Practice – CNN

- Run “7.1. CNN.ipynb"

Load pre-trained image classification models

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

```
Downloading: "https://download.pytorch.org/models/alexnet-owt-4df8aa71.pth" to /root/.cache/torch/hub/checkpoints/alexnet-owt-4df8aa71.pt
h
```

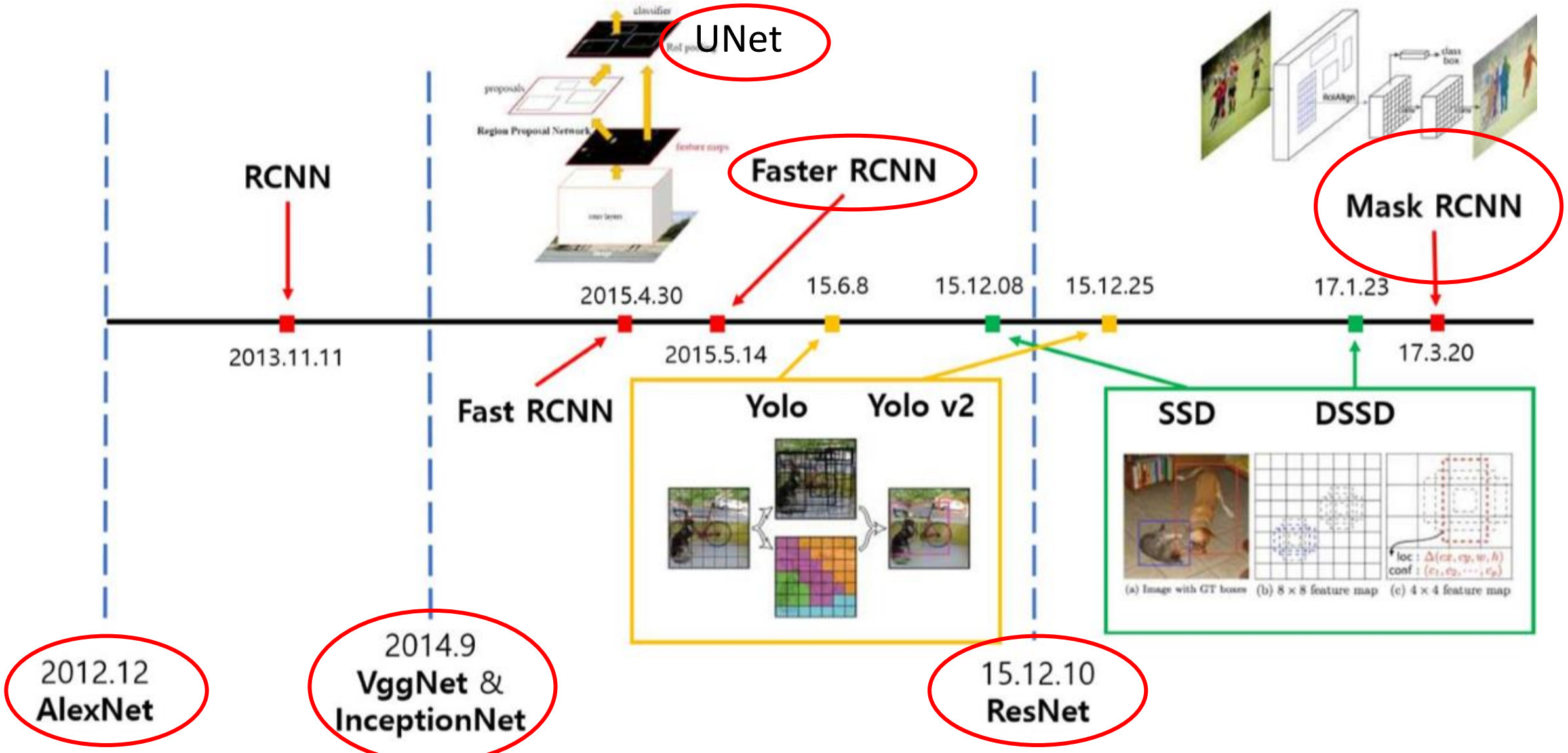
```
HBox(children=(FloatProgress(value=0.0, max=244418560.0), HTML(value='')))
```

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/

AlexNet and other CNNs

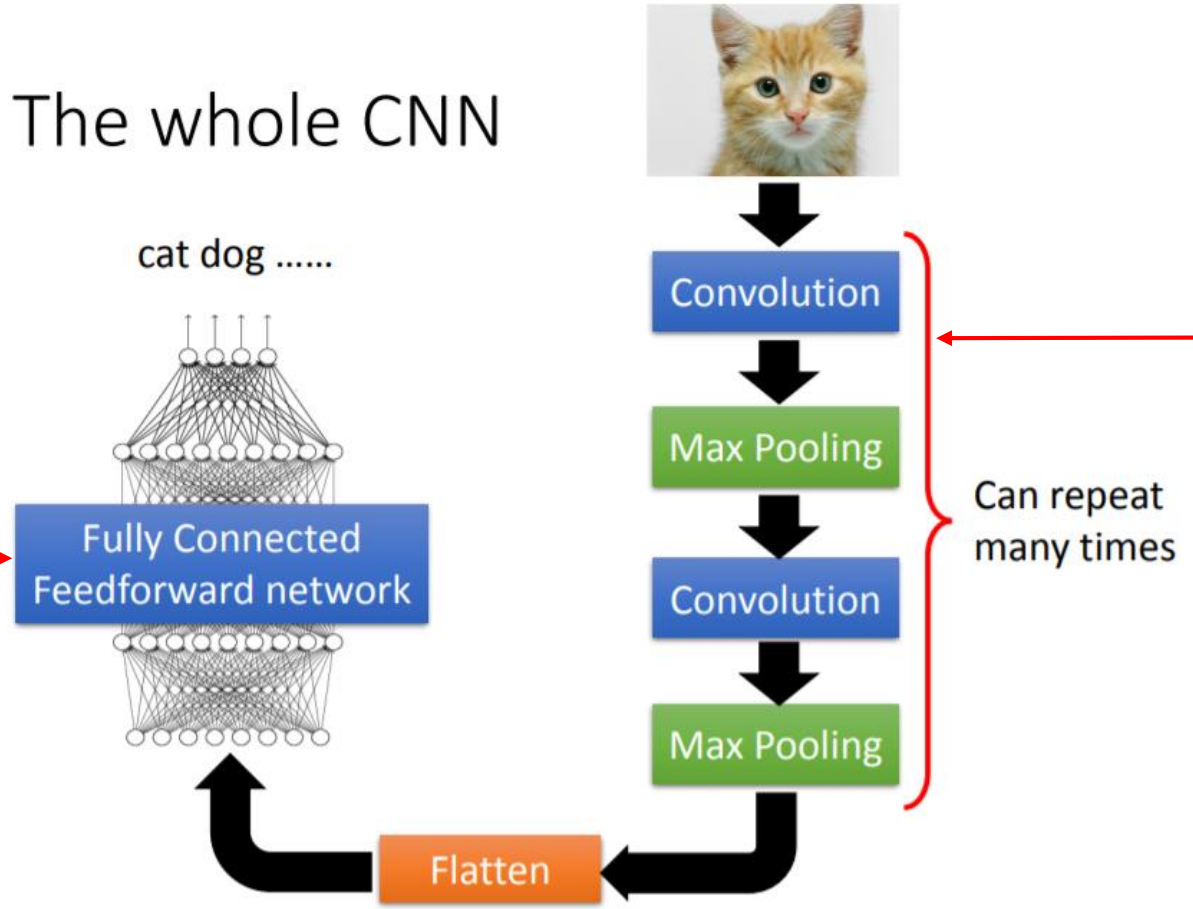


圖來源: 李春煌 FasterRCNN講義 https://youtu.be/2i9CcmJp2yI

Put model in evaluation mode and in GPU

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

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

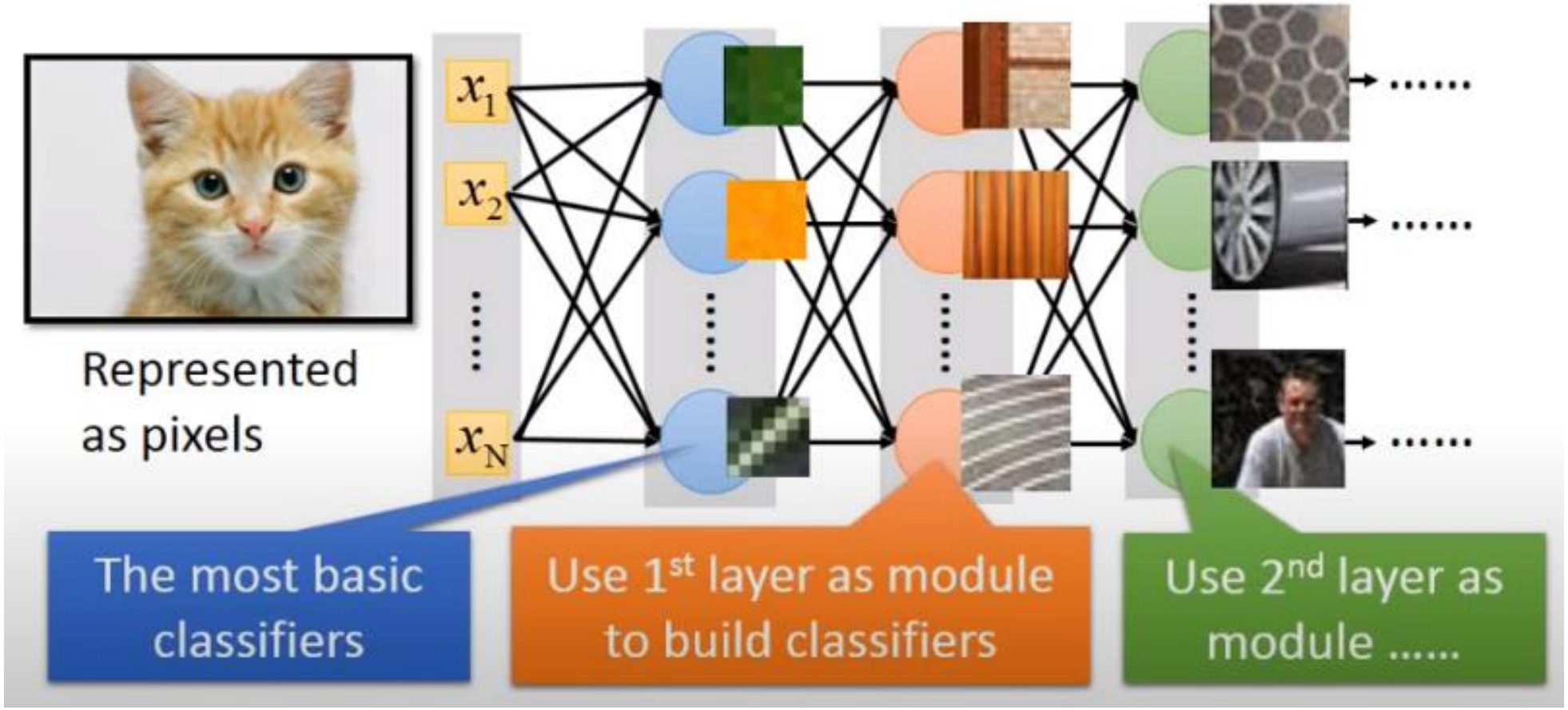



```
AlexNet(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(11, 11), stride=(4, 4), paddi
    (1): ReLU(inplace=True)
    (2): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=1
    (3): Conv2d(64, 192, kernel_size=(5, 5), stride=(1, 1), paddi
    (4): ReLU(inplace=True)
    (5): 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)
  )
)
```

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

What happens if we directly use MLP to classify images?

