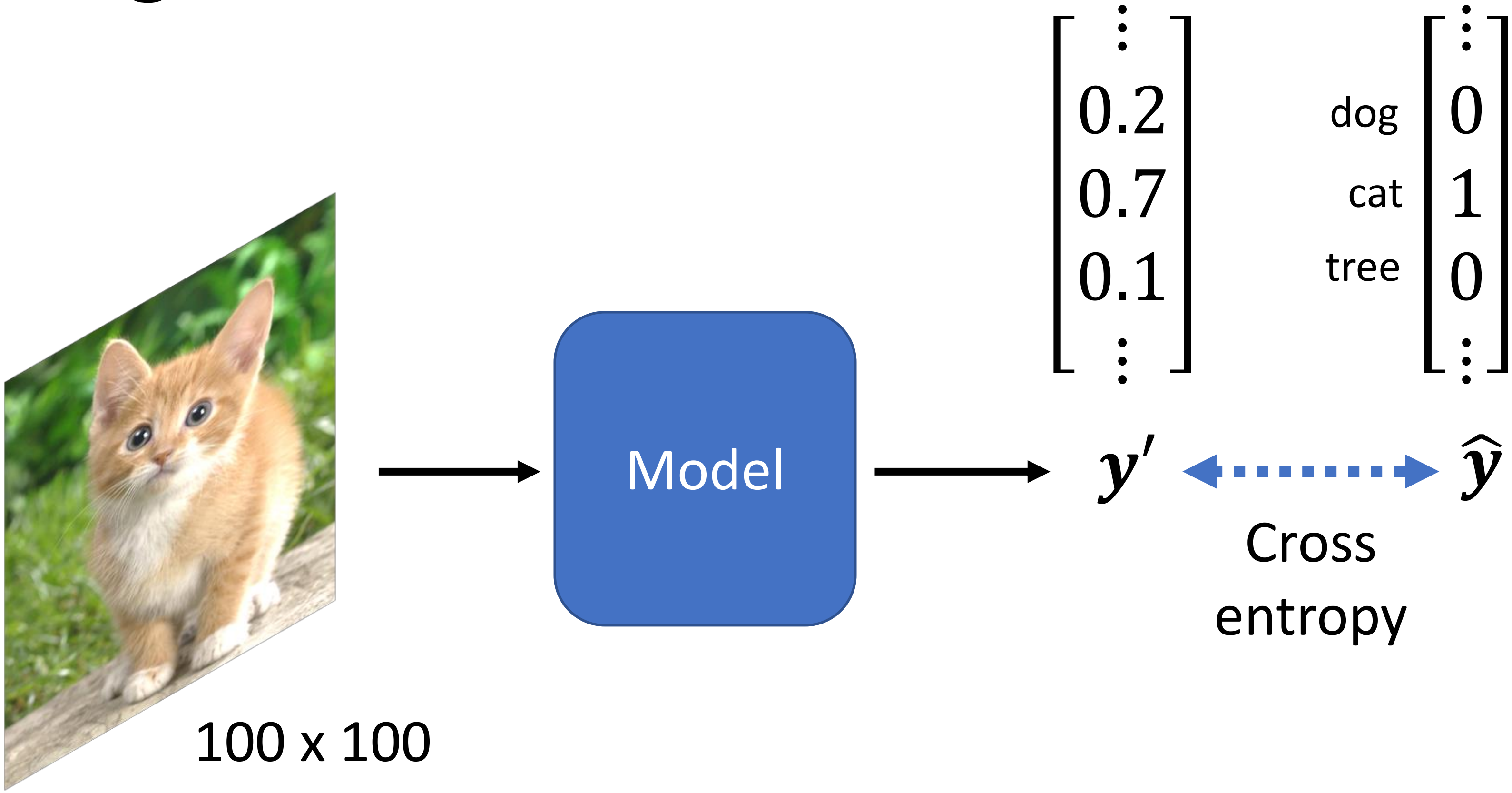
# Convolutional Neural Network (CNN)

Network Architecture designed for Image

# Image Classification



100 x 100

Model

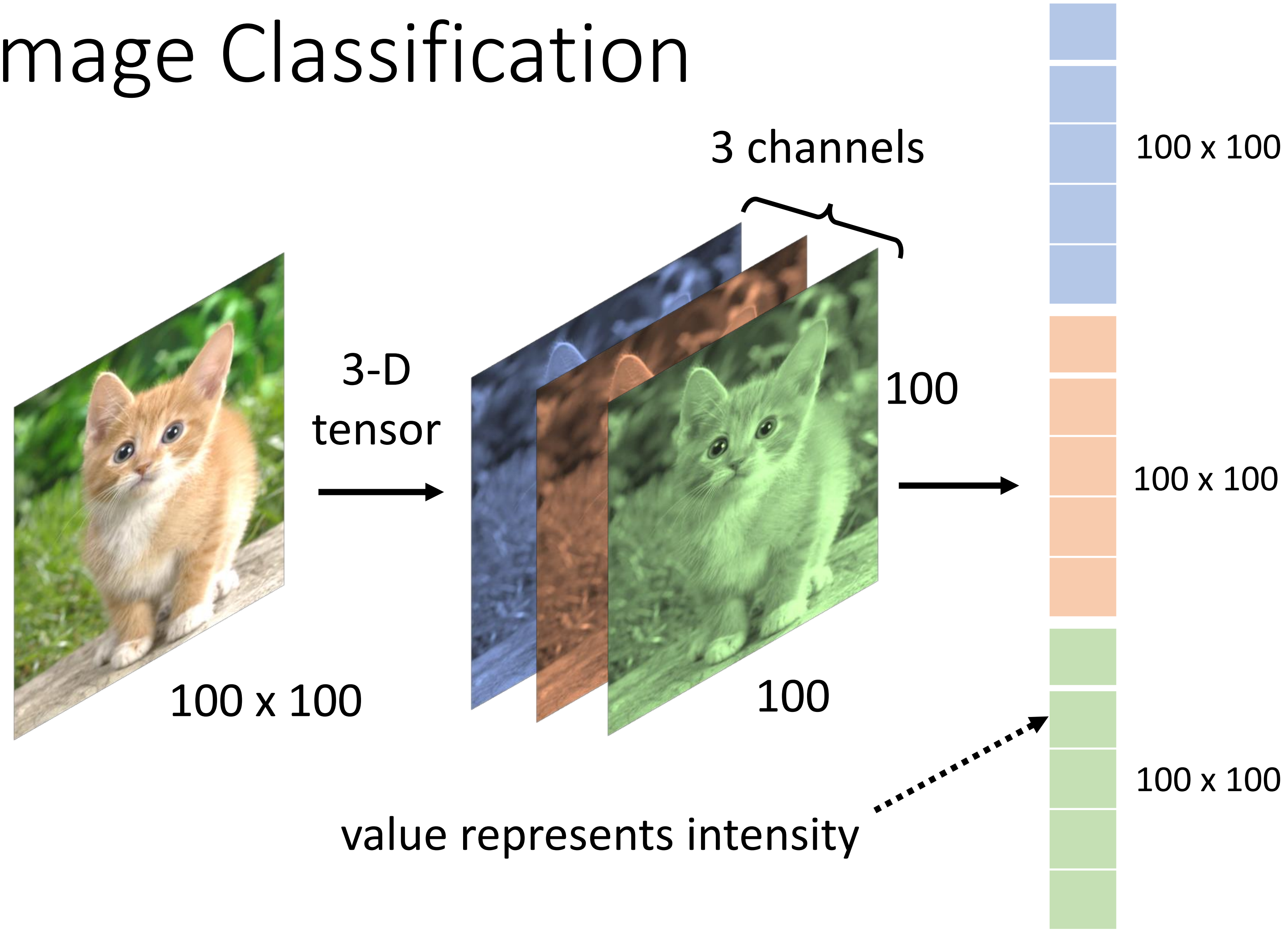
$$\boldsymbol{y}' = \begin{bmatrix} \vdots \\ 0.2 \\ 0.7 \\ 0.1 \\ \vdots \end{bmatrix} \qquad \hat{\boldsymbol{y}} = \begin{array}{r} \\ \text{dog} \\ \text{cat} \\ \text{tree} \\ \\ \end{array} \begin{bmatrix} \vdots \\ 0 \\ 1 \\ 0 \\ \vdots \end{bmatrix}$$

