

# James Webb Space Telescope





# The landscape of “mountains” and “valleys”





# A visual grouping of five galaxies



# CONVOLUTIONAL NEURAL NETWORK

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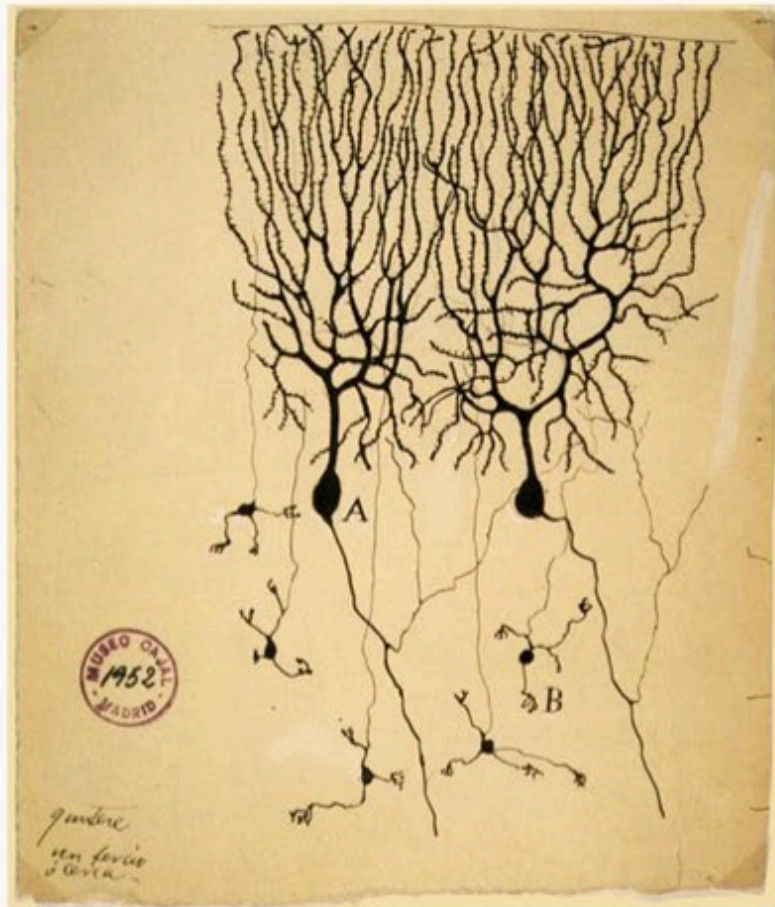
**Great visualization tool:**

**<https://poloclub.github.io/cnn-explainer/>**

Slides are based on Ming Li (University of Waterloo – Deep learning part) with some modifications