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

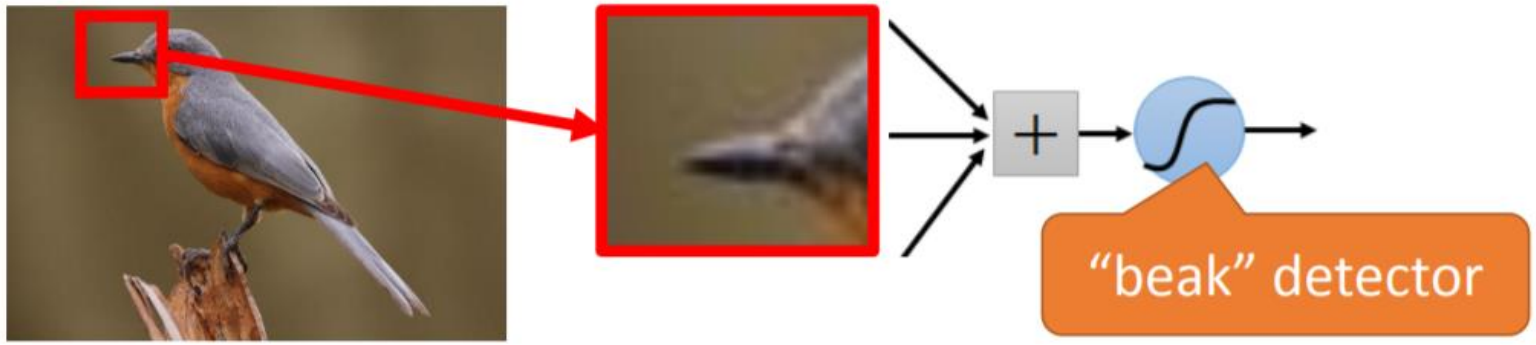


Reference: 李弘毅 ML Lecture 10 https://youtu.be/FrKWiRv254g

Some patterns are much smaller than the whole image

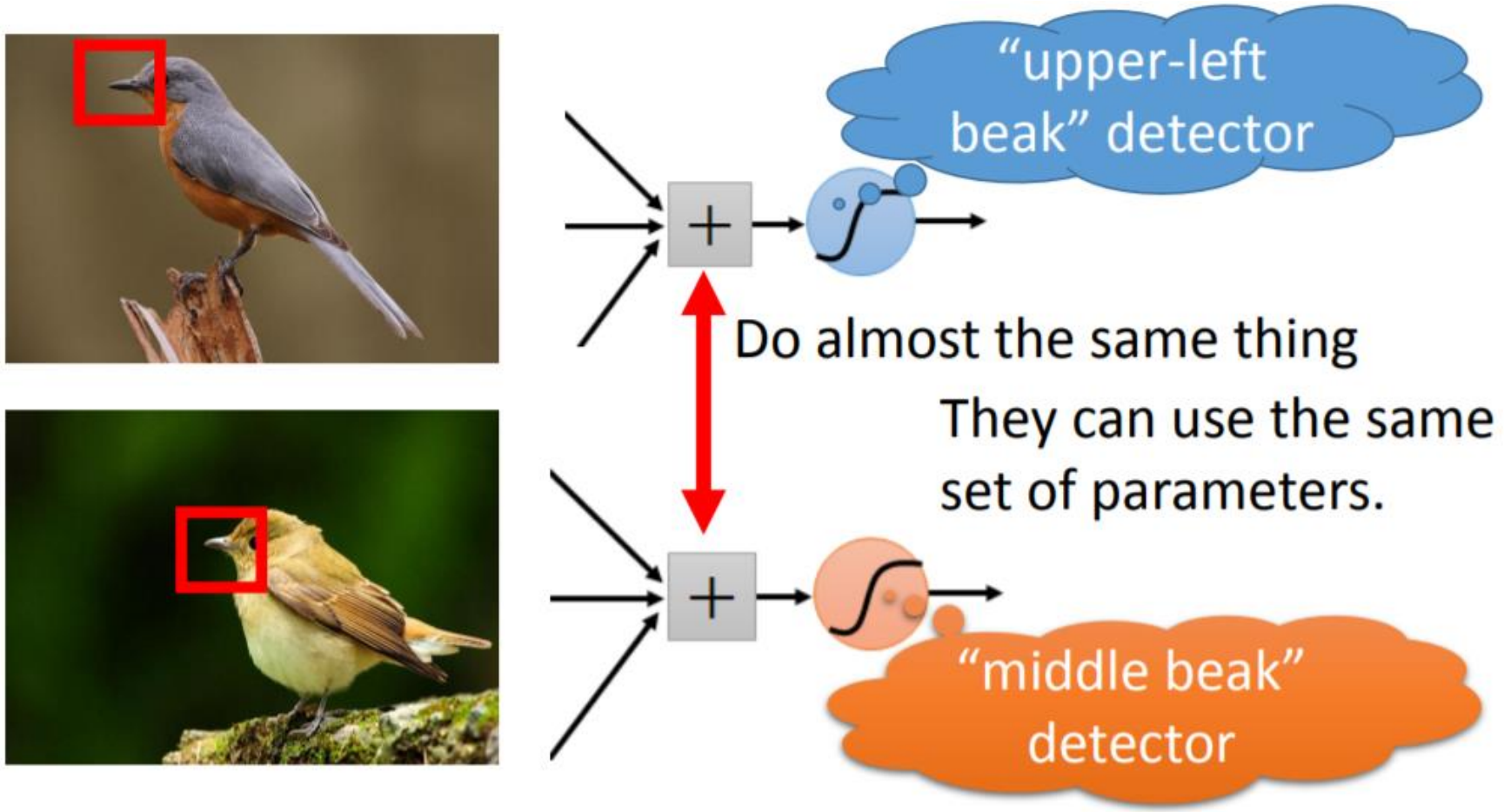
A neuron does not have to see the whole image to discover the pattern.

Connecting to small region with less parameters



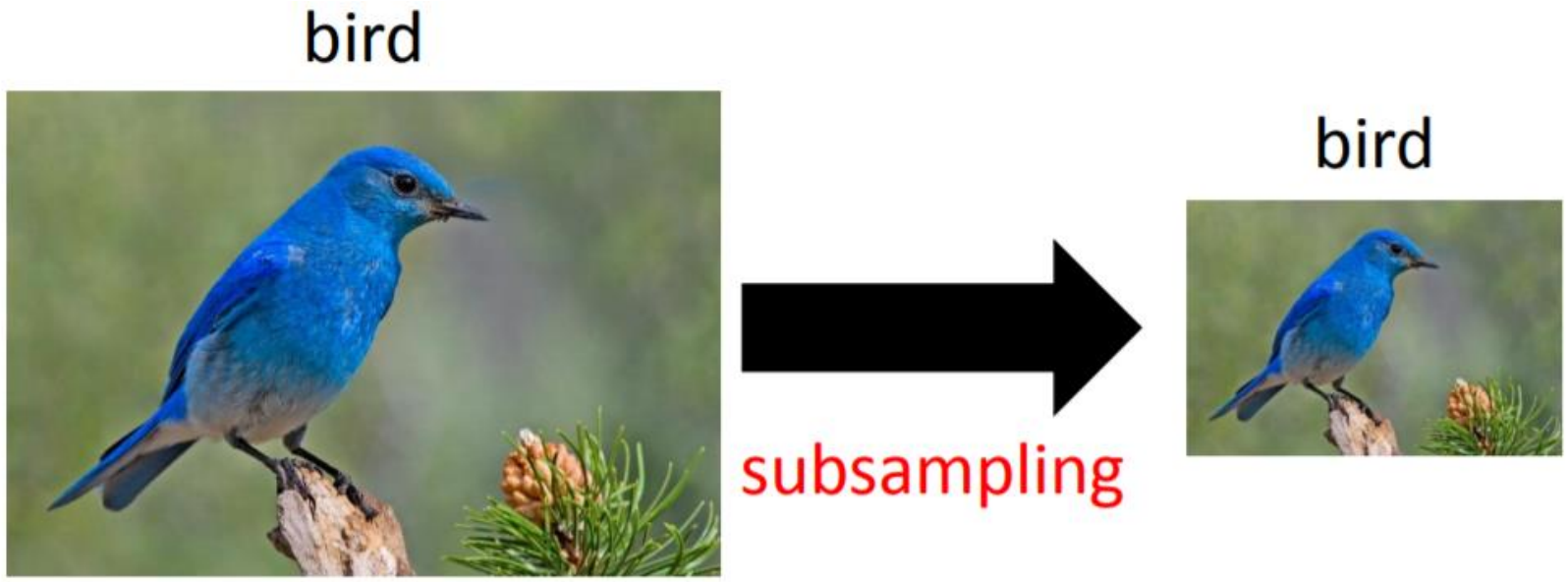
Reference: 李弘毅 ML Lecture 10 https://youtu.be/FrKWiRv254g

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

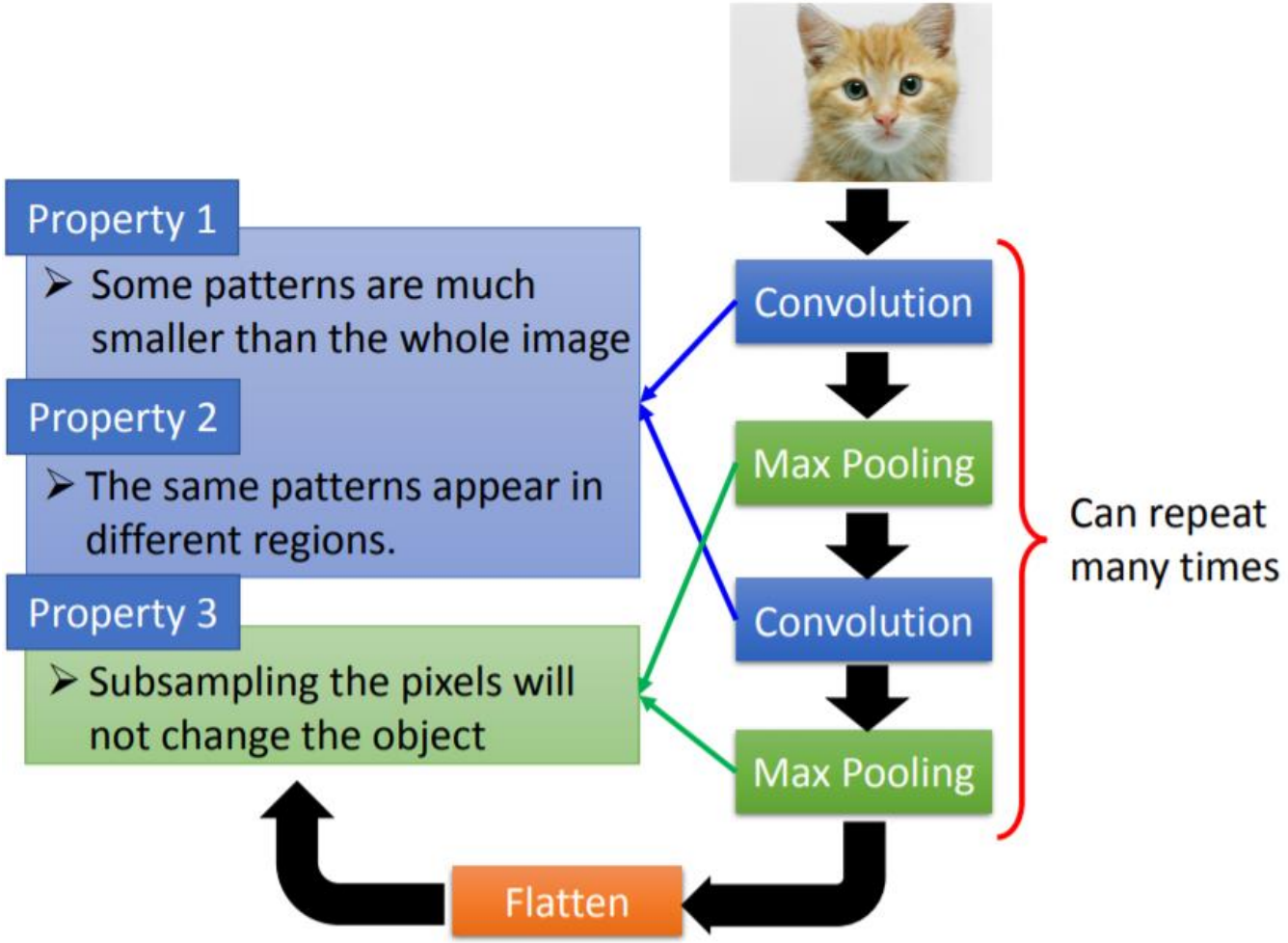


We can subsample the pixels to make image smaller

→ Less parameters for the network to process the image

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

CNN's "features" section extracts the important features from the input image through convolution and pooling operations



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()
```

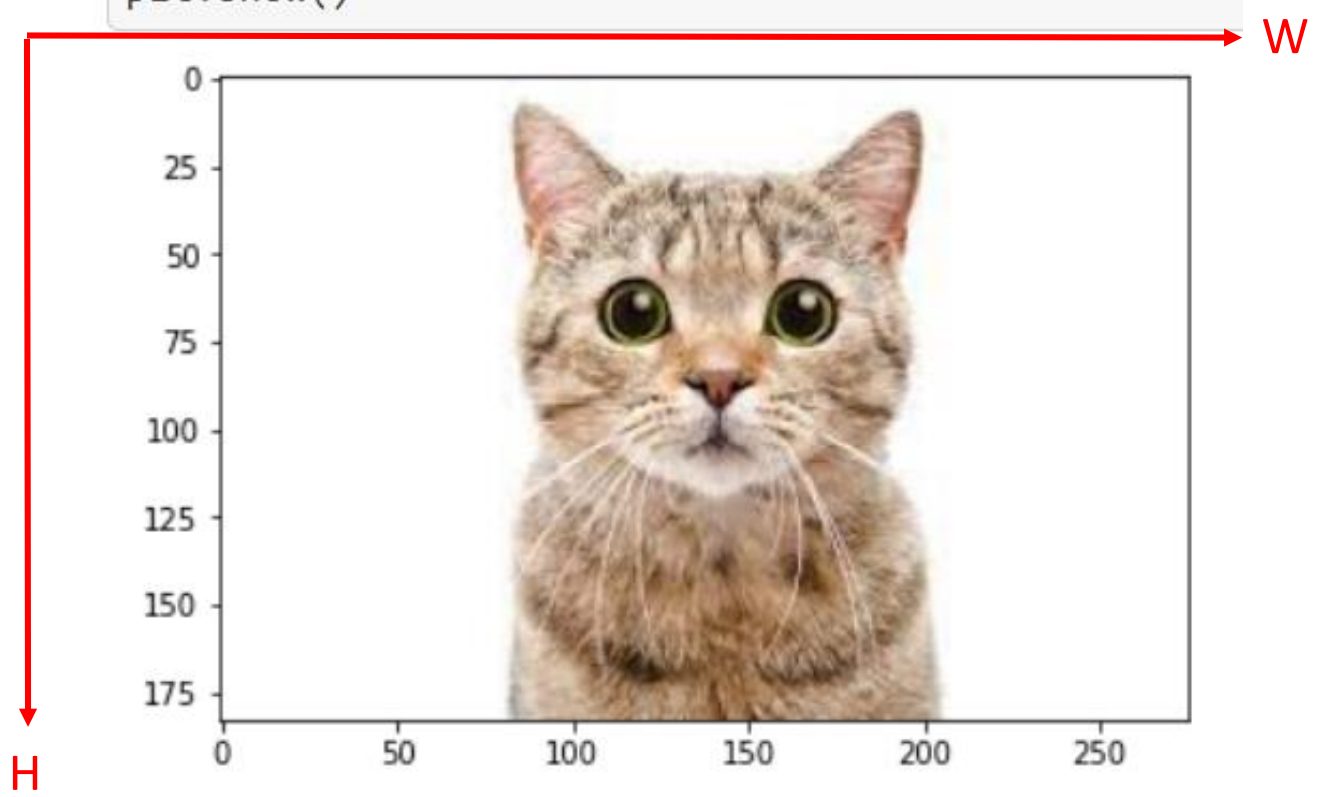


Image pre-processing

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])

Input to CNN model

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])
```

