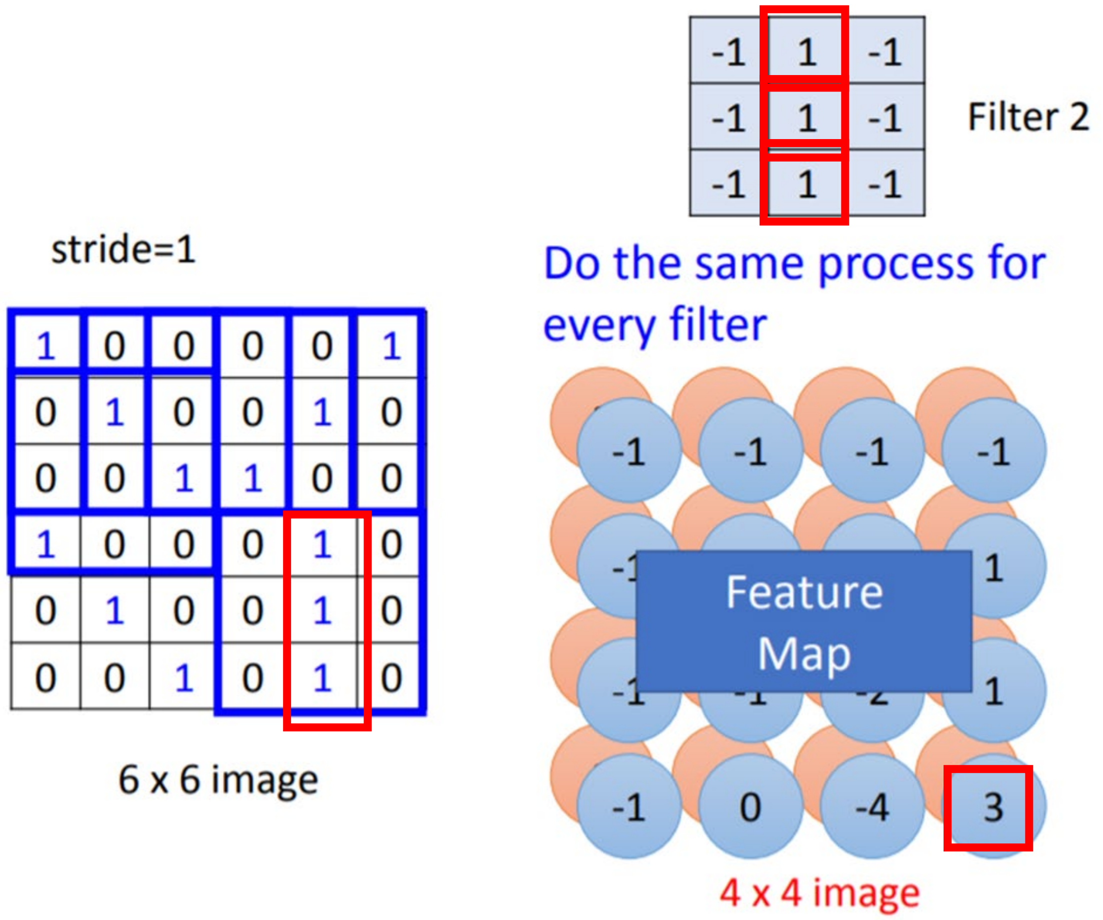
```
[13] # Visualize the first 32 of the filter weights
     import numpy as np
     fig=plt.figure(figsize=(18, 9))
     for i in range(32):
         fig.add_subplot(4, 8, i+1)
         w = weight1[i]
         ImgArray = np.zeros((w.shape[1], w.shape[2], 3))
         ImgArray[:,:,0] = w[0, :, :]
         ImgArray[:,:,1] = w[1, :, :]
         ImgArray[:,:,2] = w[2, :, :]
         ImgArray = ImgArray*0.5+0.5  # convert[-1, 1] to [0, 1]
         plt.imshow(ImgArray)
     plt.show()
```

The learned filter's weights



Feature maps

Each filter searches a small region and summarizes how the specified pattern appears in different regions in a feature map




```
In [10]: conv1 = model.features[0]
         print(conv1)
         #InChannel=3(RGB),OutChannel=64, filter size

         Conv2d(3, 64, kernel_size=(11, 11), stride=(

In [11]: weight1 = conv1.weight.data.cpu().numpy()
         print(weight1.shape)
         #64 filters, depth=3, size =11 by 11

         (64, 3, 11, 11)

In [12]: conv1_out = conv1(imageTensor.to(device))
         conv1_out.shape
         #output image (feature map) has 64 channels

Out[12]: torch.Size([1, 64, 55, 55])
```

