Lecture 9

Convolution Neural Network

Image Classification

100×100

Model

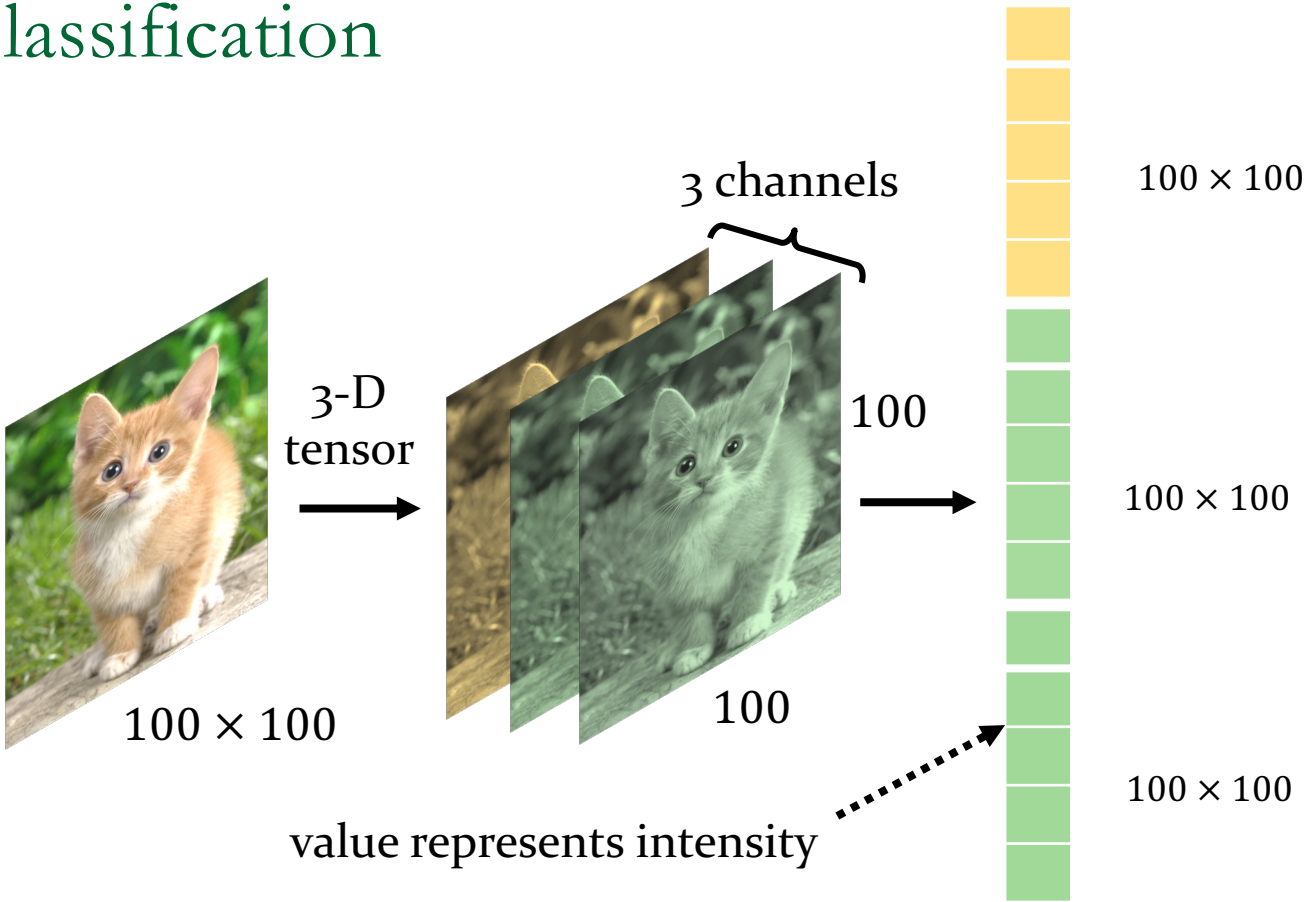
$$\begin{bmatrix} \vdots \\ 0.2 \\ 0.7 \\ 0.1 \\ \vdots \end{bmatrix} \quad y'$$

$$\begin{matrix} \\ \text{dog} \\ \text{cat} \\ \text{tree} \\ \\ \end{matrix} \begin{bmatrix} \vdots \\ 0 \\ 1 \\ 0 \\ \vdots \end{bmatrix} \quad \hat{y}$$

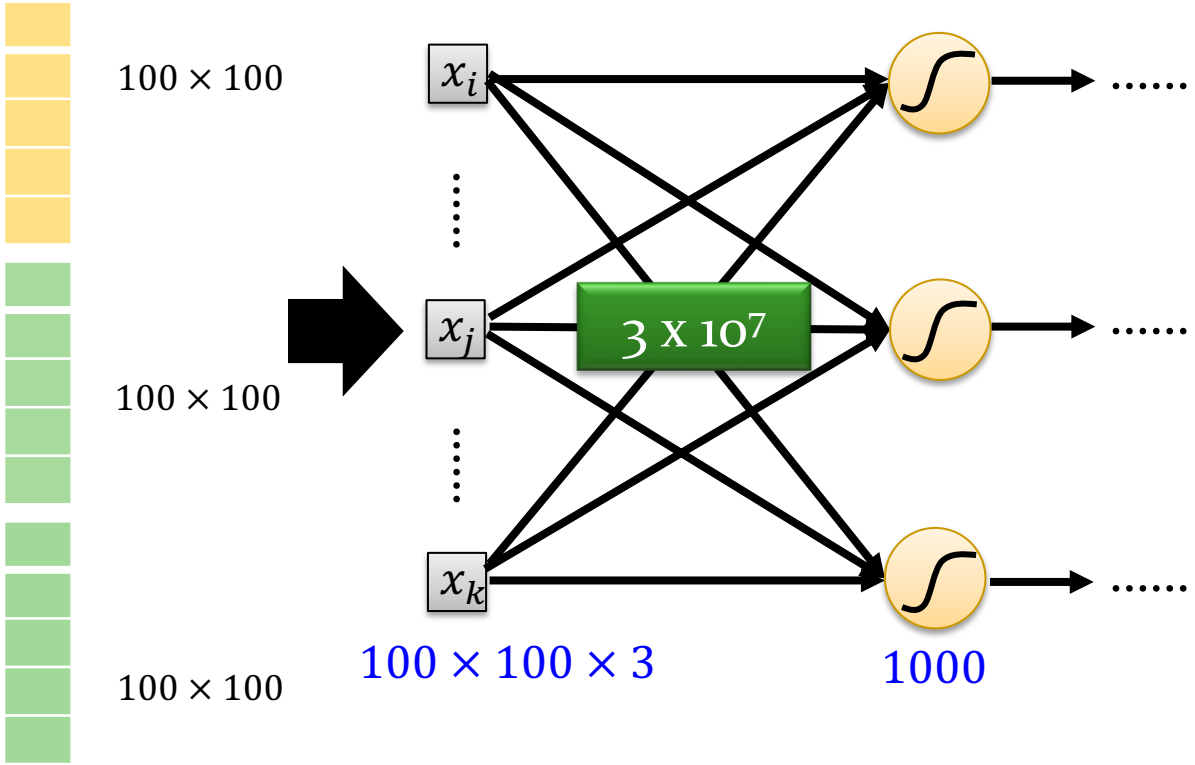
Cross entropy

(All the images to be classified have the same size.)