Convolution

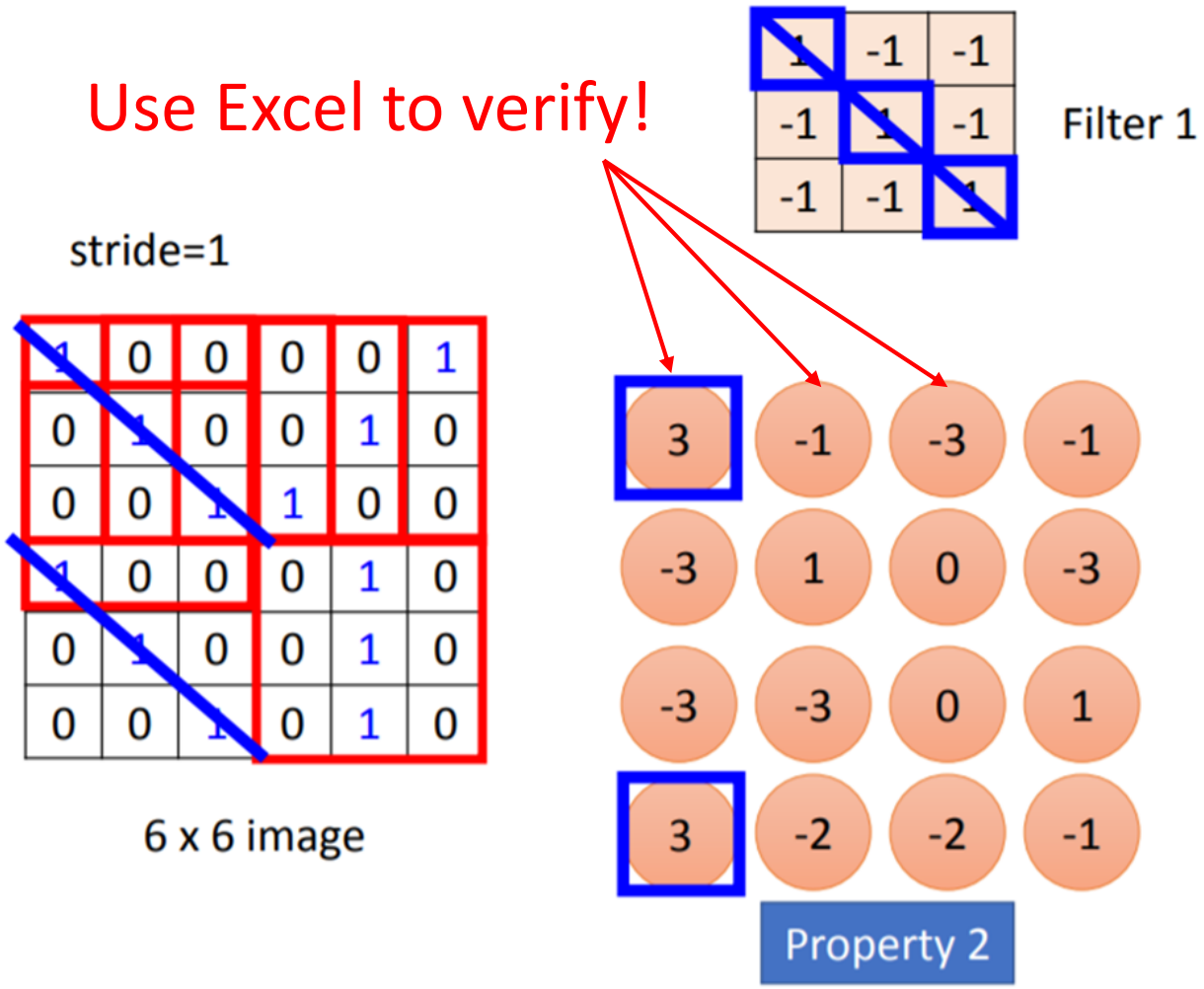
```
In [10]: conv1 = model.features[0]
         print(conv1)
         #InChannel=3(RGB),OutChannel=64, filter size=11, stride=4, padding=2

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

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])
```

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

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

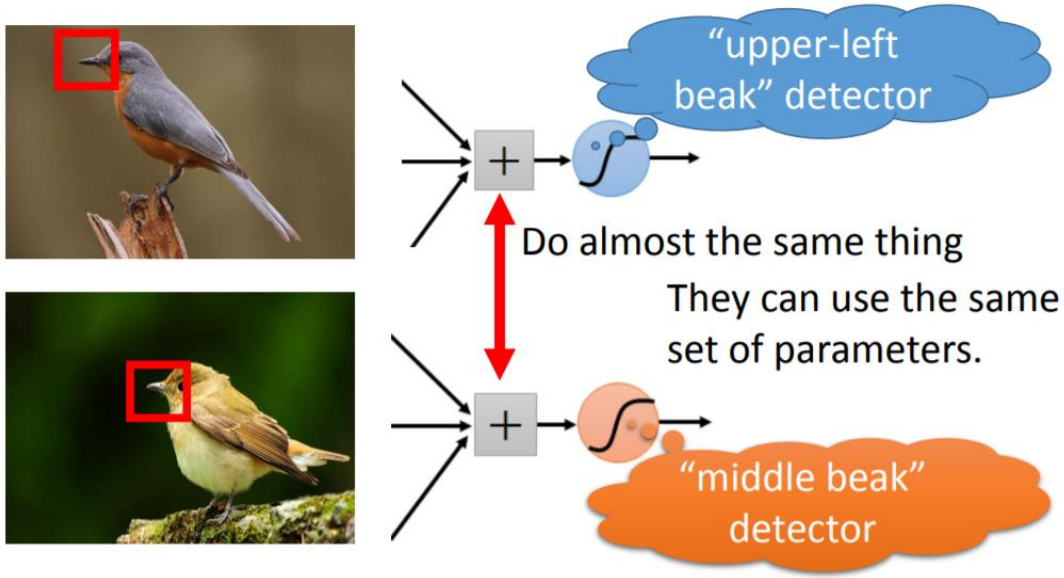
Filter searches a particular pattern in different regions

Use Excel to verify!



Property 2

- The same patterns appear in different regions.



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

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

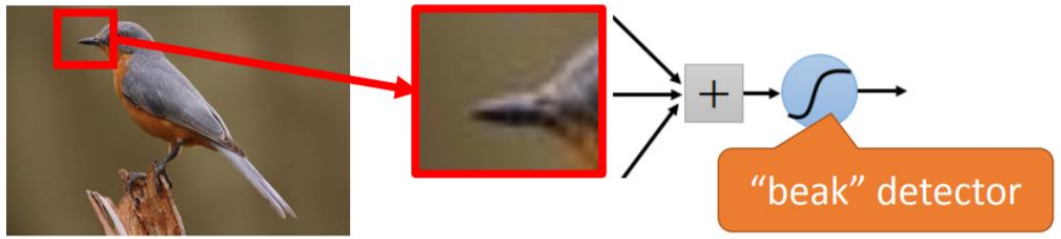
Property 1 Each filter detects a small pattern (3 x 3).

Property 1

- Some patterns are much smaller than the whole image

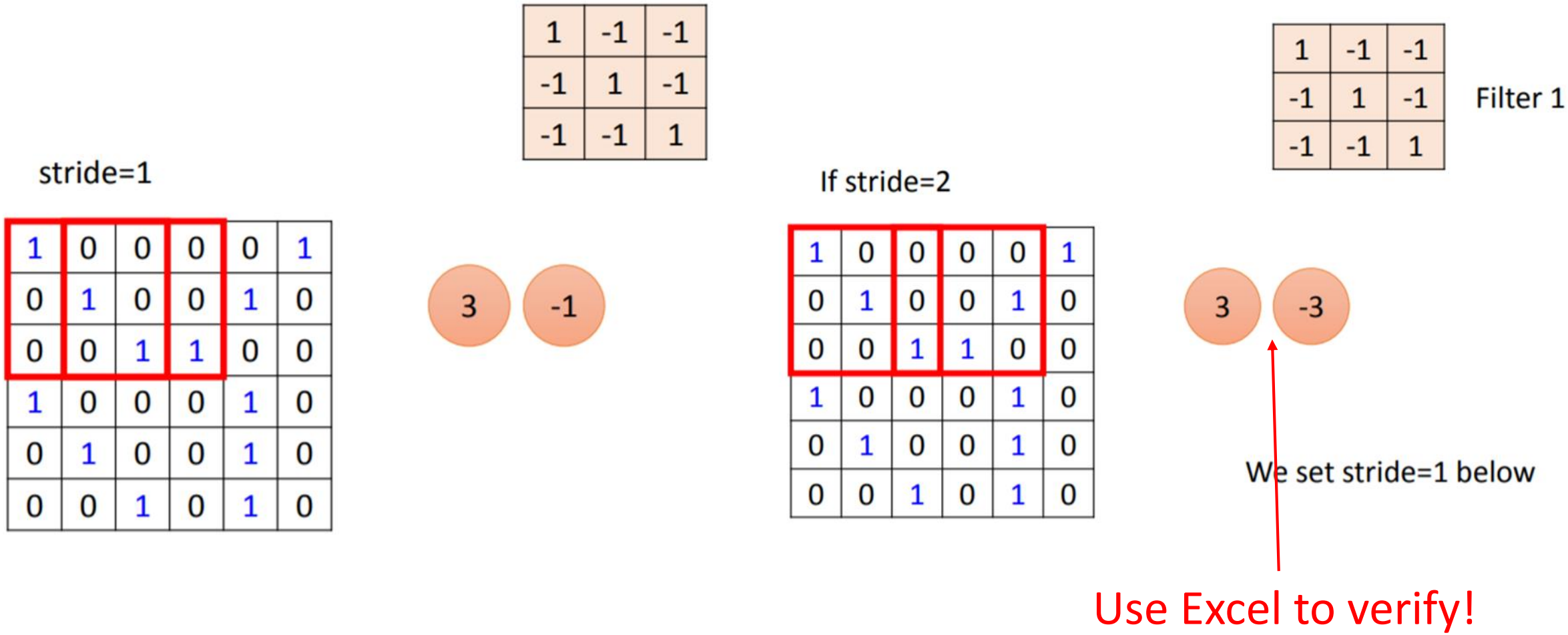
A neuron does not have to see the whole image to discover the pattern.