Reference: 李弘毅 ML Lecture 10 https://youtu.be/FrKWiRv254g

Feature map's width and height

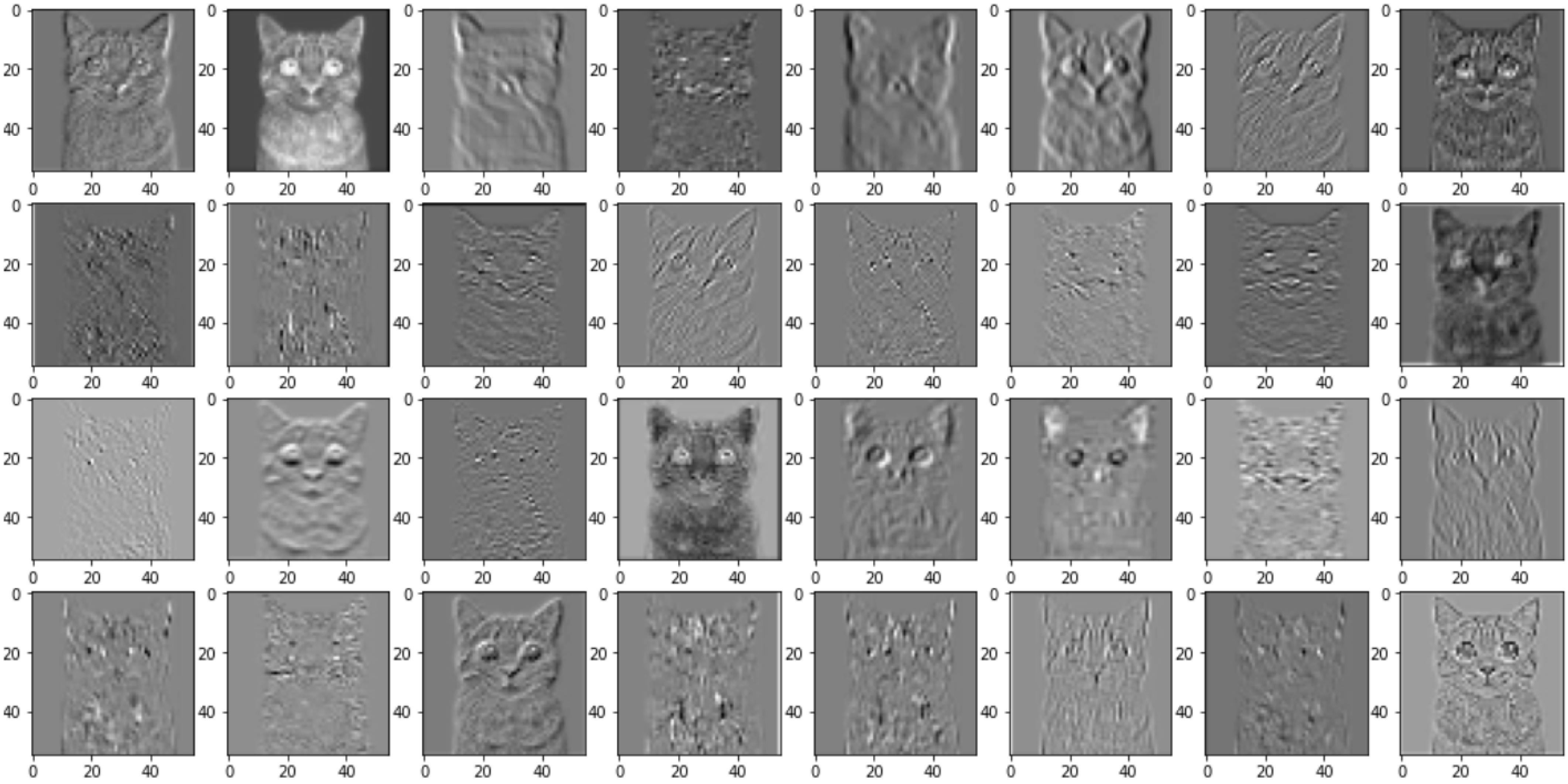
```
In [12]: conv1_out = conv1(imageTensor.to(device))
         conv1_out.shape
         #output image (feature map) has 64 channels

Out[12]: torch.Size([1, 64, 55, 55])
```

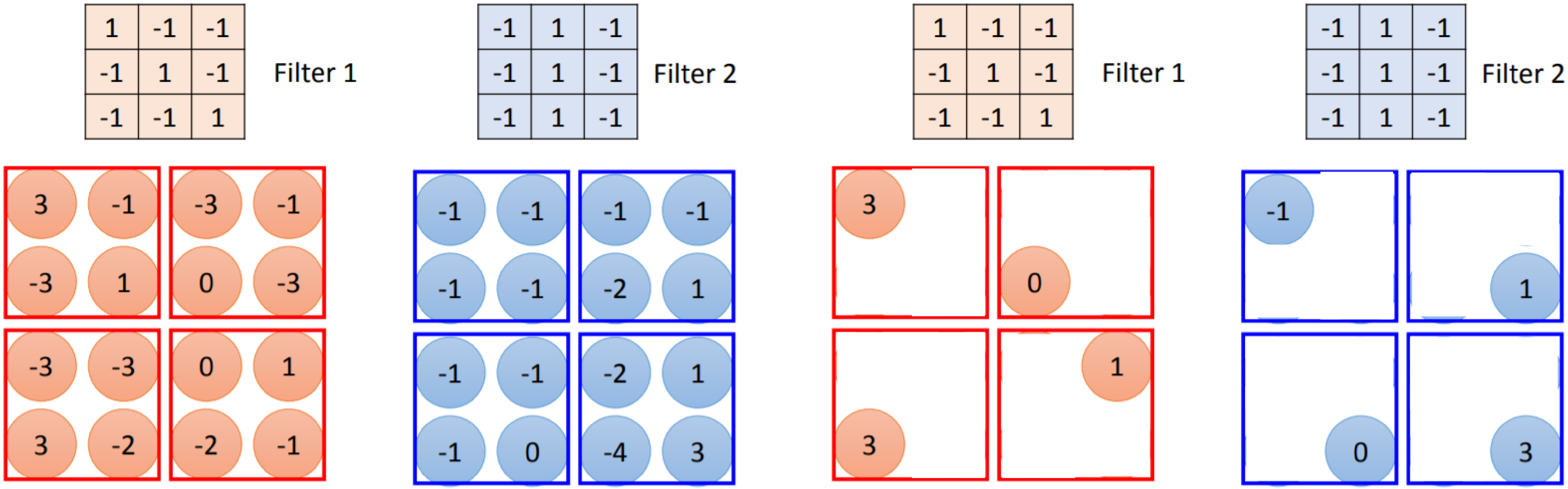
$$\frac{224 + 2 \times 2 - 11}{4} + 1 = 55.25$$