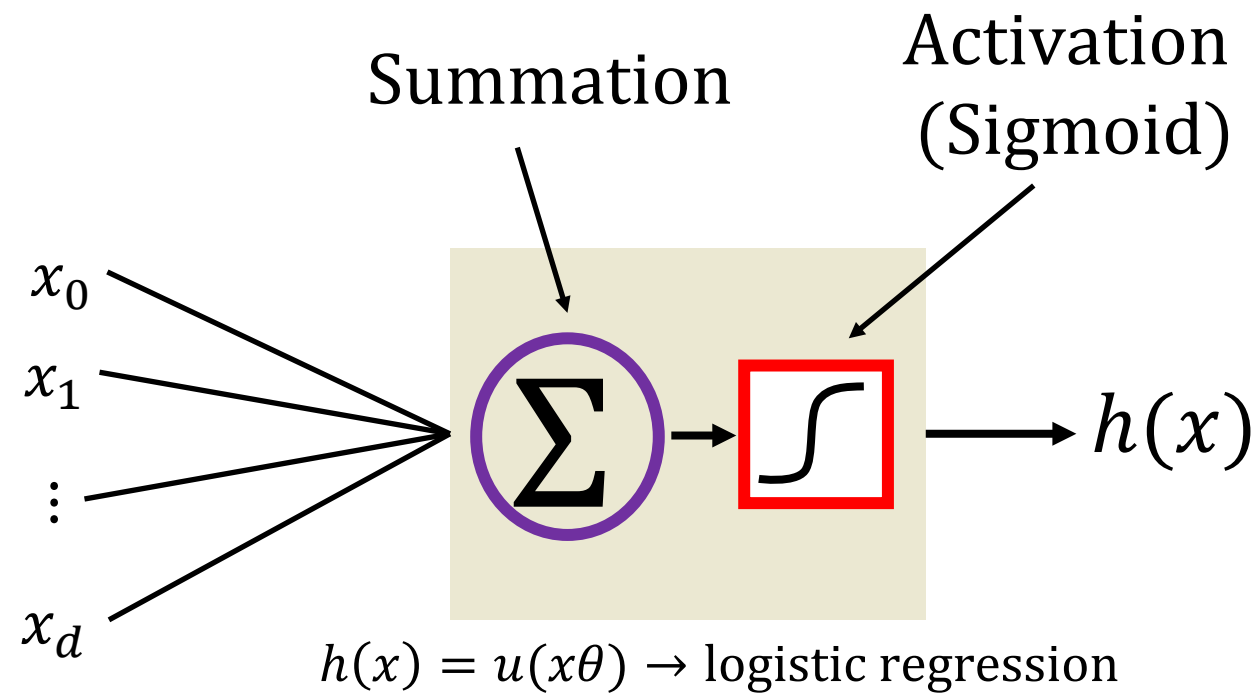
# Inspiration from Biological Neurons



The first drawing of a brain cells by Santiago Ramón y Cajal in 1899

**Neurons:** core components of brain and the nervous system consisting of

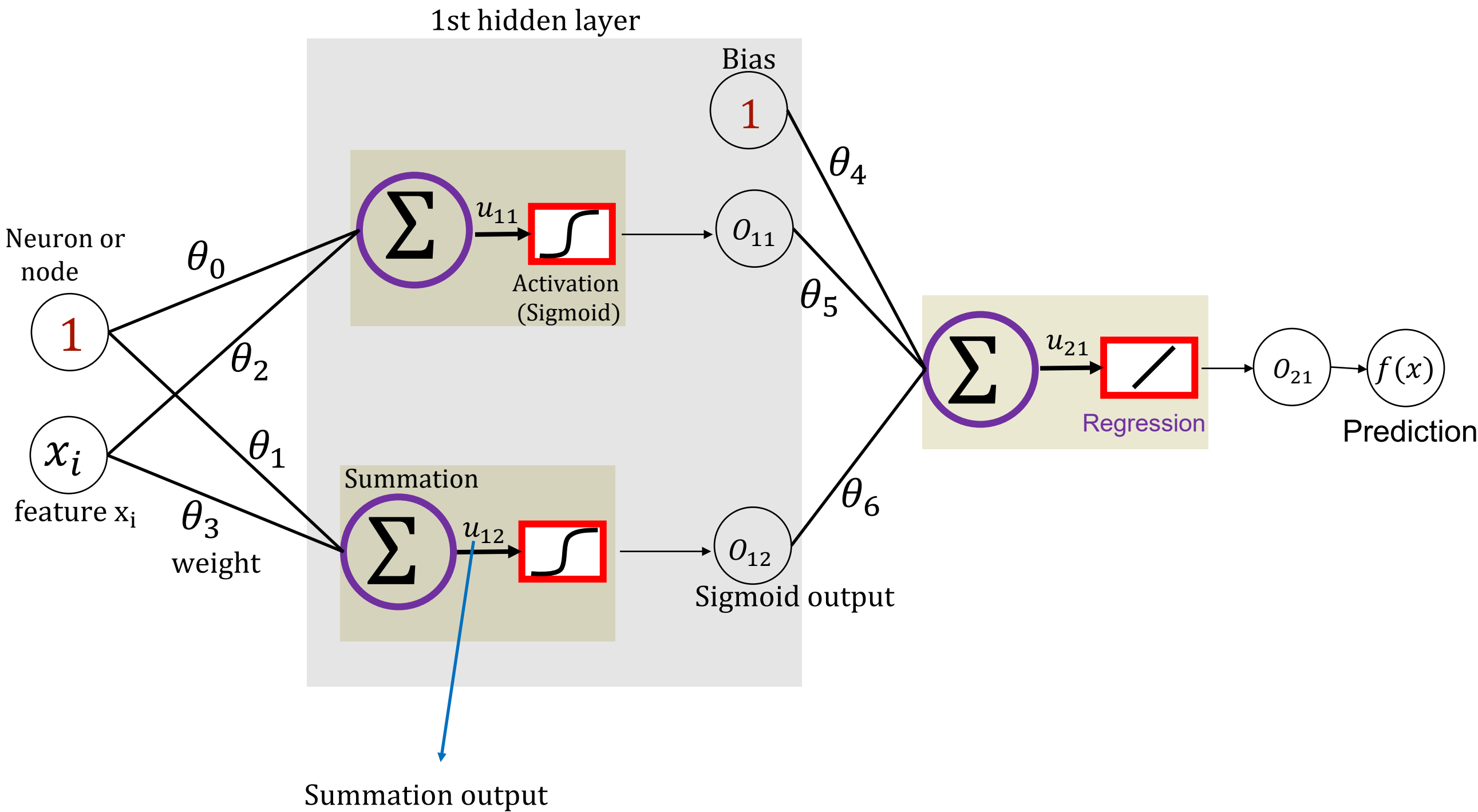
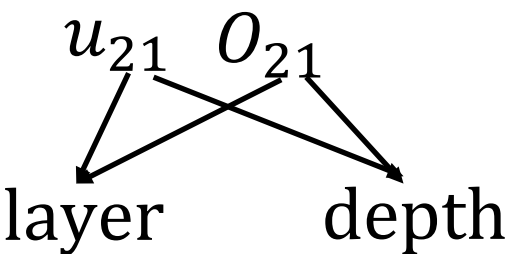
1. Dendrites that collect information from other neurons
2. An axon that generates outgoing spikes