Connecting to small region with less parameters



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

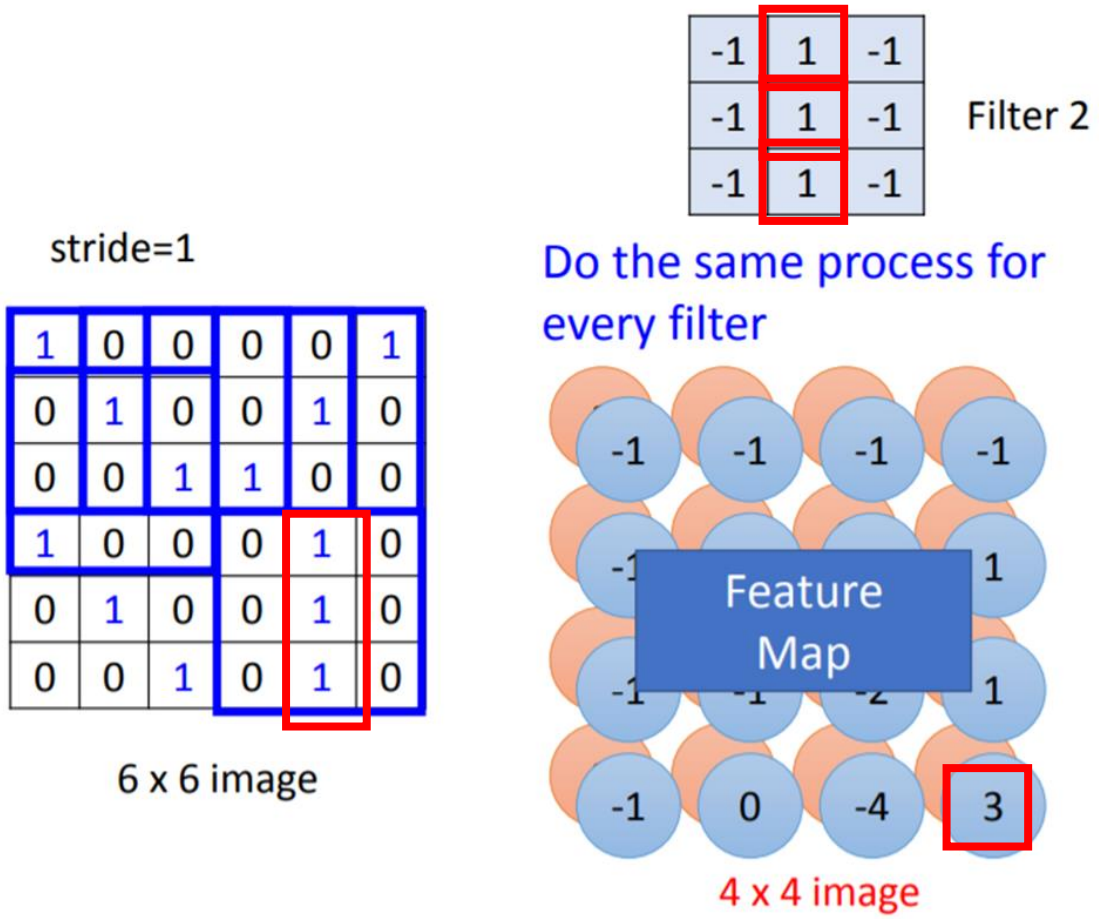
Stride determines how filter shifts



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

Feature maps

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

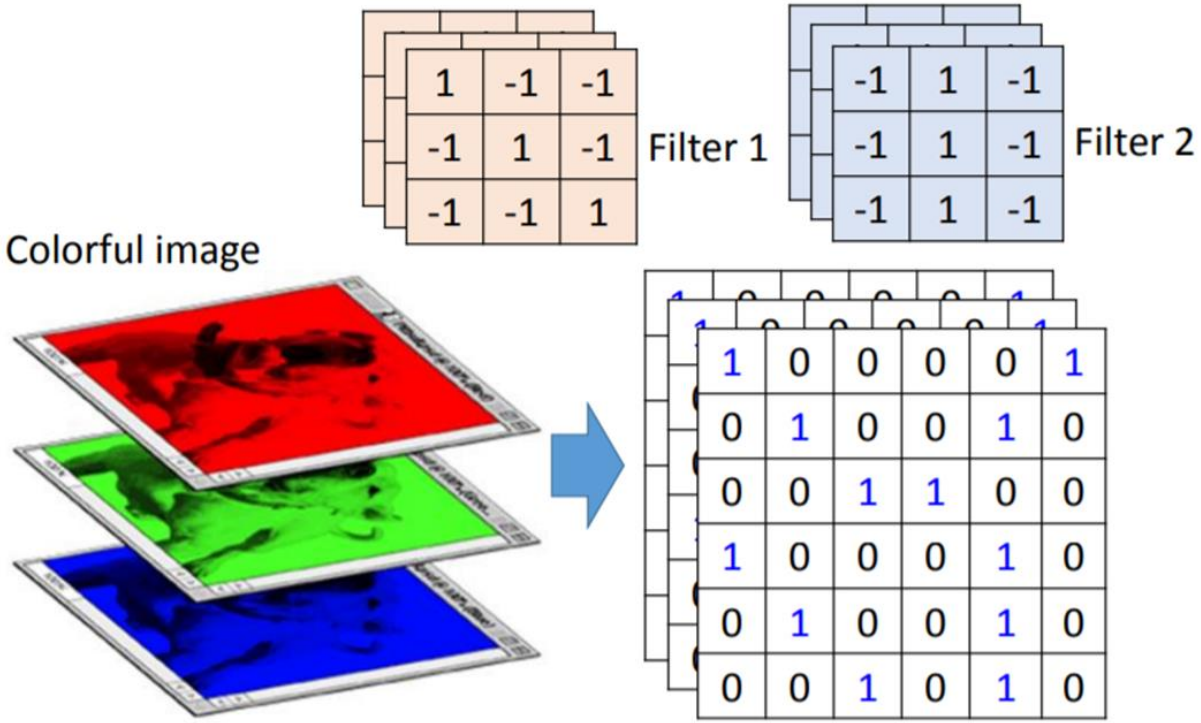



```
In [10]: conv1 = model.features[0]
         print(conv1)
         #InChannel=3(RGB),OutChannel=64, filter size

         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

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)
```

64 filters, each filter has 3 channels

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

After convolution, the input image (3 channels) is converted to a feature map with *k* channels, *k* is the number of filters.

[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))
```

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

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

64 filters, each has 3 channels, are applied to the input image (with 3 channels RGB)

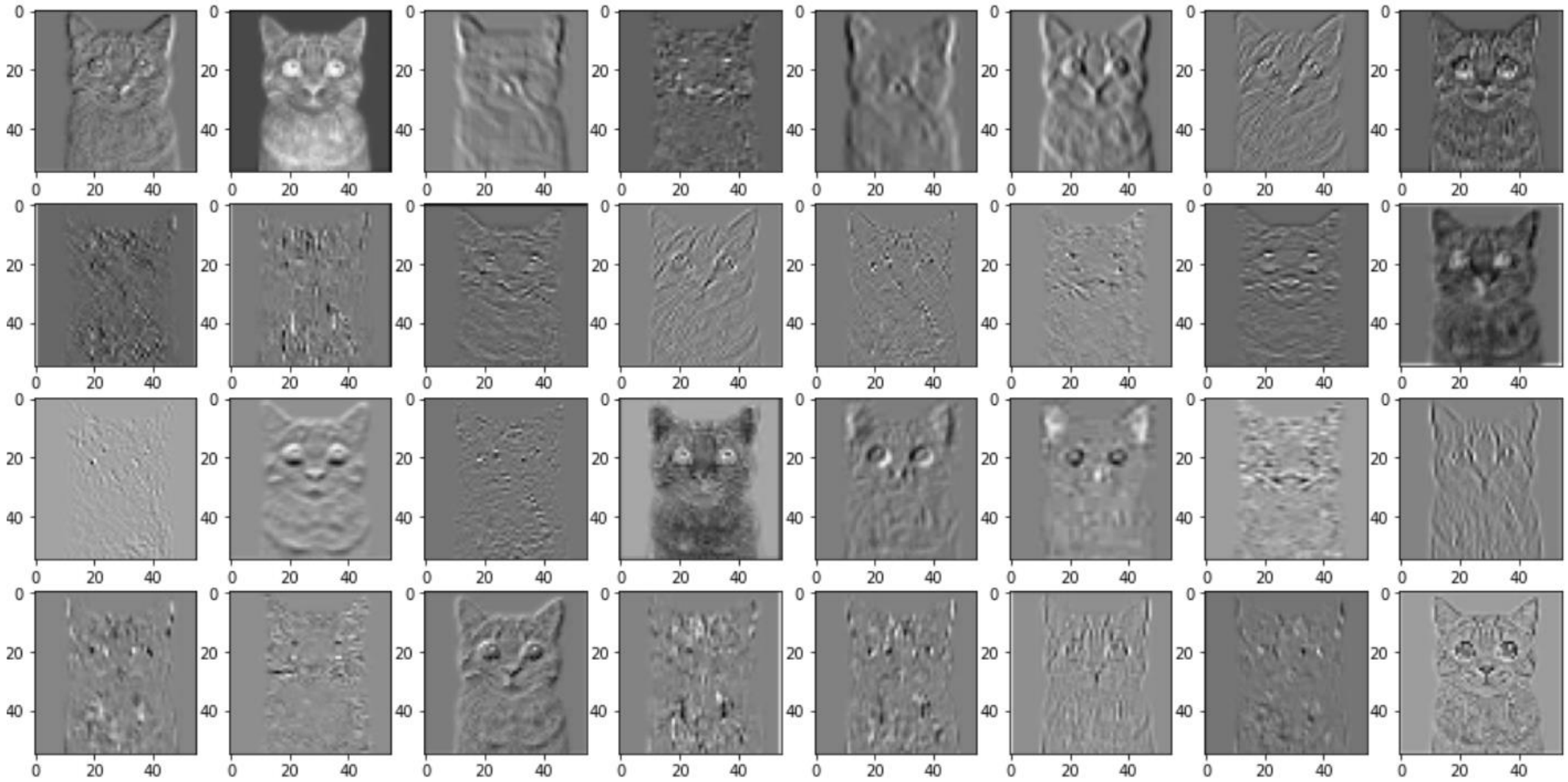
[12]:
```
conv1_out = conv1(imageTensor.to(device))
conv1_out.shape
#output image (feature map) has 64 channels
```

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

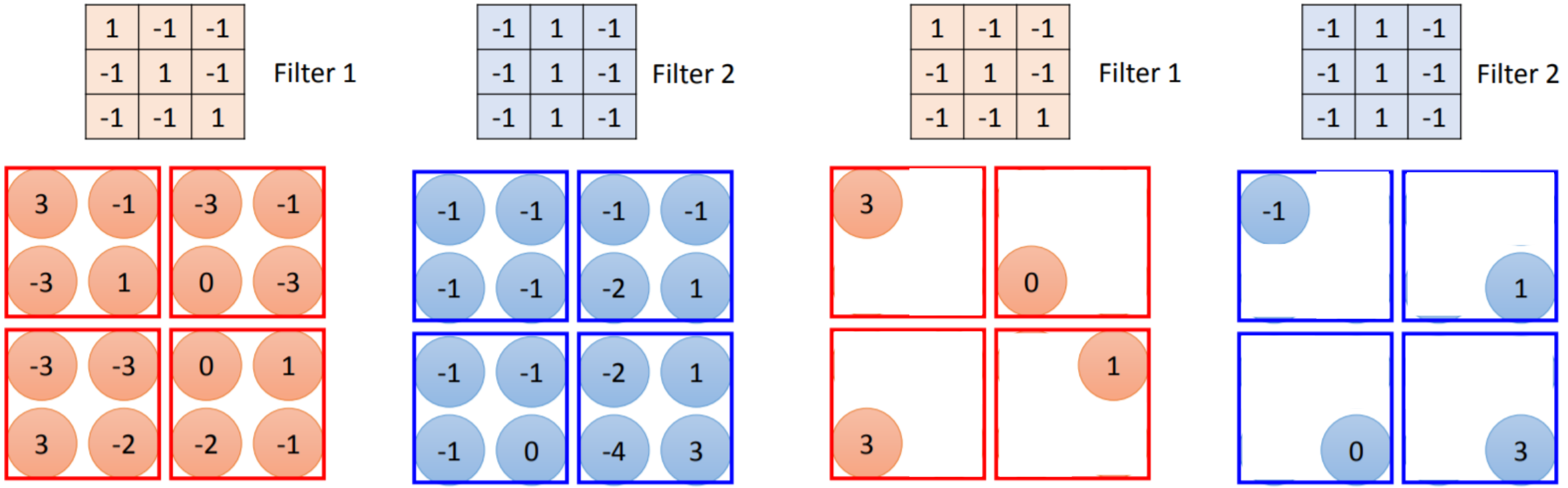
After convolution, the output image (feature map) has 64 channels

[13]:
```
# Visualize the first 32 channels of the output feature map
imgArray=conv1_out[0].data.cpu().numpy()
fig=plt.figure(figsize=(18, 9))
for i in range(32):
    fig.add_subplot(4, 8, i+1)
    plt.imshow(imgArray[i], cmap='gray')
plt.show()
```

After convolution, the input image (3 channels) is converted to a feature map with *k* channels, *k* is the number of filters.

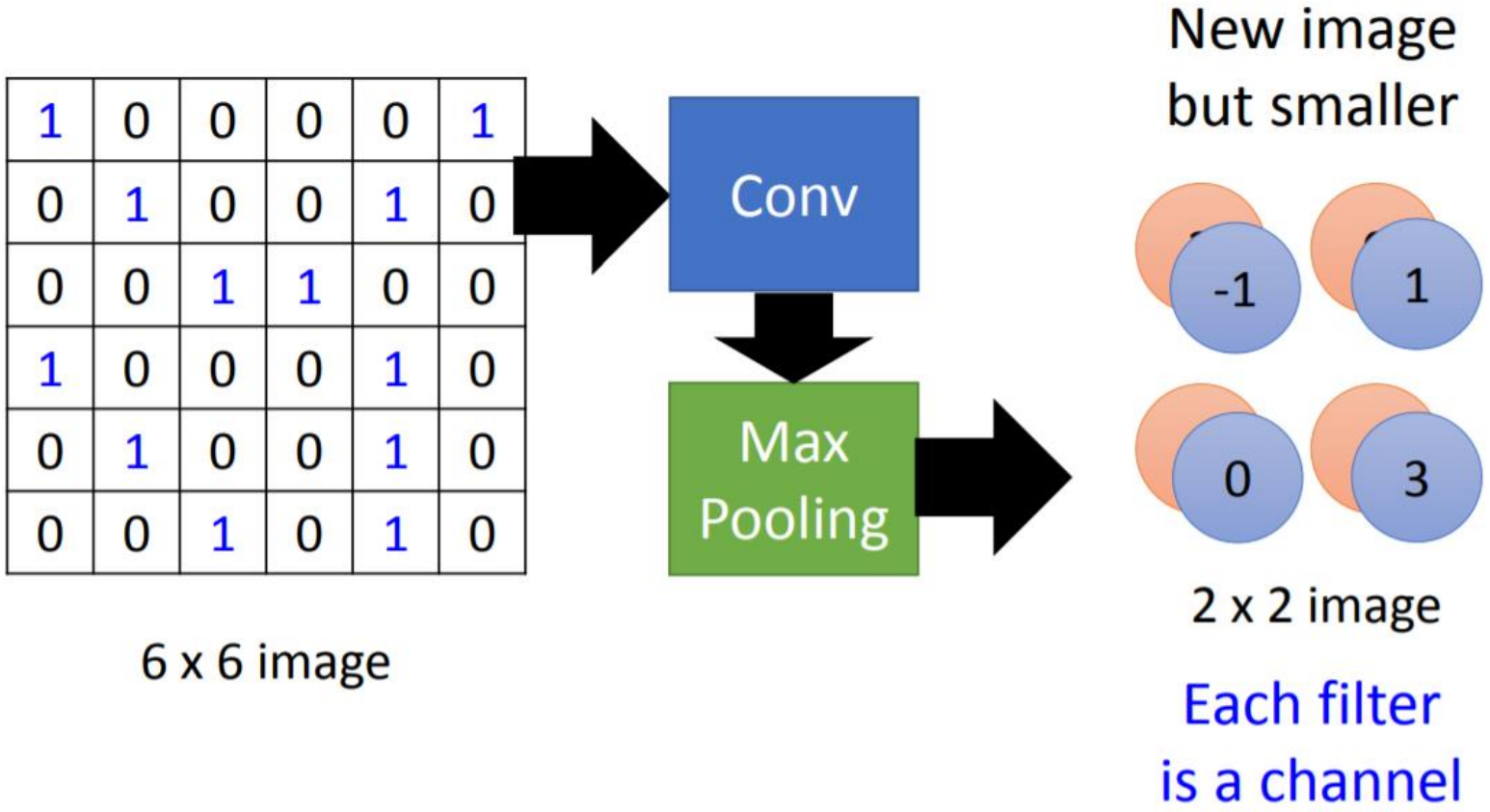


Max pooling



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

After convolution and pooling, the input image (3 channels) is converted to a feature map of smaller size with *k* channels, *k* is the number of filters.



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

After convolution and pooling, the input image (3 channels) is converted to a feature map of smaller size with *k* channels, *k* is the number of filters.

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])
```