$\boldsymbol{y}'$ $\longleftrightarrow$ $\hat{\boldsymbol{y}}$

Cross entropy

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

# Image Classification



3-D tensor

100 x 100

3 channels

100

100

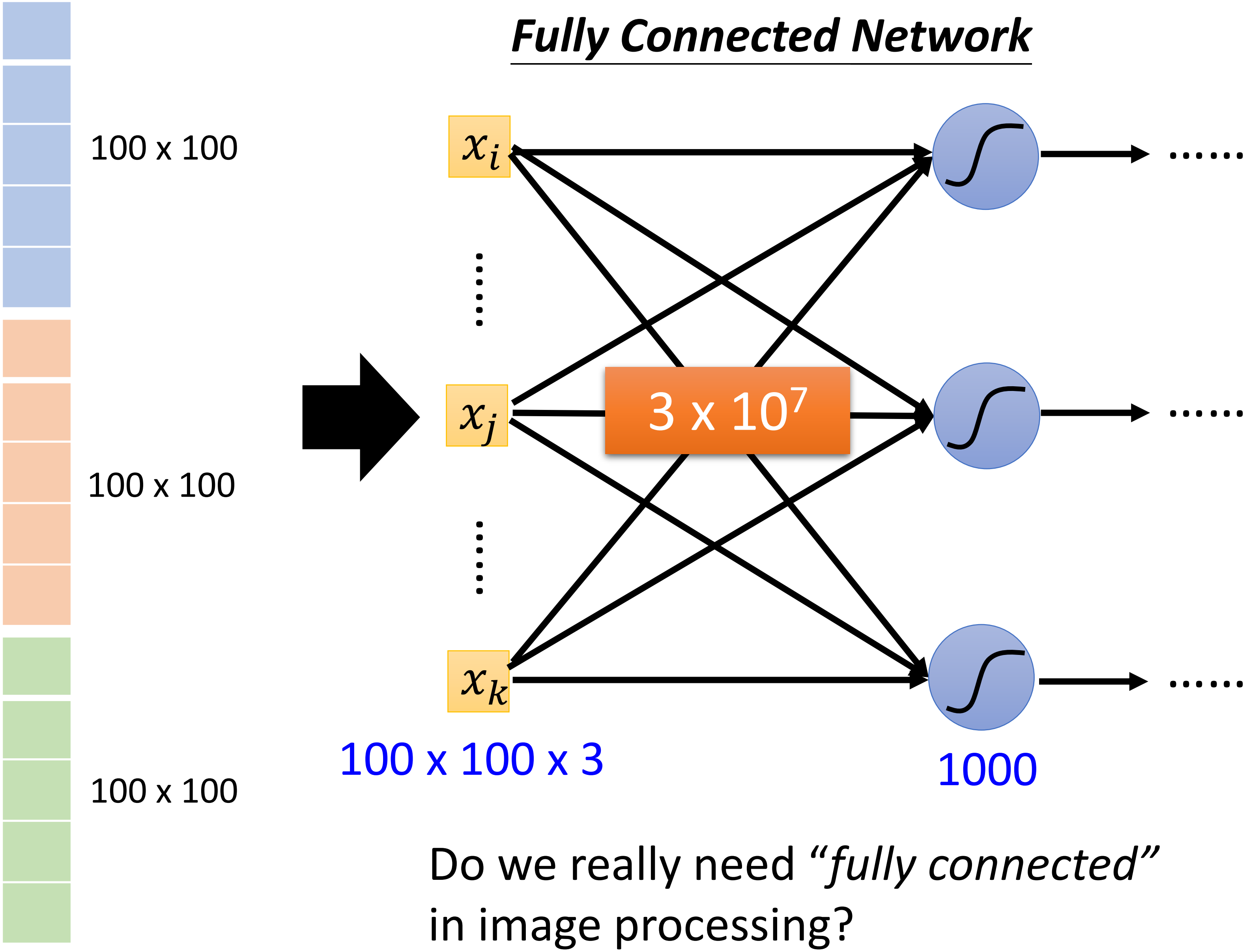
100 x 100

100 x 100

100 x 100

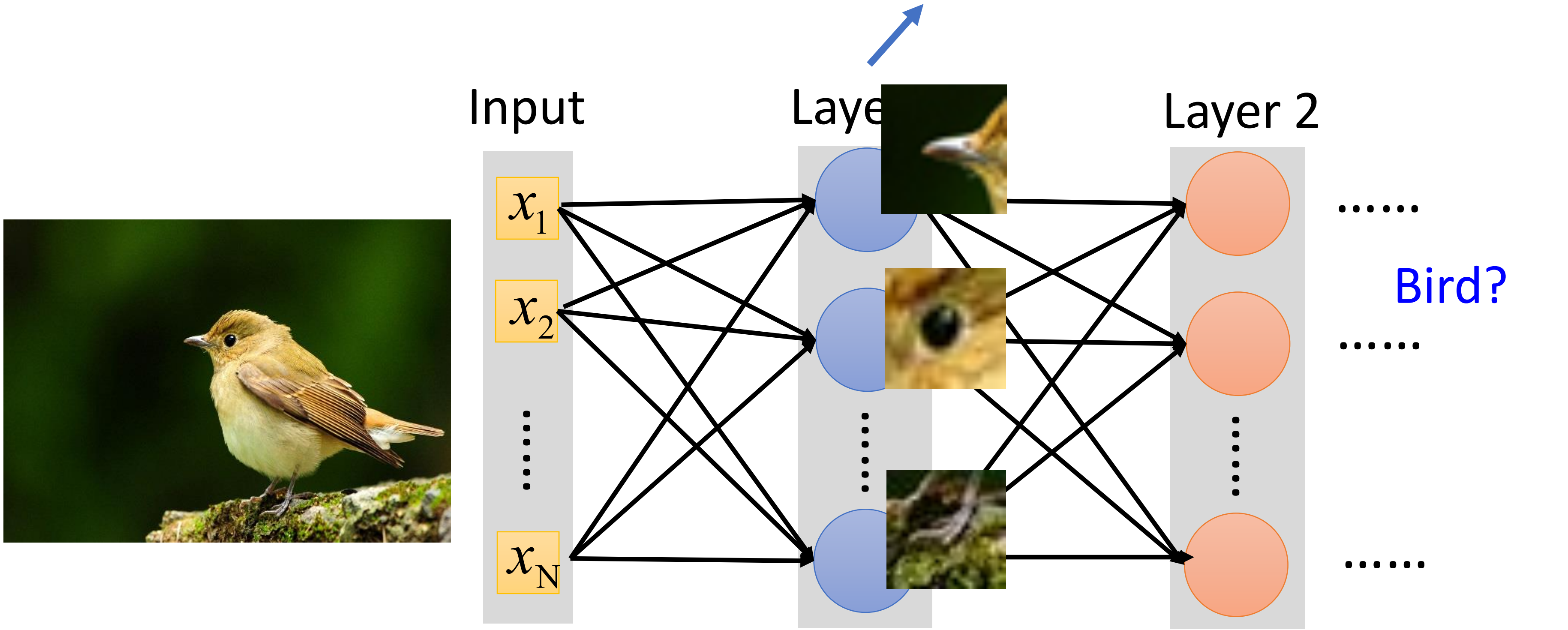
value represents intensity

# ***Fully Connected Network***



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

# Observation 1



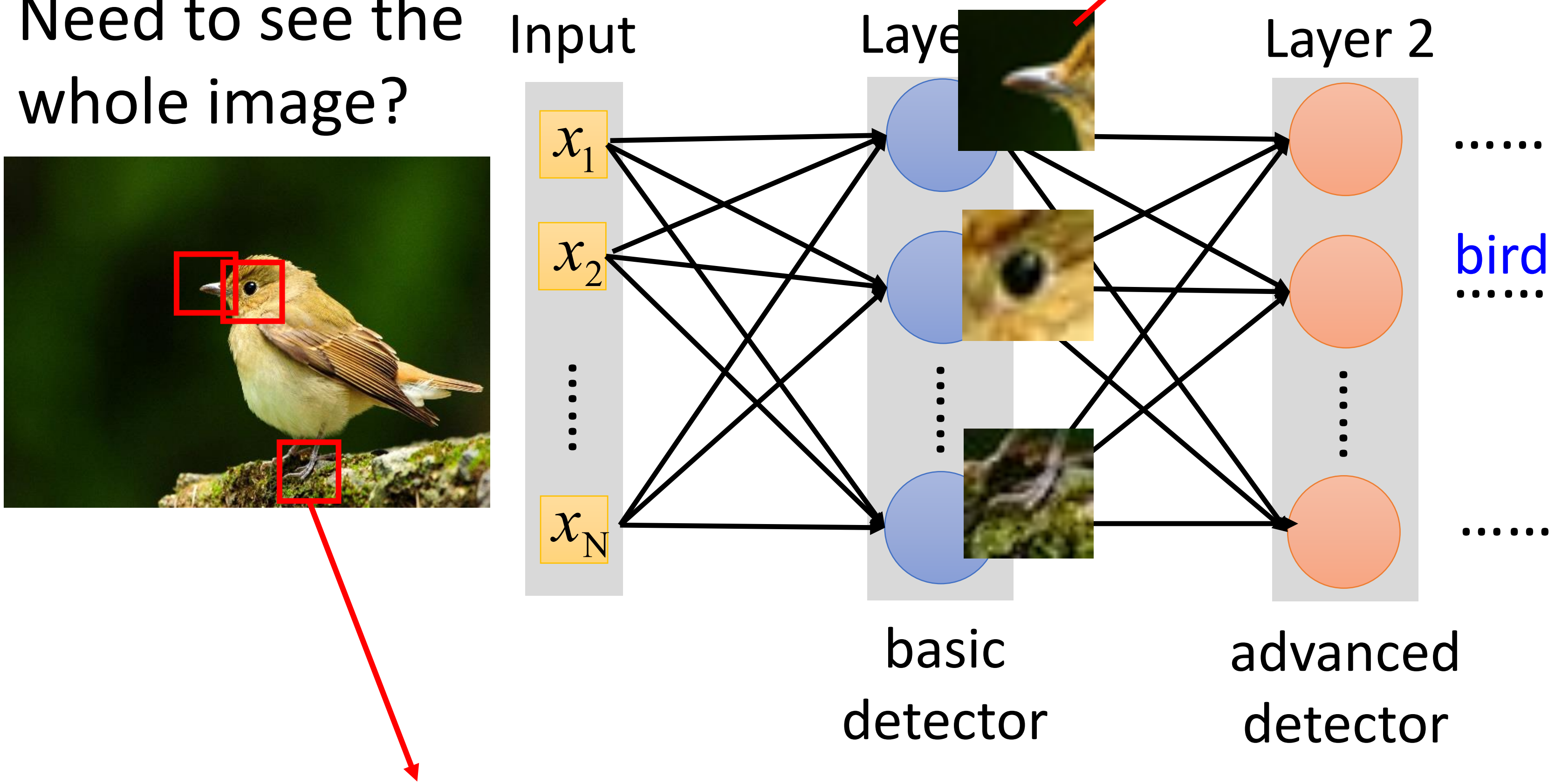
Perhaps human also identify birds in a similar way … ☺

https://www.dcard.tw/f/funny/p/233833012

# Observation 1

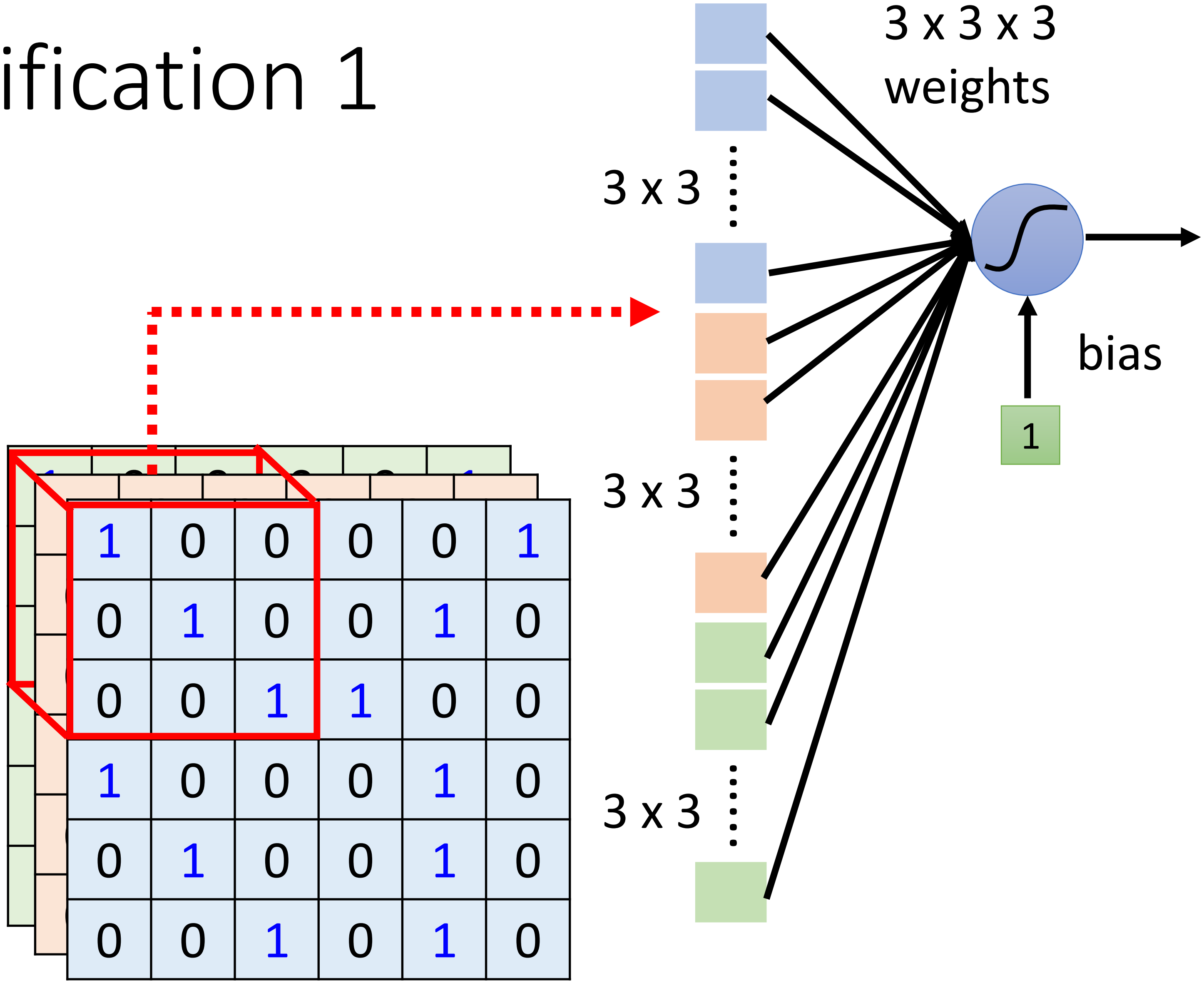
A neuron does not have to see the whole image.

Need to see the whole image?



Some patterns are much smaller than the whole image.

# Simplification 1



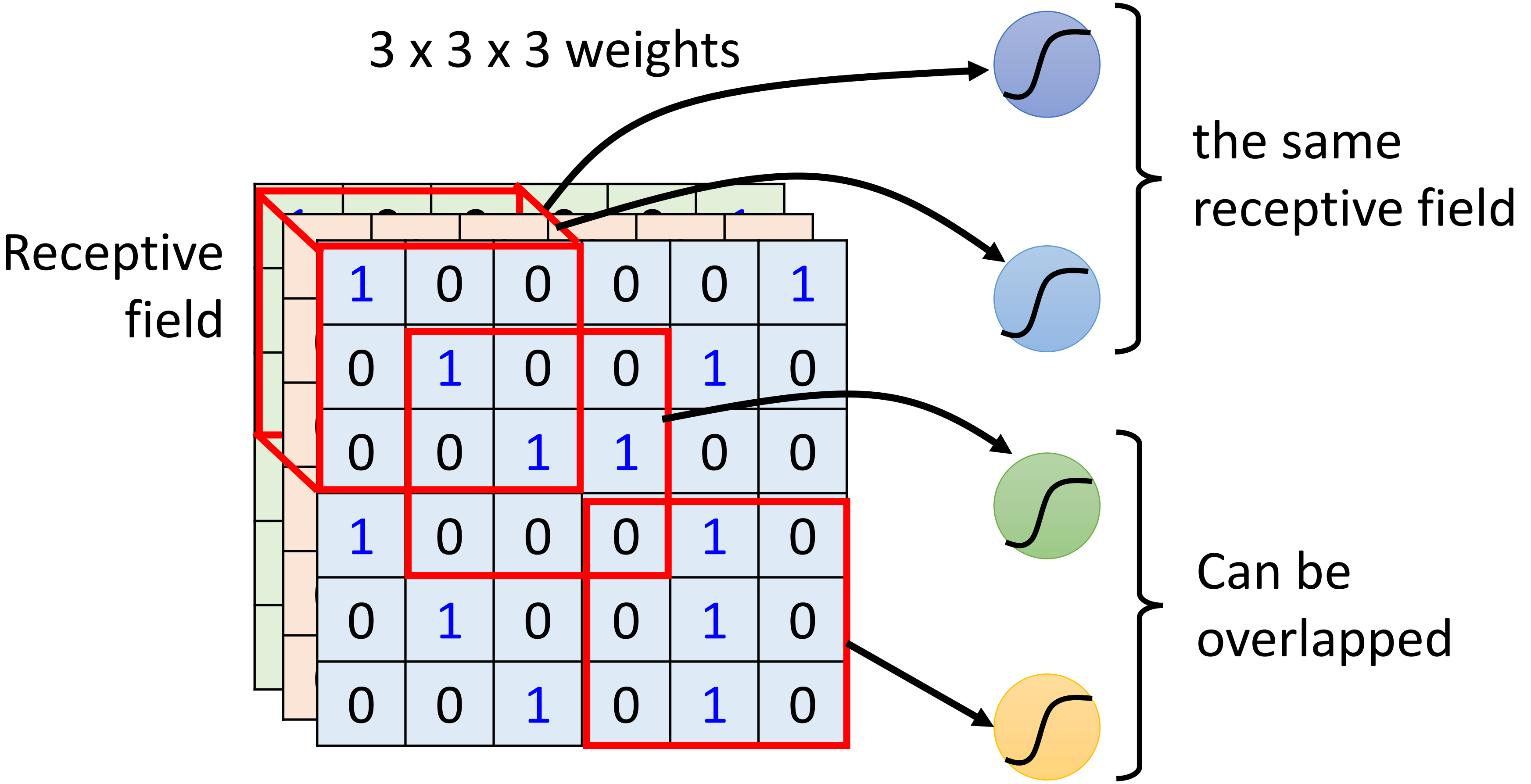
|  |  |  |  |  |  |
|---|---|---|---|---|---|
| 1 | 0 | 0 | 0 | 0 | 1 |
| 0 | 1 | 0 | 0 | 1 | 0 |
| 0 | 0 | 1 | 1 | 0 | 0 |
| 1 | 0 | 0 | 0 | 1 | 0 |
| 0 | 1 | 0 | 0 | 1 | 0 |
| 0 | 0 | 1 | 0 | 1 | 0 |