$$H_{out} = \frac{H_{in} + 2 \times padding - kernel\ size}{Stride} + 1$$

First 32 channels of the output feature map, shape = 55x55x64

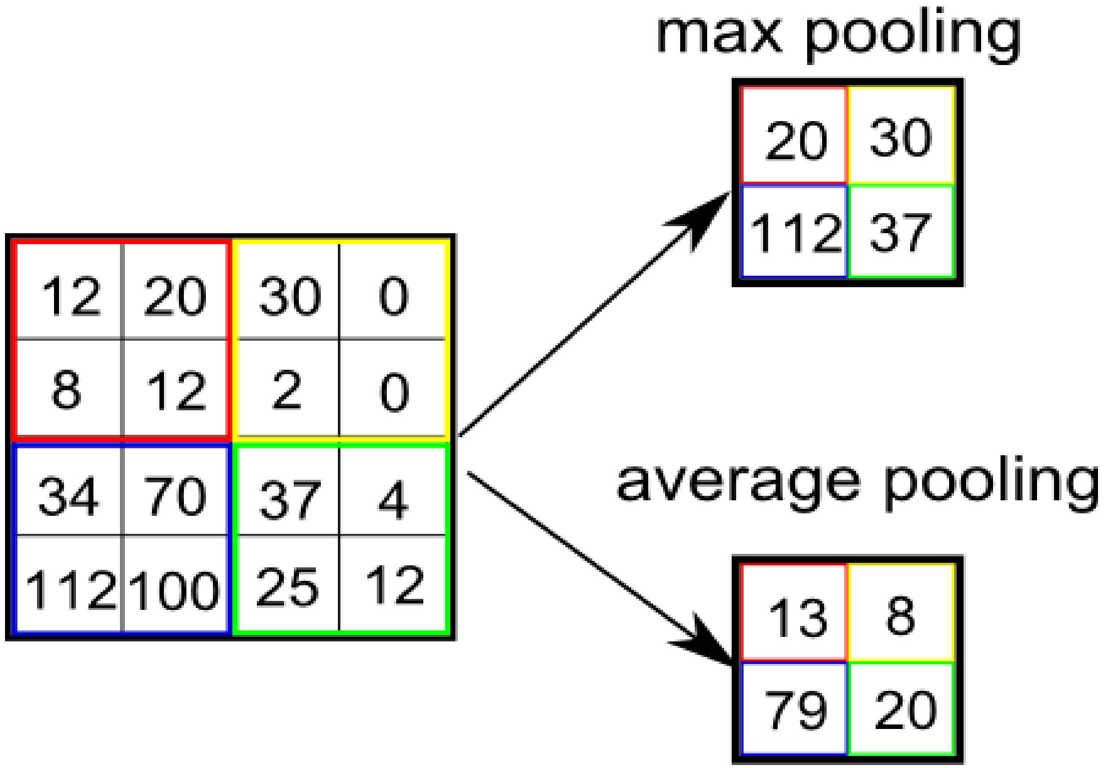


Max pooling

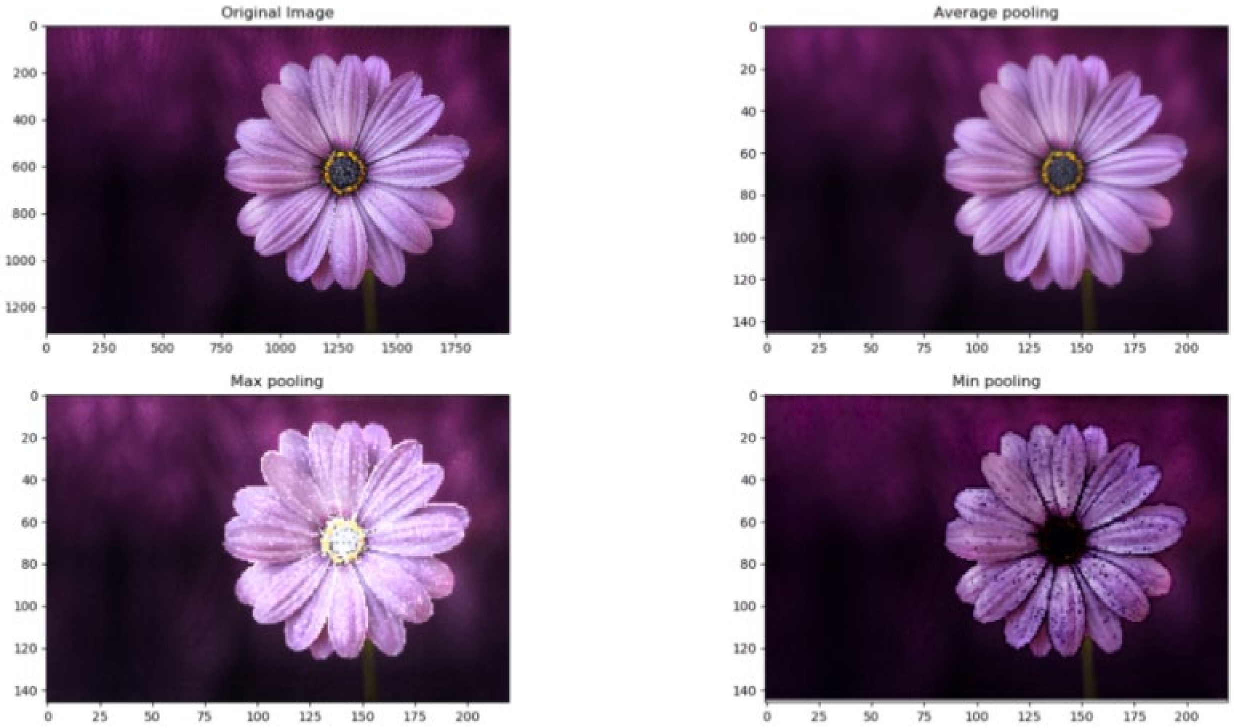


Reference: 李弘毅 ML Lecture 10 https://youtu.be/FrKWiRv254g

Max pooling



(Singhal, 2017)



圖來源: https://medium.com/@bdhuma/which-pooling-method-is-better-maxpooling-vs-minpooling-vs-average-pooling-95fb03f45a9

