

2019  
怪兽  
学堂

CNN

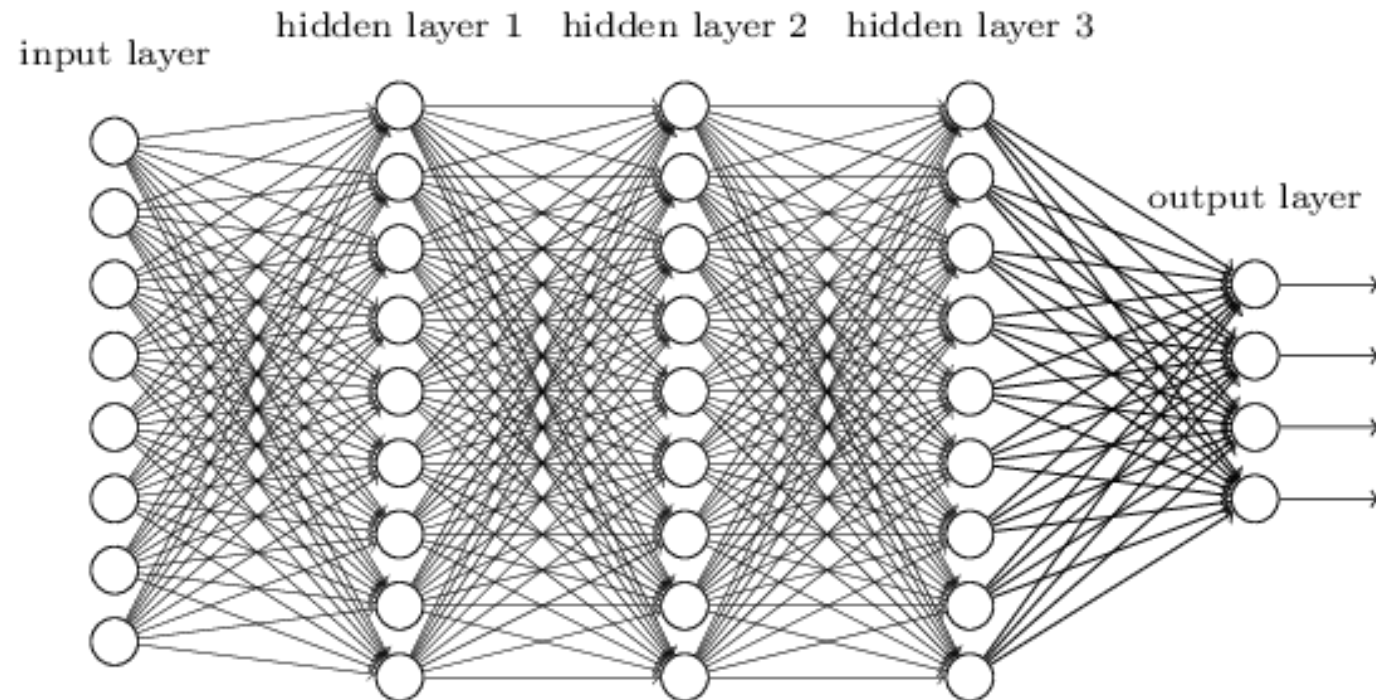


虾米

2019-03

# CNN

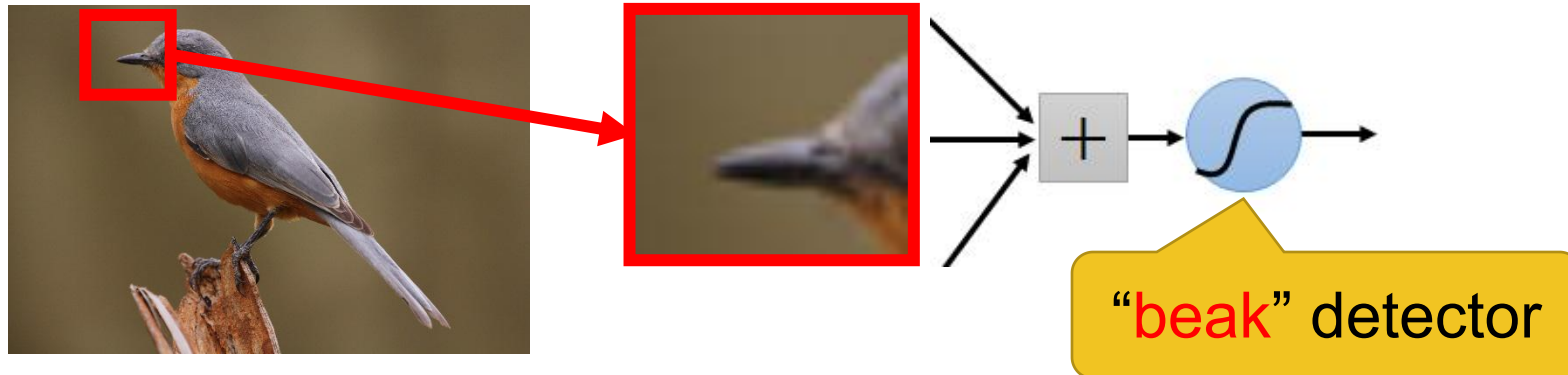
- We know it is good to learn a small model.
- From this fully connected model, do we really need all the edges?
- Can some of these be shared?



# Consider learning an image:

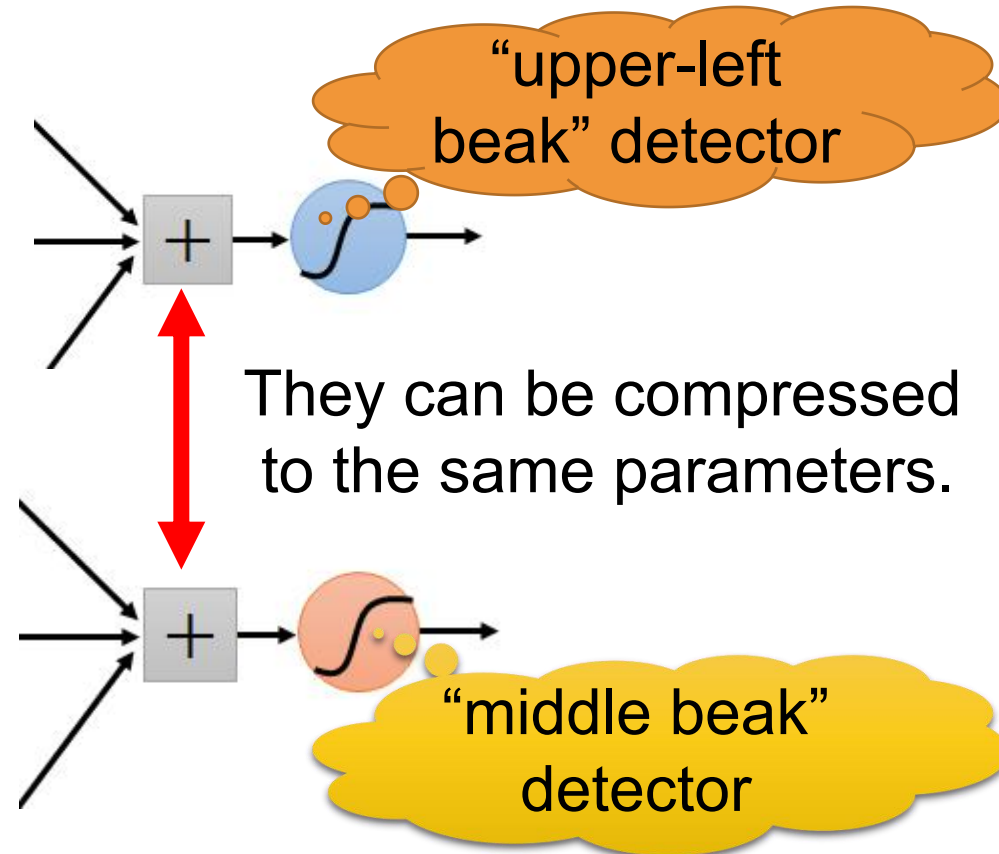
- Some patterns are much smaller than the whole image

Can represent a small region with fewer parameters



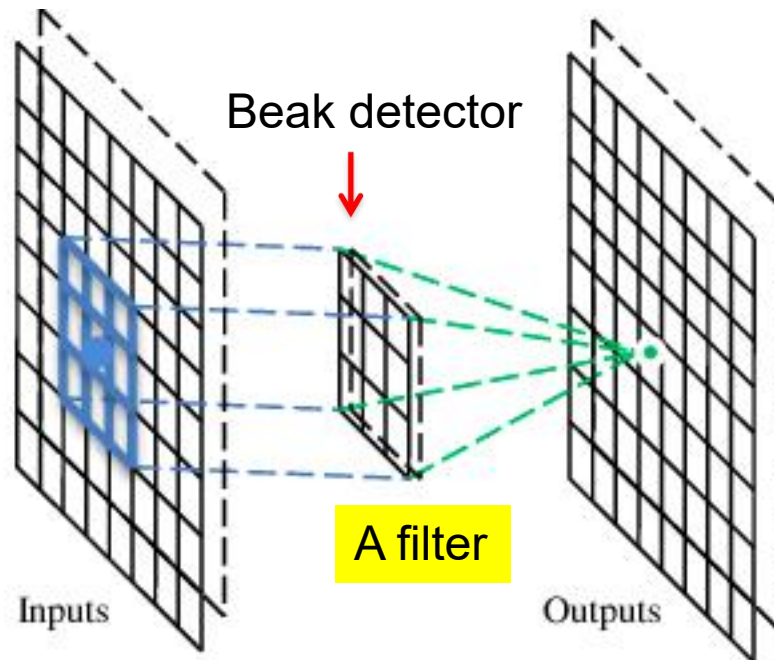
Same pattern appears in different places:  
They can be compressed!