Receptive field

感受野

# Simplification 1

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



3 x 3 x 3 weights

Receptive field

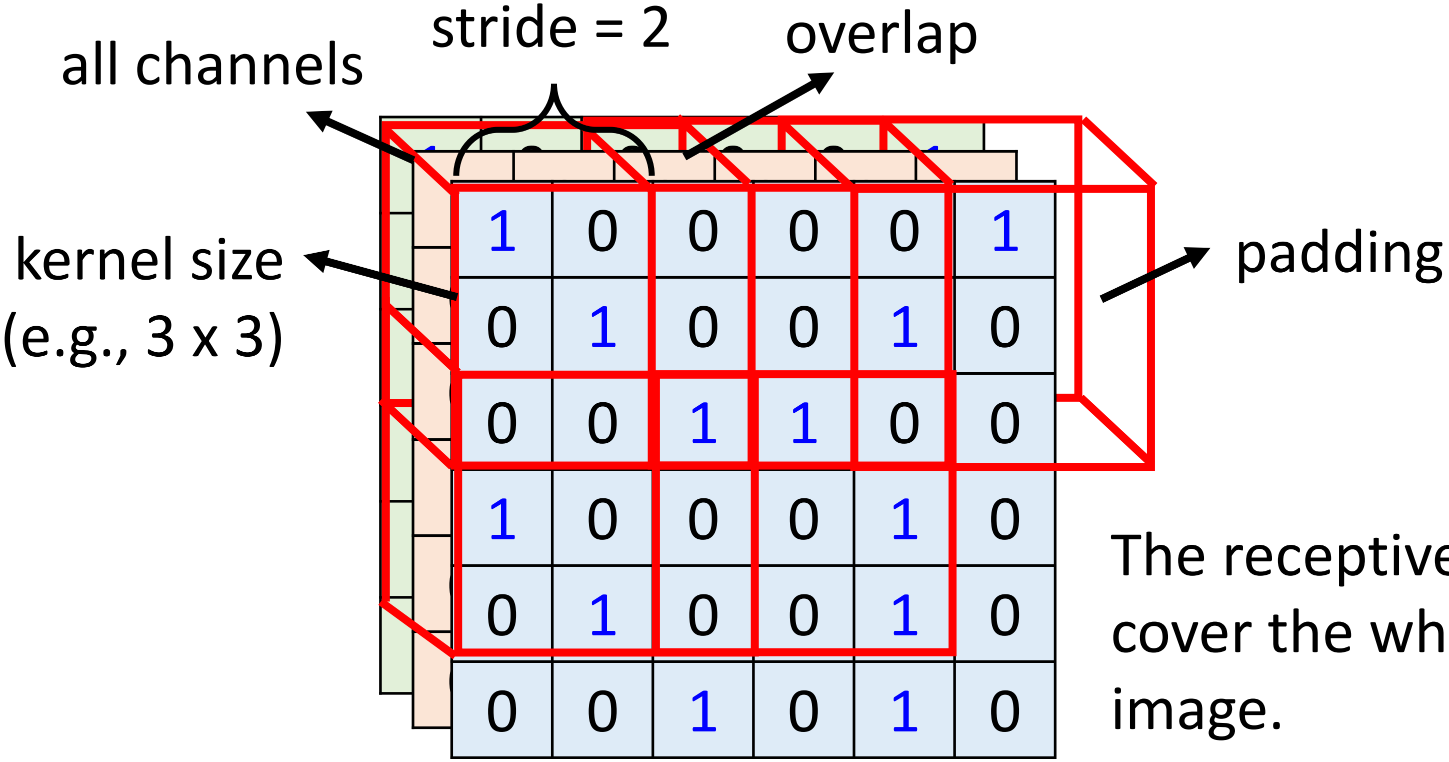
the same receptive field

Can be overlapped

| | | | | | |
|---|---|---|---|---|---|
| 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 |

# Simplification 1 – Typical Setting

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

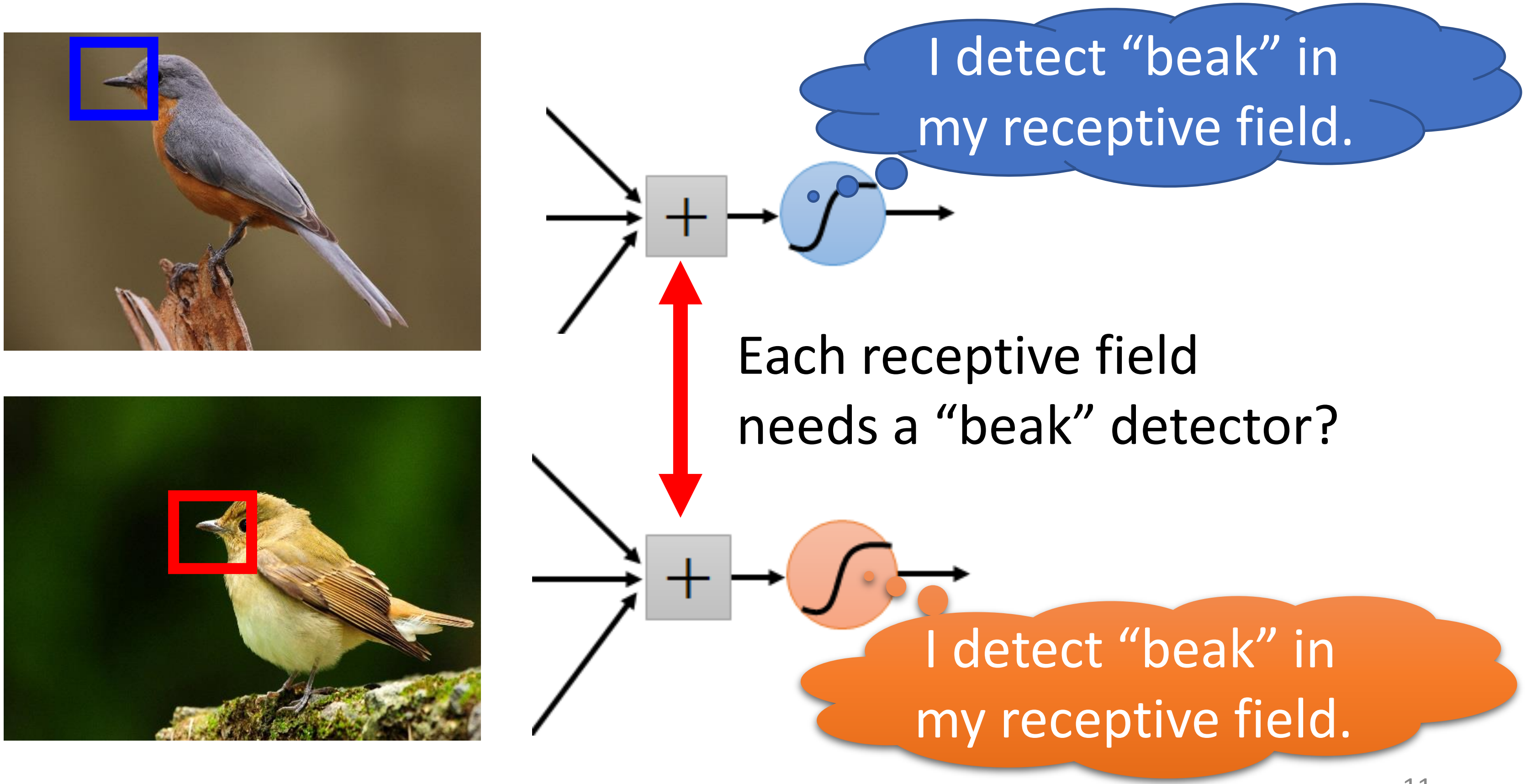


|   |   |   |   |   |   |
|---|---|---|---|---|---|
| 1 | 0 | 0 | 0 | 0 | 1 |
| 0 | 1 | 0 | 0 | 1 | 0 |
| 0 | 0 | 1 | 1 | 0 | 0 |
| 1 | 0 | 0 | 0 | 1 | 0 |
| 0 | 1 | 0 | 0 | 1 | 0 |
| 0 | 0 | 1 | 0 | 1 | 0 |

The receptive fields cover the whole image.

# Observation 2

- The same patterns appear in different regions.

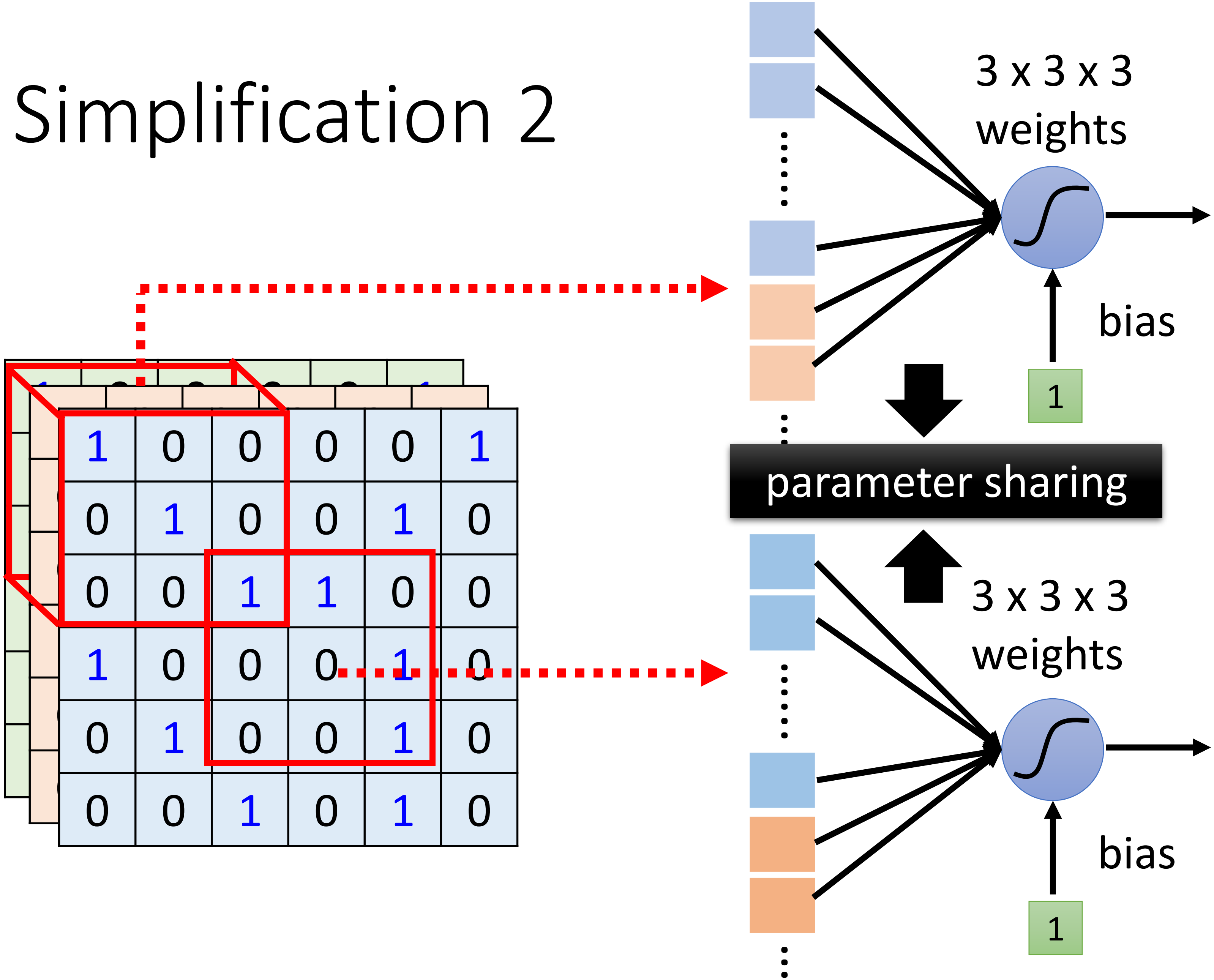


I detect “beak” in my receptive field.

Each receptive field needs a “beak” detector?

I detect “beak” in my receptive field.