Apply max pooling to the feature map from 1st convolution

features[1, 2]

```
[14]: conv1_pooling = model.features[1:3]
conv1_out1 = conv1_pooling(conv1_out)
print(conv1_out1.shape)
imgArray=conv1_out1[0].data.cpu().numpy()
fig=plt.figure(figsize=(18, 9))
for i in range(32): #visualize the first 32 channe
  fig.add_subplot(4, 8, i+1)
  plt.imshow(imgArray[i], cmap='gray')
plt.show()
```

```
torch.Size([1, 64, 27, 27])
```

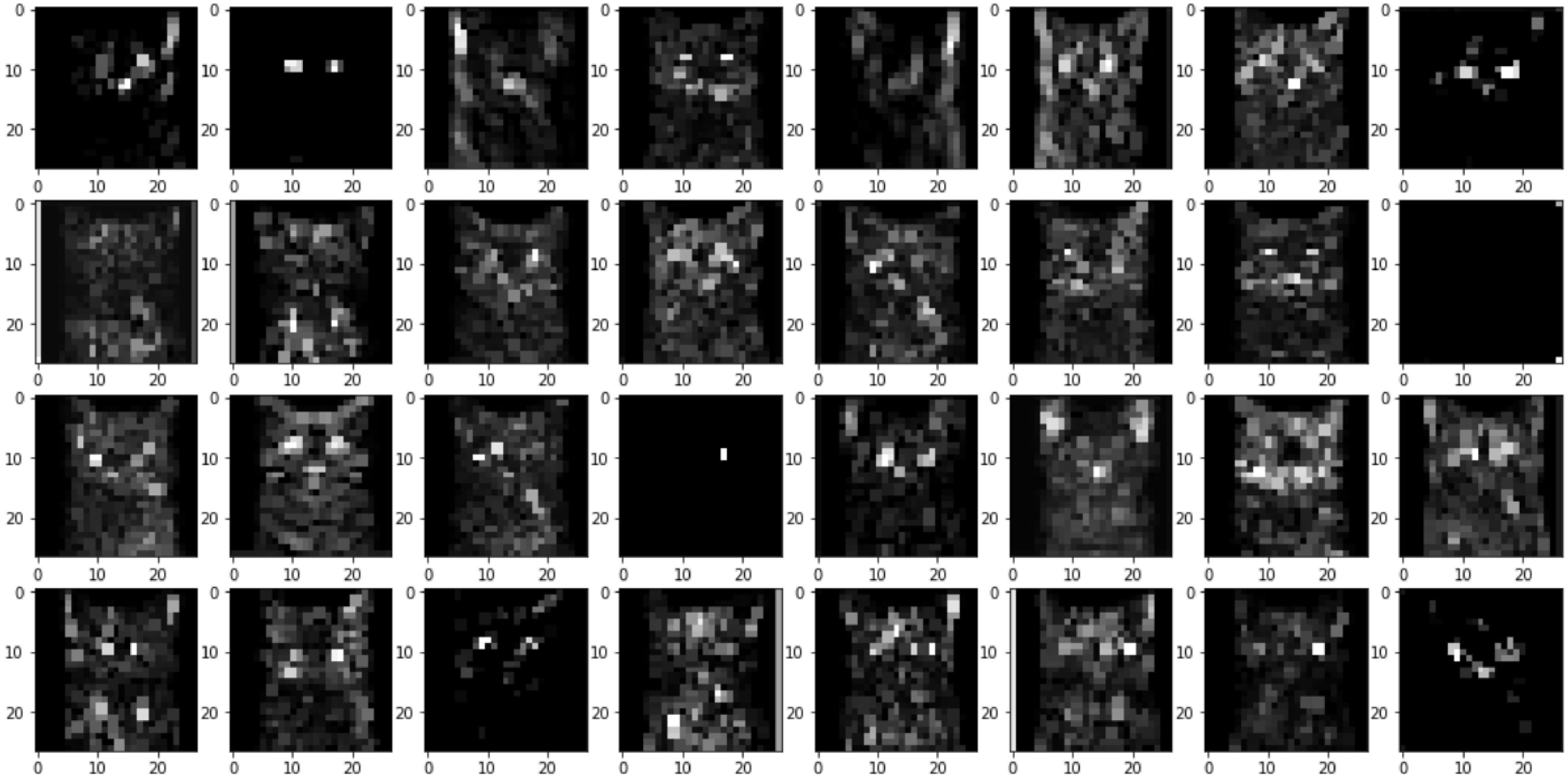
$$\frac{55+2\times 2-3}{2}+1=27$$

$$H_{out}=\frac{H_{in}+2\times padding-kernel\ size}{Stride}+1$$

```
AlexNet(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(11, 11), stride=(4, 4), padd
    (1): ReLU(inplace=True)
    (2): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=
    (3): Conv2d(64, 192, kernel_size=(5, 5), stride=(1, 1), padd
    (4): ReLU(inplace=True)
    (5): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=
    (6): Conv2d(192, 384, kernel_size=(3, 3), stride=(1, 1), pad
    (7): ReLU(inplace=True)
    (8): Conv2d(384, 256, kernel_size=(3, 3), stride=(1, 1), pad
    (9): ReLU(inplace=True)
    (10): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), pa
    (11): ReLU(inplace=True)
    (12): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation
  )
```