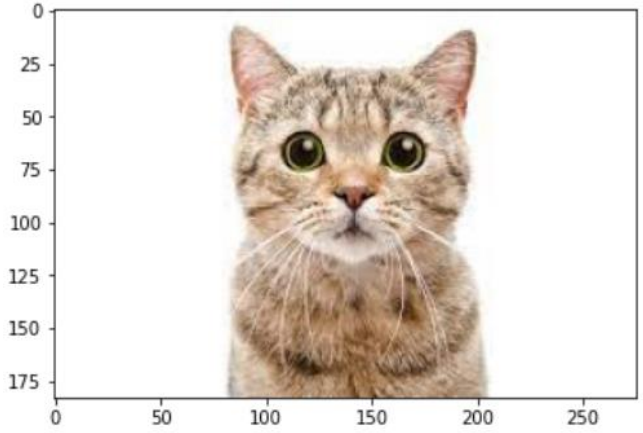
$$\frac{55 + 2 \times 2 - 3}{2} + 1 = 27$$

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

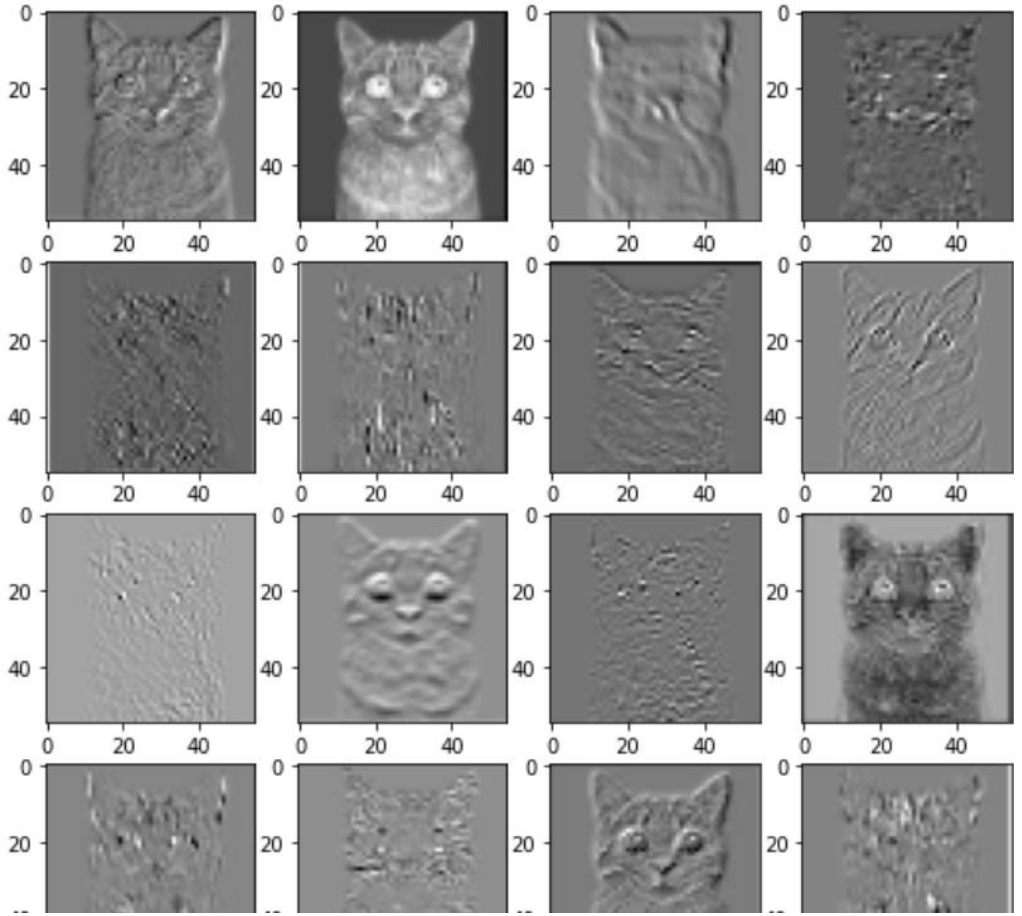
```
AlexNet(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(11, 11), stride=(4, 4), padd
    (1): ReLU(inplace=True)
    (2): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=
    (3): Conv2d(64, 192, kernel_size=(5, 5), stride=(1, 1), padd
    (4): ReLU(inplace=True)
    (5): MaxPool2d(kernel_size=3, 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
  )
```

After convolution and pooling, the input image (3 channels) is converted to a feature map of smaller size with *k* channels, *k* is the number of filters.

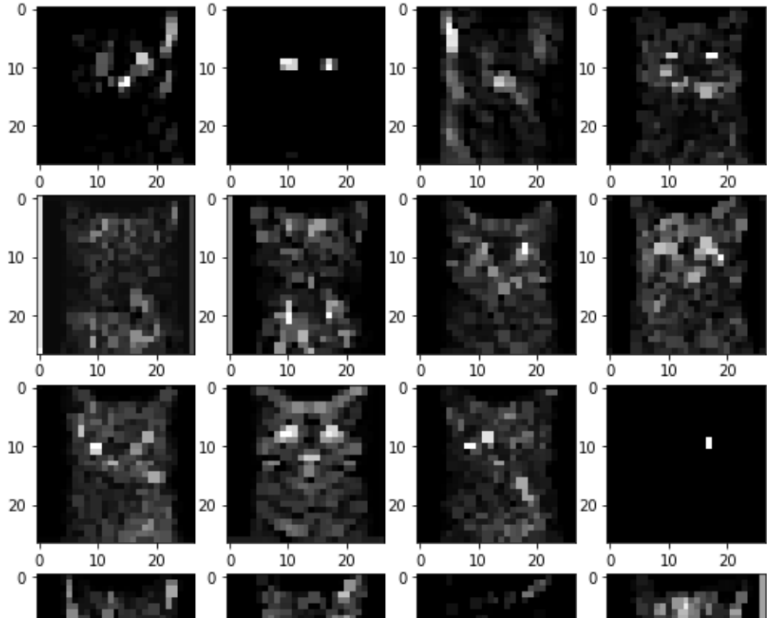
Input image



Output feature map after convolution



Output feature map after pooling



2nd convolution

```
[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])
```

After convolution, the output feature map has 192 channels

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

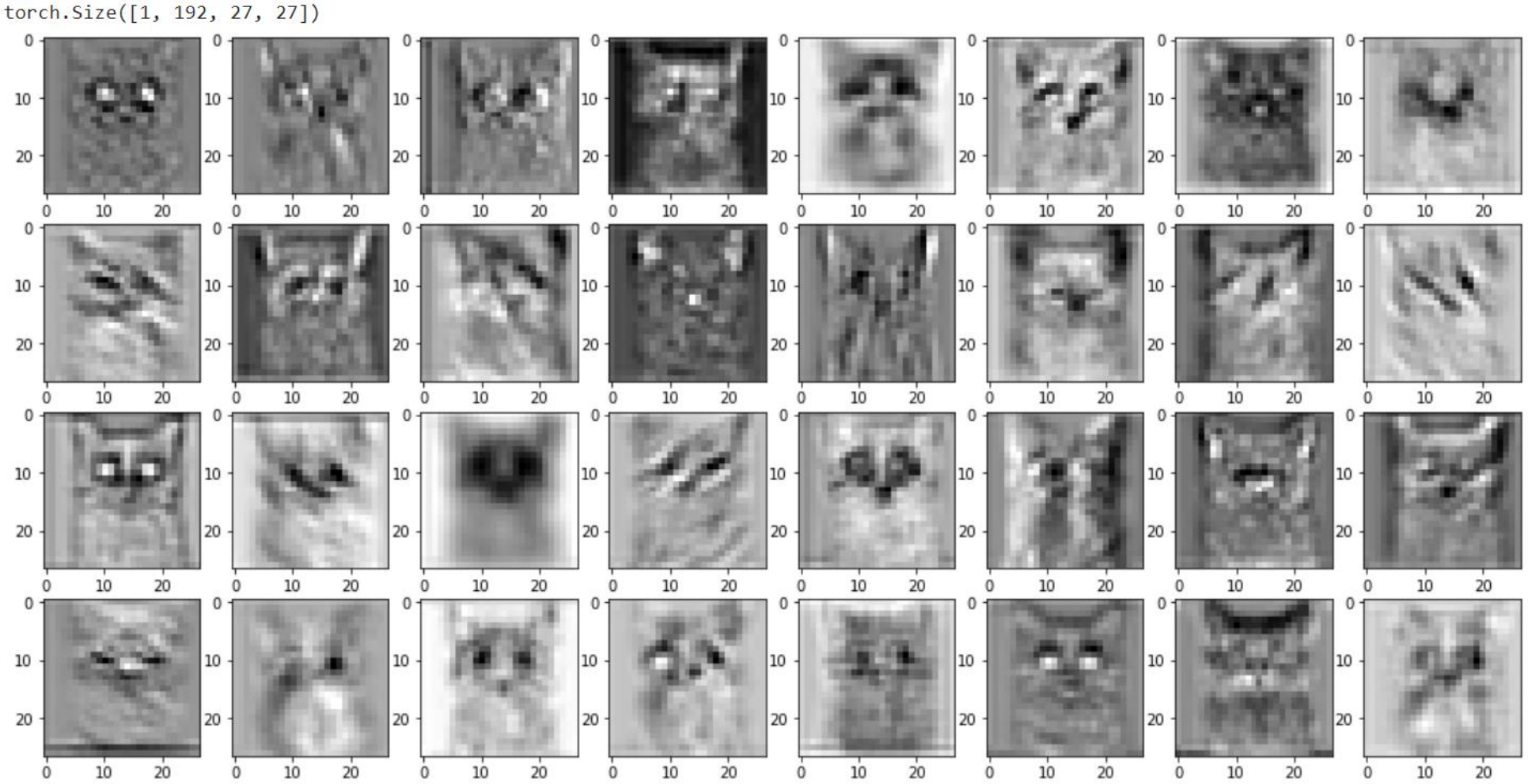
$$H_{out} = \frac{H_{in} + 2 \times padding - kernel\ size}{Stride} + 1$$

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

```
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

Feature map after 2nd convolution



Max pooling after 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])
```

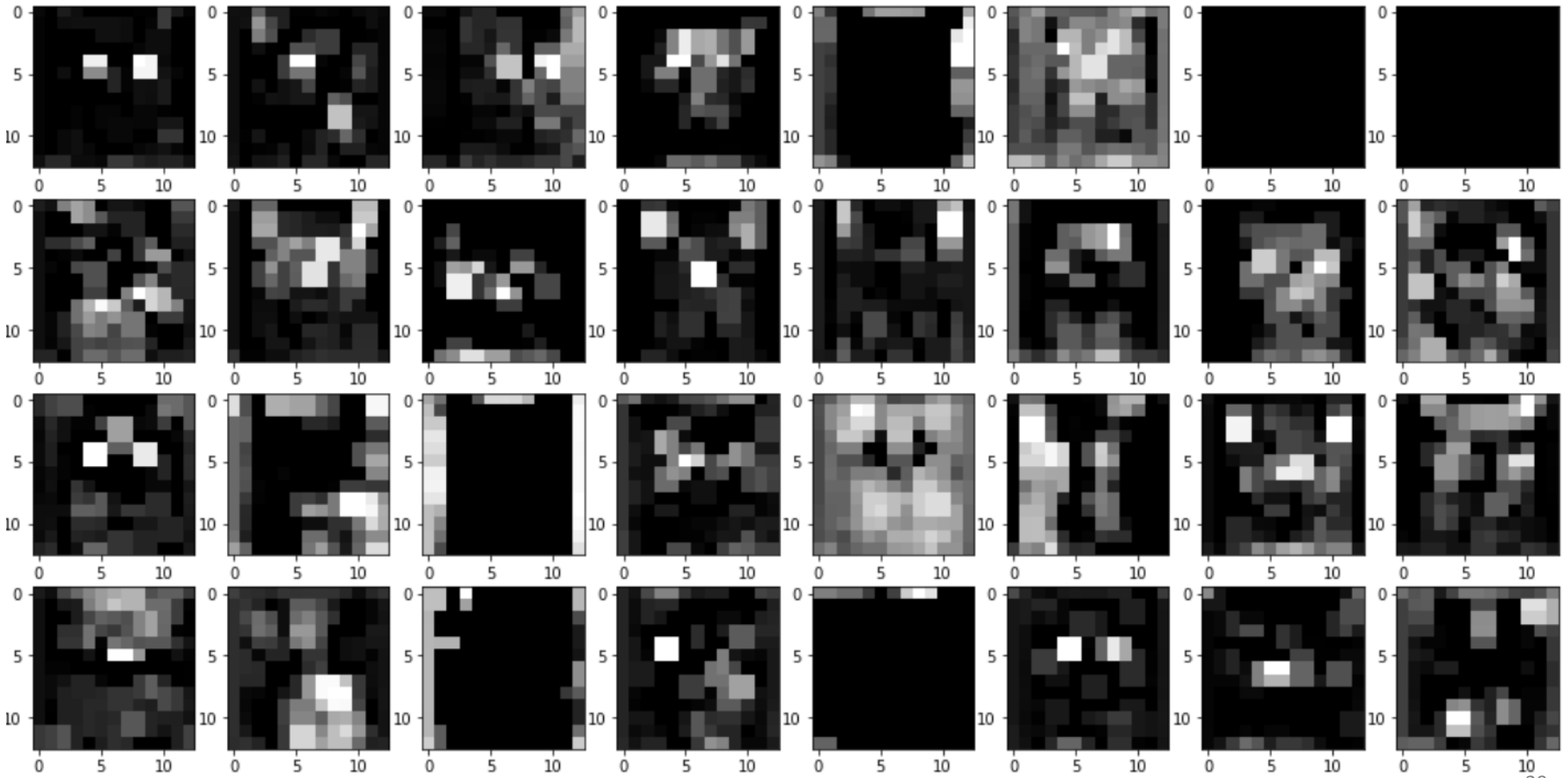
$$\frac{27 + 2 \times 0 - 3}{2} + 1 = 13$$