What about training a lot of such “small” detectors  
and each detector must “move around”.



# A convolutional layer

A CNN is a neural network with some convolutional layers (and some other layers). A convolutional layer has a number of filters that does convolutional operation.



# Convolution

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

**These are the network parameters to be learned.**

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

Filter 1

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

Filter 2

⋮ ⋮

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

# Convolution

stride=1

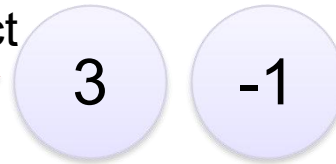
1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

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

Filter 1

Dot  
product





# Convolution

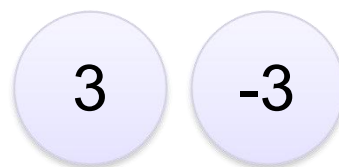
If stride=2

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

6 x 6 image

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

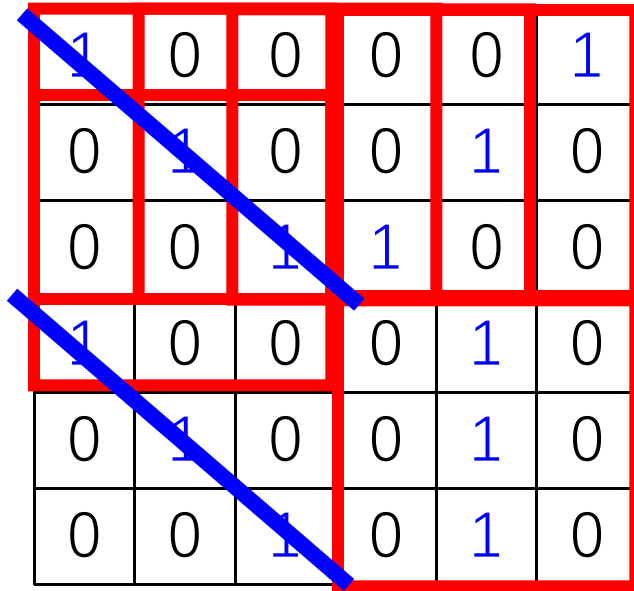
Filter 1





# Convolution

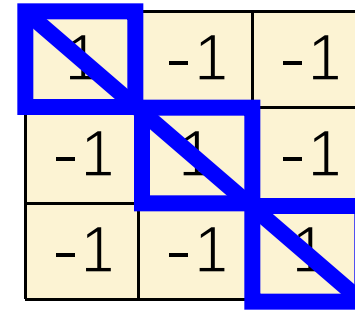
stride=1



A 6x6 grid of numbers representing an image. The values are: Row 1: 1, 0, 0, 0, 0, 1; Row 2: 0, 1, 0, 0, 1, 0; Row 3: 0, 0, 1, 1, 0, 0; Row 4: 1, 0, 0, 0, 1, 0; Row 5: 0, 1, 0, 0, 1, 0; Row 6: 0, 0, 1, 0, 1, 0. A 3x3 red bounding box highlights the top-left corner (rows 1-3, columns 1-3). A blue diagonal line runs from the top-left cell (1,1) to the bottom-right cell (6,6).

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

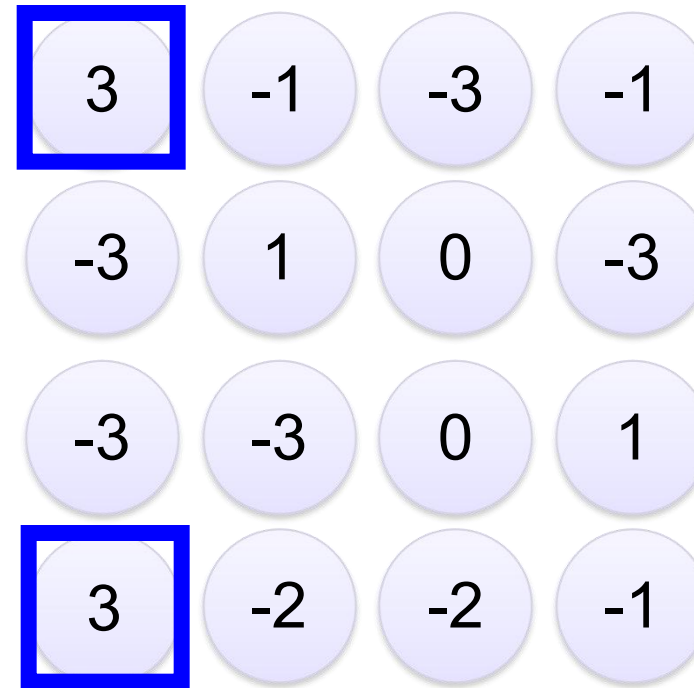
6 x 6 image



A 3x3 grid of numbers representing a filter. The values are: Row 1: 1, -1, -1; Row 2: -1, 1, -1; Row 3: -1, -1, 1. A blue diagonal line runs from the top-left cell (1,1) to the bottom-right cell (3,3).

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

Filter 1



A 4x4 grid of circles representing the output of the convolution. The values are: Row 1: 3, -1, -3, -1; Row 2: -3, 1, 0, -3; Row 3: -3, -3, 0, 1; Row 4: 3, -2, -2, -1. The top-left circle (3) and the bottom-left circle (3) are highlighted with a blue square border.

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

# Convolution

stride=1

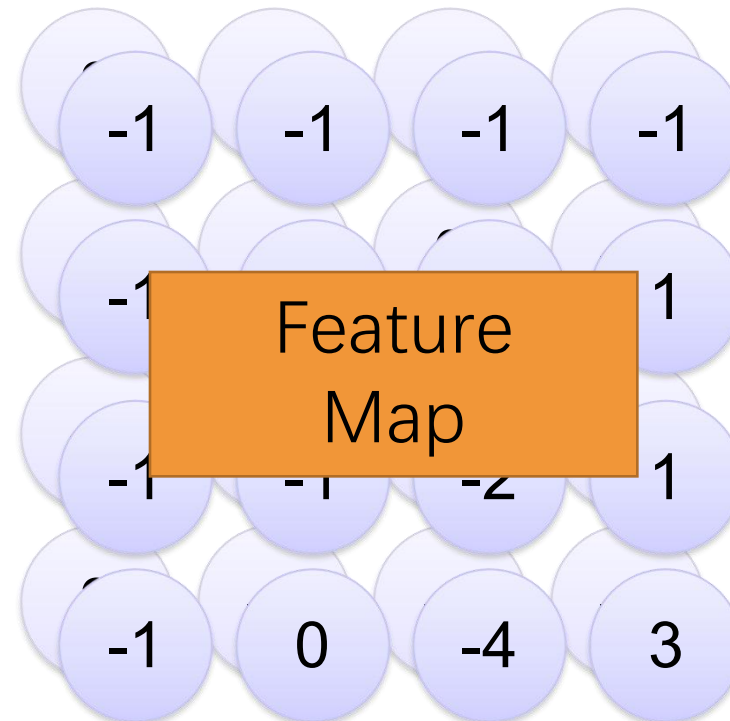
1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image