Image Classification

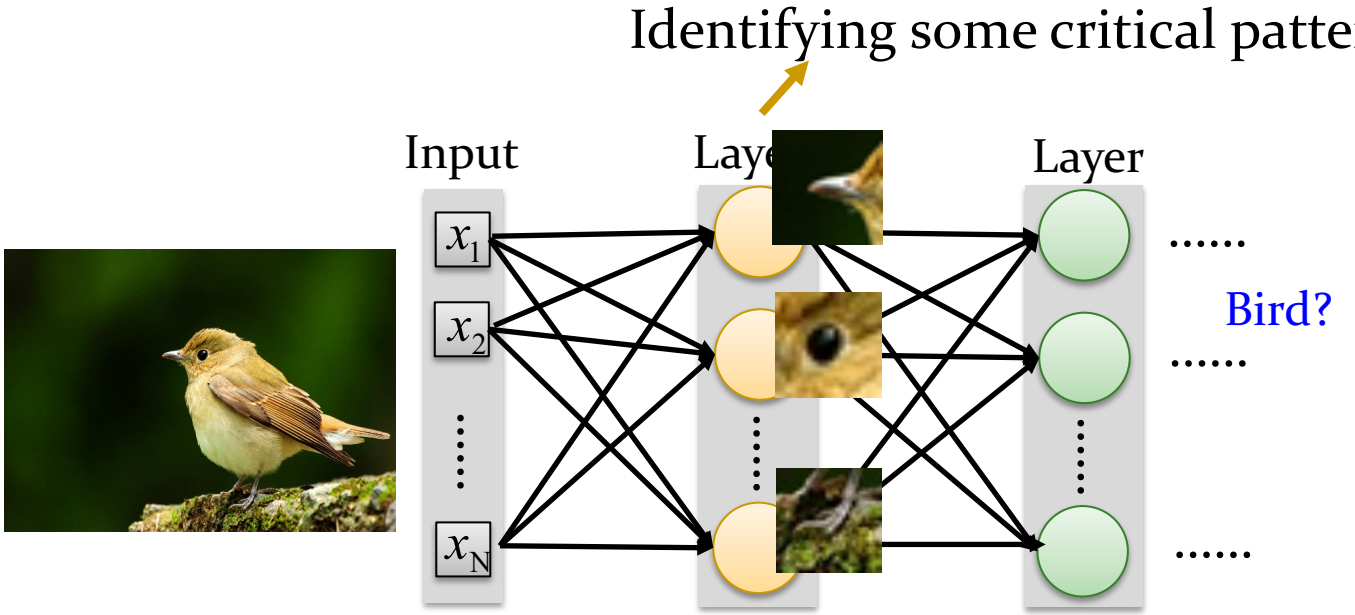


Fully Connected Network



Do we really need "fully connected" in image processing?

Observation 1

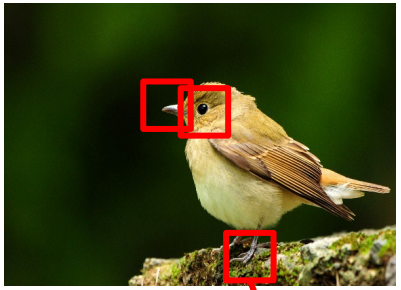


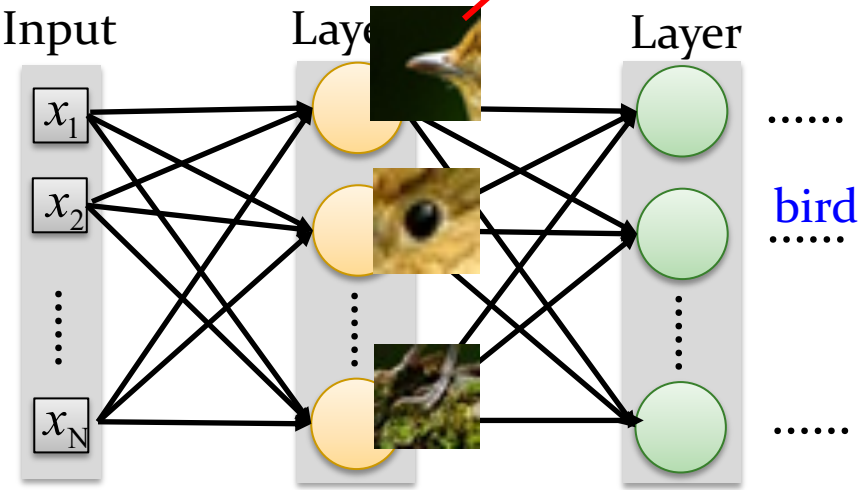
Perhaps human also identify birds in a similar way … ☺

Observation 1

A neuron does not have to see the whole image.

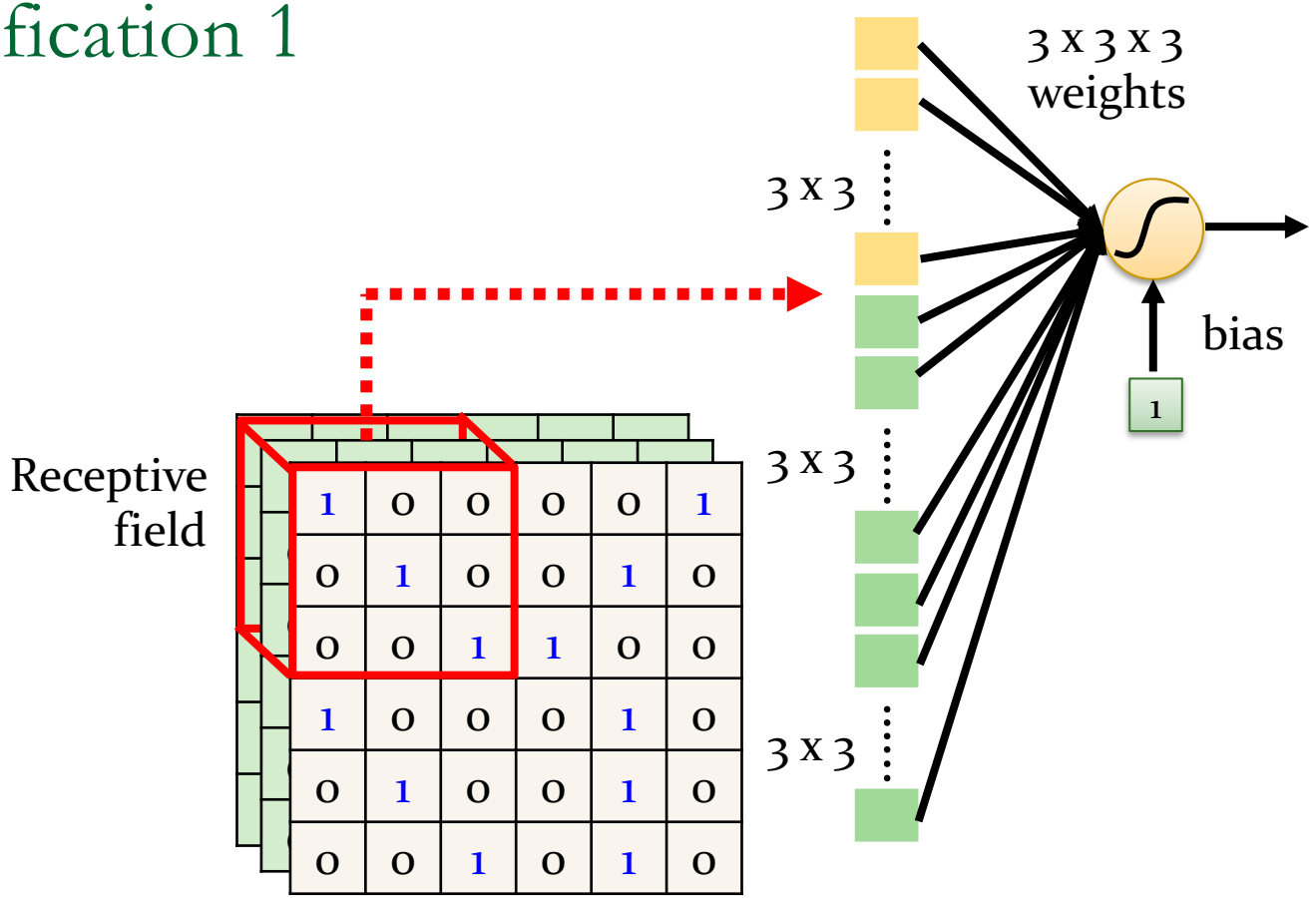
Need to see the whole image?