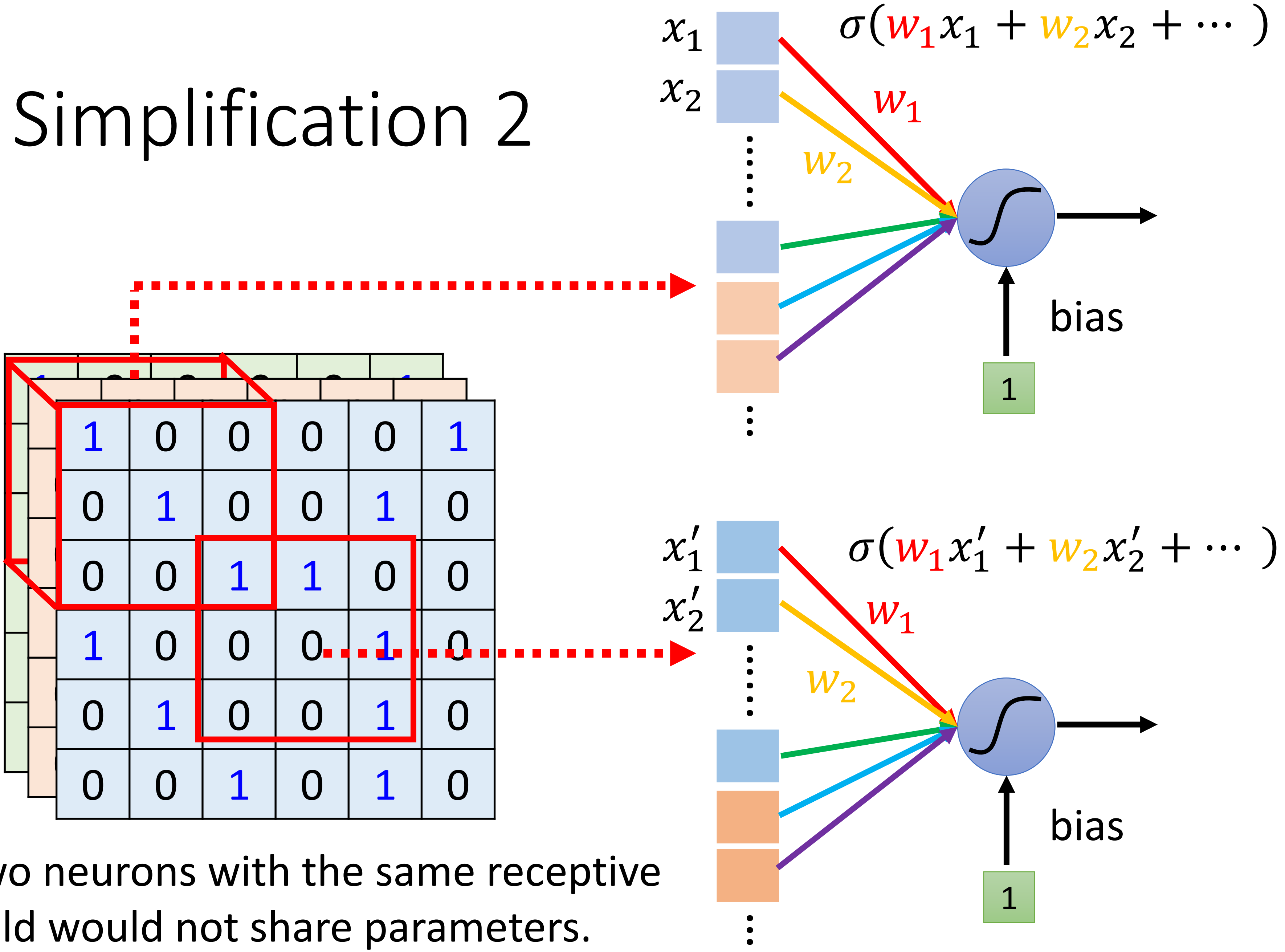
# Simplification 2



| | | | | | |
|---|---|---|---|---|---|
| 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 |

parameter sharing

# Simplification 2



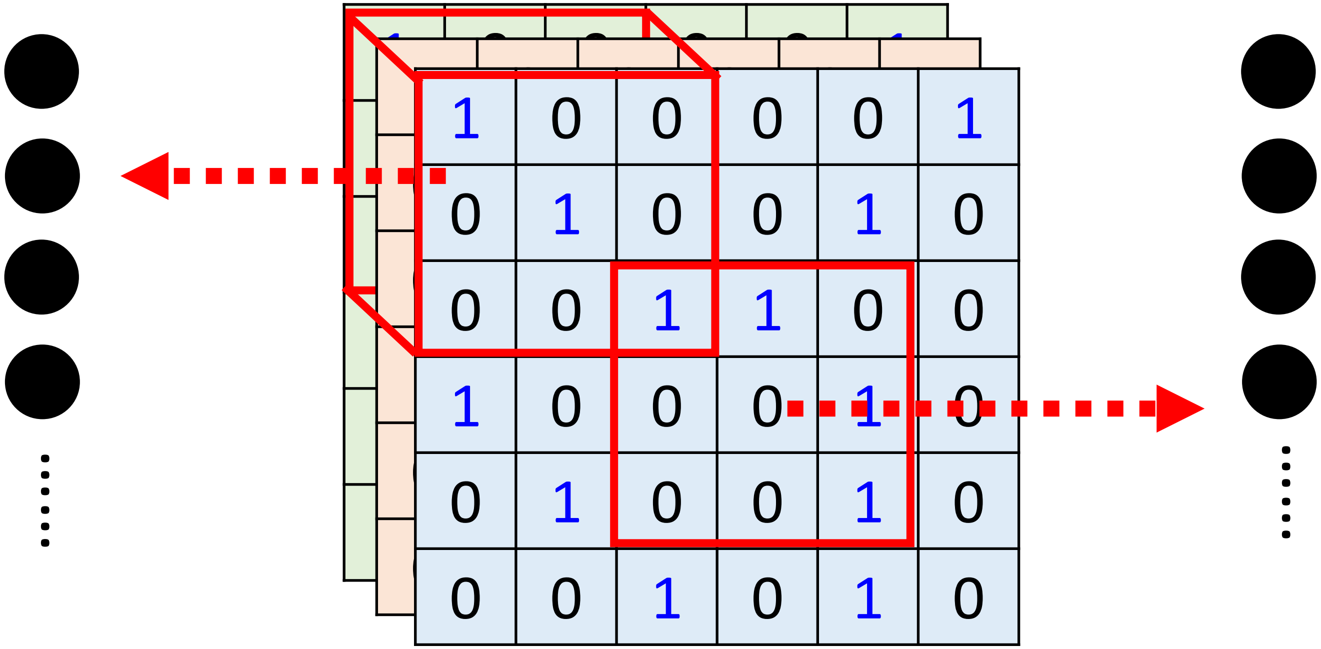
|  |  |  |  |  |  |
|---|---|---|---|---|---|
| 1 | 0 | 0 | 0 | 0 | 1 |
| 0 | 1 | 0 | 0 | 1 | 0 |
| 0 | 0 | 1 | 1 | 0 | 0 |
| 1 | 0 | 0 | 0 | 1 | 0 |
| 0 | 1 | 0 | 0 | 1 | 0 |
| 0 | 0 | 1 | 0 | 1 | 0 |

$\sigma(w_1 x_1 + w_2 x_2 + \cdots)$
$x_1$
$x_2$
$w_1$
$w_2$
bias
1
$\sigma(w_1 x_1' + w_2 x_2' + \cdots)$
$x_1'$
$x_2'$
$w_1$
$w_2$
bias
1

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).

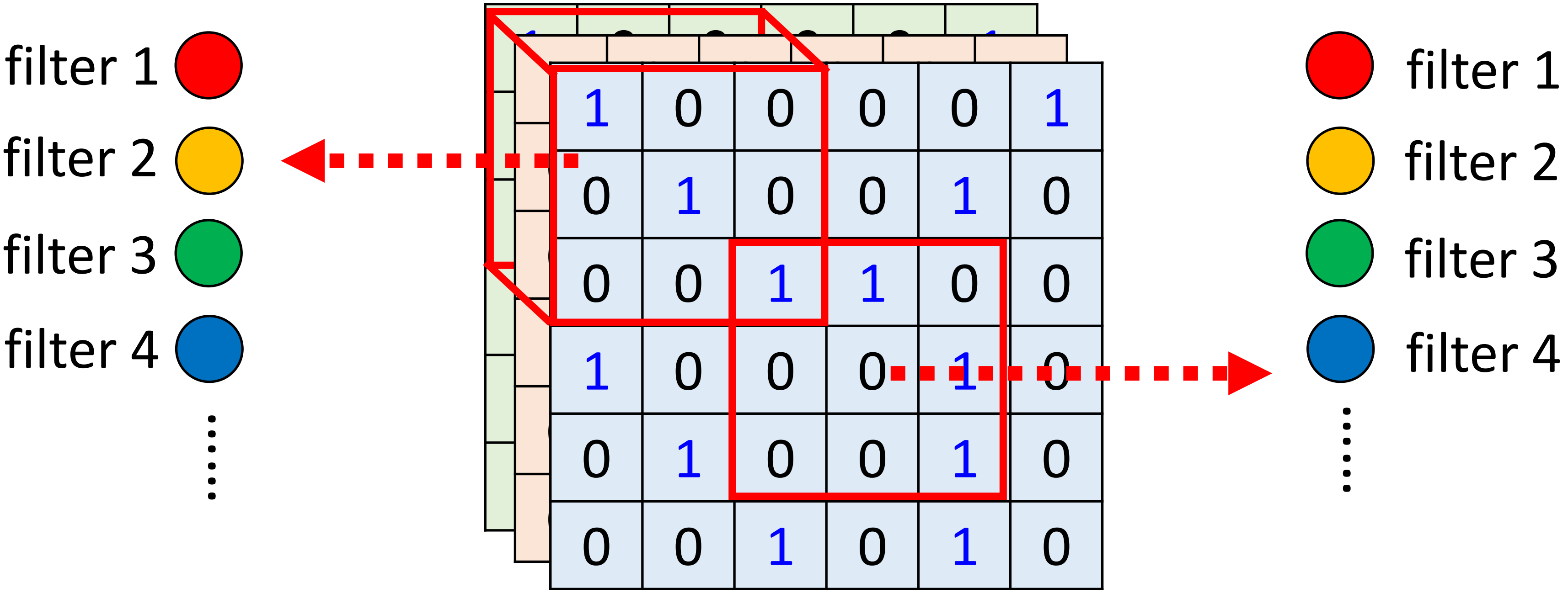


| | | | | | |
|---|---|---|---|---|---|
| 1 | 0 | 0 | 0 | 0 | 1 |
| 0 | 1 | 0 | 0 | 1 | 0 |
| 0 | 0 | 1 | 1 | 0 | 0 |
| 1 | 0 | 0 | 0 | 1 | 0 |
| 0 | 1 | 0 | 0 | 1 | 0 |
| 0 | 0 | 1 | 0 | 1 | 0 |

# Simplification 2 – Typical Setting

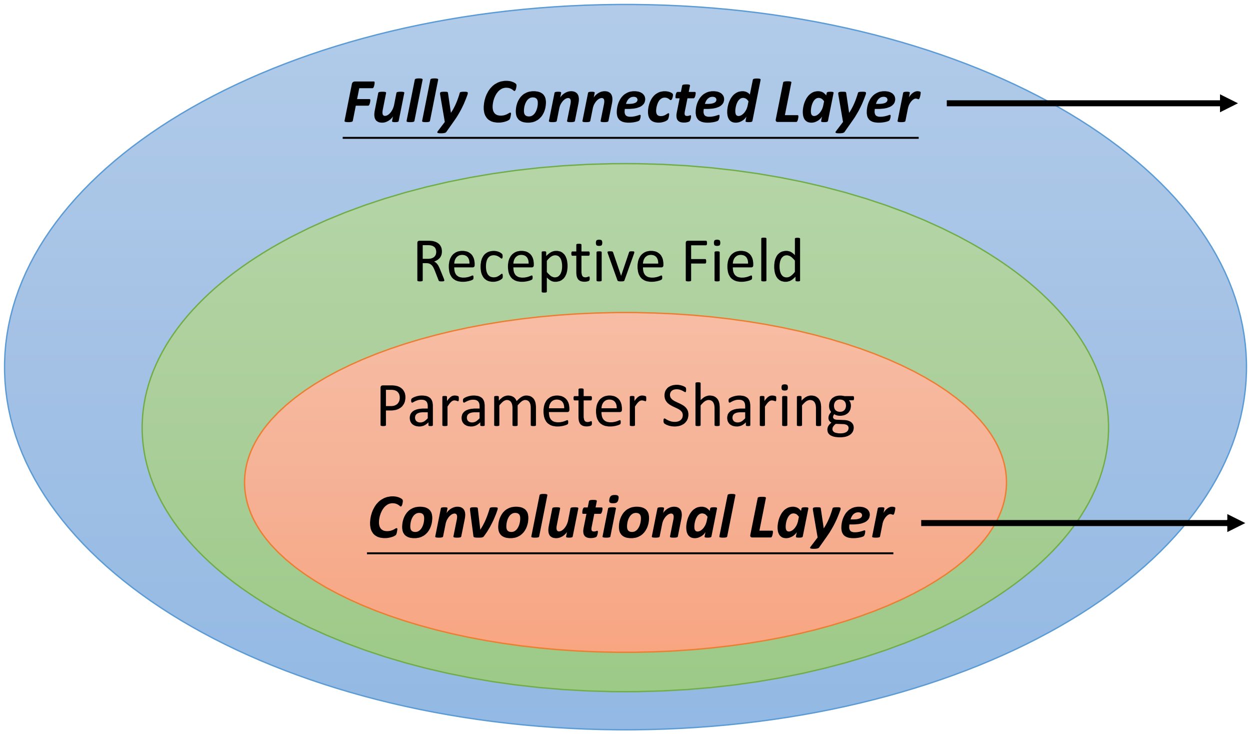
Each receptive field has a set of neurons (e.g., 64 neurons).