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

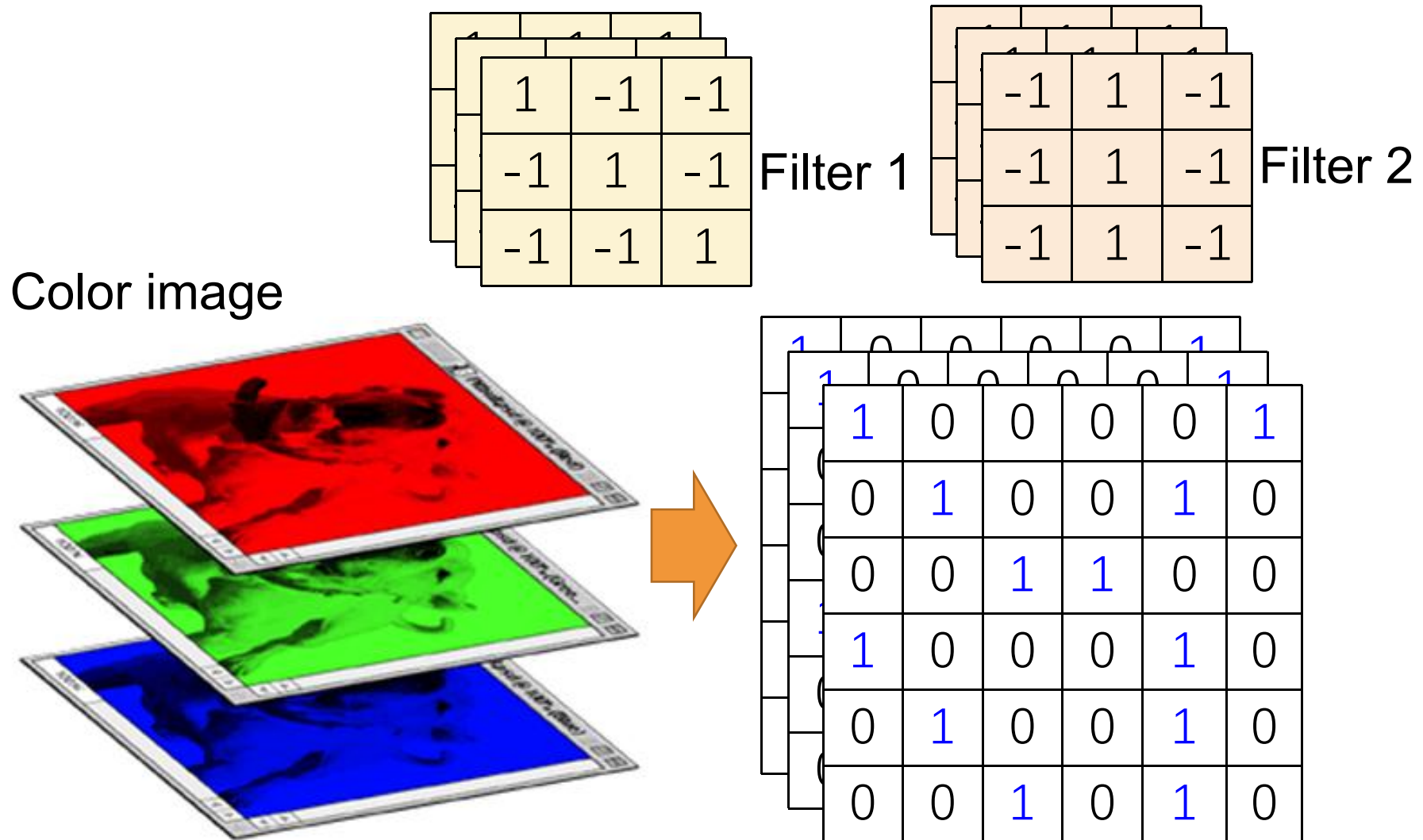
Filter 2

Repeat this for each filter

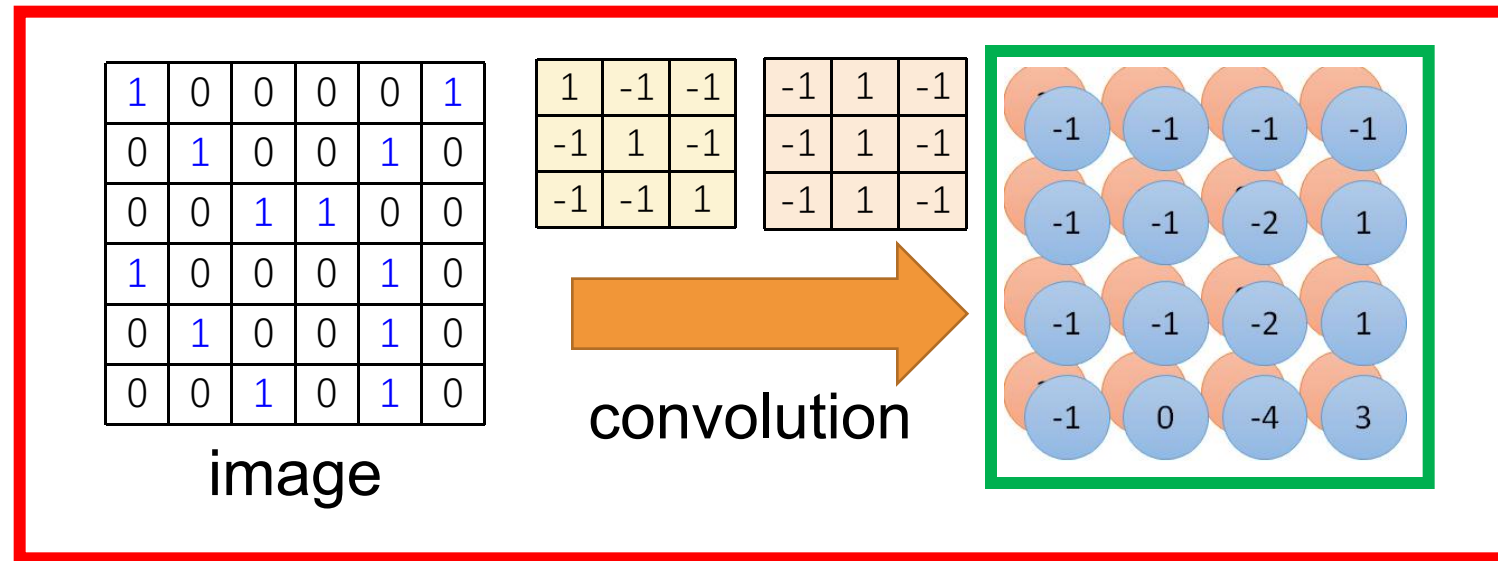


Two 4 x 4 images  
Forming 2 x 4 x 4 matrix

# Color image: RGB 3 channels

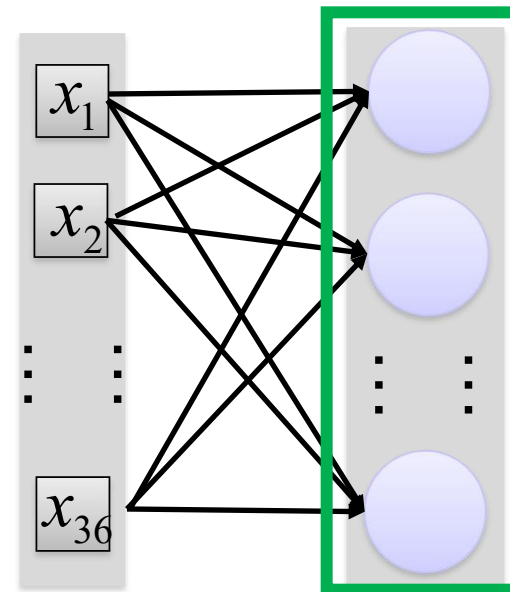