PYTORCH

First 32 channels of the output feature map from max pooling, shape = 27x27x64



2^{nd} convolution

192 filters, each has 64 channels, are applied to the input feature map (with 64 channels)

```
[15]: conv2 = model.features[3]
      conv2_out = conv2(conv1_out1)
      print(conv2_out.shape)
      imgArray=conv2_out[0].data.cpu().numpy()
      fig=plt.figure(figsize=(18, 9))
      for i in range(32): #visualize the first 32 channels
        fig.add_subplot(4, 8, i+1)
        plt.imshow(imgArray[i], cmap='gray')
      plt.show()

      torch.Size([1, 192, 27, 27])
```

```
AlexNet(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(11, 11), stride=(4, 4), padd
    (1): ReLU(inplace=True)
    (2): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=
    (3): Conv2d(64, 192, kernel_size=(5, 5), stride=(1, 1), padd
    (4): ReLU(inplace=True)
    (5): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=
    (6): Conv2d(192, 384, kernel_size=(3, 3), stride=(1, 1), pad
    (7): ReLU(inplace=True)
    (8): Conv2d(384, 256, kernel_size=(3, 3), stride=(1, 1), pad
    (9): ReLU(inplace=True)
    (10): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), pa
    (11): ReLU(inplace=True)
    (12): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation
  )
```

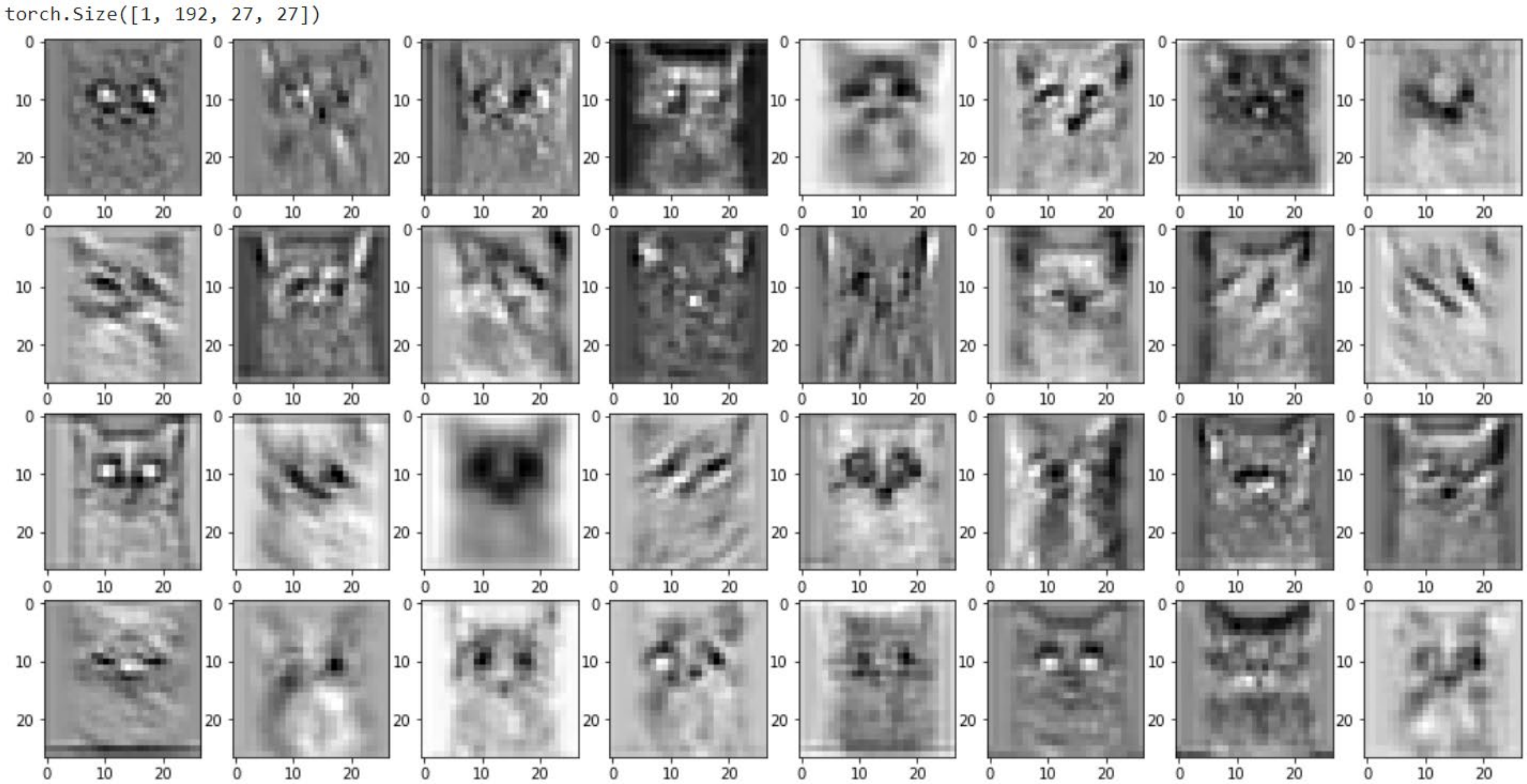
After convolution, the output feature map has 192 channels

$$\frac{27 + 2 \times 2 - 5}{1} + 1 = 27$$

$$H_{out} = \frac{H_{in} + 2 \times padding - kernel\ size}{Stride} + 1$$

PYTORCH

Feature map after 2nd convolution



Apply max pooling to the feature map from 2nd convolution

features[4, 5]

```
[16]: conv2_pooling = model.features[4:6]
conv2_out1 = conv2_pooling(conv2_out)
print(conv2_out1.shape)
imgArray=conv2_out1[0].data.cpu().numpy()
fig=plt.figure(figsize=(18, 9))
for i in range(32): #visualize the first 32 channels
  fig.add_subplot(4, 8, i+1)
  plt.imshow(imgArray[i], cmap='gray')
plt.show()
```