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



| | | | | | |
|---|---|---|---|---|---|
| 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 |

# Benefit of Convolutional Layer



***Fully Connected Layer*** → Jack of all trades, master of none

Receptive Field

Parameter Sharing

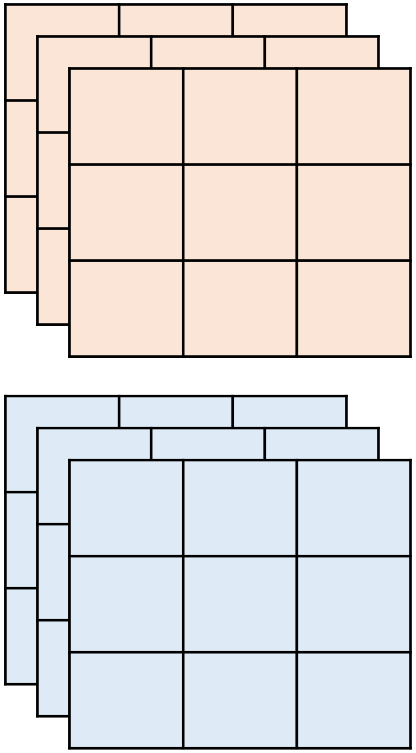
***Convolutional Layer*** → Larger model bias (for image)

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

Another story based on ***filter*** ☺

# Convolutional Layer

Convolution



Filter 1

3 x 3 x channel tensor

Filter 2

3 x 3 x channel tensor

⋮

channel = 3 (colorful)

channel = 1 (black and white)

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

# 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

⋮

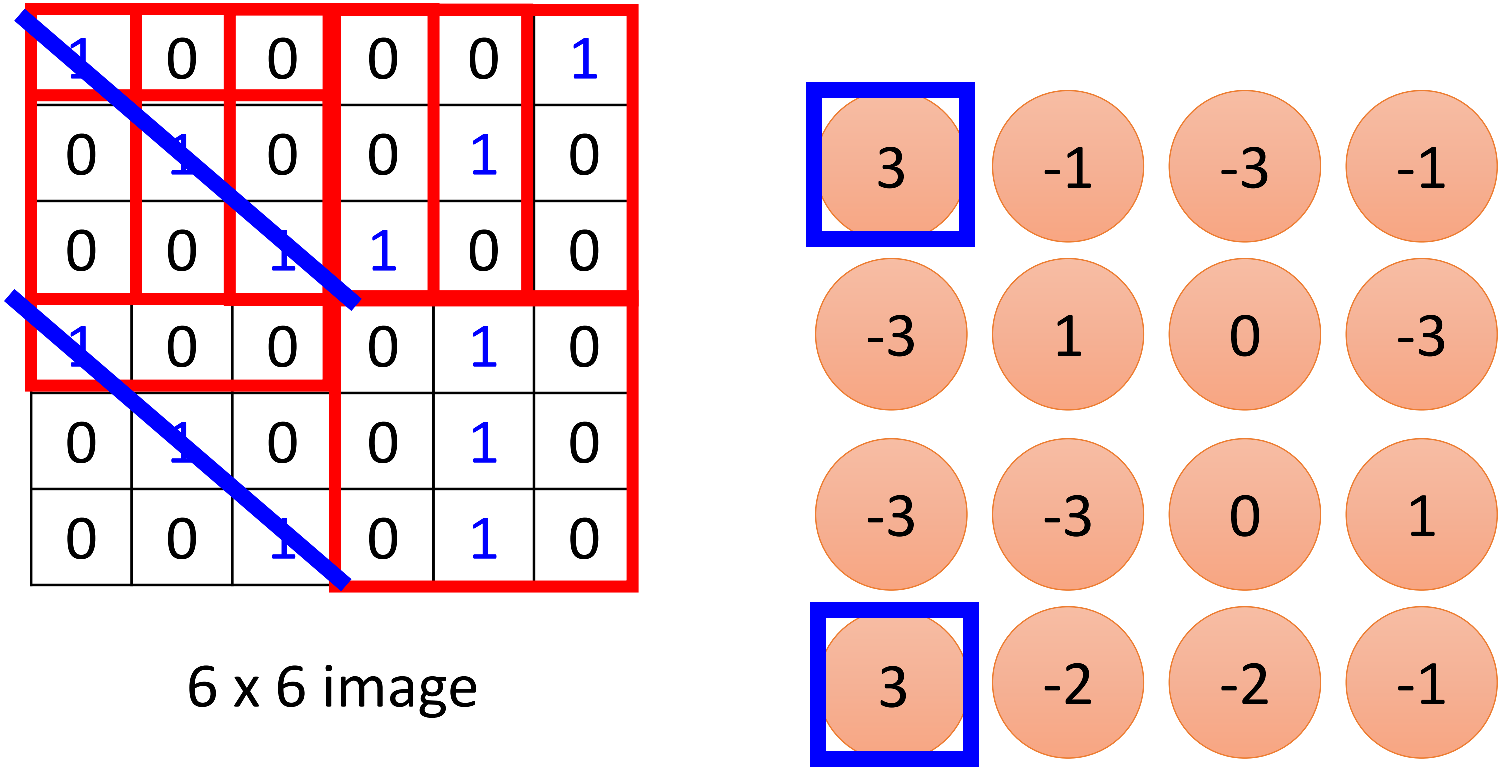
(The values in the filters are unknown parameters.)

# Convolutional Layer

|  |  |  |
|---|---|---|
| 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 |

# Convolutional Layer

| | | |
|---|---|---|
| -1 | 1 | -1 |
| -1 | 1 | -1 |
| -1 | 1 | -1 |

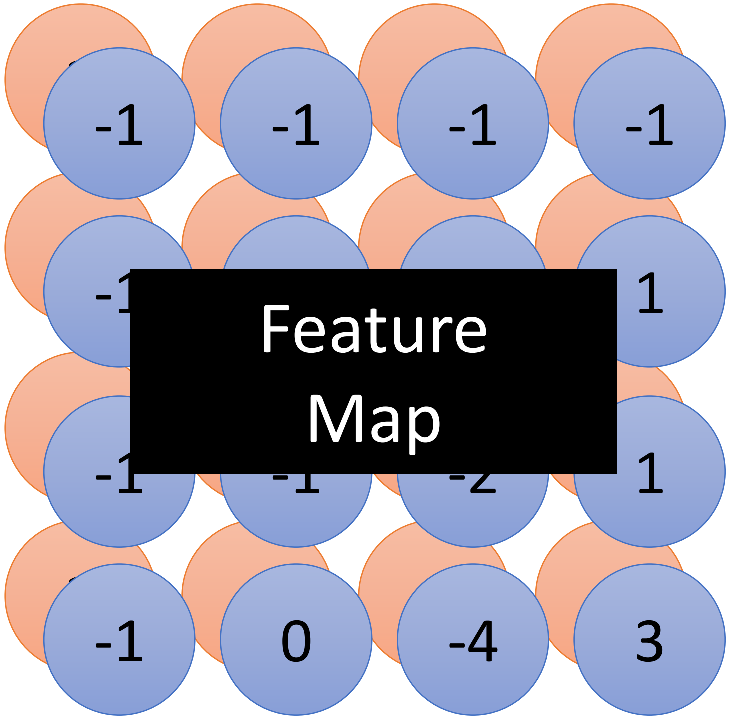
Filter 2

stride=1

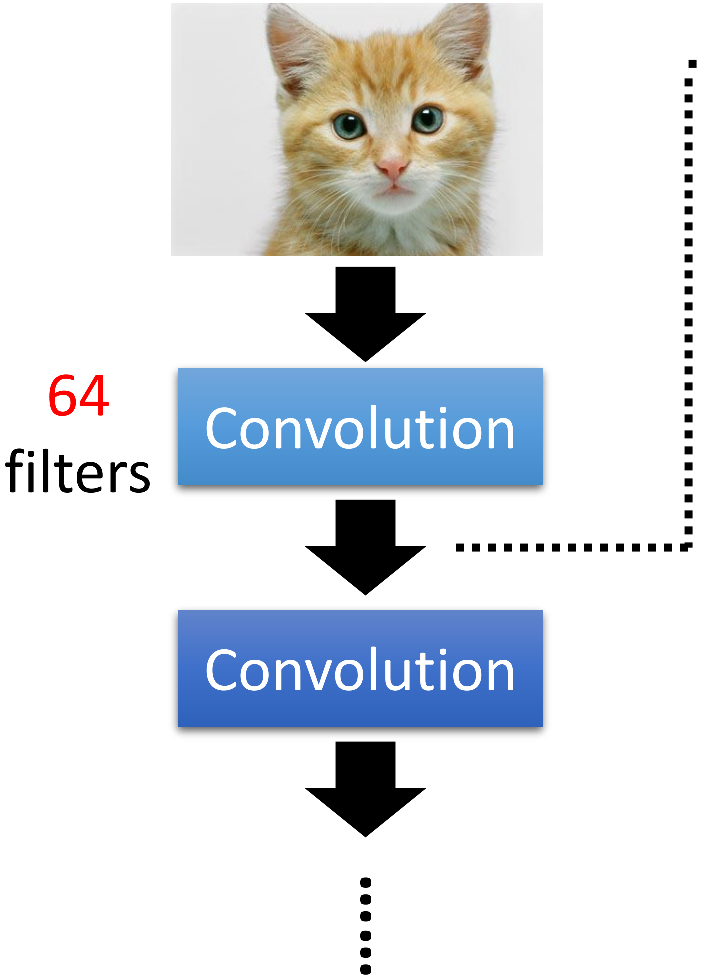
| | | | | | |
|---|---|---|---|---|---|
| 1 | 0 | 0 | 0 | 0 | 1 |
| 0 | 1 | 0 | 0 | 1 | 0 |
| 0 | 0 | 1 | 1 | 0 | 0 |
| 1 | 0 | 0 | 0 | 1 | 0 |
| 0 | 1 | 0 | 0 | 1 | 0 |
| 0 | 0 | 1 | 0 | 1 | 0 |