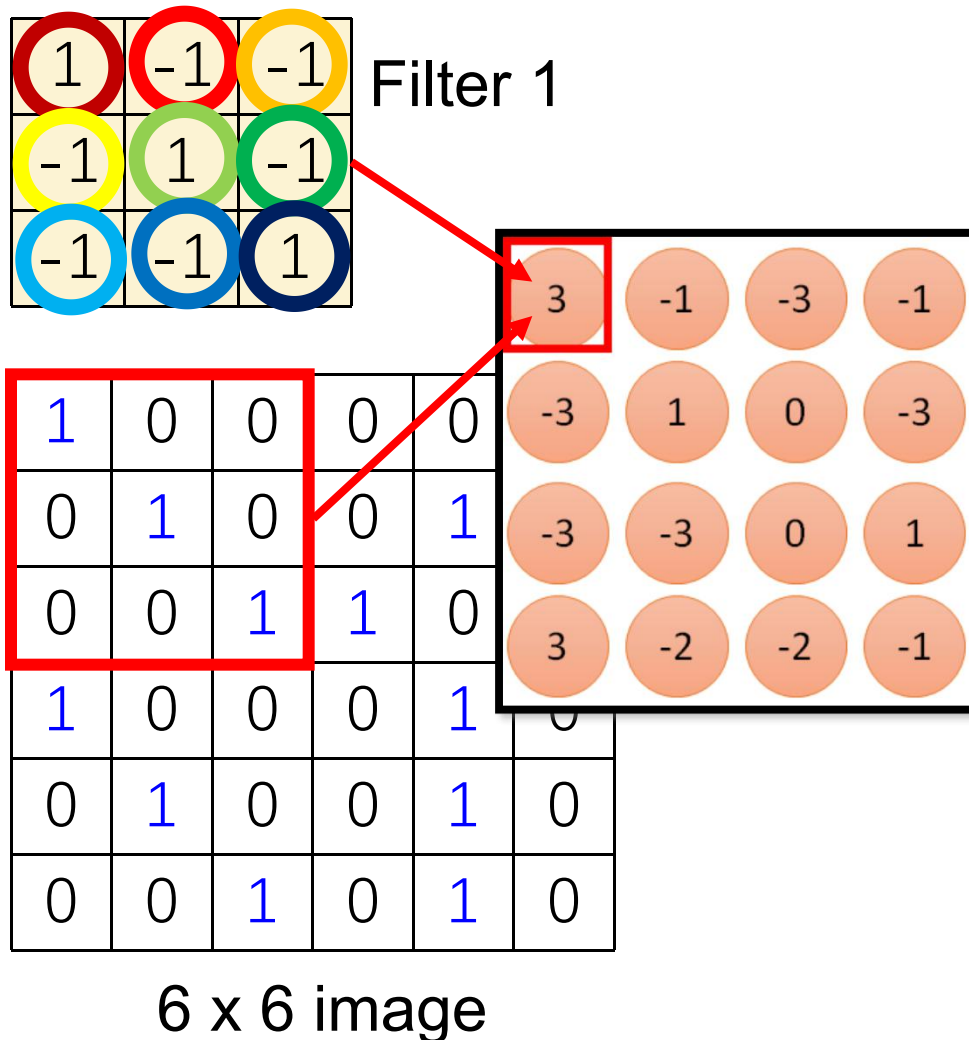
# Convolution v.s. Fully Connected



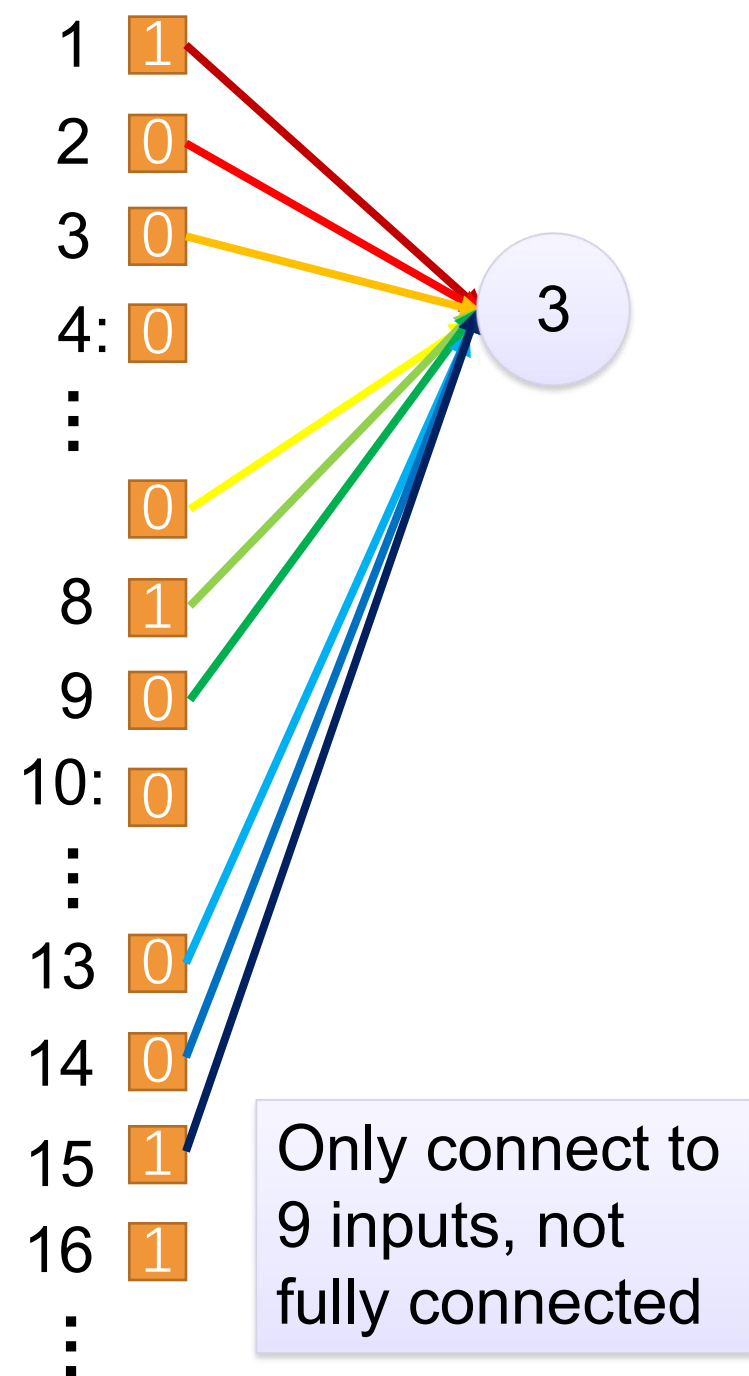
Fully-  
connected

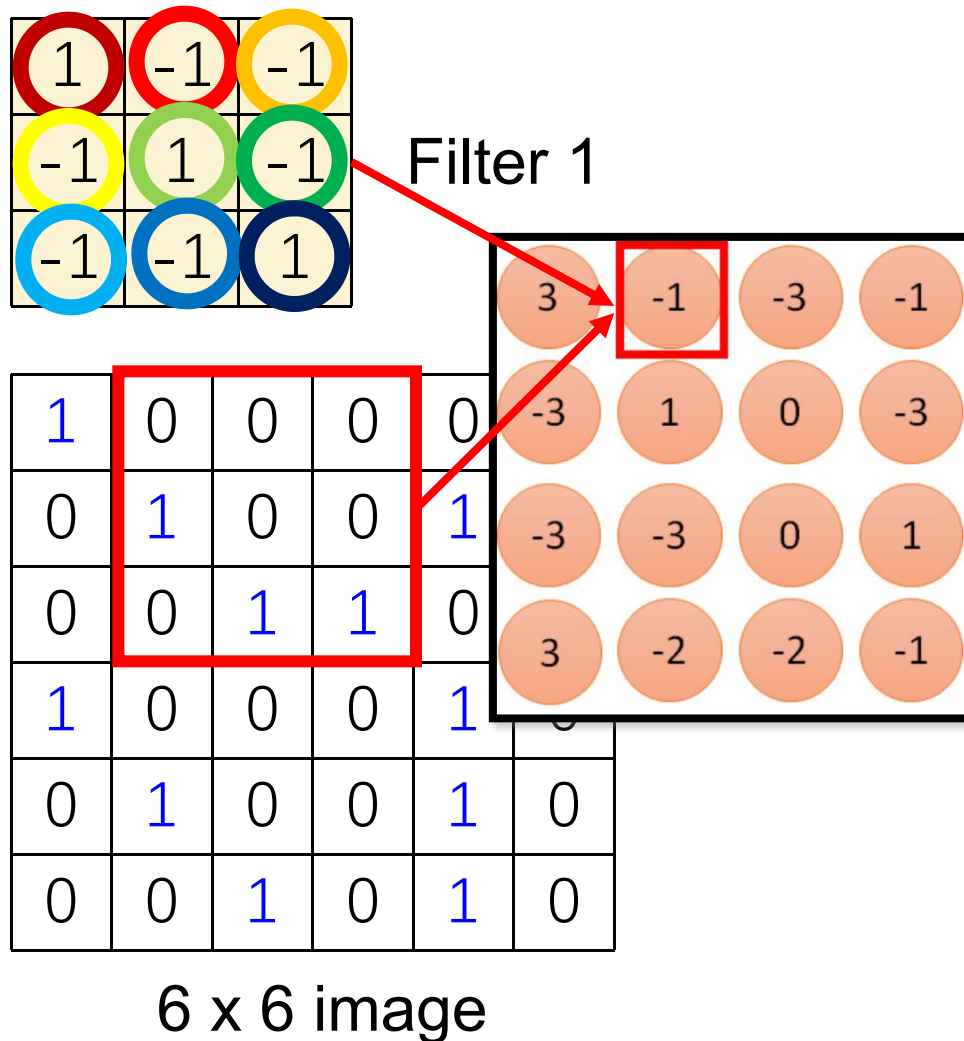
1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0





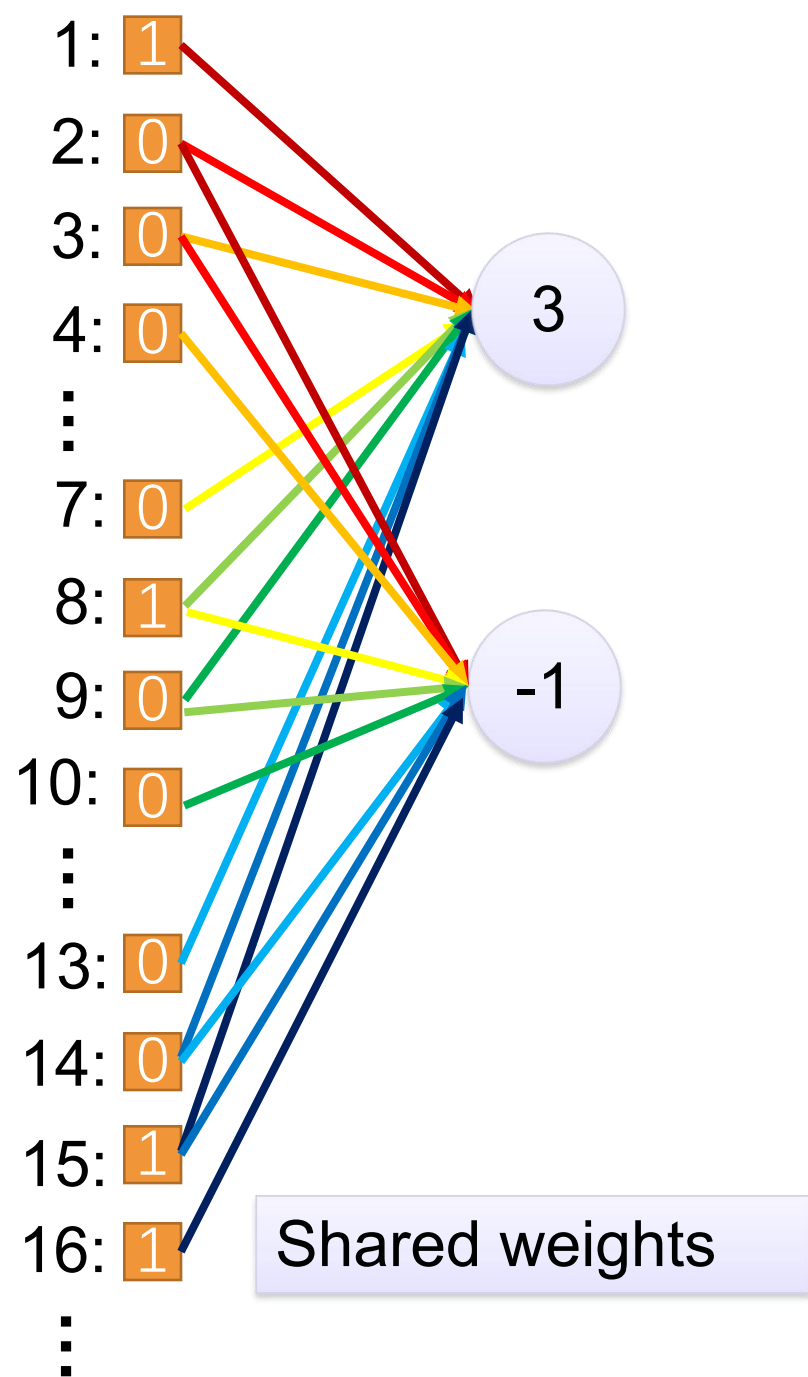
fewer parameters!