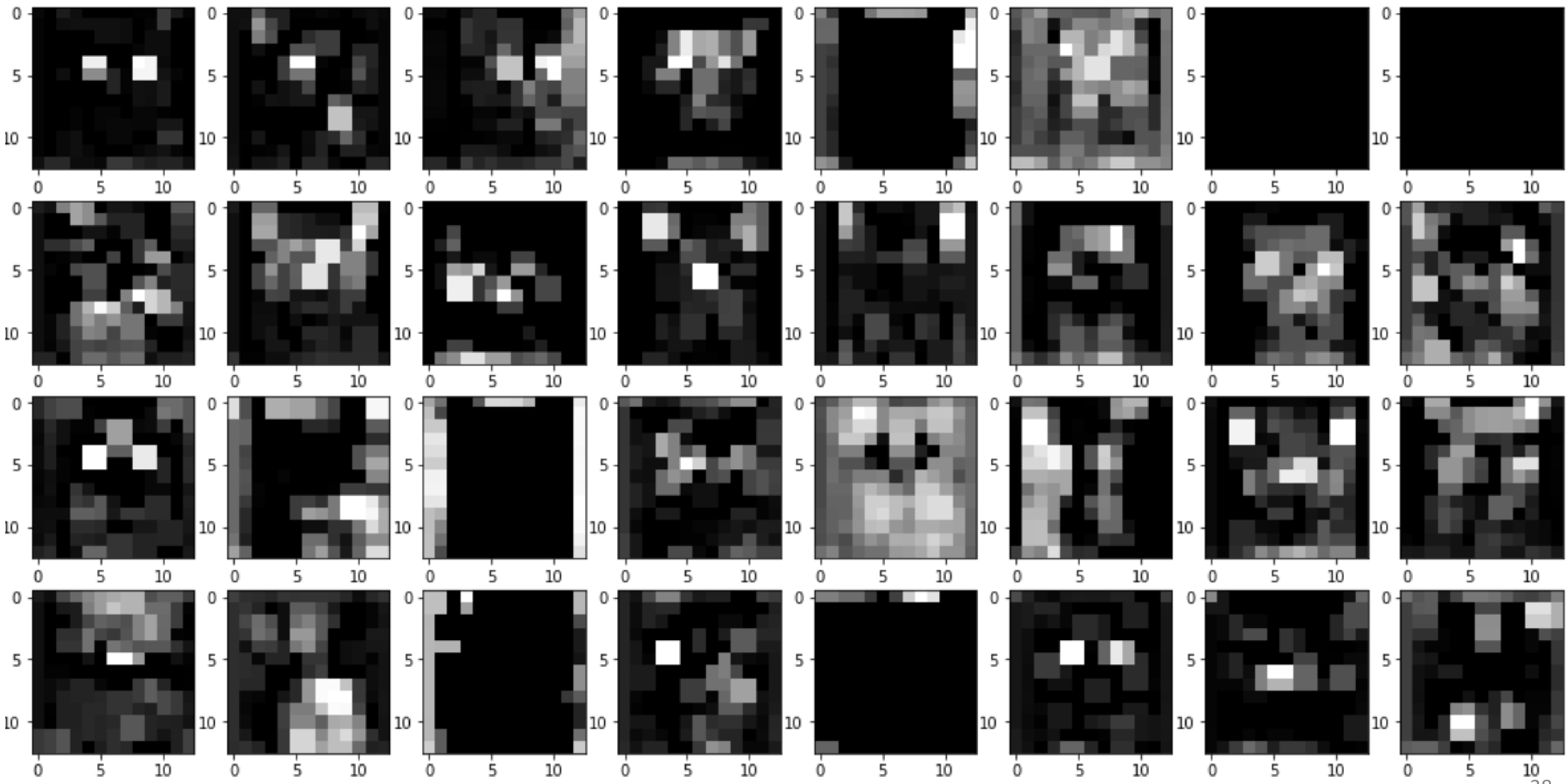
```
torch.Size([1, 192, 13, 13])
```

$$\frac{27 + 2 \times 0 - 3}{2} + 1 = 13$$

$$H_{out} = \frac{H_{in} + 2 \times padding - kernel\ size}{Stride} + 1$$

```
AlexNet(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(11, 11), stride=(4, 4), padd
    (1): ReLU(inplace=True)
    (2): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=
    (3): Conv2d(64, 192, kernel_size=(5, 5), stride=(1, 1), padd
    (4): ReLU(inplace=True)
    (5): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=
    (6): Conv2d(192, 384, kernel_size=(3, 3), stride=(1, 1), pad
    (7): ReLU(inplace=True)
    (8): Conv2d(384, 256, kernel_size=(3, 3), stride=(1, 1), pad
    (9): ReLU(inplace=True)
    (10): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), pa
    (11): ReLU(inplace=True)
    (12): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation
  )
```

Feature map after 2nd convolution and max pooling



3rd convolution

394 filters, each has 192 channels, are applied to the input feature map (with 192 channels)

[17]:
```
conv3 = model.features[6]
conv3_out = conv3(conv2_out1)
print(conv3_out.shape)
imgArray=conv3_out[0].data.cpu().numpy()
fig=plt.figure(figsize=(18, 9))
for i in range(32): #visualize the first 32 channels
  fig.add_subplot(4, 8, i+1)
  plt.imshow(imgArray[i], cmap='gray')
plt.show()
```

```
torch.Size([1, 384, 13, 13])
```