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

```
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
  )
```

PYTORCH

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

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

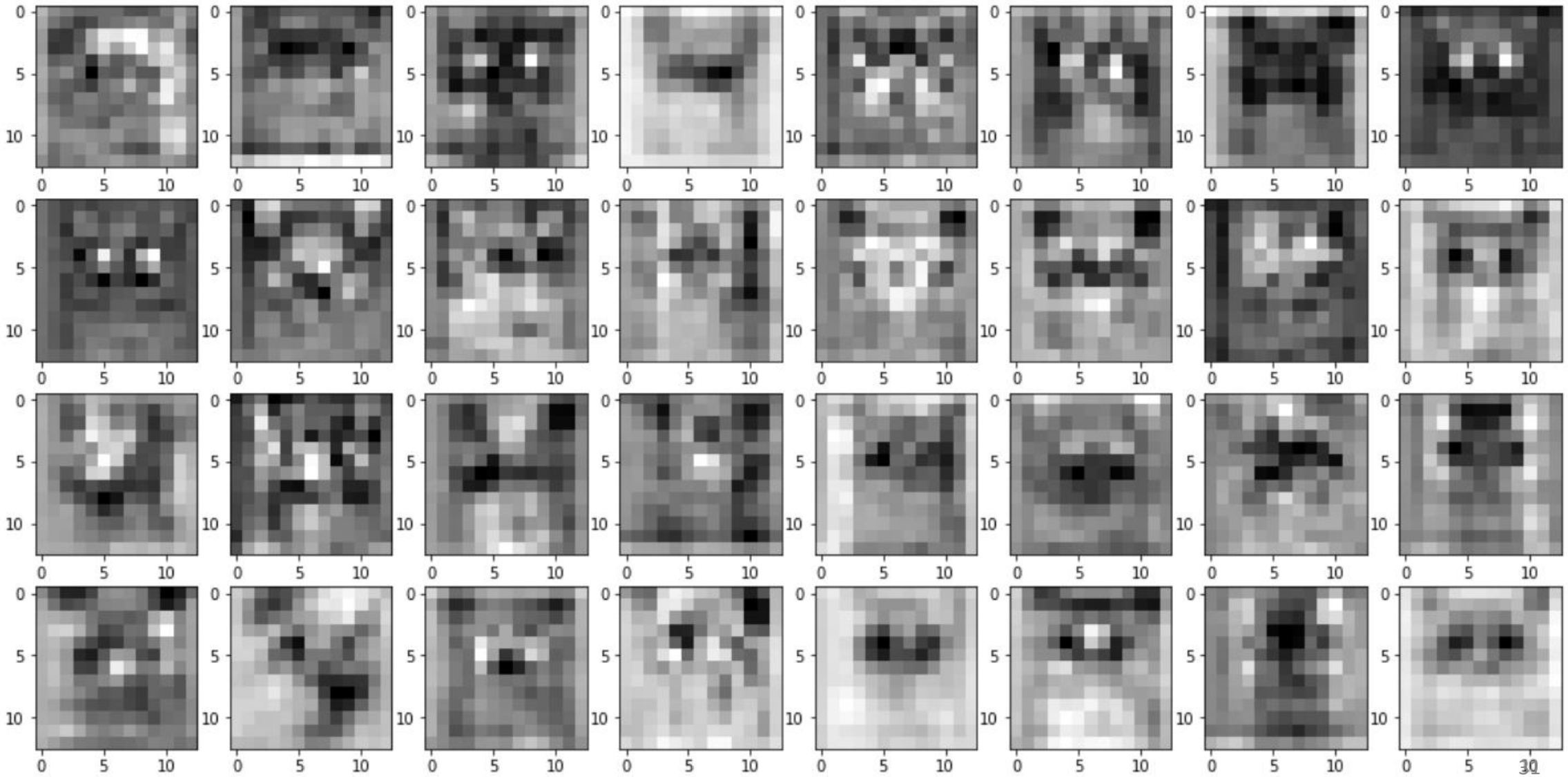
```
AlexNet(
  (features): Sequential(
    (0): Conv2d(3, 64, kernel_size=(11, 11), stride=(4, 4), padd
    (1): ReLU(inplace=True)
    (2): MaxPool2d(kernel_size=3, stride=2, padding=0, dilation=
    (3): Conv2d(64, 192, kernel_size=(5, 5), stride=(1, 1), padd
    (4): ReLU(inplace=True)
    (5): MaxPool2d(kernel_size=3, 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
  )
```

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

PYTORCH

Feature map after 3rd convolution

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



Max pooling after 3rd convolution

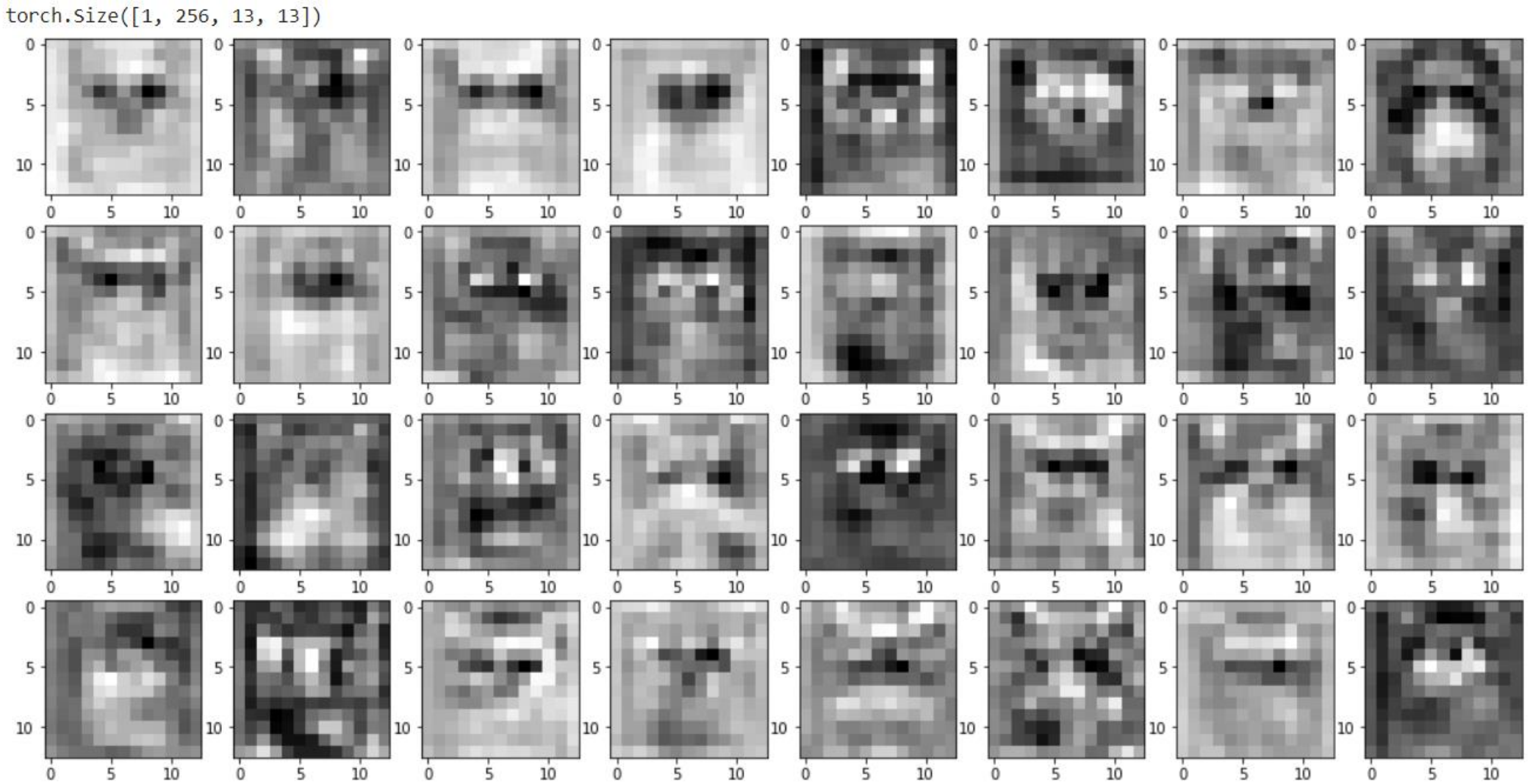
features[7, 8]

```
[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
  )
```

Google colab PYTORCH

Feature map after 3rd convolution and max pooling



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 – What does CNN learn?

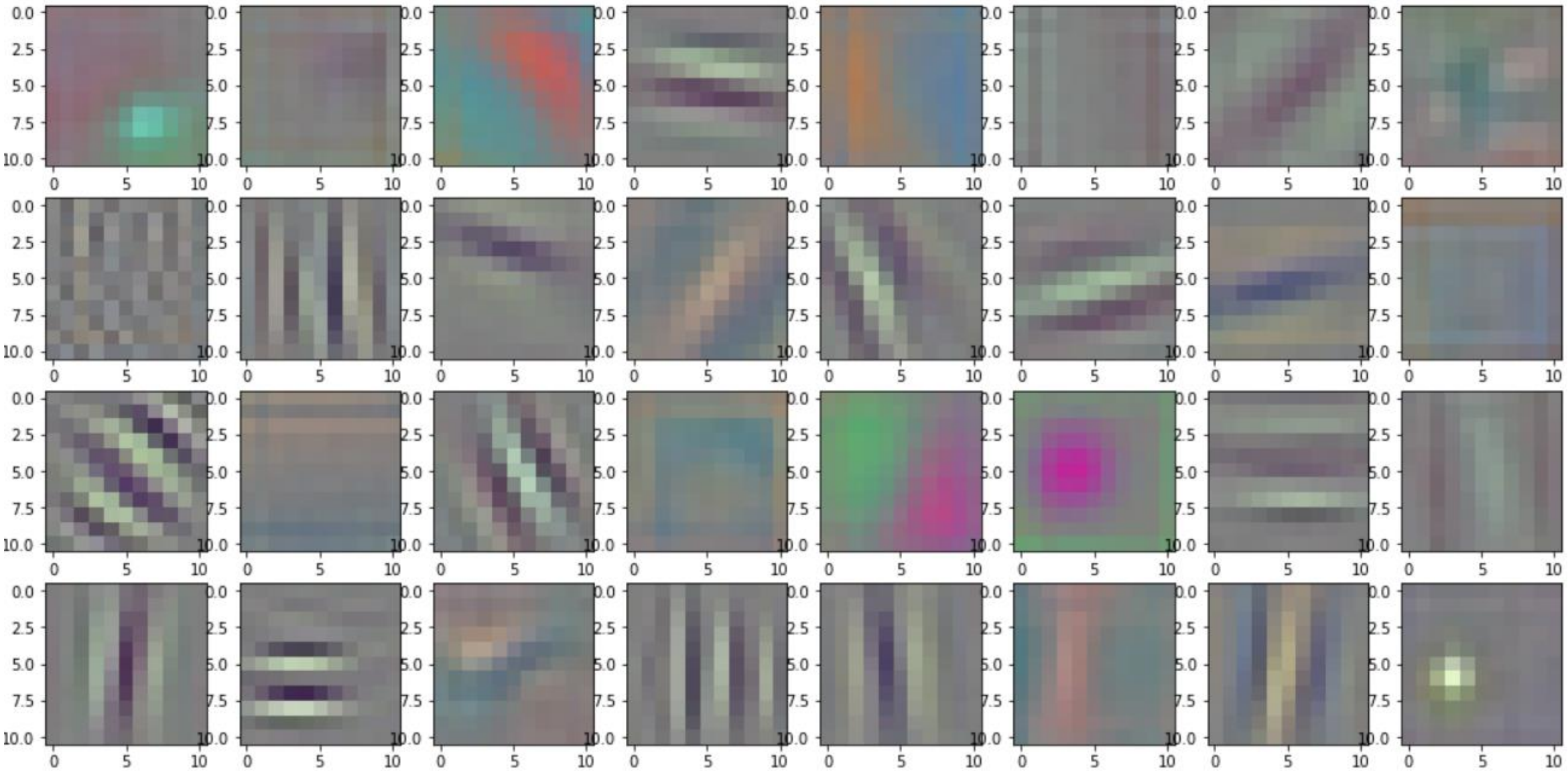
- Run “7.2. What does CNN learn.ipynb"