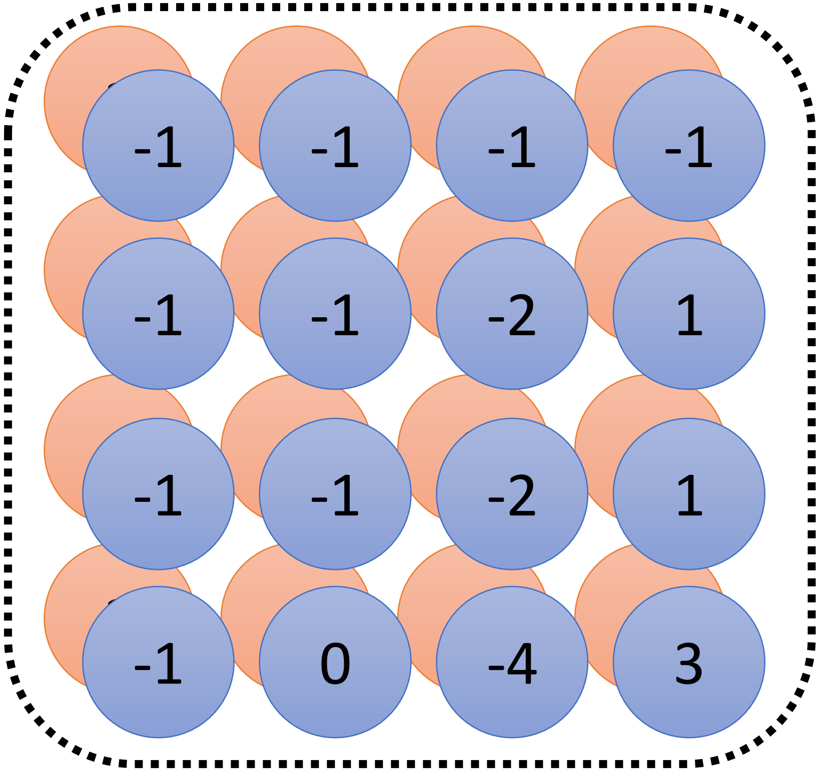
6 x 6 image

Do the same process for every filter



# *Convolutional Layer*

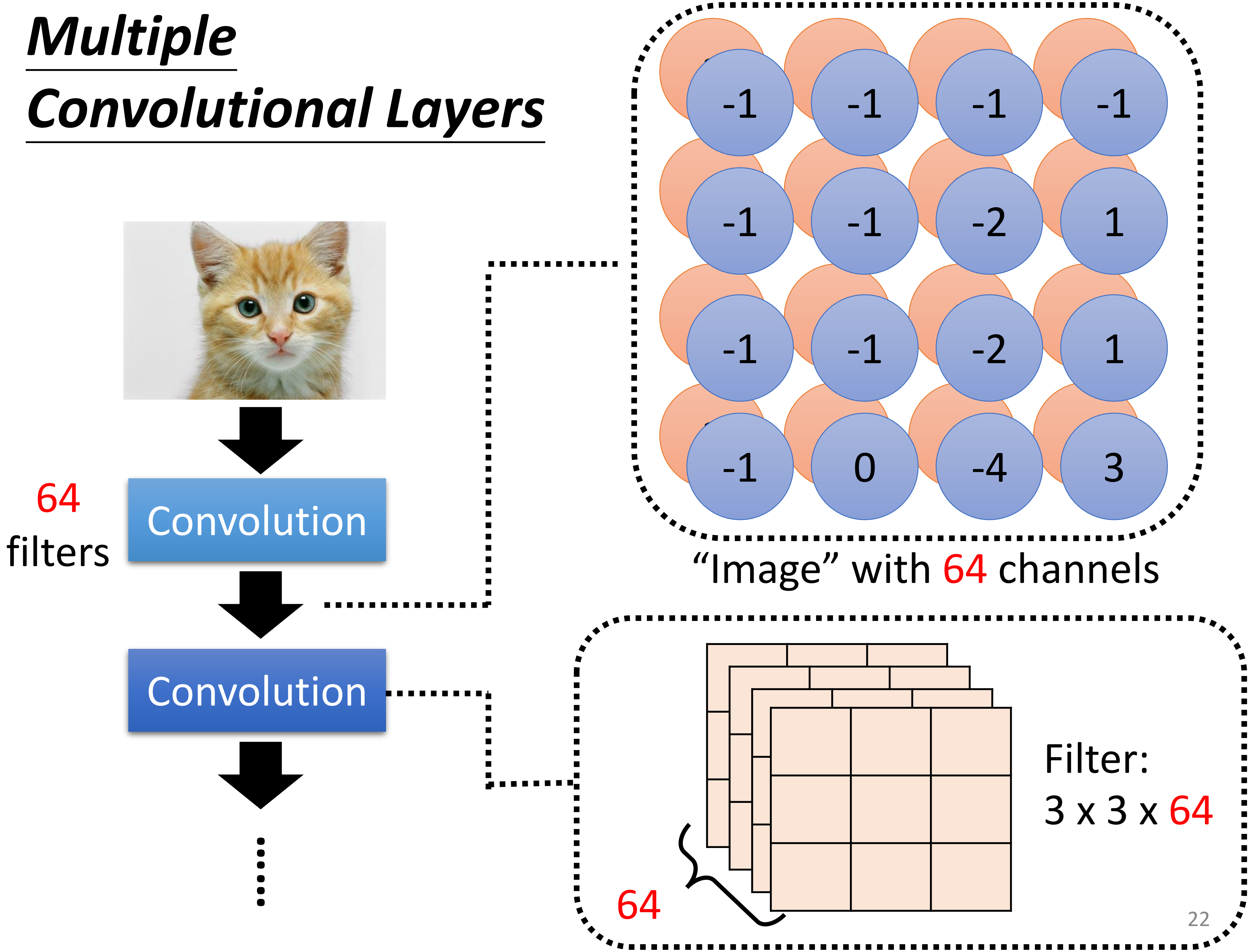




| | | | |
|---|---|---|---|
| -1 | -1 | -1 | -1 |
| -1 | -1 | -2 | 1 |
| -1 | -1 | -2 | 1 |
| -1 | 0 | -4 | 3 |

“Image” with 64 channels

# *Multiple Convolutional Layers*

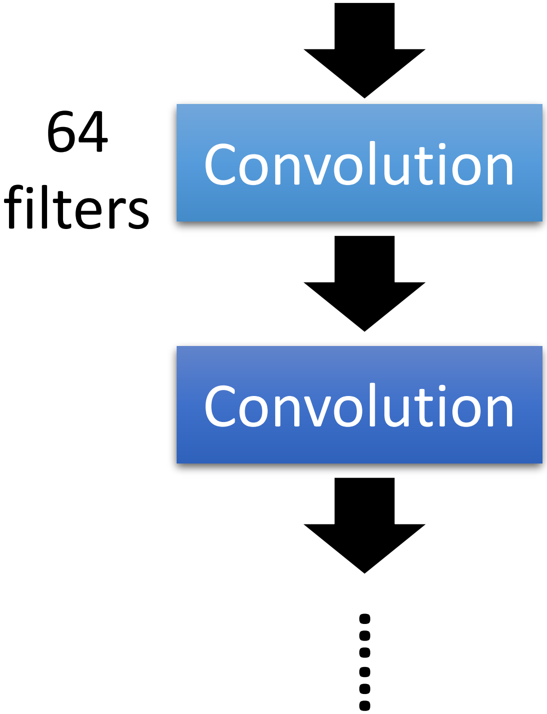


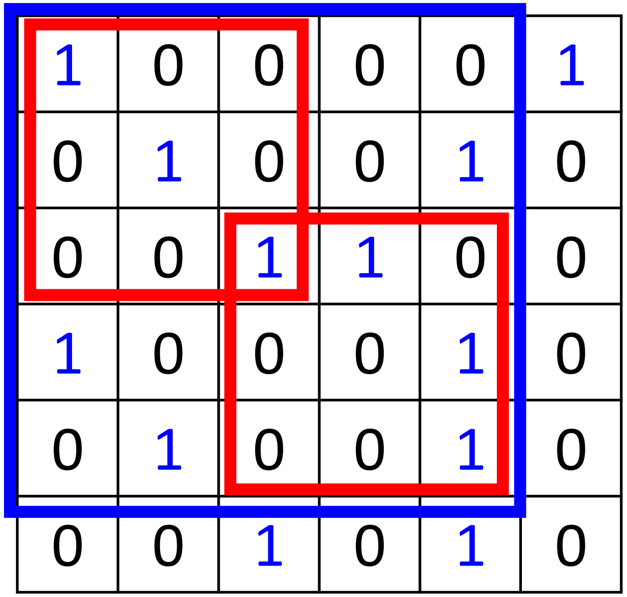
|  |  |  |  |
|---|---|---|---|
| -1 | -1 | -1 | -1 |
| -1 | -1 | -2 | 1 |
| -1 | -1 | -2 | 1 |
| -1 | 0 | -4 | 3 |

“Image” with 64 channels

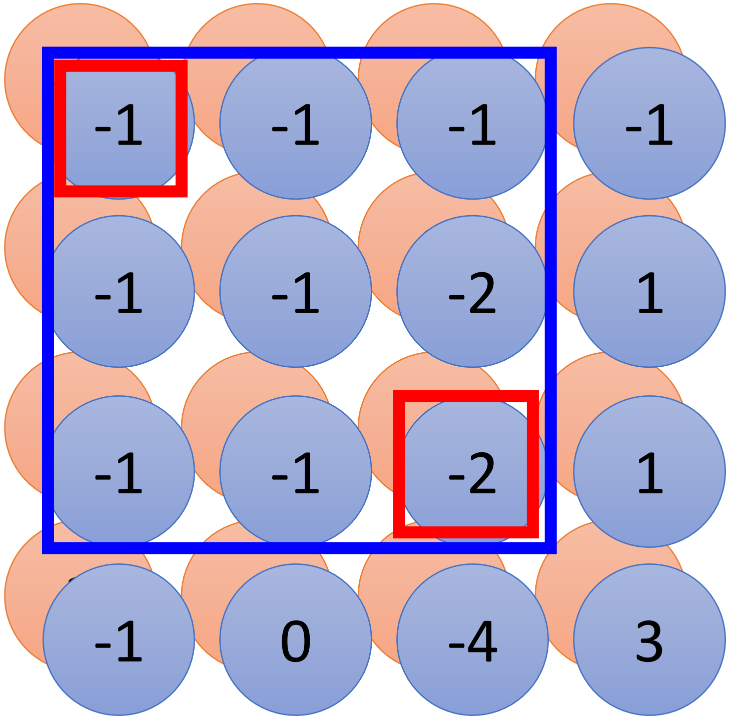
Filter:
3 x 3 x 64

# *Multiple Convolutional Layers*



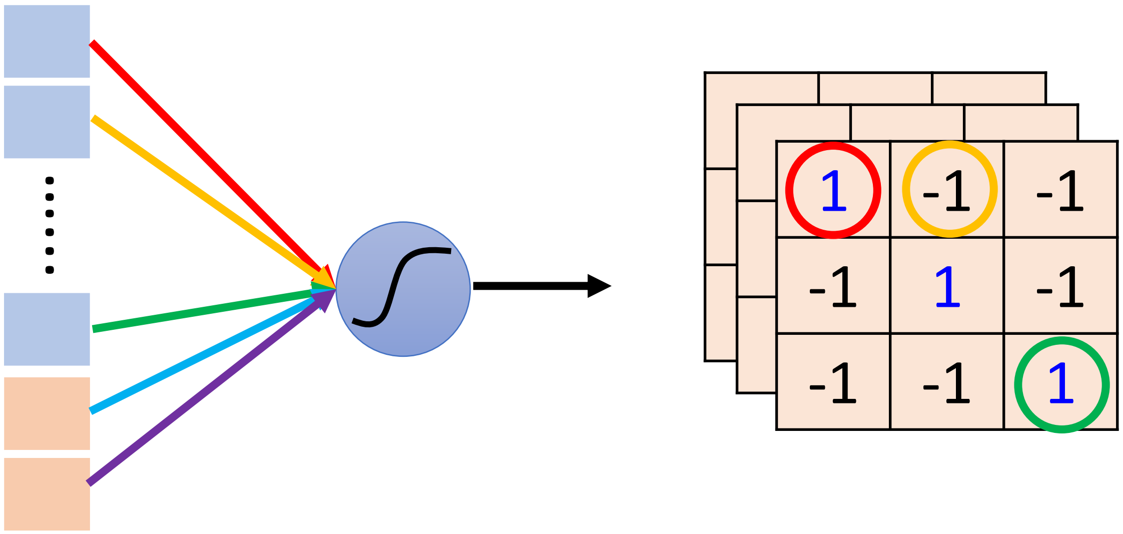


| | | | | | |
|---|---|---|---|---|---|
| 1 | 0 | 0 | 0 | 0 | 1 |
| 0 | 1 | 0 | 0 | 1 | 0 |
| 0 | 0 | 1 | 1 | 0 | 0 |
| 1 | 0 | 0 | 0 | 1 | 0 |
| 0 | 1 | 0 | 0 | 1 | 0 |
| 0 | 0 | 1 | 0 | 1 | 0 |



| | | | |
|---|---|---|---|
| -1 | -1 | -1 | -1 |
| -1 | -1 | -2 | 1 |
| -1 | -1 | -2 | 1 |
| -1 | 0 | -4 | 3 |

# Comparison of Two Stories



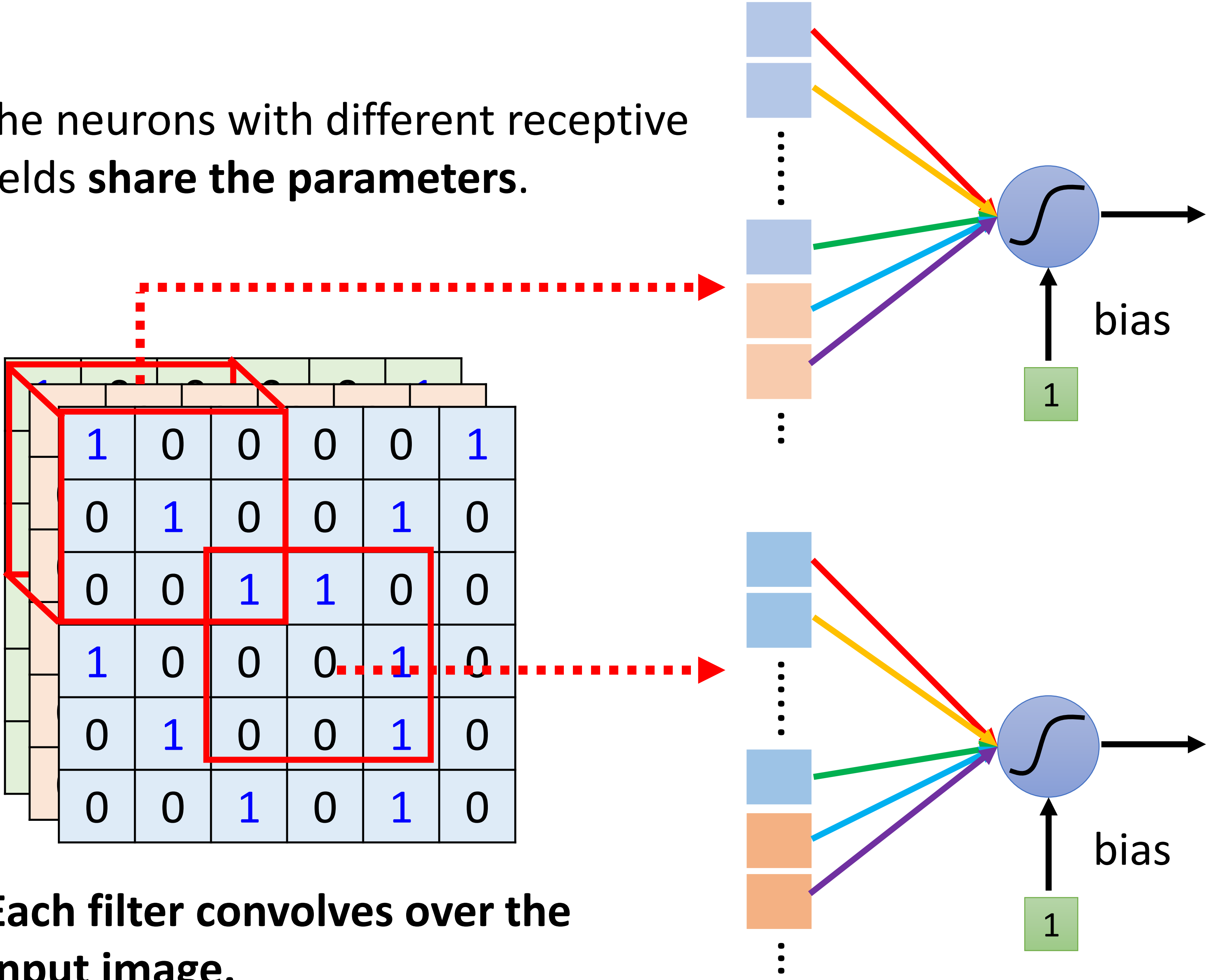
|  |  |  |
|---|---|---|
| 1 | -1 | -1 |
| -1 | 1 | -1 |
| -1 | -1 | 1 |

Filter
3 x 3 x channel
tensor

Receptive
field

(ignore bias in this slide)

The neurons with different receptive fields **share the parameters**.



|   |   |   |   |   |   |
|---|---|---|---|---|---|
| 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 |