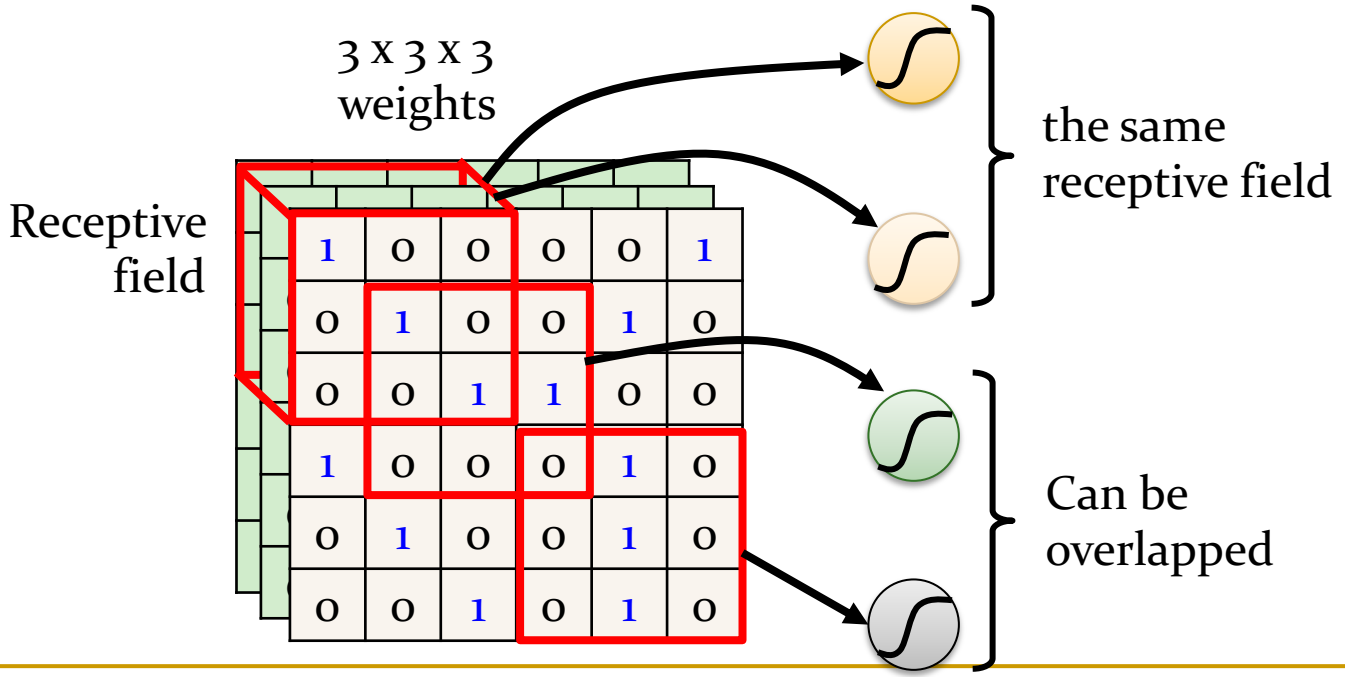
Some patterns are much smaller than the whole image.

Simplification 1



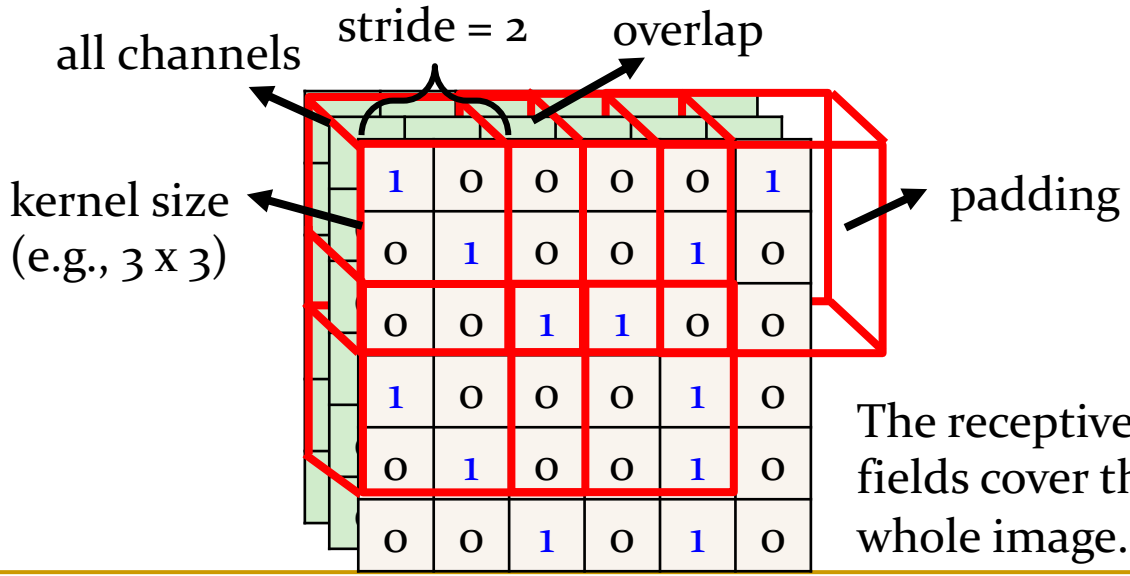
Simplification 1

- Can different neurons have different sizes of receptive field?
- Cover only some channels?
- Not square receptive field?



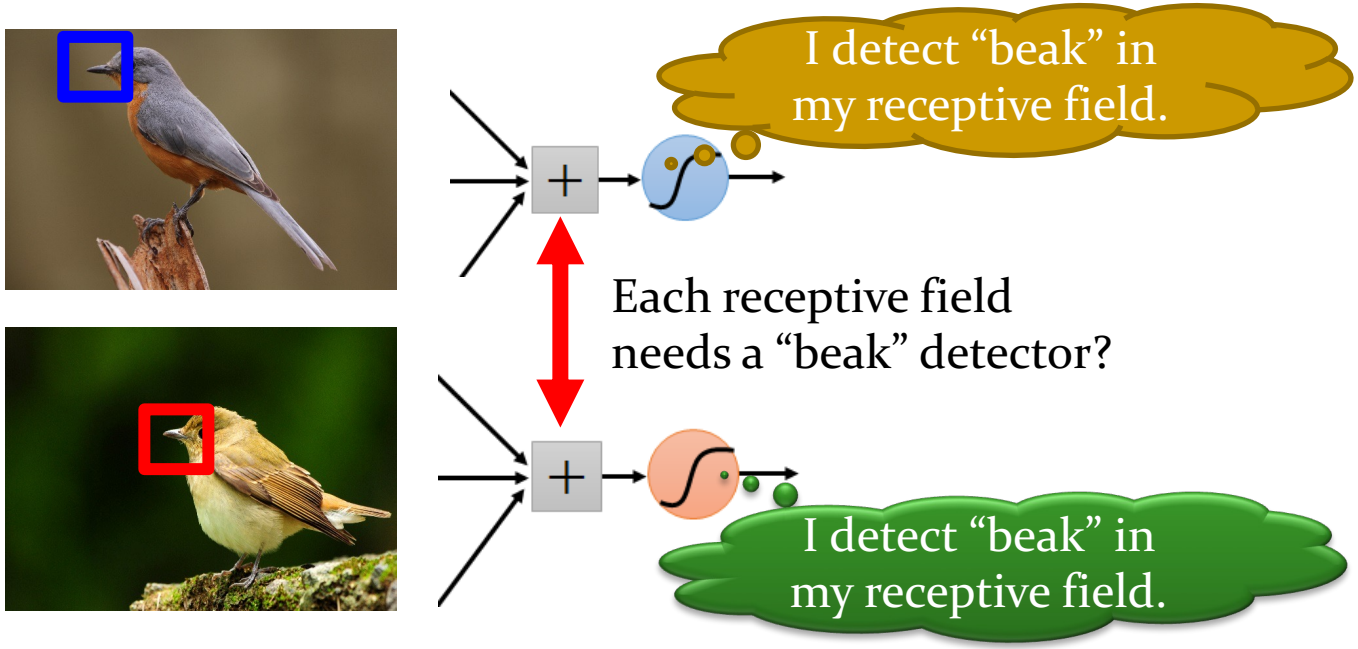
Simplification 1 – Typical Setting

Each receptive field has a set of neurons (e.g., 64 neurons).