Visualize the learned filter's weights

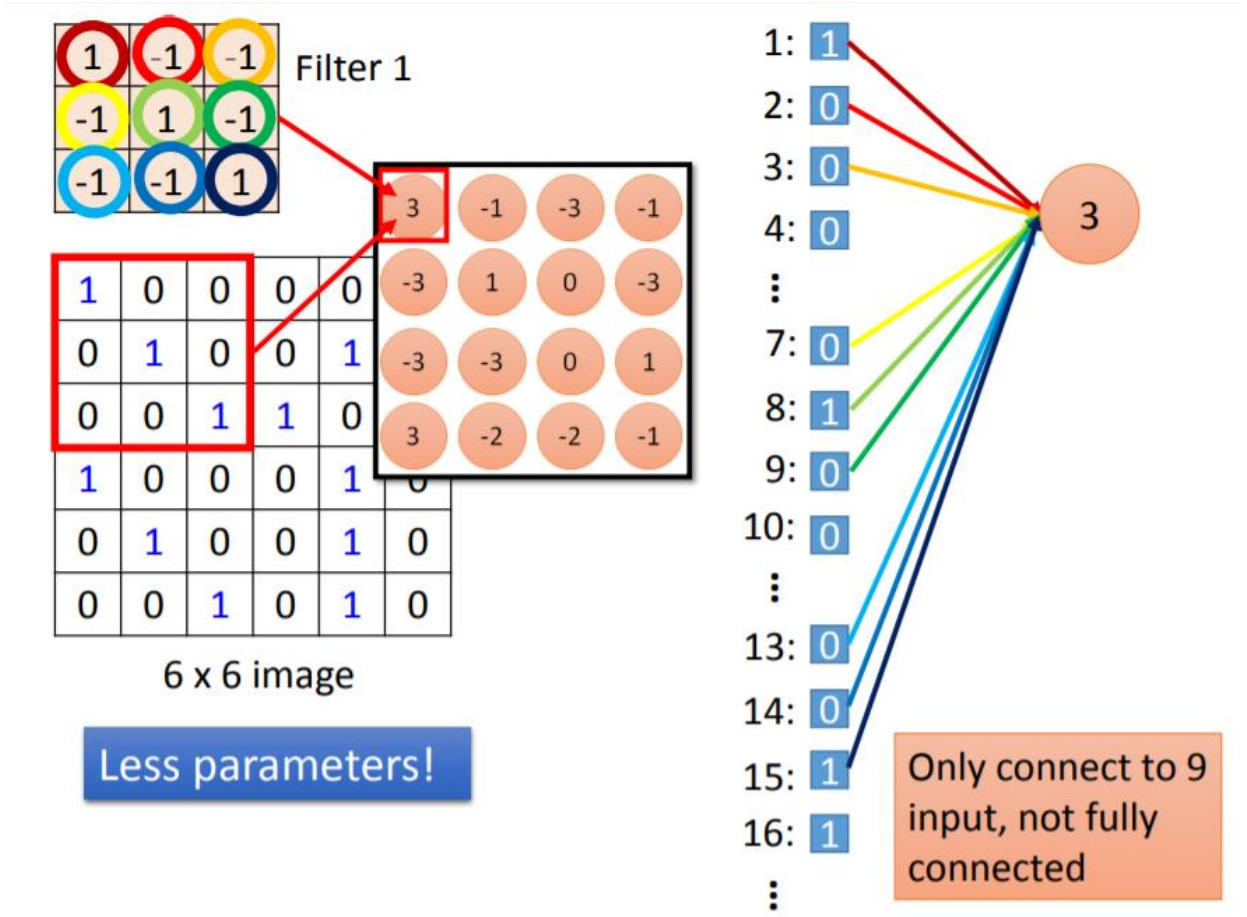
[4]:
```
import numpy as np
import matplotlib.pyplot as plt

conv1 = model.features[0]
weight1 = conv1.weight.data.cpu().numpy()
print(weight1.shape)
#(64, 3, 11, 11)

# Visualize the first 32 of the filter weights
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()
```

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

Visualize the learned filter's weights

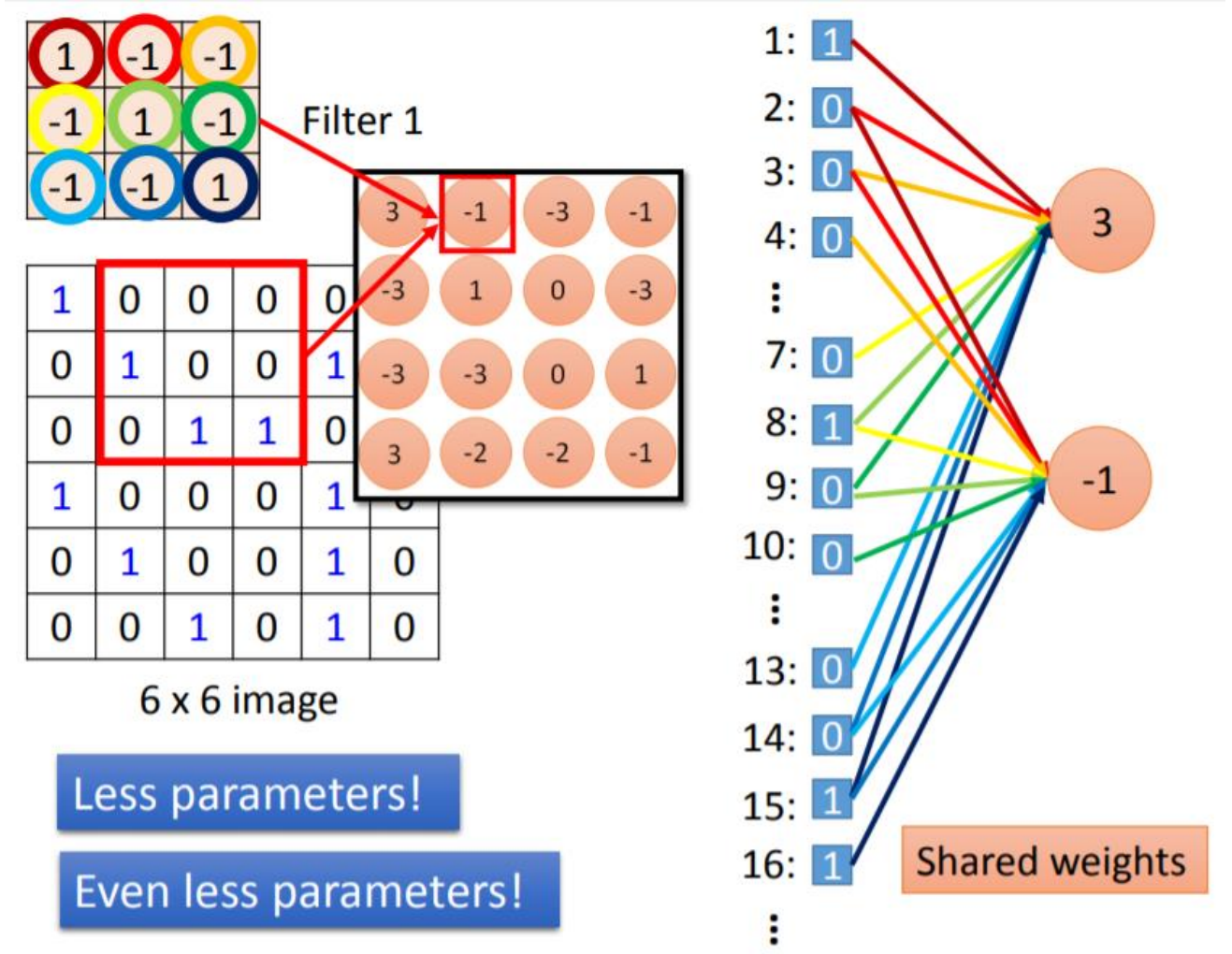


Convolution can be represented as partially connected NN, which has less parameters and is less complicated than the fully connected NN.



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

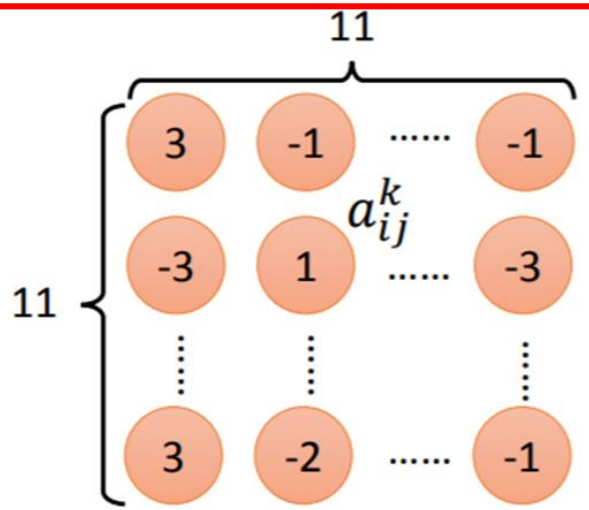
Only the weight of the 1st convolution filters can be directly visualized. How to interpret the filter weights of other convolution layers?

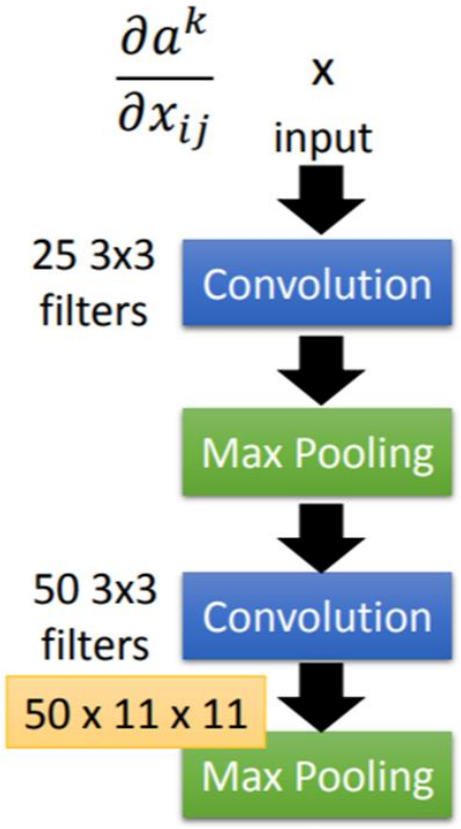
How to use gradient ascent to implement this in PyTorch?

The output of the k-th filter is a 11 x 11 matrix.

Degree of the activation of the k-th filter: $a^k = \sum_{i=1}^{11} \sum_{j=1}^{11} a_{ij}^k$

$x^* = arg \max_x a^k$ (gradient ascent)





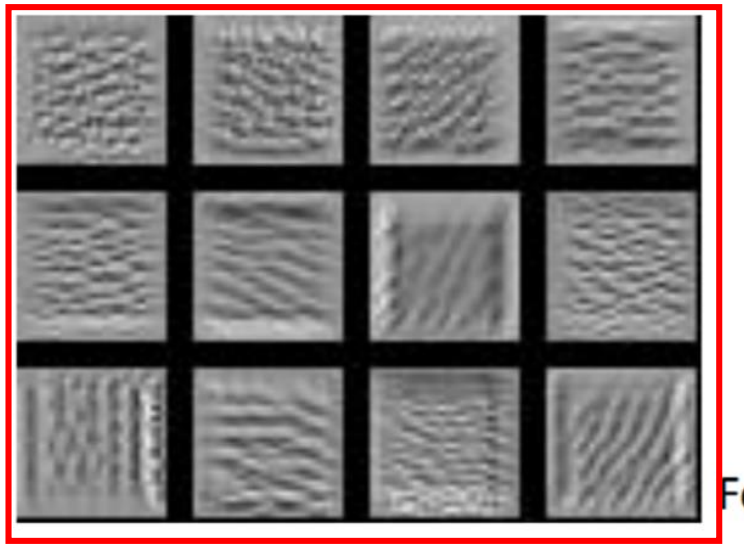
Reference: 李弘毅 ML Lecture 10 https://youtu.be/FrKWiRv254g

With MNIST data set, in the convolution layer, the filters detects a particular texture pattern.

The output of the k-th filter is a 11 x 11 matrix.

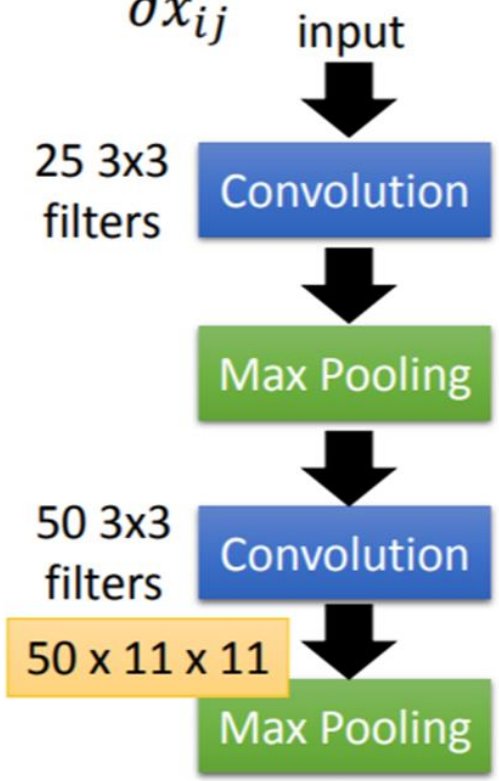
Degree of the activation of the k-th filter: $a^k = \sum_{i=1}^{11} \sum_{j=1}^{11} a_{ij}^k$

$x^* = arg \max_x a^k$ (gradient ascent)



For each filter

$\frac{\partial a^k}{\partial x_{ij}}$



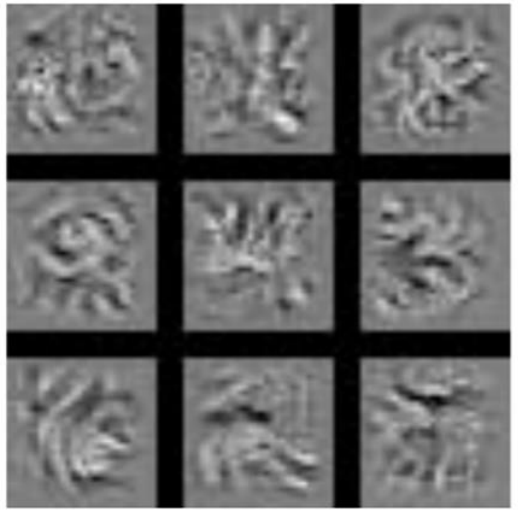
How to implement this in PyTorch?