**Each filter convolves over the input image.**

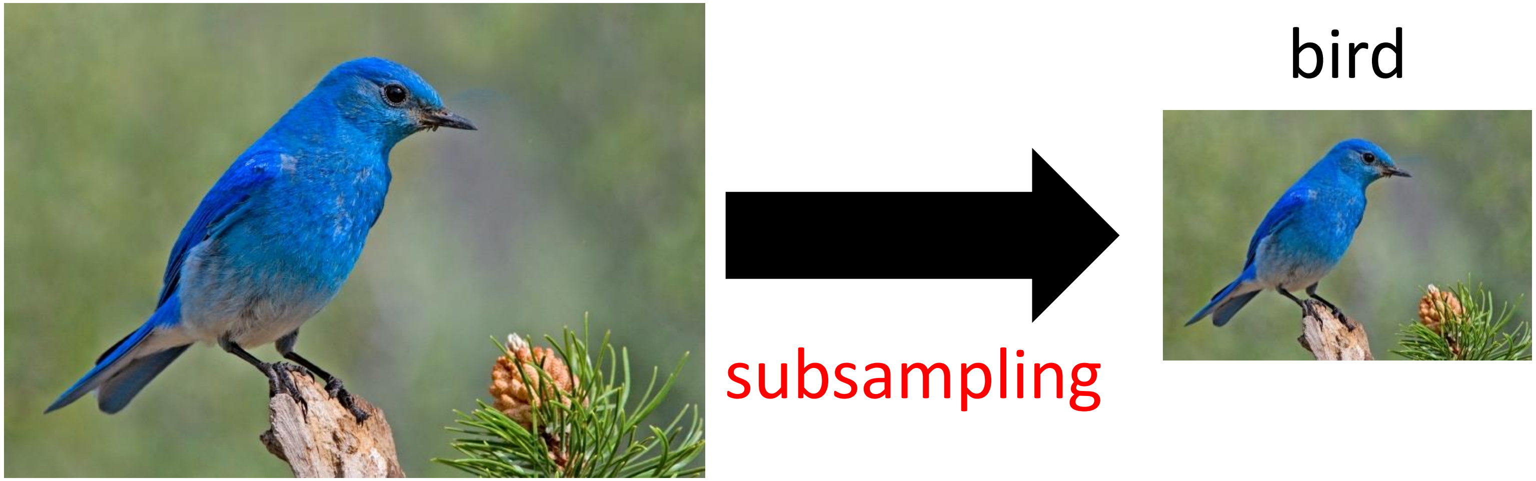
# Convolutional Layer

| ***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



bird

subsampling

bird

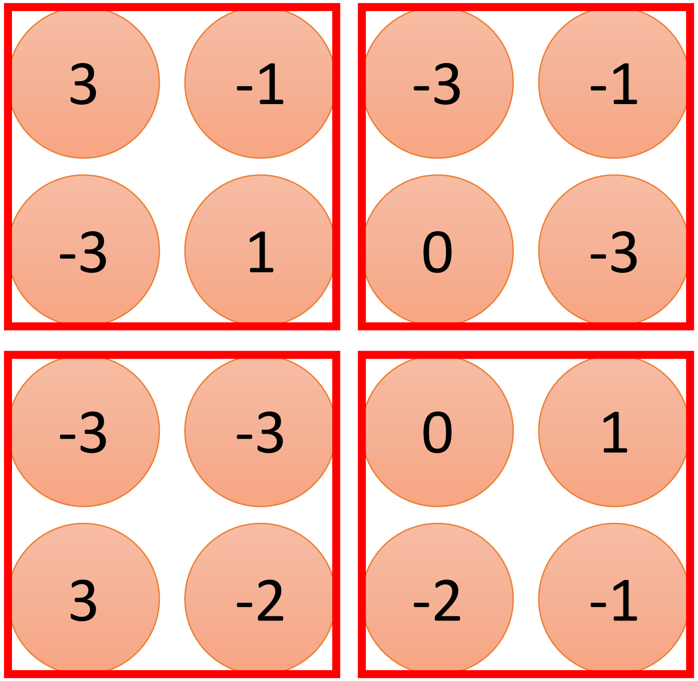
# Pooling – Max Pooling

| | | |
|---|---|---|
| 1 | -1 | -1 |
| -1 | 1 | -1 |
| -1 | -1 | 1 |

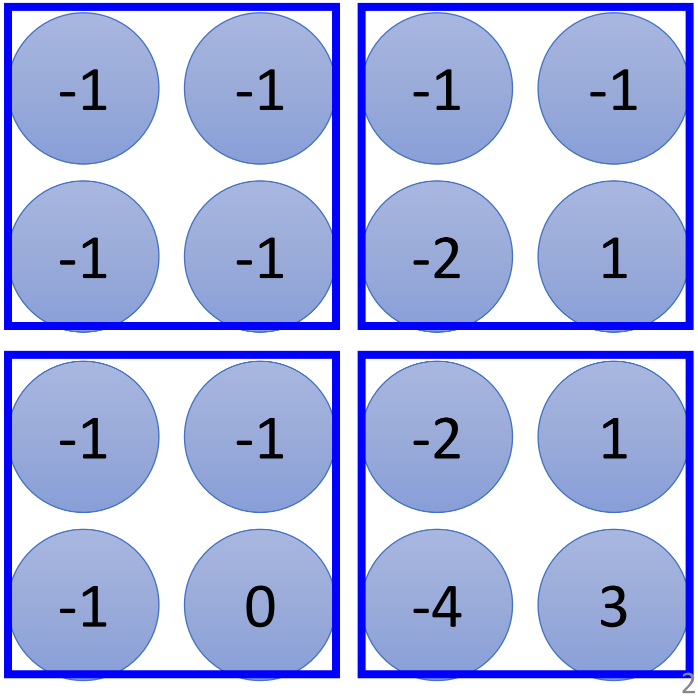
Filter 1

| | | |
|---|---|---|
| -1 | 1 | -1 |
| -1 | 1 | -1 |
| -1 | 1 | -1 |

Filter 2

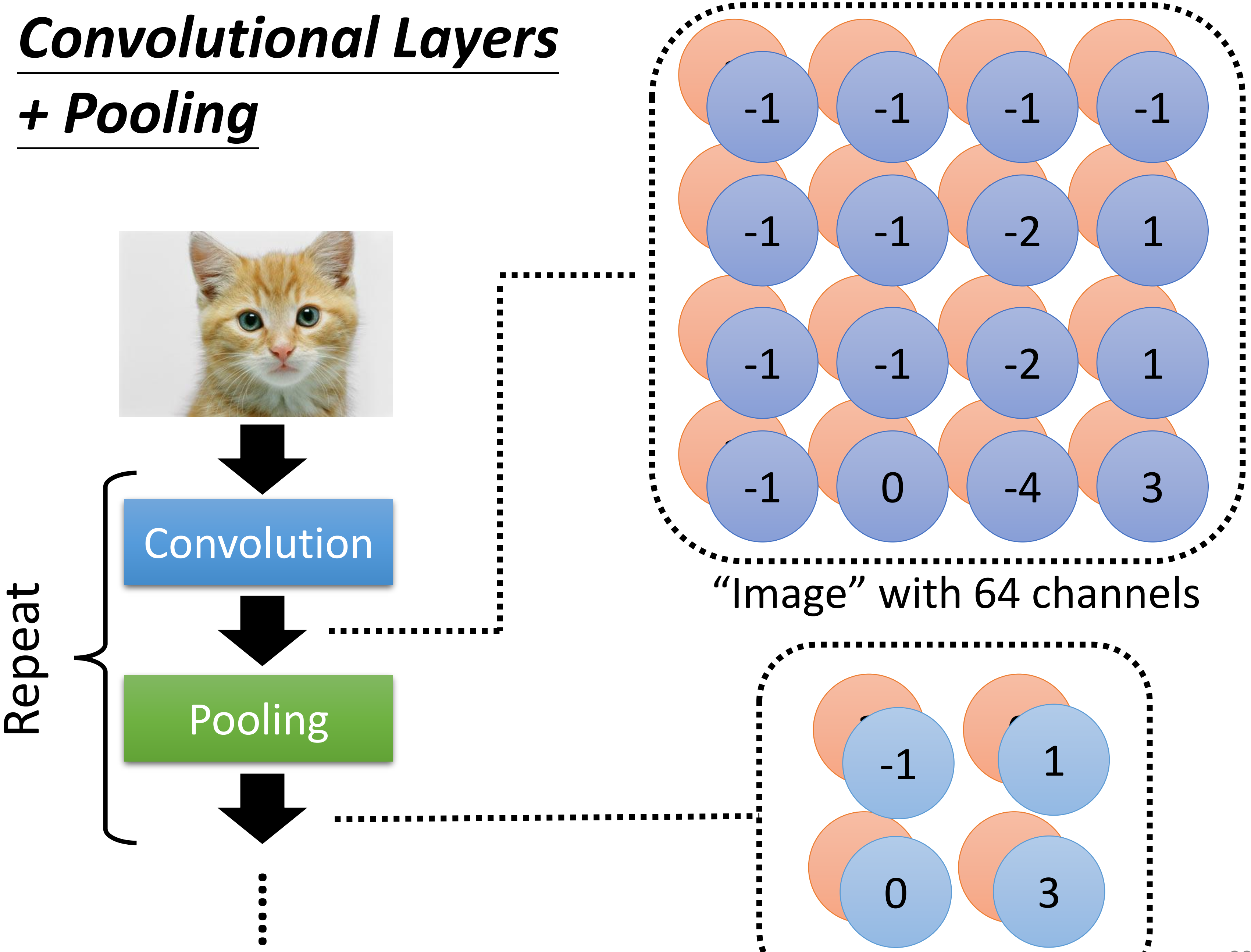


| | | | |
|---|---|---|---|
| 3 | -1 | -3 | -1 |
| -3 | 1 | 0 | -3 |
| -3 | -3 | 0 | 1 |
| 3 | -2 | -2 | -1 |



| | | | |
|---|---|---|---|
| -1 | -1 | -1 | -1 |
| -1 | -1 | -2 | 1 |
| -1 | -1 | -2 | 1 |
| -1 | 0 | -4 | 3 |

# *Convolutional Layers + Pooling*

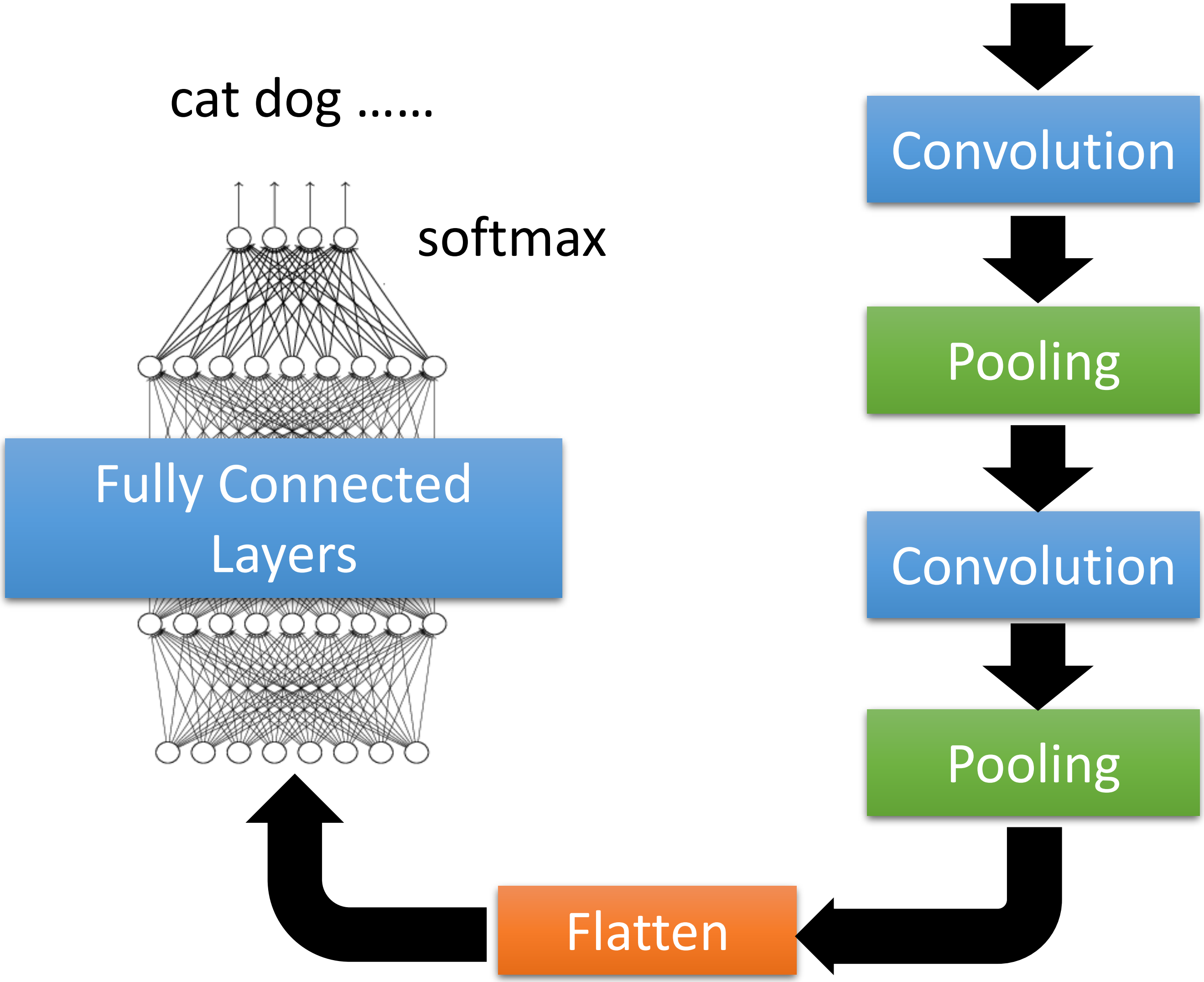


|  |  |  |  |
|---|---|---|---|
| -1 | -1 | -1 | -1 |
| -1 | -1 | -2 | 1 |
| -1 | -1 | -2 | 1 |
| -1 | 0 | -4 | 3 |