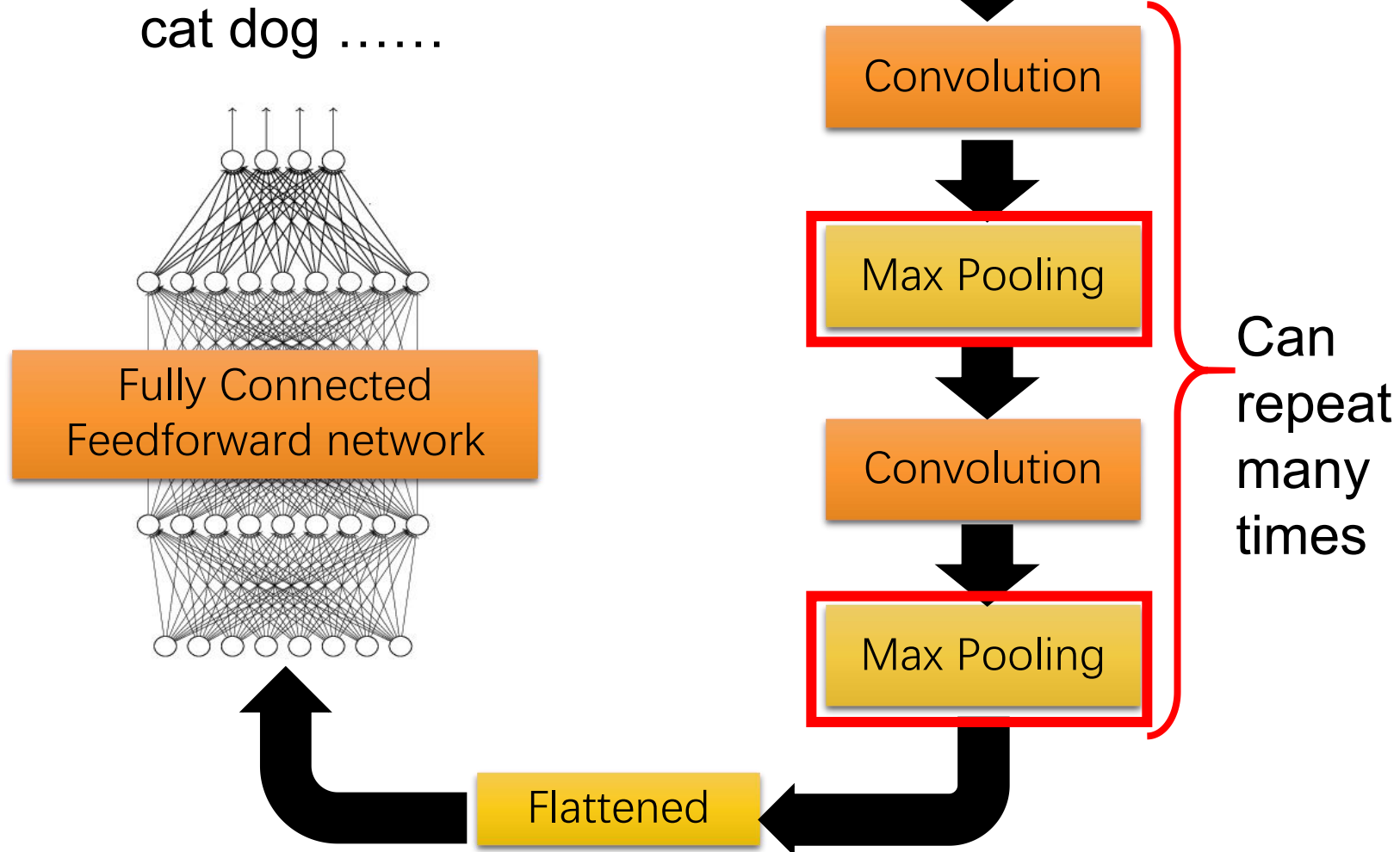


Fewer parameters

Even fewer parameters



# The whole CNN





# 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

# Why Pooling

- Subsampling pixels will not change the object

bird



Subsampling

bird



We can subsample the pixels to make image smaller



fewer parameters to characterize the image

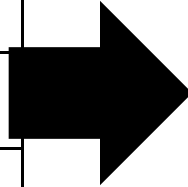
# A CNN compresses a fully connected network in two ways:

- Reducing number of connections
- Shared weights on the edges
- Max pooling further reduces the complexity