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

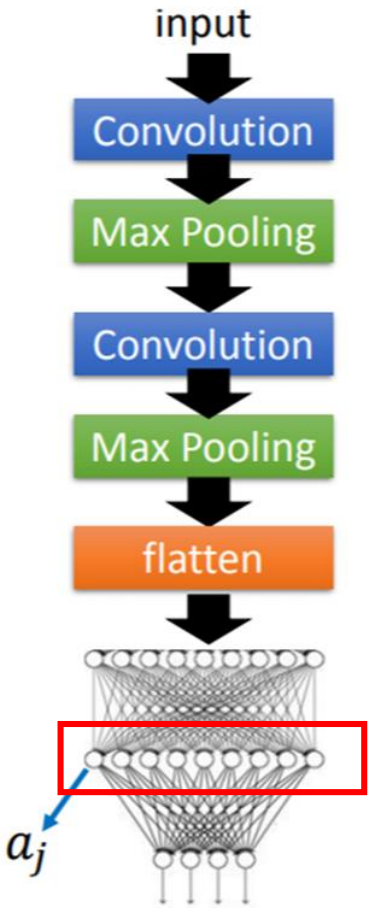
In the hidden layer of the fully-connected NN, each neuron detects an overall pattern in the picture rather than a particular texture pattern.

Find an image maximizing the output of neuron:

$$x^* = arg \max_x a^j$$



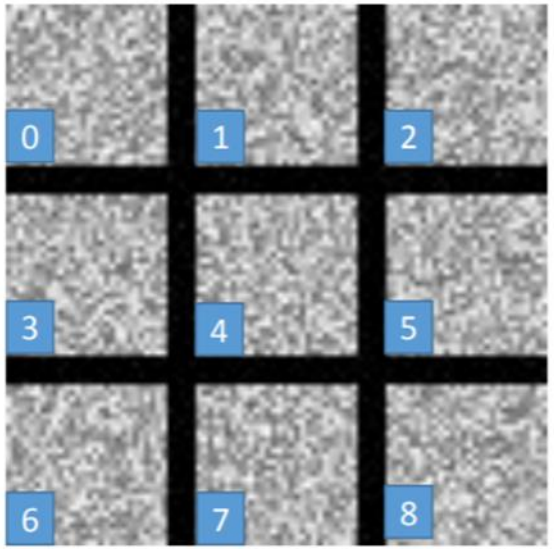
Each figure corresponds to a neuron



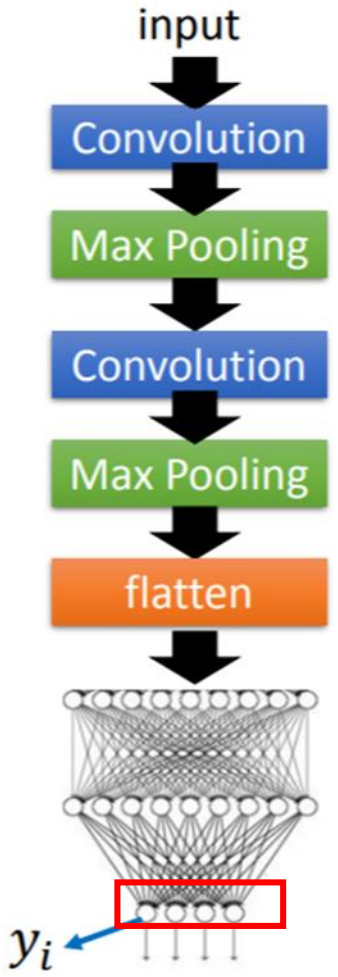
Reference: 李弘毅 ML Lecture 10 https://youtu.be/FrKWiRv254g

If we watch the output layer node, it is easy to see that CNN is easily fooled.

$x^* = arg\max_x y^i$ Can we see digits?



Deep Neural Networks are Easily Fooled
https://www.youtube.com/watch?v=M2IebCN9Ht4



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

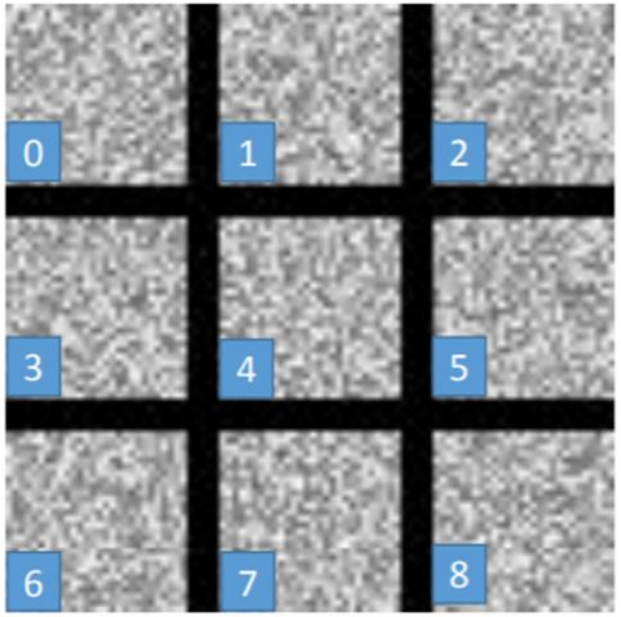
Adding regularization to the objective function to force most pixels be "NO INK"

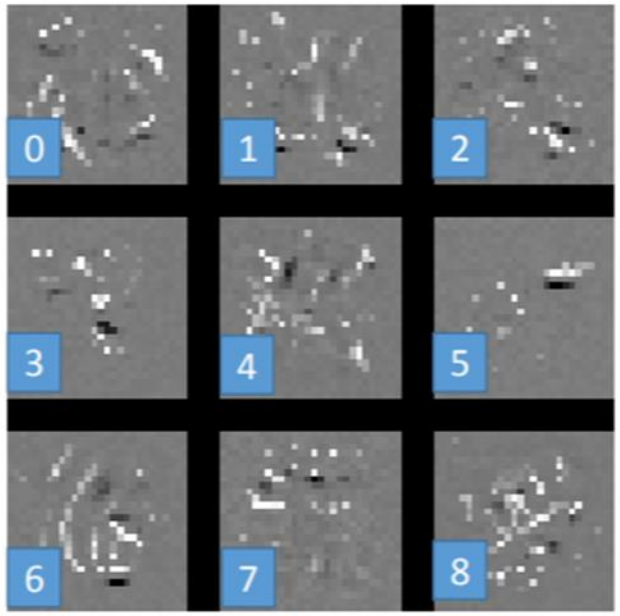
$$x^* = arg\max_x y^i$$

$$x^* = arg\max_x \left(y^i - \sum_{i,j} |x_{ij}| \right)$$

Over all pixel values

Here white pixels indicate ink, and black pixels indicate “NO INK”.



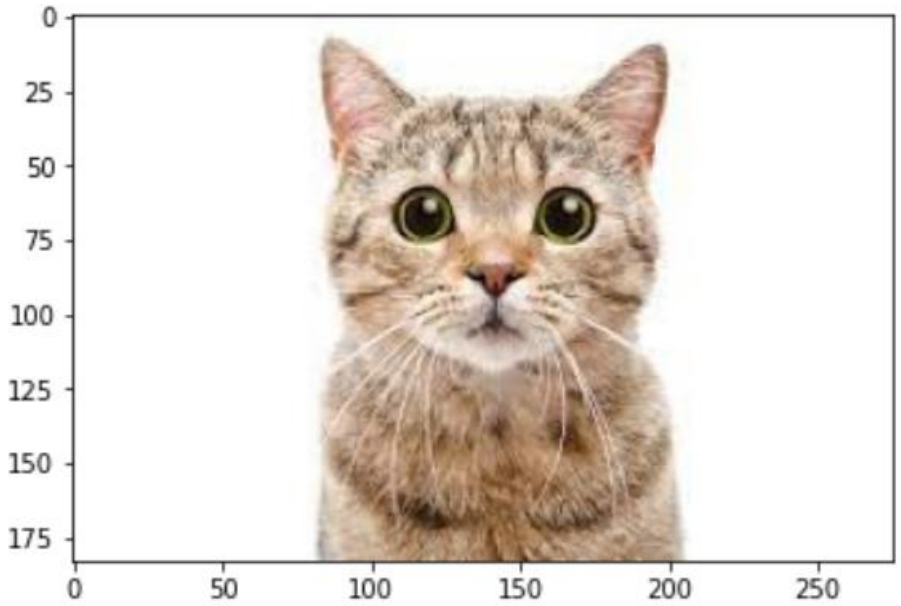


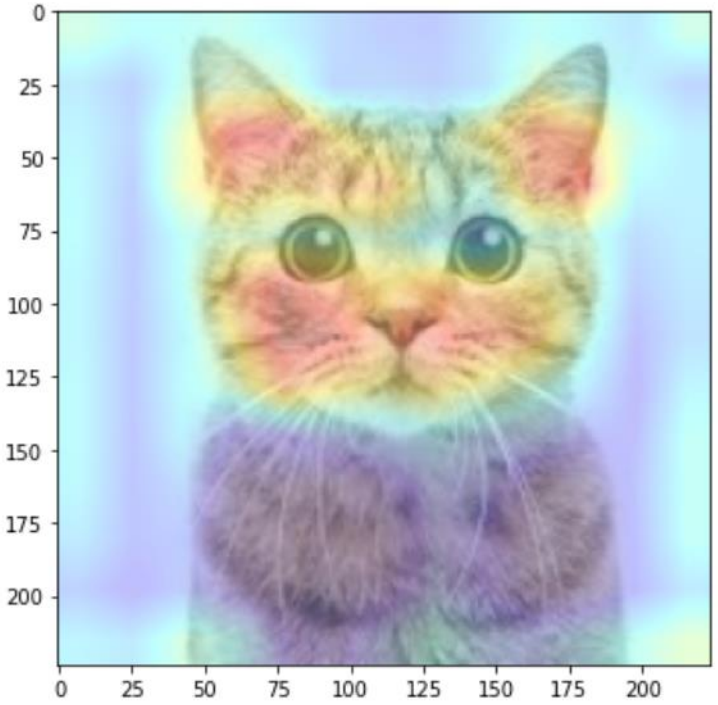
L1 regularization to force xij=0, i.e., force most pixels to be black, NO INK (as only small part of the image has ink)

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

Practice – What does CNN learn?

- Run “7.3 GradCAM.ipynb"





HW4

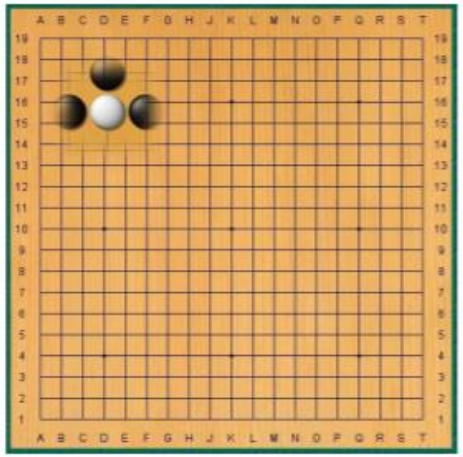
	Class index predicted by the model	Class index you assigned
AlexNet		
VGG		
ResNet18		

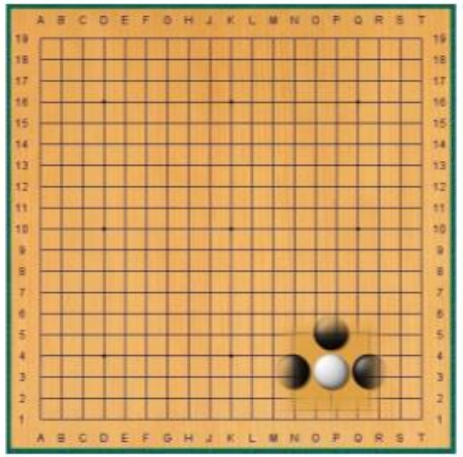
Use CNN in Alpha GO

- Some patterns are much smaller than the whole image

  Alpha Go uses 5 x 5 for first layer

- The same patterns appear in different regions.





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

Use CNN in Alpha GO

Neural network architecture. The input to the policy network is a $19 \times 19 \times 48$ image stack consisting of 48 feature planes. The first hidden layer zero pads the input into a 23×23 image, then convolves k filters of kernel size 5×5 with stride 1 with the input image and applies a rectifier nonlinearity. Each of the subsequent hidden layers 2 to 12 zero pads the respective previous hidden layer into a 21×21 image, then convolves k filters of kernel size 3×3 with stride 1, again followed by a rectifier nonlinearity. The final layer convolves 1 filter of kernel size 1×1 with stride 1, with a different bias for each position, and applies a softmax function. The Extended Data Table 3 additionally show the results of training with $k = 128$, 256 and 384 filters.

Alpha Go does not use Max Pooling .....

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