After convolution, the output feature map has 394 channels

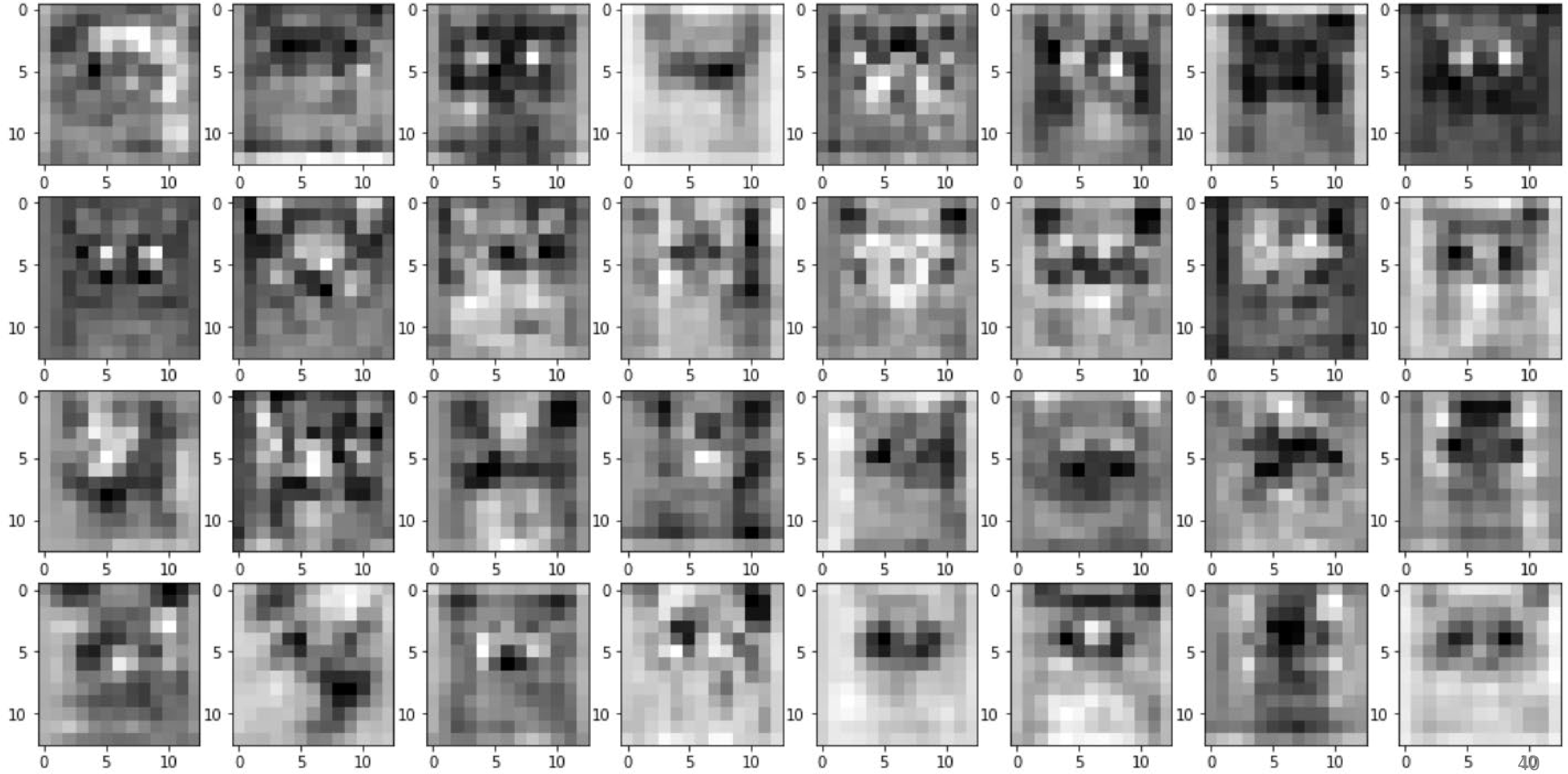
$$\frac{13 + 2 \times 1 - 3}{1} + 1 = 13$$

$$H_{out} = \frac{H_{in} + 2 \times padding - kernel\ size}{Stride} + 1$$

```
AlexNet(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(11, 11), stride=(4, 4), padd
    (1): ReLU(inplace=True)
    (2): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=
    (3): Conv2d(64, 192, kernel_size=(5, 5), stride=(1, 1), padd
    (4): ReLU(inplace=True)
    (5): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=
    (6): Conv2d(192, 384, kernel_size=(3, 3), stride=(1, 1), pad
    (7): ReLU(inplace=True)
    (8): Conv2d(384, 256, kernel_size=(3, 3), stride=(1, 1), pad
    (9): ReLU(inplace=True)
    (10): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), pa
    (11): ReLU(inplace=True)
    (12): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation
  )
```

Feature map after 3^{rd} convolution

```
torch.Size([1, 384, 13, 13])
```



Apply max pooling to feature map from 3rd convolution

features[7, 8]