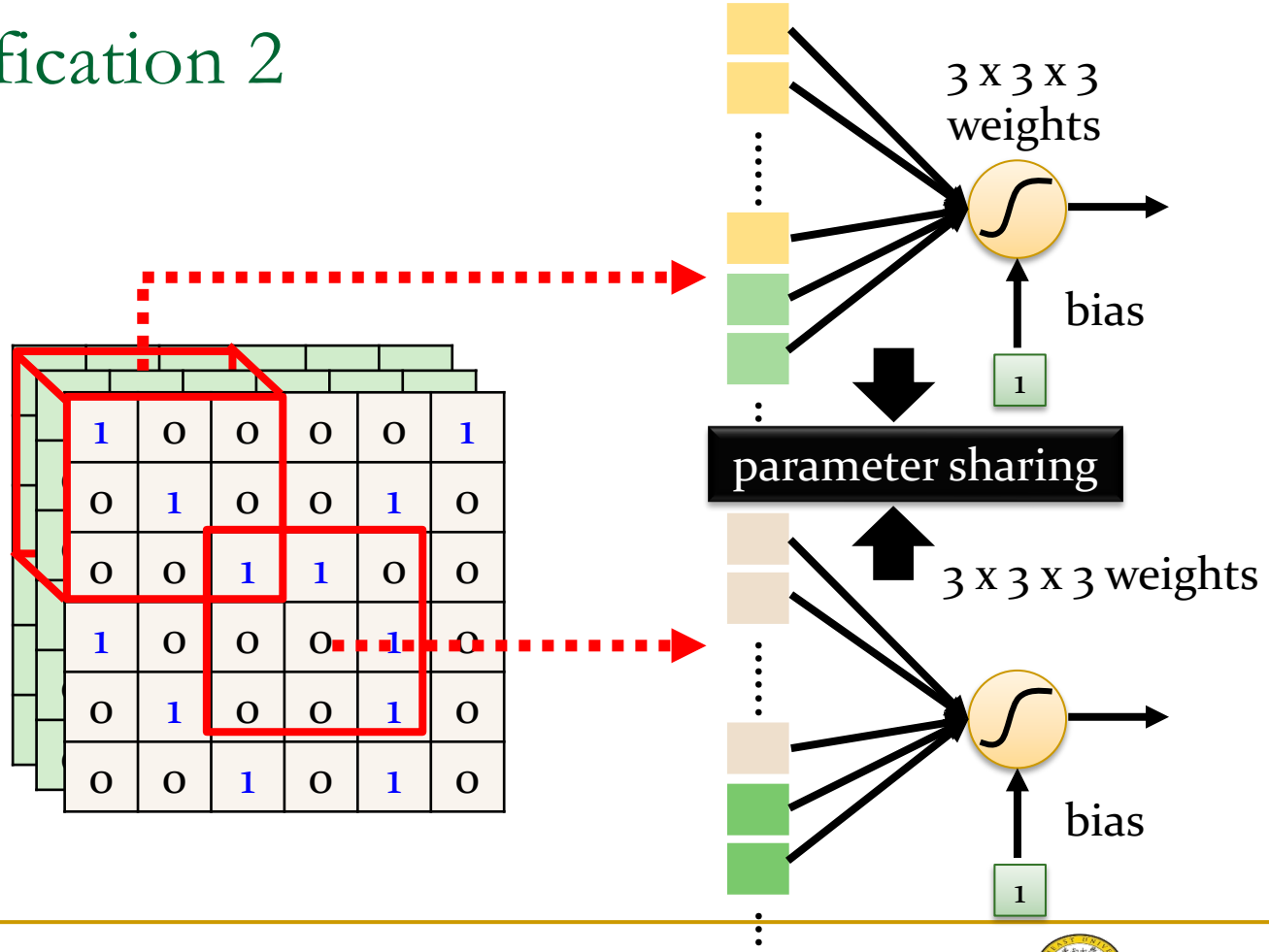


Observation 2

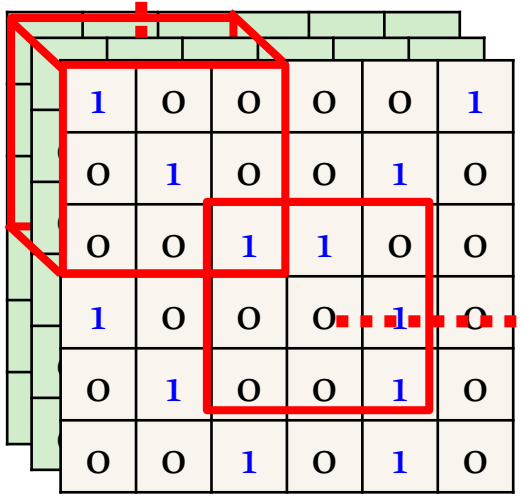
- The same patterns appear in different regions.

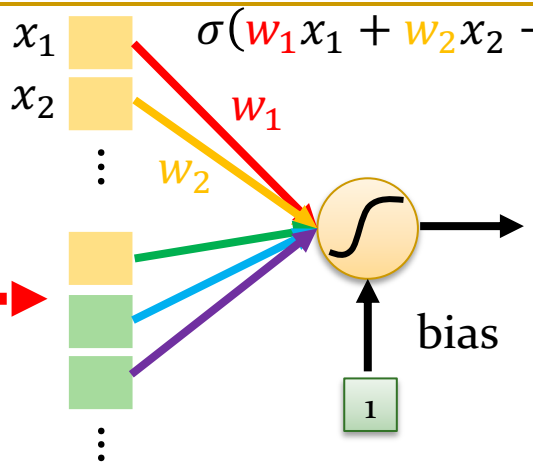


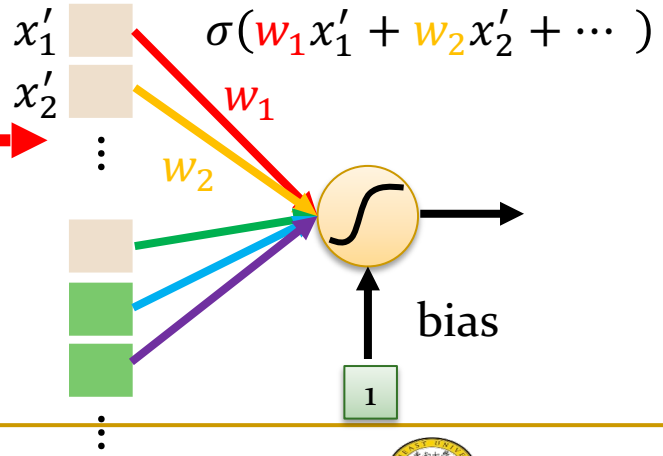
Simplification 2



Simplification 2



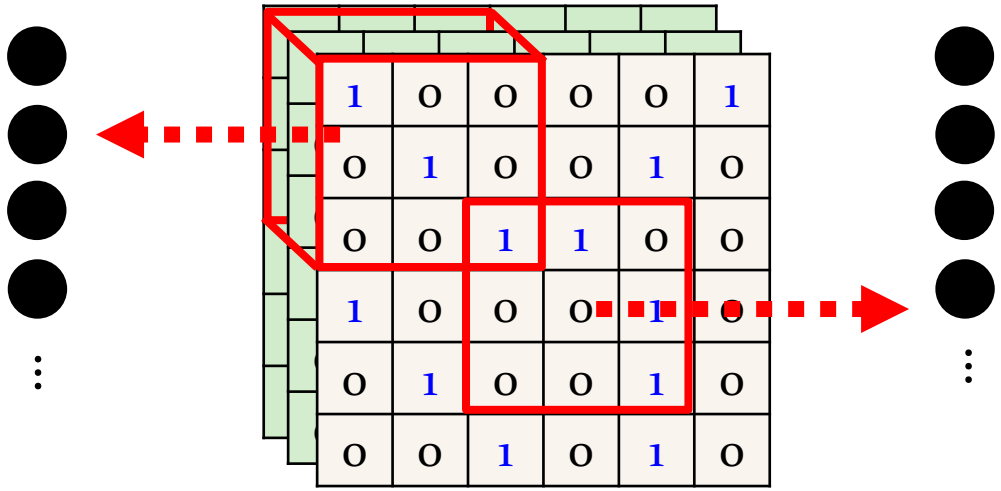




Two neurons with the same receptive field would not share parameters.