# Max Pooling

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

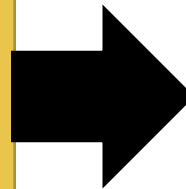
6 x 6 image



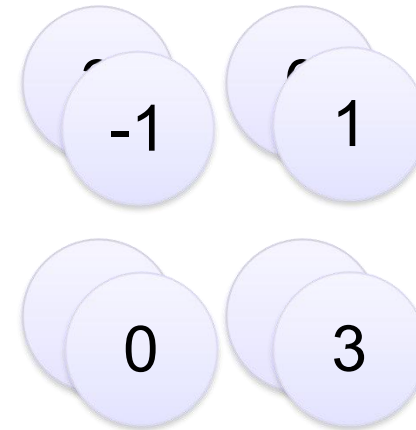
Conv



Max  
Pooling



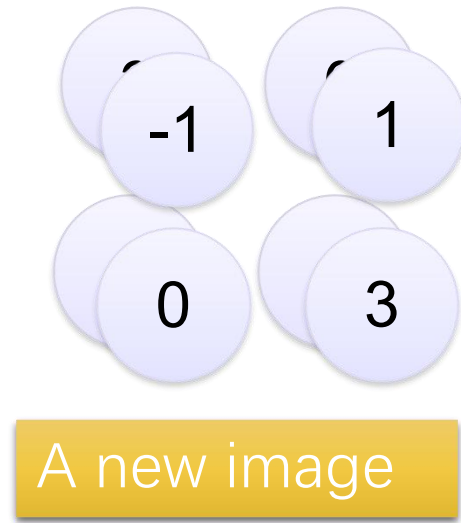
New image  
but smaller



2 x 2 image

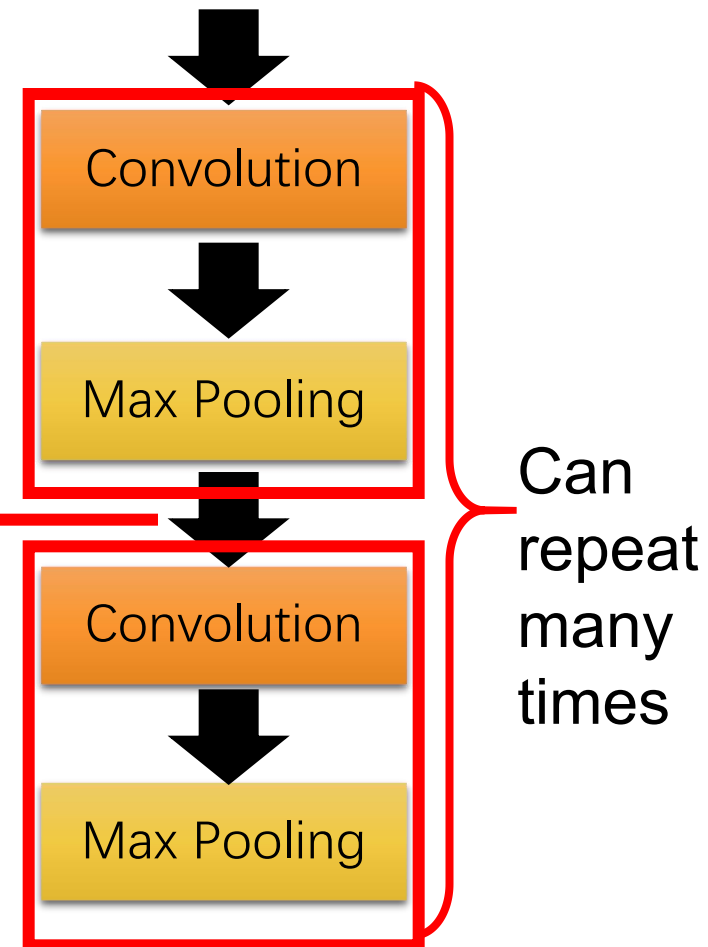
Each filter  
is a channel

# The whole CNN



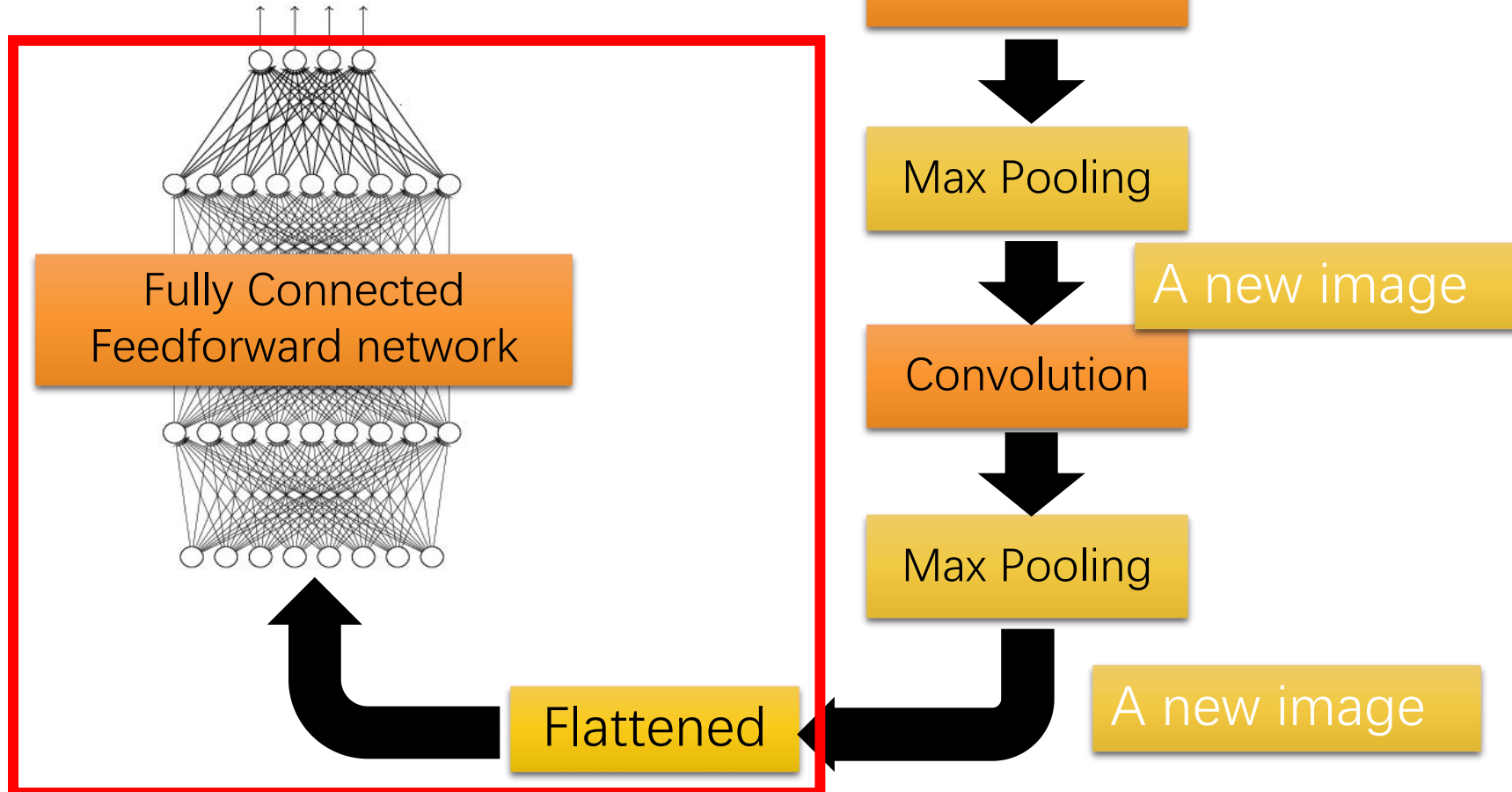
Smaller than the original image

The number of channels is the number of filters

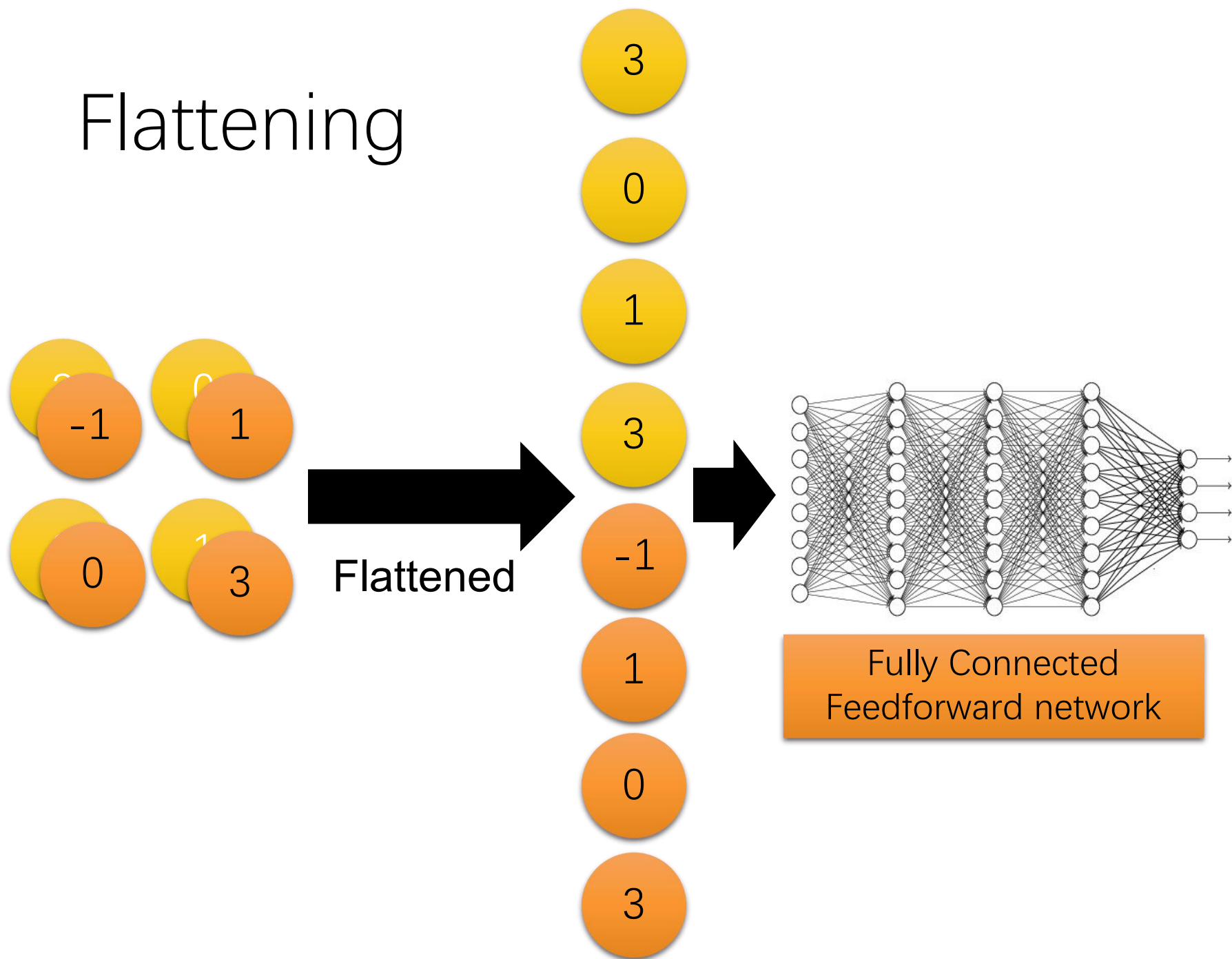


# The whole CNN

cat dog .....



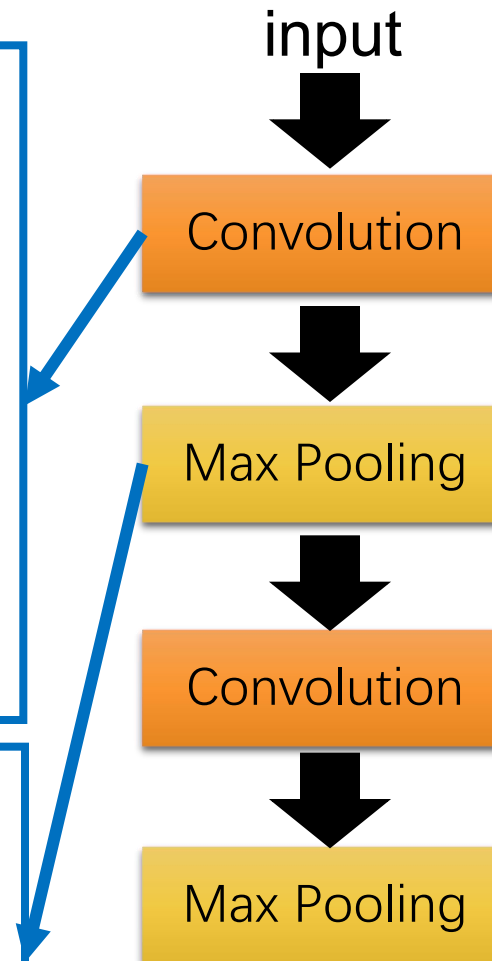
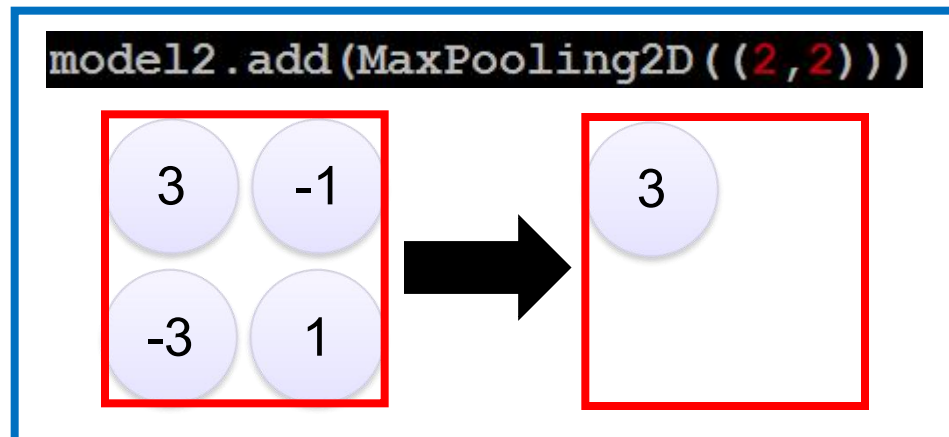
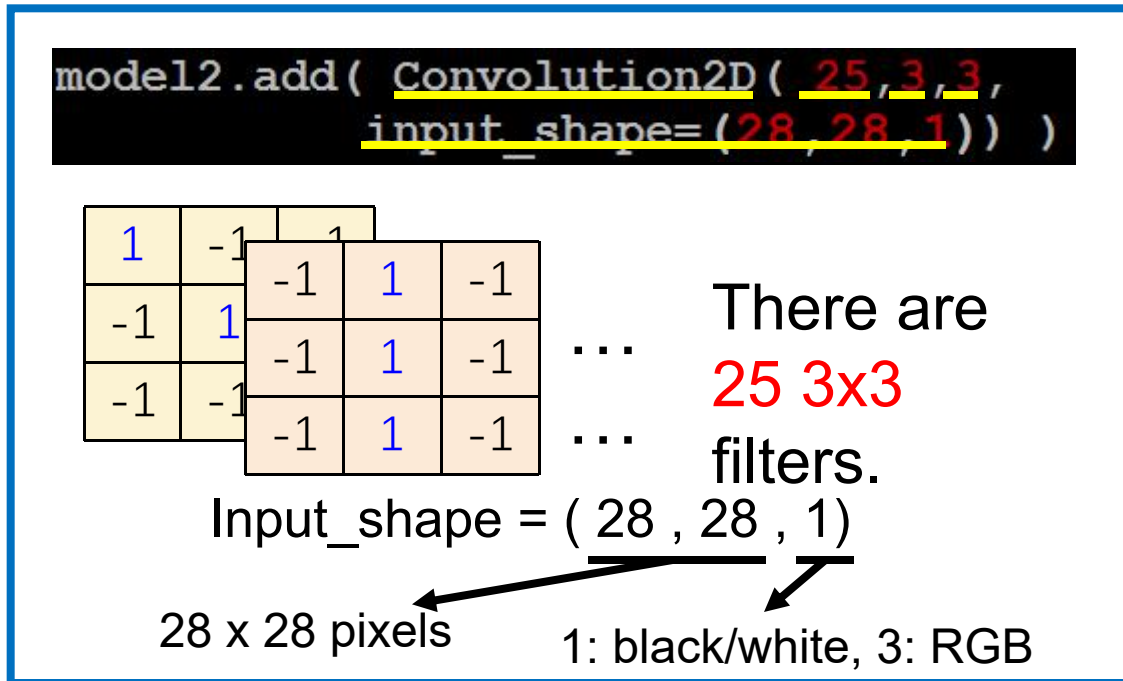
# Flattening