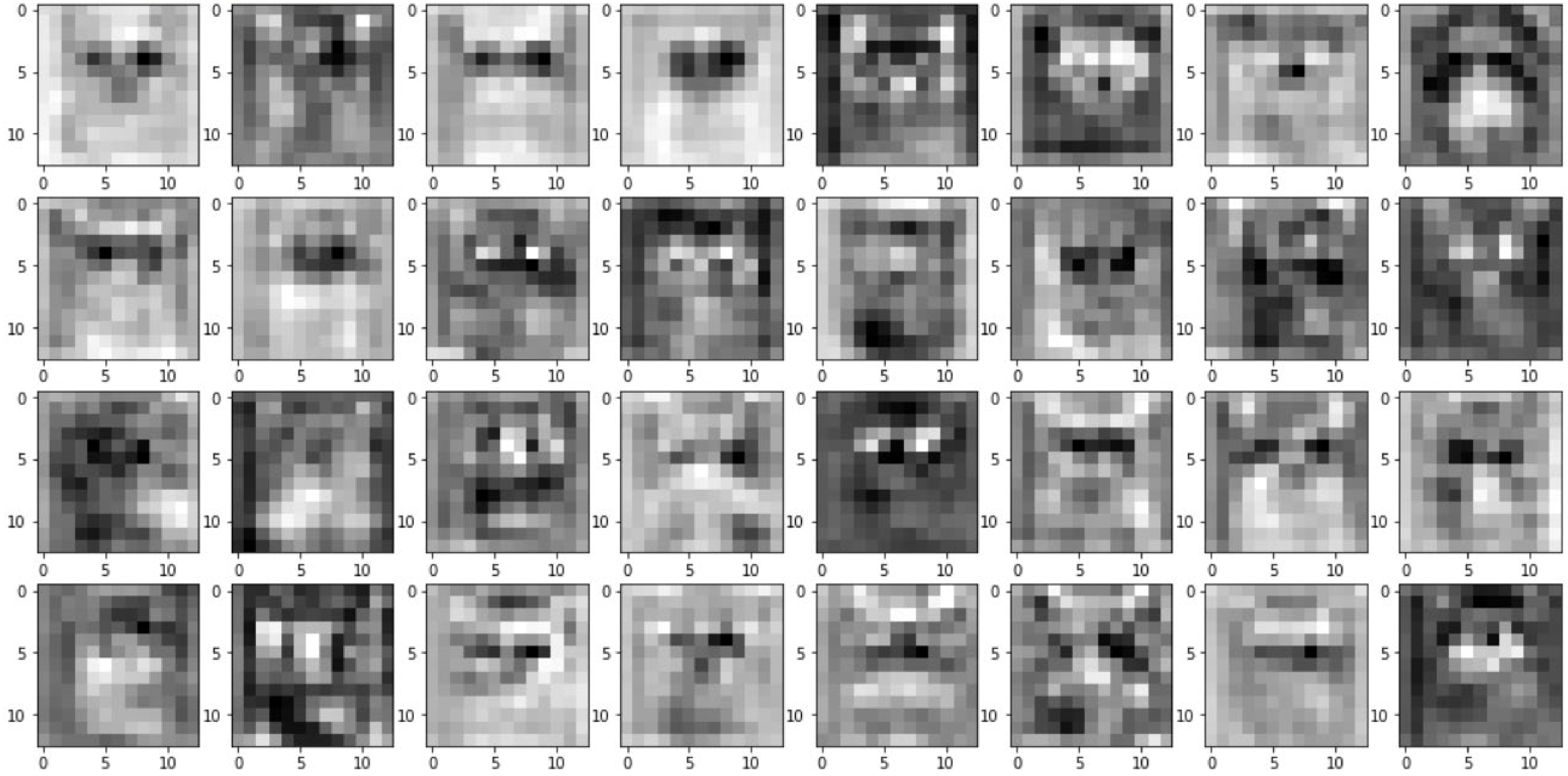
```
[18]: conv3_pooling = model.features[7:9]
      conv3_out1 = conv3_pooling(conv3_out)
      print(conv3_out1.shape)
      imgArray=conv3_out1[0].data.cpu().numpy()
      fig=plt.figure(figsize=(18, 9))
      for i in range(32): #visualize the first 32 channels
        fig.add_subplot(4, 8, i+1)
        plt.imshow(imgArray[i], cmap='gray')
      plt.show()

      torch.Size([1, 256, 13, 13])
```

```
AlexNet(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(11, 11), stride=(4, 4), padd
    (1): ReLU(inplace=True)
    (2): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=
    (3): Conv2d(64, 192, kernel_size=(5, 5), stride=(1, 1), padd
    (4): ReLU(inplace=True)
    (5): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=
    (6): Conv2d(192, 384, kernel_size=(3, 3), stride=(1, 1), pad
    (7): ReLU(inplace=True)
    (8): Conv2d(384, 256, kernel_size=(3, 3), stride=(1, 1), pad
    (9): ReLU(inplace=True)
    (10): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), pa
    (11): ReLU(inplace=True)
    (12): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation
  )
```

Feature map after 3rd convolution and max pooling

```
torch.Size([1, 256, 13, 13])
```



Flatten

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

      AvgPoolLayer = model.avgpool
      out2 = AvgPoolLayer(out1)
      print(out2.shape)
```

```
torch.Size([1, 256, 6, 6])
torch.Size([1, 256, 6, 6])
```

After last convolution and max pooling, the output feature map has 256 channels

$$256 \times 6 \times 6 = 9216$$

```
(features): Sequential(
  (0): Conv2d(3, 64, kernel_size=(11, 11), stride=(4, 4), padding=(2, 2))
  (1): ReLU(inplace=True)
  (2): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1, ceil_mode=False)
  (3): Conv2d(64, 192, kernel_size=(5, 5), stride=(1, 1), padding=(2, 2))
  (4): ReLU(inplace=True)
  (5): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1, ceil_mode=False)
  (6): Conv2d(192, 384, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (7): ReLU(inplace=True)
  (8): Conv2d(384, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (9): ReLU(inplace=True)
  (10): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (11): ReLU(inplace=True)
  (12): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1, ceil_mode=False)
)
(avgpool): AdaptiveAvgPool2d(output_size=(6, 6))
(classifier): Sequential(
  (0): Dropout(p=0.5, inplace=False)
  (1): Linear(in_features=9216, out_features=4096, bias=True)
  (2): ReLU(inplace=True)
  (3): Dropout(p=0.5, inplace=False)
  (4): Linear(in_features=4096, out_features=4096, bias=True)
  (5): ReLU(inplace=True)
  (6): Linear(in_features=4096, out_features=1000, bias=True)
)
```

Practice: Draw the structure of AlexNet

```
(features): Sequential(
  (0): Conv2d(3, 64, kernel_size=(11, 11), stride=(4, 4), padding=(2, 2))
  (1): ReLU(inplace=True)
  (2): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1, ceil_mode=False)
  (3): Conv2d(64, 192, kernel_size=(5, 5), stride=(1, 1), padding=(2, 2))
  (4): ReLU(inplace=True)
  (5): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1, ceil_mode=False)
  (6): Conv2d(192, 384, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (7): ReLU(inplace=True)
  (8): Conv2d(384, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (9): ReLU(inplace=True)
  (10): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (11): ReLU(inplace=True)
  (12): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1, ceil_mode=False)
)
(avgpool): AdaptiveAvgPool2d(output_size=(6, 6))
(classifier): Sequential(
  (0): Dropout(p=0.5, inplace=False)
  (1): Linear(in_features=9216, out_features=4096, bias=True)
  (2): ReLU(inplace=True)
  (3): Dropout(p=0.5, inplace=False)
  (4): Linear(in_features=4096, out_features=4096, bias=True)
  (5): ReLU(inplace=True)
  (6): Linear(in_features=4096, out_features=1000, bias=True)
)
```