Simplification 2 – Typical Setting

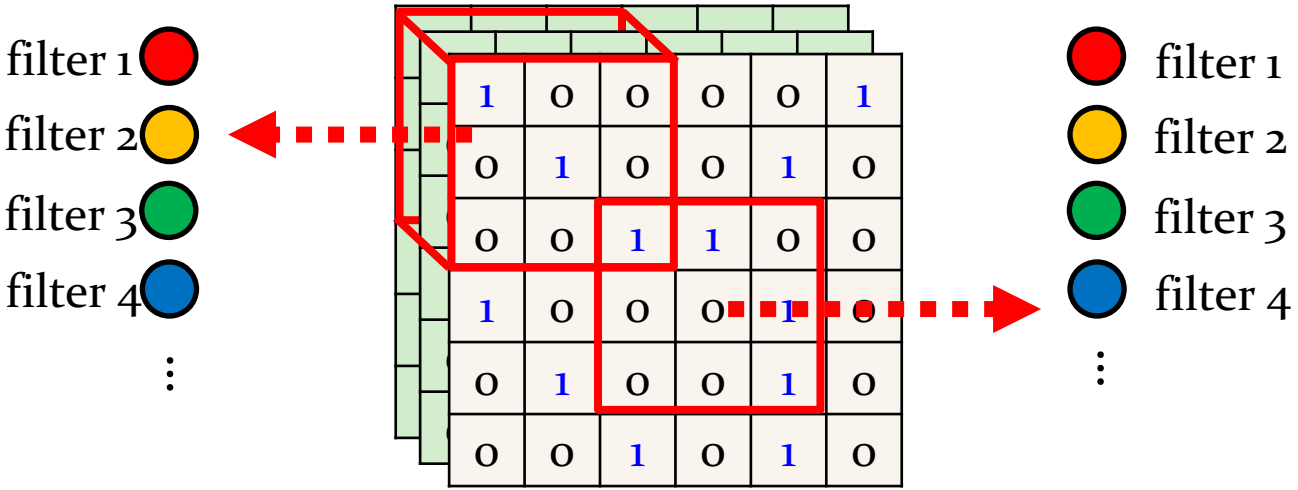
Each receptive field has a set of neurons (e.g., 64 neurons).



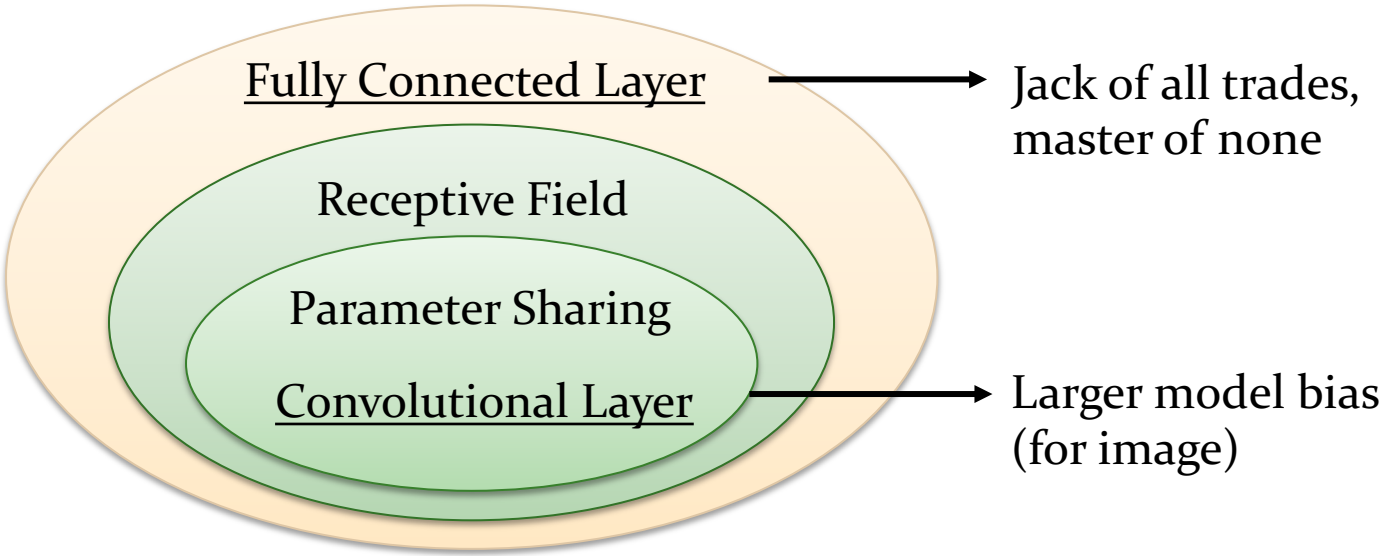
Simplification 2 – Typical Setting

Each receptive field has a set of neurons (e.g., 64 neurons).

Each receptive field has the neurons with the same set of parameters.



Benefit of Convolutional Layer



- Some patterns are much smaller than the whole image.
- The same patterns appear in different regions.

Convolutional Layer

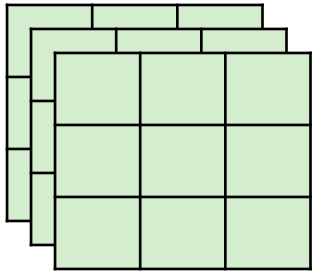
Another story based on filter ☺

Convolution

channel = 3 (colorful)

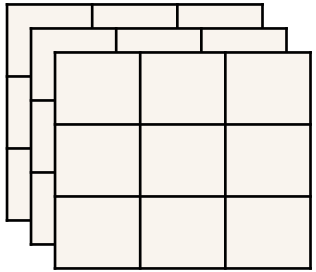
channel = 1 (black and white)

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



Filter 1

3 x 3 x channel tensor

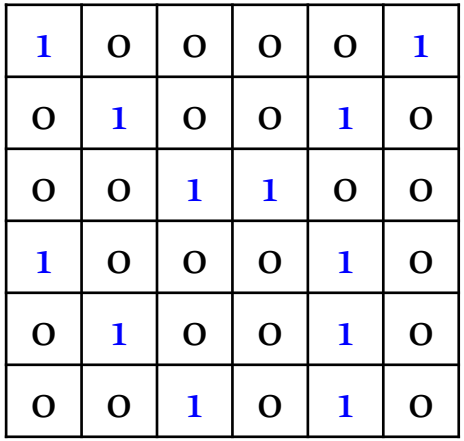


Filter 2

3 x 3 x channel tensor

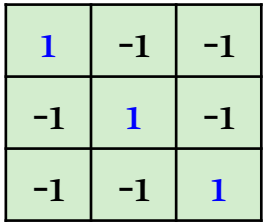
Convolutional Layer

Consider channel = 1
(black and white image)



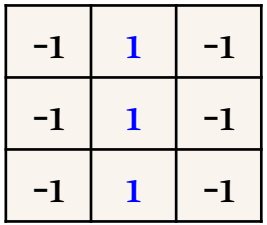
1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image



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

Filter 1



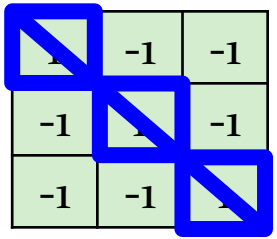
-1	1	-1
-1	1	-1
-1	1	-1

Filter 2

⋮ ⋮

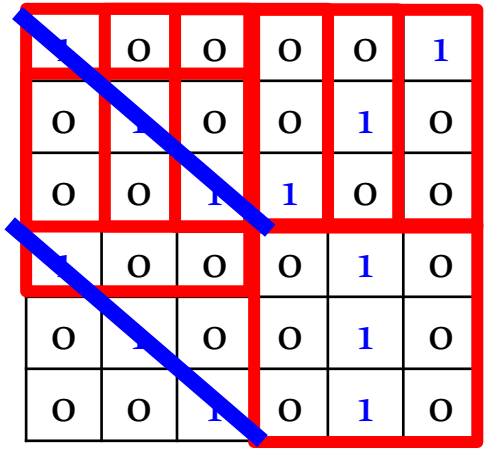
(The values in the filters are unknown parameters.)