$$\text{output} = \text{activation}(x\theta + b)$$

Name of the neuron	Activation function: $\text{activation}(z)$
Linear unit	$x\theta$
Threshold/sign unit	$\text{sign}(x\theta)$
Sigmoid unit	$\frac{1}{1 + \exp(x\theta)}$
Rectified linear unit (ReLU)	$\max(0, x\theta)$
Tanh unit	$\tanh(x\theta)$

# NN Regression

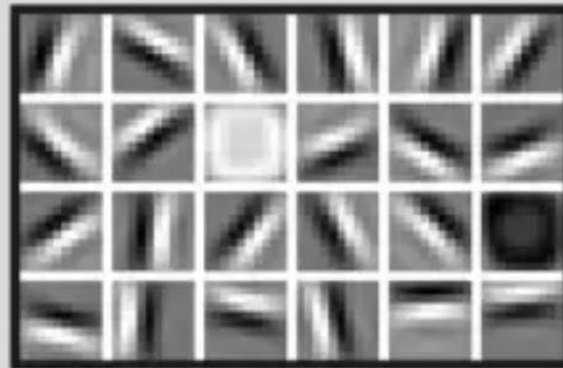


# FACIAL RECOGNITION

Deep-learning neural networks use layers of increasingly complex rules to categorize complicated shapes such as faces.



Layer 1: The computer identifies pixels of light and dark.



Layer 2: The computer learns to identify edges and simple shapes.



Layer 3: The computer learns to identify more complex shapes and objects.