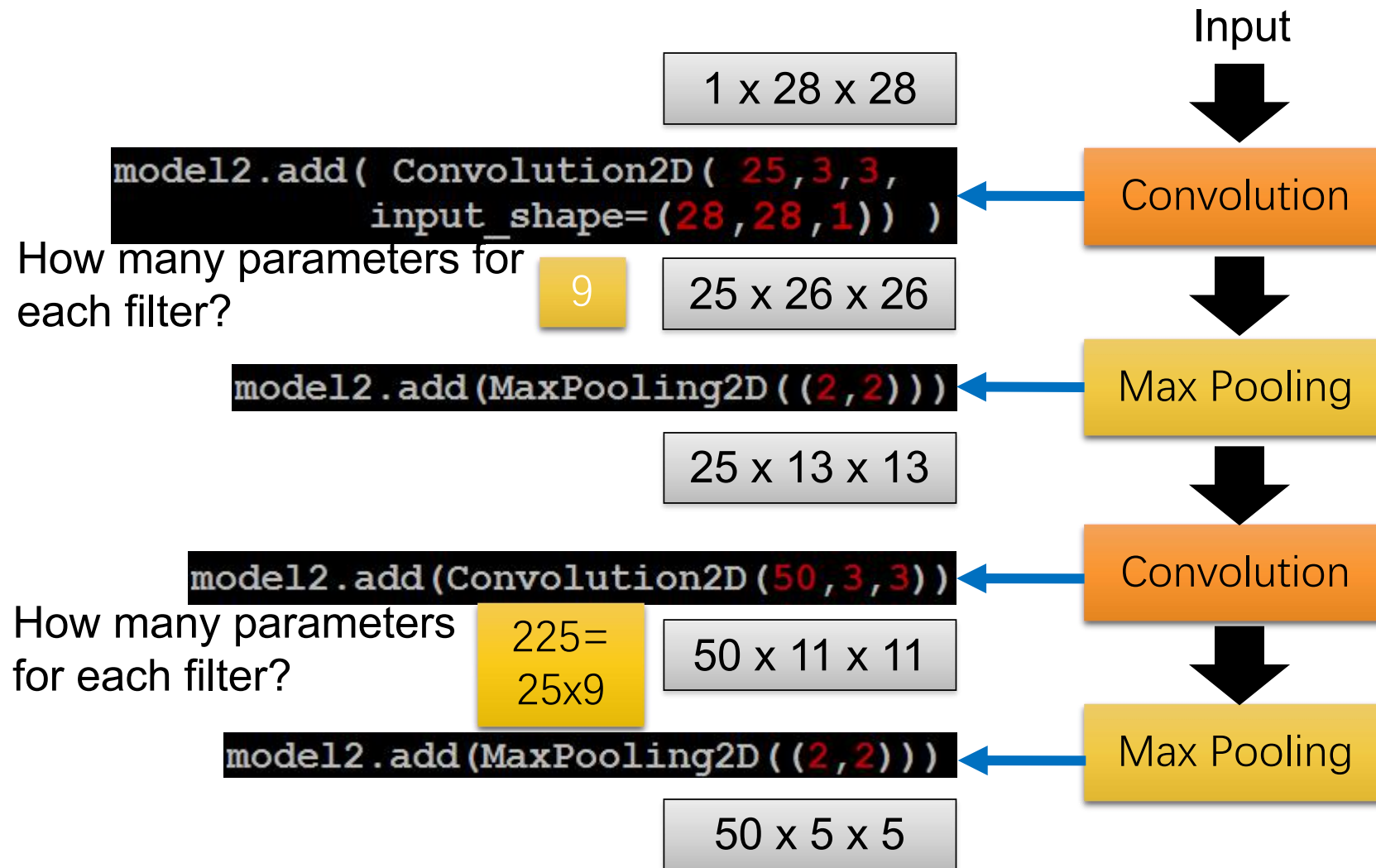
# CNN in Keras

Only modified the *network structure* and *input format (vector -> 3-D tensor)*



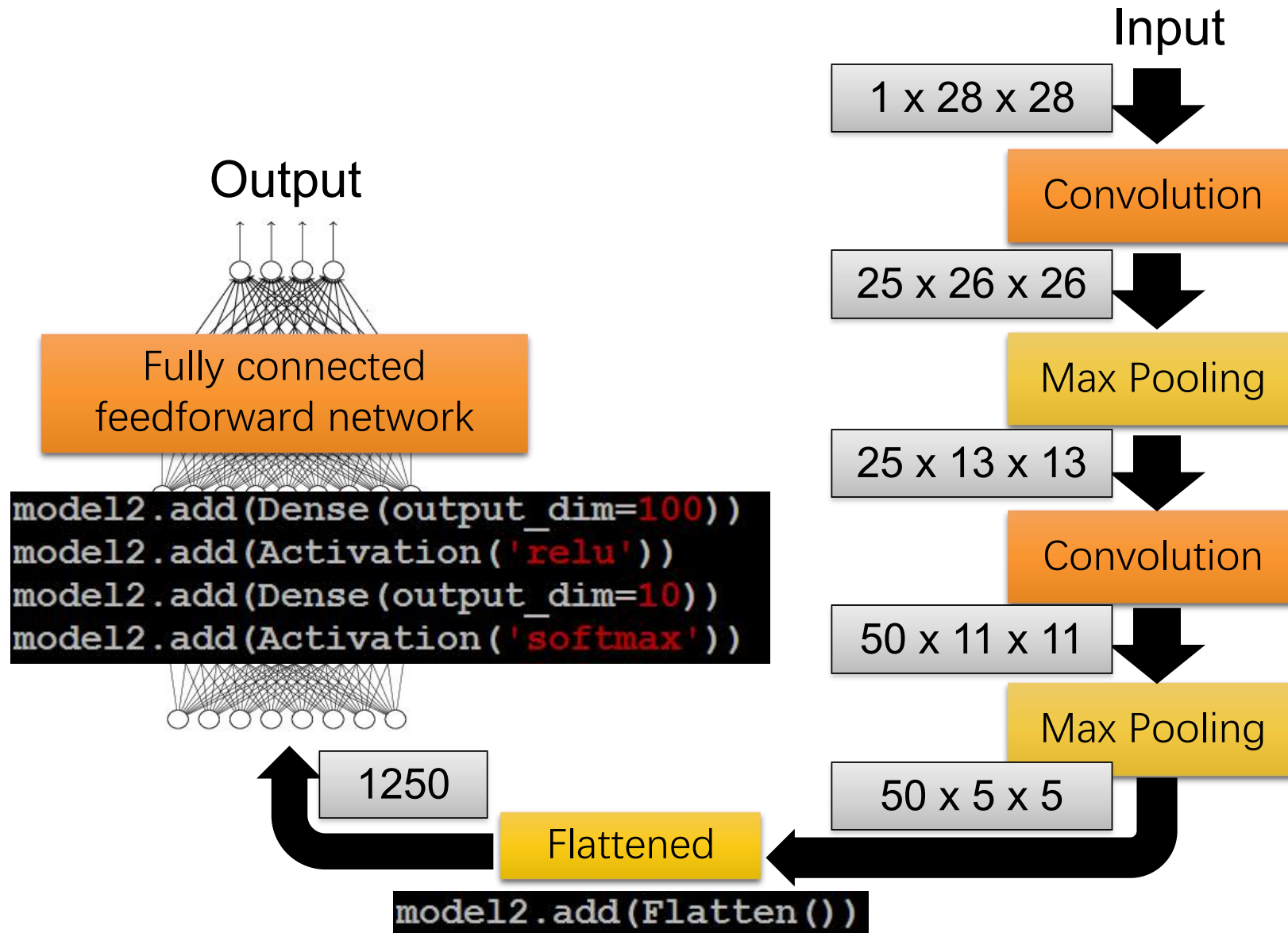
# CNN in Keras

Only modified the *network structure* and *input format (vector -> 3-D array)*

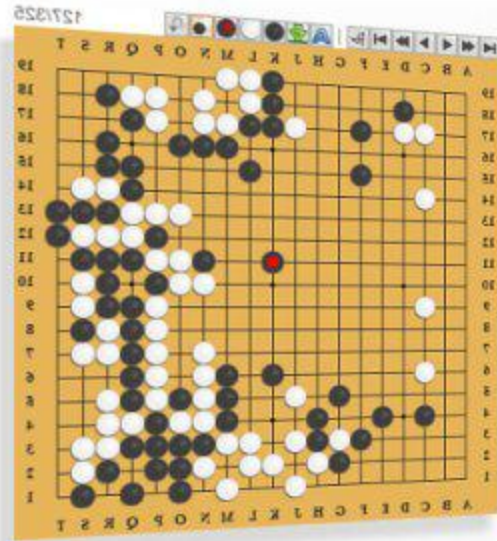


# CNN in Keras

Only modified the *network structure* and *input format (vector -> 3-D array)*



# AlphaGo



19 x 19 matrix

Black: 1

white: -1

none: 0



Neural  
Network



Next move  
(19 x 19  
positions)