Convolutional Layer

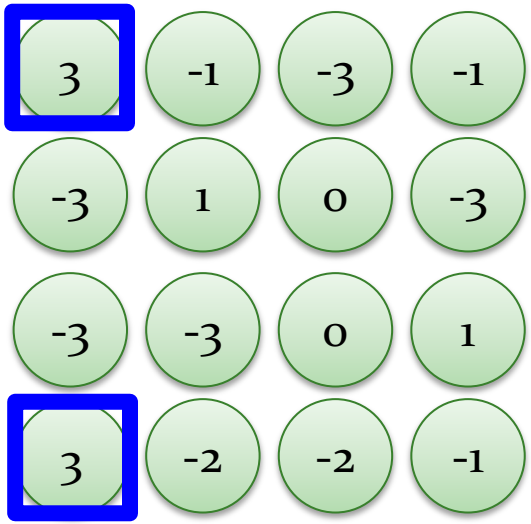


Filter 1

stride=1



6 x 6 image



Convolutional Layer

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

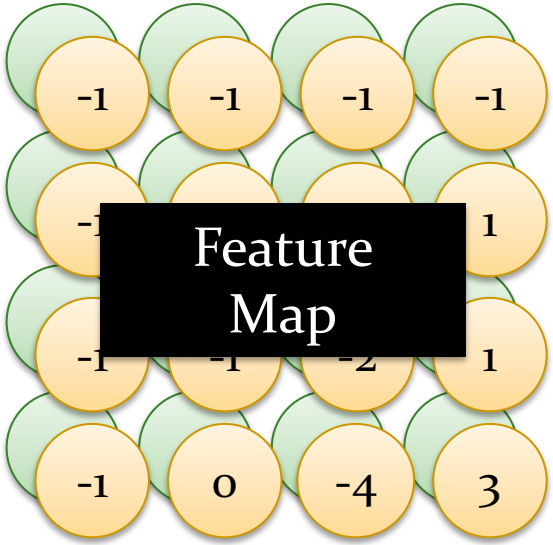
Filter 2

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

Do the same process for every filter

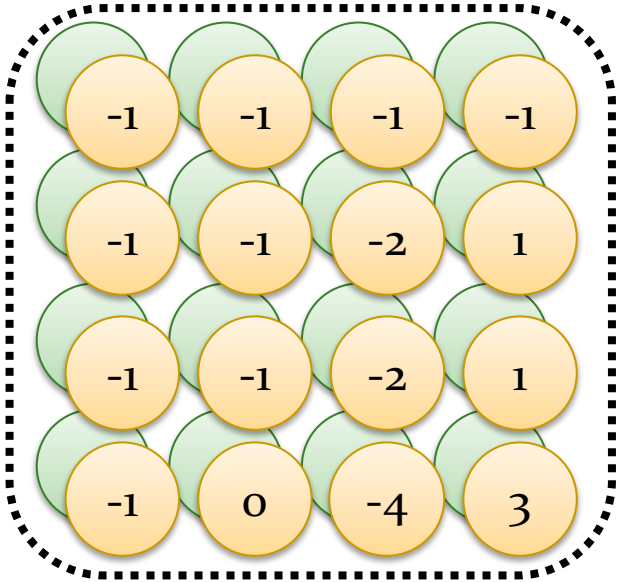


Convolutional Layer

64 filters

Convolution

Convolution



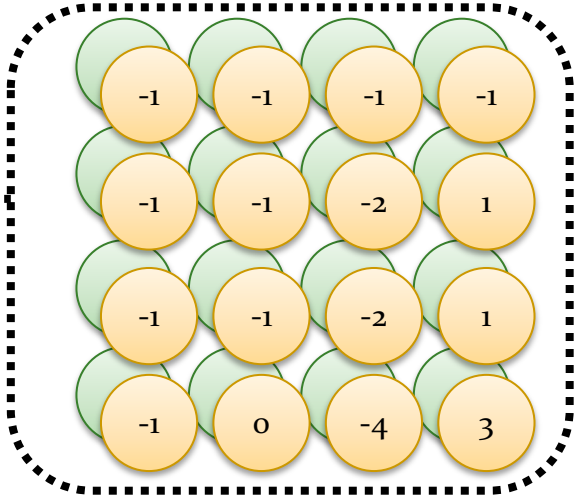
"Image" with 64 channels

Multiple Convolutional Layer

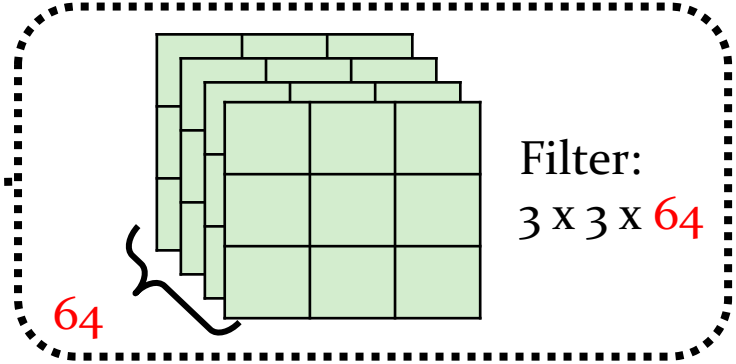
64 filters

Convolution

Convolution



"Image" with 64 channels

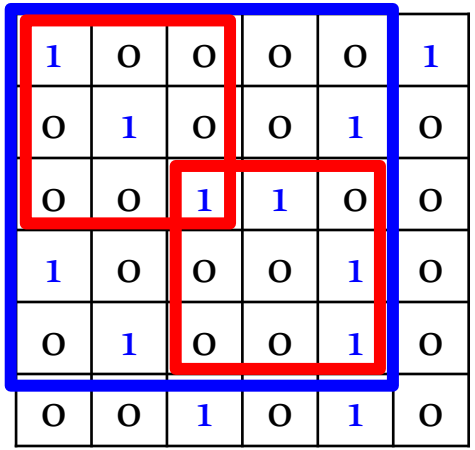


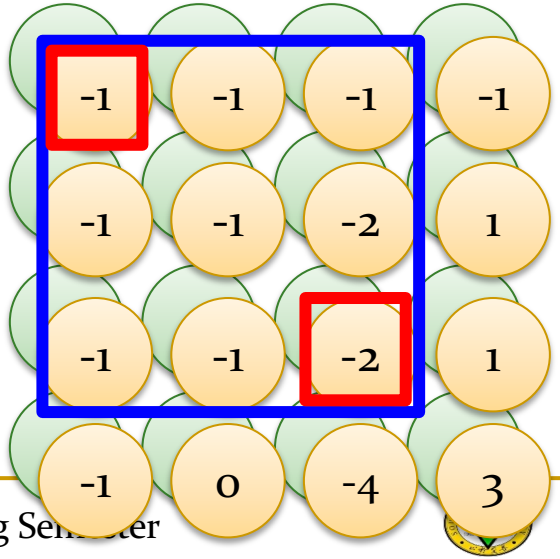
Multiple Convolutional Layer

64 filters

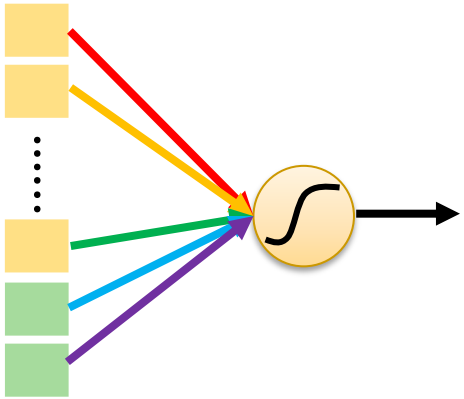
Convolution

Convolution

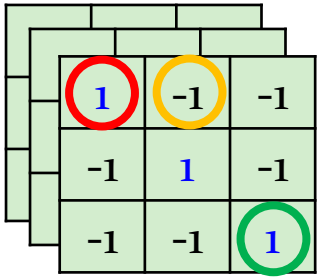