“Image” with 64 channels

|  |  |
|---|---|
| -1 | 1 |
| 0 | 3 |

# The whole CNN



cat dog ……

softmax

Fully Connected Layers

Convolution

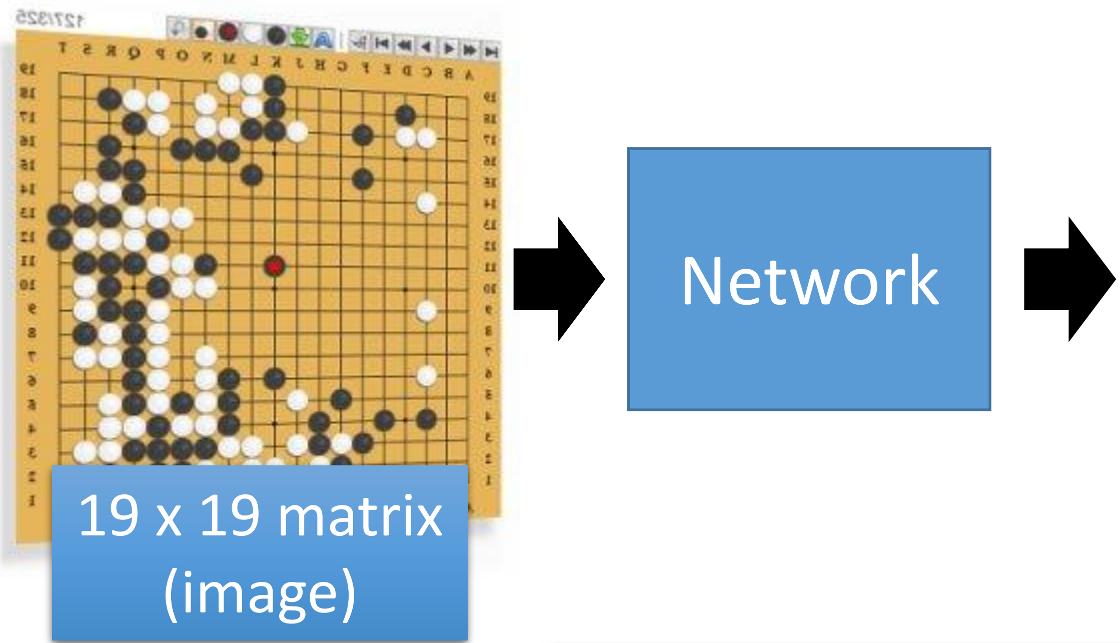
Pooling

Convolution

Pooling

Flatten

# Application: Playing Go



19 x 19 matrix (image)

Network

Next move (19 x 19 positions)

19 x 19 classes

48 channels in Alpha Go

Black: 1

white: -1

none: 0

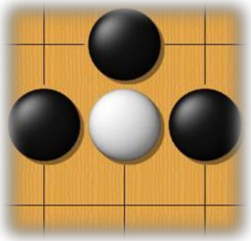
Fully-connected network can be used

But CNN performs much better.

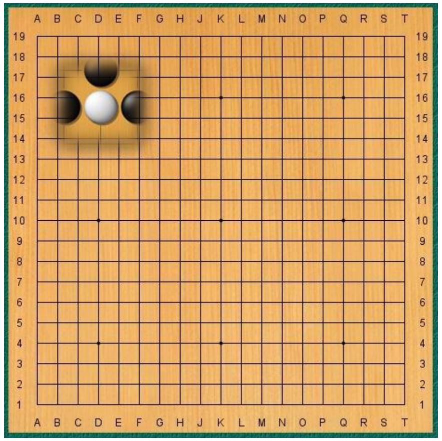
# Why CNN for Go playing?

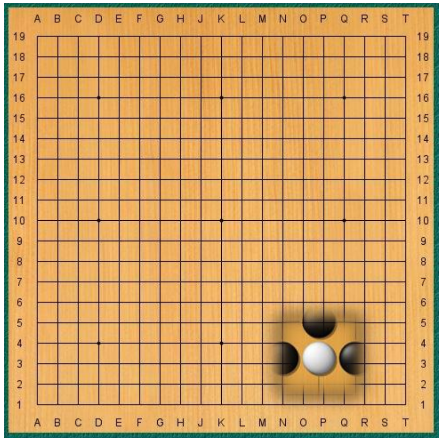
- Some patterns are much smaller than the whole image

Alpha Go uses 5 x 5 for first layer



- The same patterns appear in different regions.



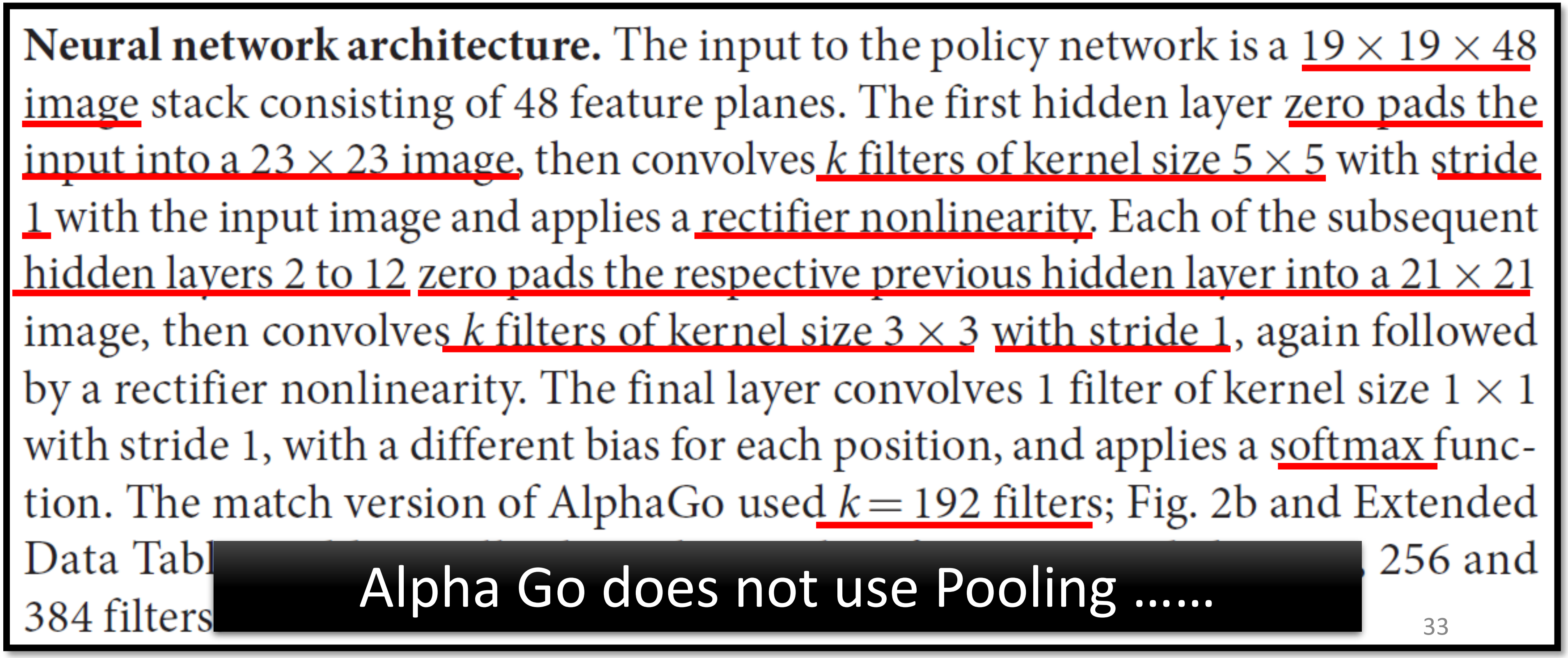


# Why CNN for Go playing?

- Subsampling the pixels will not change the object

➡ Pooling

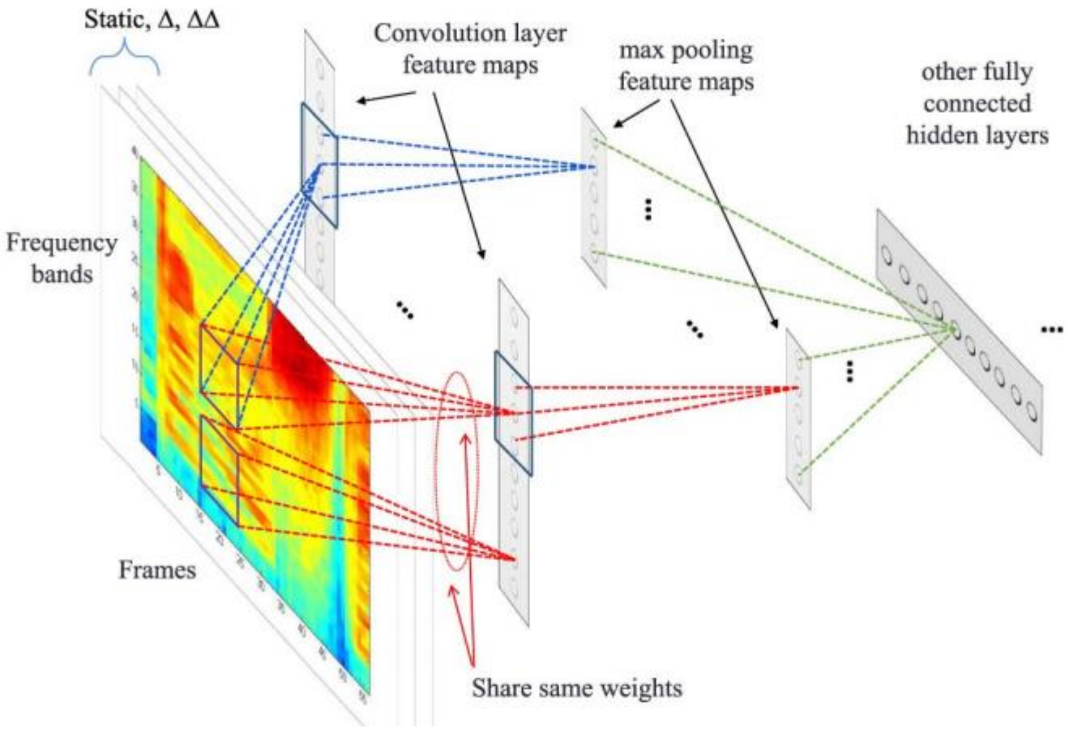
How to explain this???



**Neural network architecture.** The input to the policy network is a 19 × 19 × 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 , 256 and 384 filters

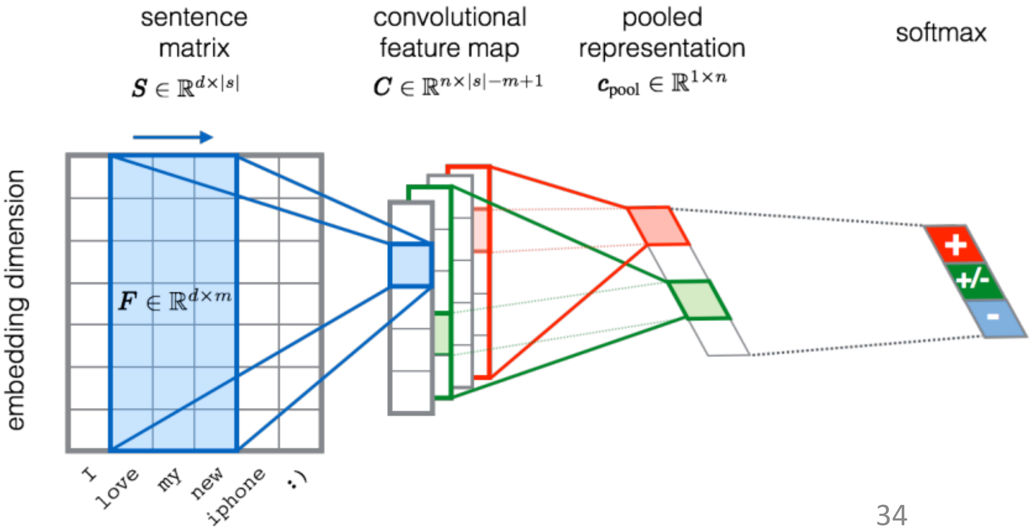
Alpha Go does not use Pooling ……

# More Applications



## Speech

https://dl.acm.org/doi/10.1109/TASLP.2014.2339736


sentence matrix
$S \in \mathbb{R}^{d\times|s|}$
convolutional feature map
$C \in \mathbb{R}^{n\times|s|-m+1}$
pooled representation
$c_{\text{pool}} \in \mathbb{R}^{1\times n}$
softmax
embedding dimension
$F \in \mathbb{R}^{d\times m}$
+
+/-
-
I
love
my
new
iphone
:)

## Natural Language Processing

https://www.aclweb.org/anthology/S15-2079/

# To learn more …

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

*Spatial Transformer Layer*

https://youtu.be/SoCywZ1hZak

(in Mandarin)