Fully-connected feedforward  
network can be used

But CNN performs much better

# AlphaGo's policy network

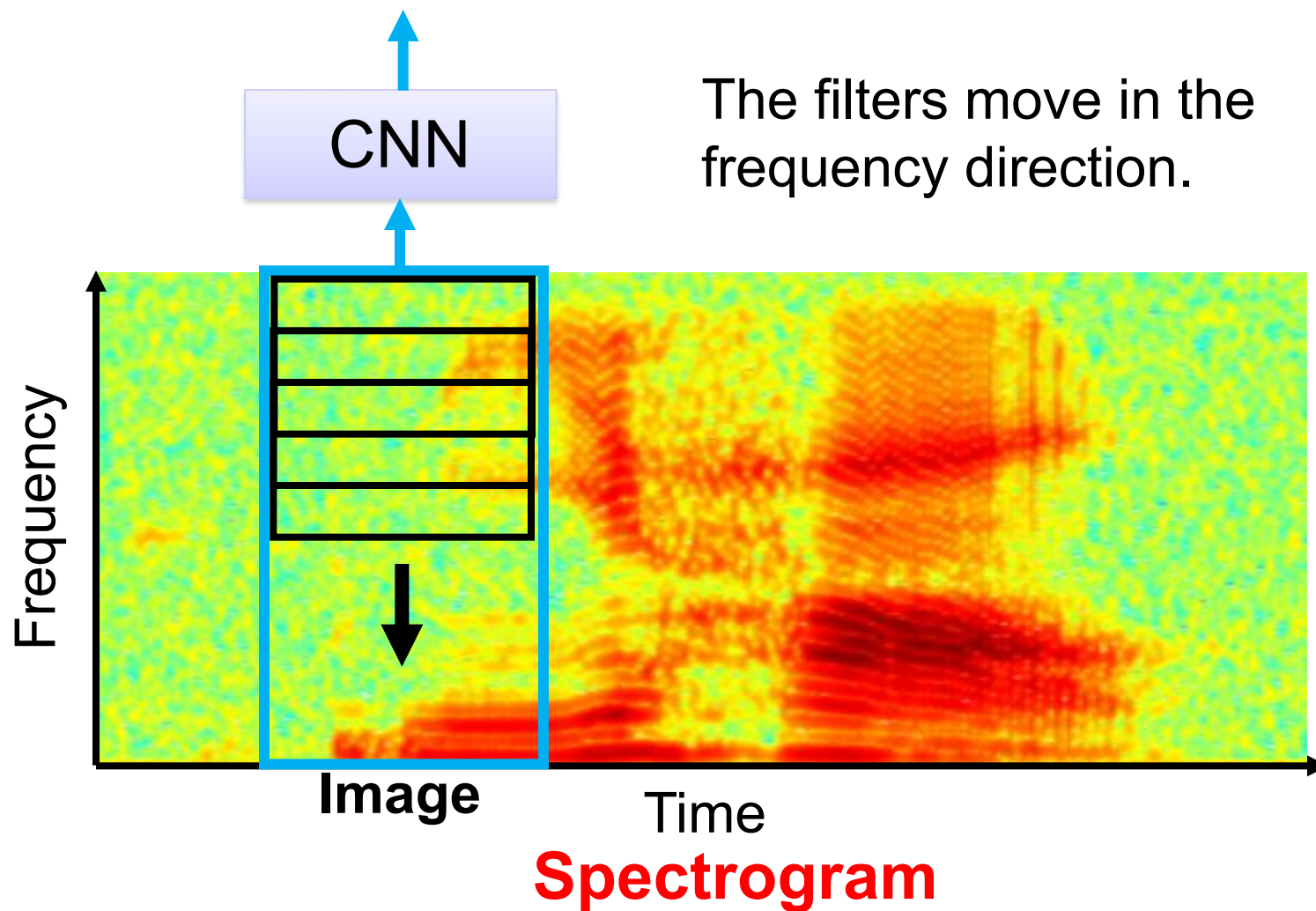
The following is quotation from their Nature article:

Note: AlphaGo does not use Max Pooling.

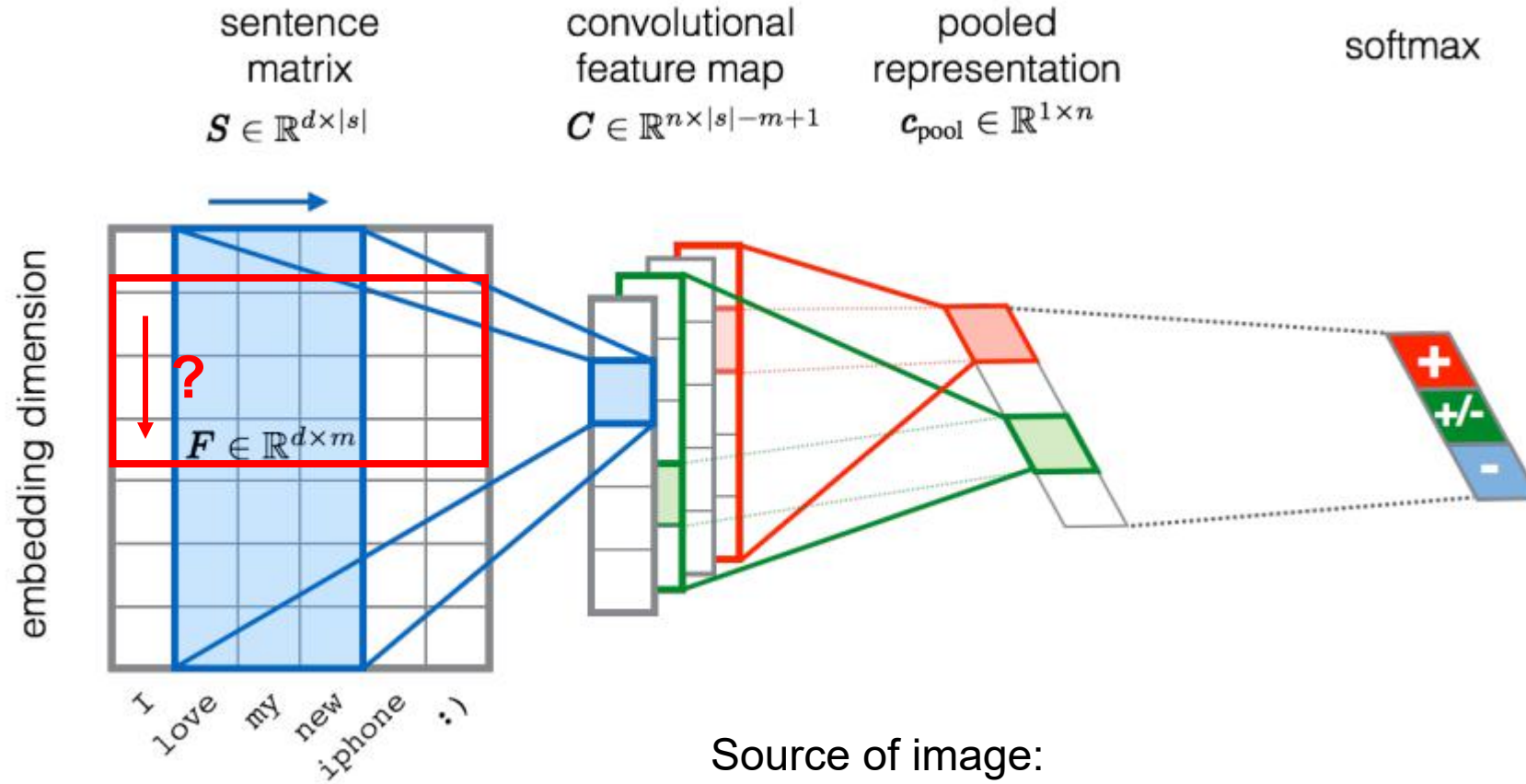
**Neural network architecture.** The input to the policy network is a  $19 \times 19 \times 48$  image stack consisting of 48 feature planes. The first hidden layer zero pads the input into a  $23 \times 23$  image, then convolves  $k$  filters of kernel size  $5 \times 5$  with stride 1 with the input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



# CNN in speech recognition



# CNN in text classification



Source of image:  
<http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.703.6858&rep=rep1&type=pdf>



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THANKS