Comparison of Two Stories



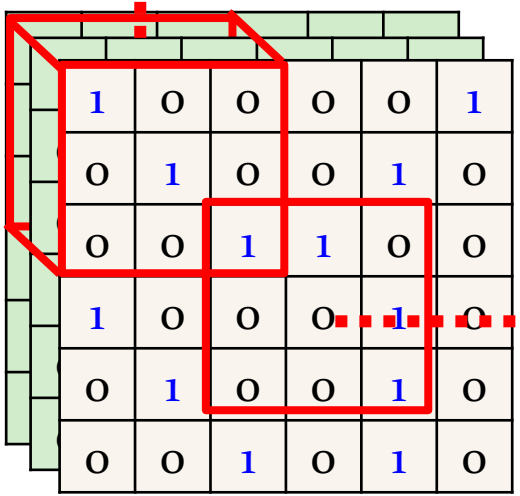
Receptive field



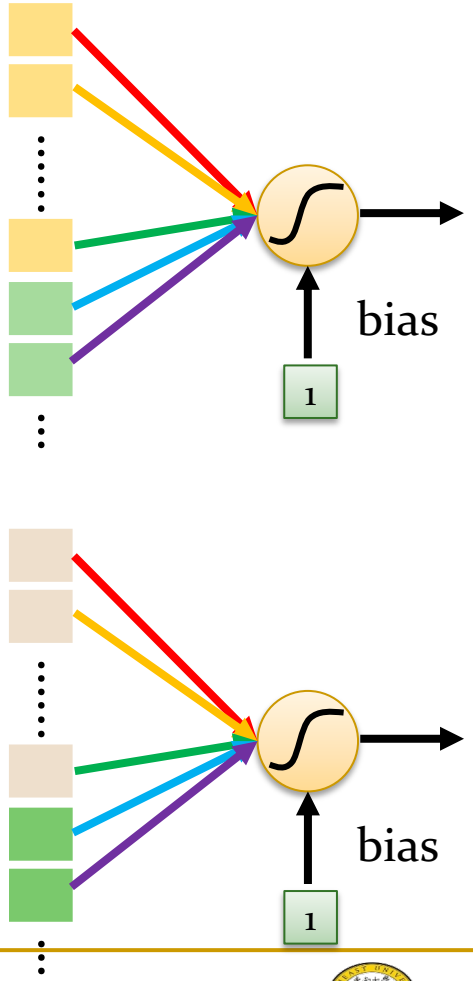
Filter
3 × 3 × channel
tensor

(ignore bias in this slide)

The neurons with different receptive fields share the parameters.



Each filter convolves over the input image.



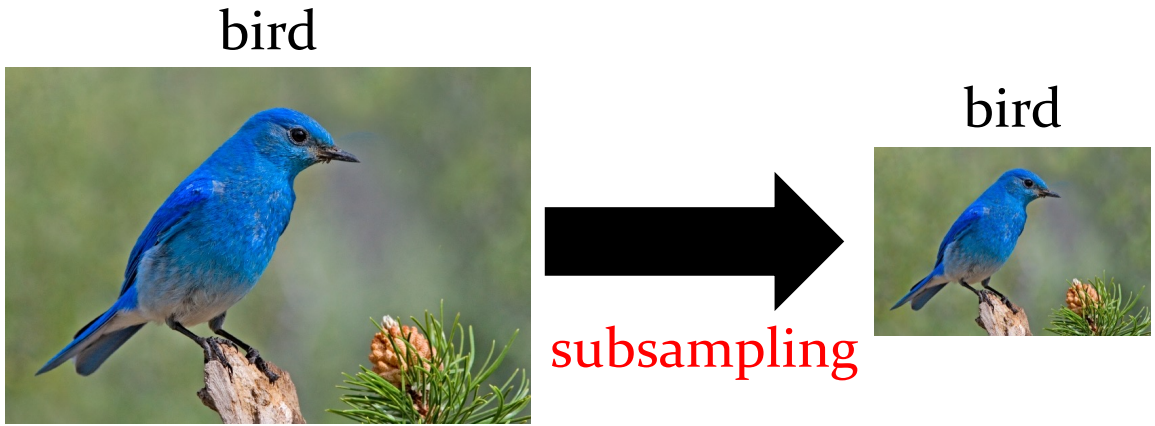
Convolutional Layer

Neuron Version Story	Filter Version Story
Each neuron only considers a receptive field.	There are a set of filters detecting small patterns.
The neurons with different receptive fields share the parameters.	Each filter convolves over the input image.

They are the same story.

Observation 3

- Subsampling the pixels will not change the object



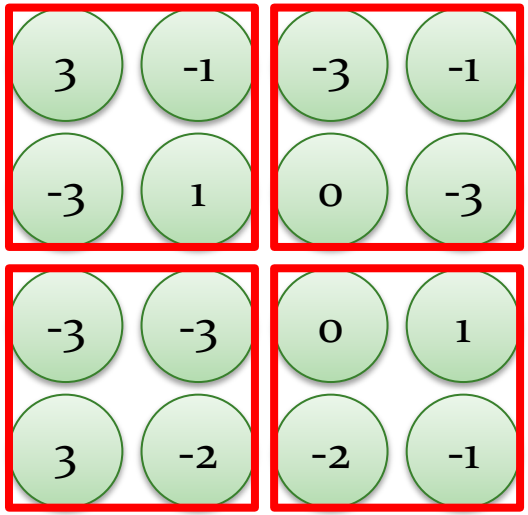
Pooling – Max Pooling

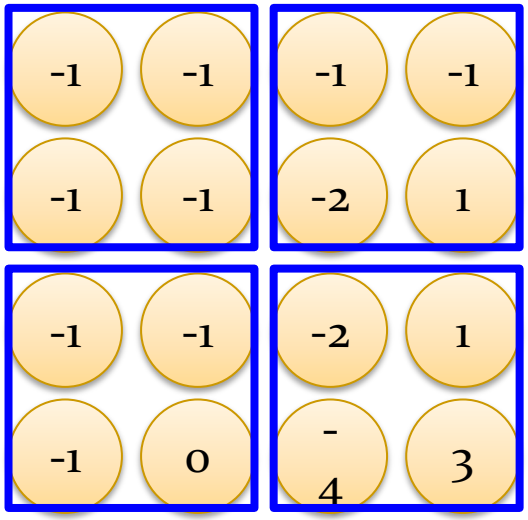
1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

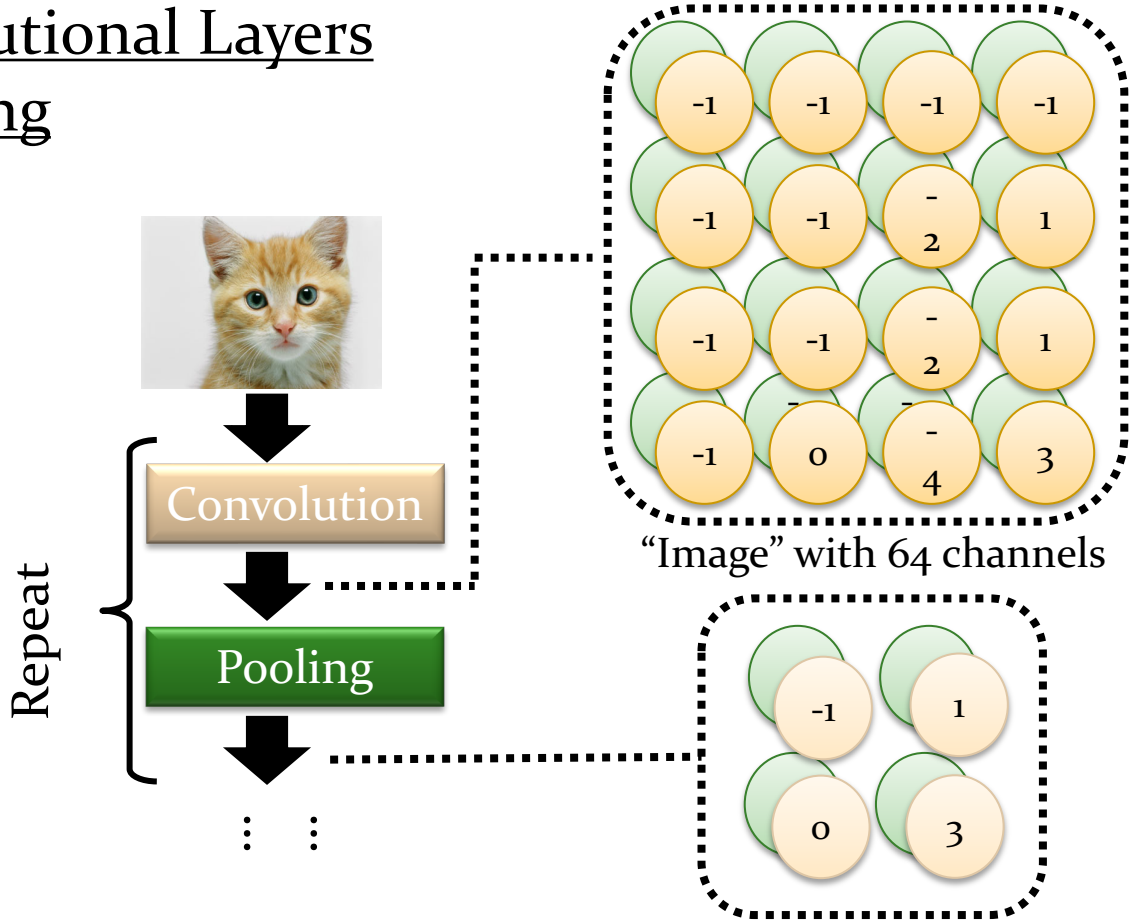
-1	1	-1
-1	1	-1
-1	1	-1

Filter 2

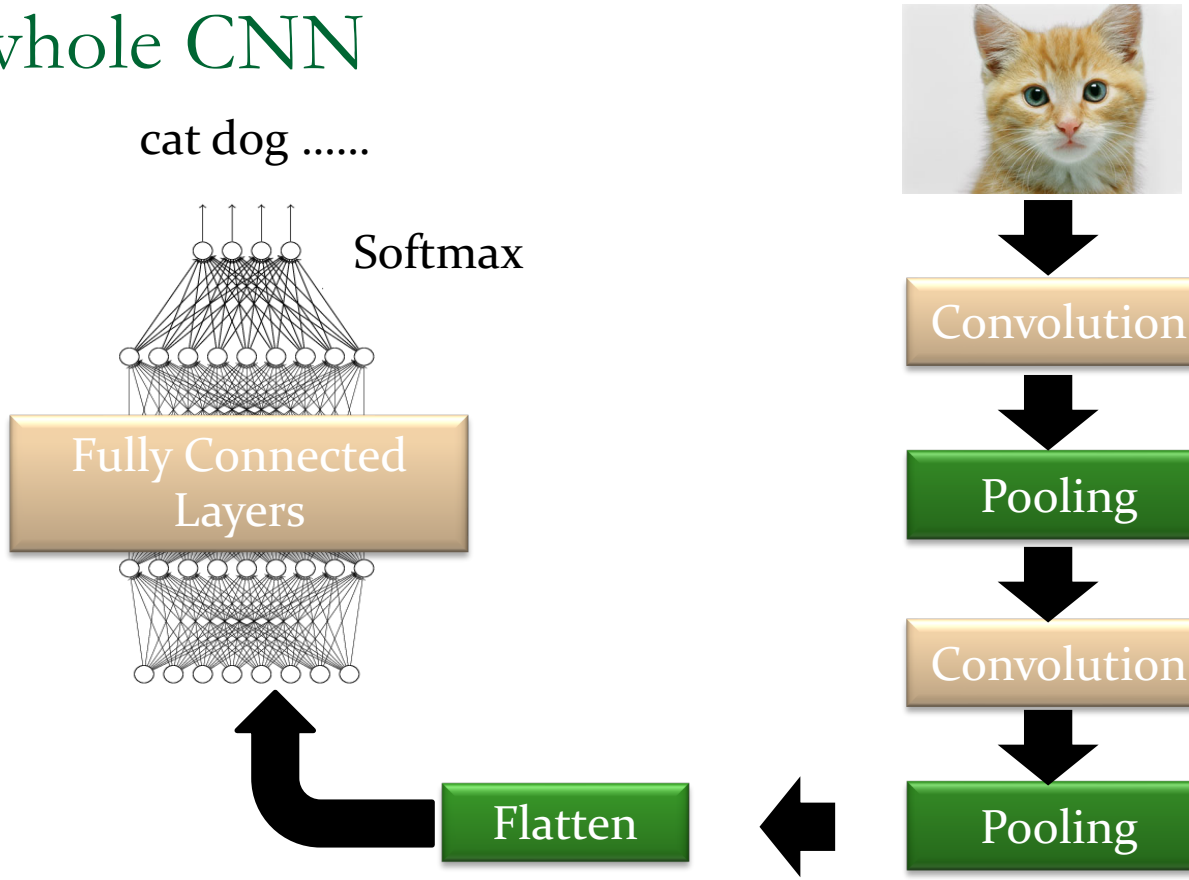




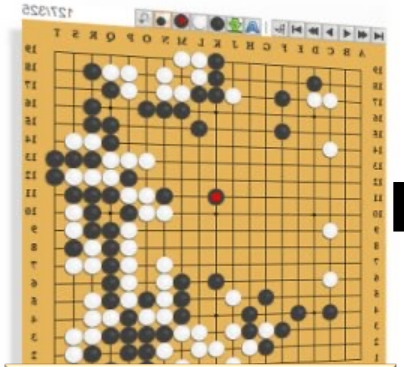
Convolutional Layers + Pooling



The whole CNN



Application: Playing Go



19 × 19 matrix (image)

Network

Next move (19 × 19 positions)

19 × 19 classes

48 channels in Alpha Go

Black: 1

white: −1

none: 0

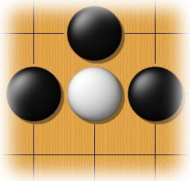
Fully-connected network can be used

But CNN performs much better.

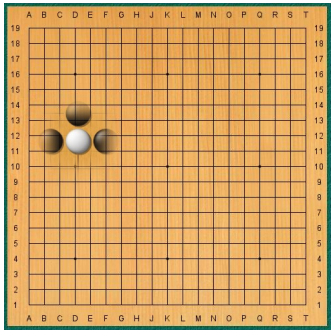
Why CNN for Go playing?

- Some patterns are much smaller than the whole image

Alpha Go uses 5 × 5 for first layer



- The same patterns appear in different regions.



Why CNN for Go playing?

- Subsampling the pixels will not change the object

Pooling

How to explain this???

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 match version of AlphaGo used $k = 192$ filters; Fig. 2b and Extended Data Tabl[illegible] 256 and 384 filters

Alpha Go does not use Pooling .....

```
import torch.nn as nn
import torch.nn.functional as F


class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(3, 6, 5)
        self.pool = nn.MaxPool2d(2, 2)
        self.conv2 = nn.Conv2d(6, 16, 5)
        self.fc1 = nn.Linear(16 * 5 * 5, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)

    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        x = x.view(-1, 16 * 5 * 5)
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x


net = Net()
```

```
import torch.optim as optim

criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(net.parameters(), lr=0.001, momentum=0.9)
```

```
for epoch in range(2):  # 多批次循环


    running_loss = 0.0
    for i, data in enumerate(trainloader, 0):
        # 获取输入
        inputs, labels = data

        # 梯度置0
        optimizer.zero_grad()

        # 正向传播，反向传播，优化
        outputs = net(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()
```

To learn more …

- CNN is not invariant to scaling and rotation (we need data augmentation ☺).

Summary

- RNNs allow a lot of flexibility in architecture design
- Vanilla RNNs are simple but don't work very well
- Backward flow of gradients in RNN can explode or vanish.
- Exploding is controlled with gradient clipping. Vanishing is controlled with additive interactions (LSTM)
- Common to use LSTM or GRU: their additive interactions improve gradient flow
- Better/simpler architectures are a hot topic of current research, as well as new paradigms for reasoning over sequences
- Better understanding (both theoretical and empirical) is needed.