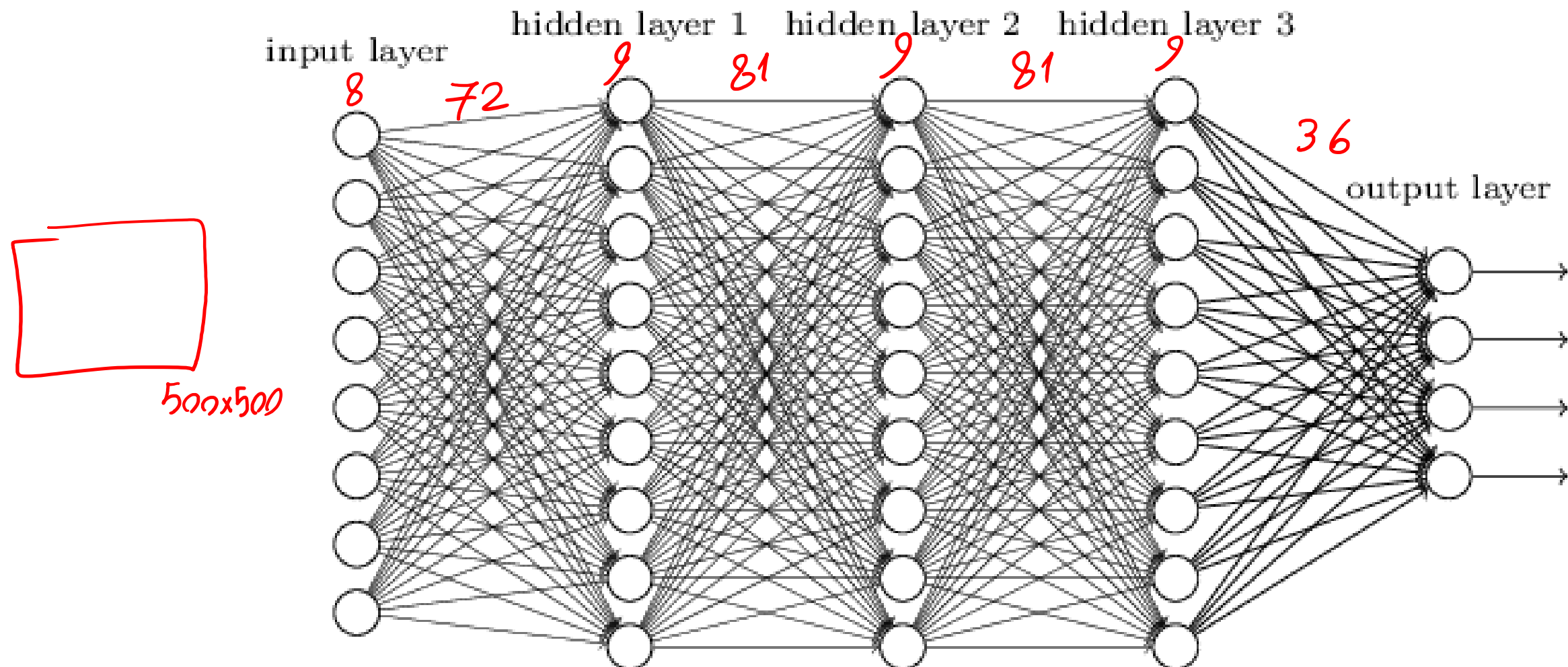


Layer 4: The computer learns which shapes and objects can be used to define a human face.



# Smaller Network: CNN

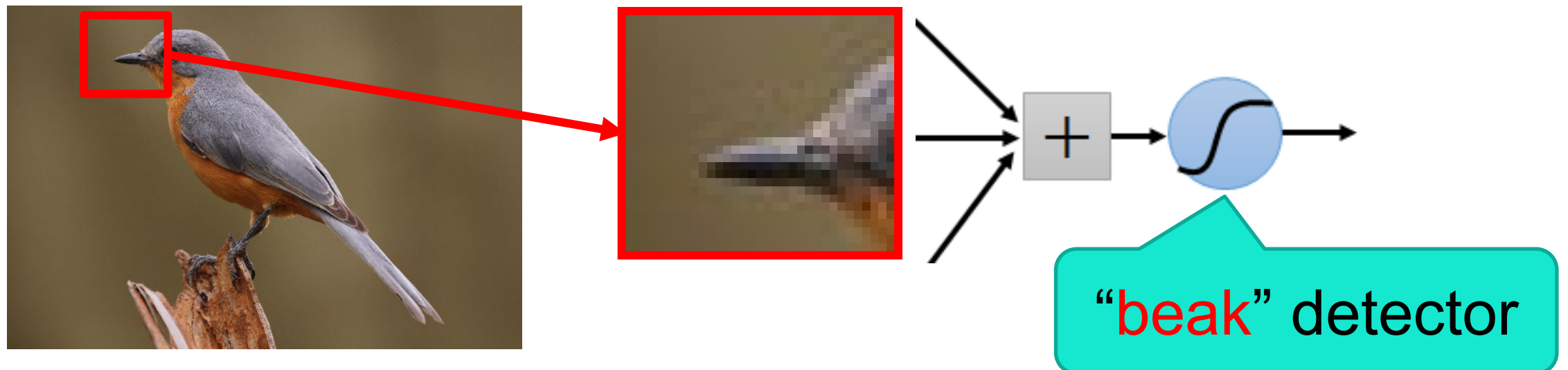
- We know it is good to learn a small model.
- From this fully connected model, do we really need all the edges?
- Can some of these be shared?



# Consider learning an image:

- Some patterns are much smaller than the whole image

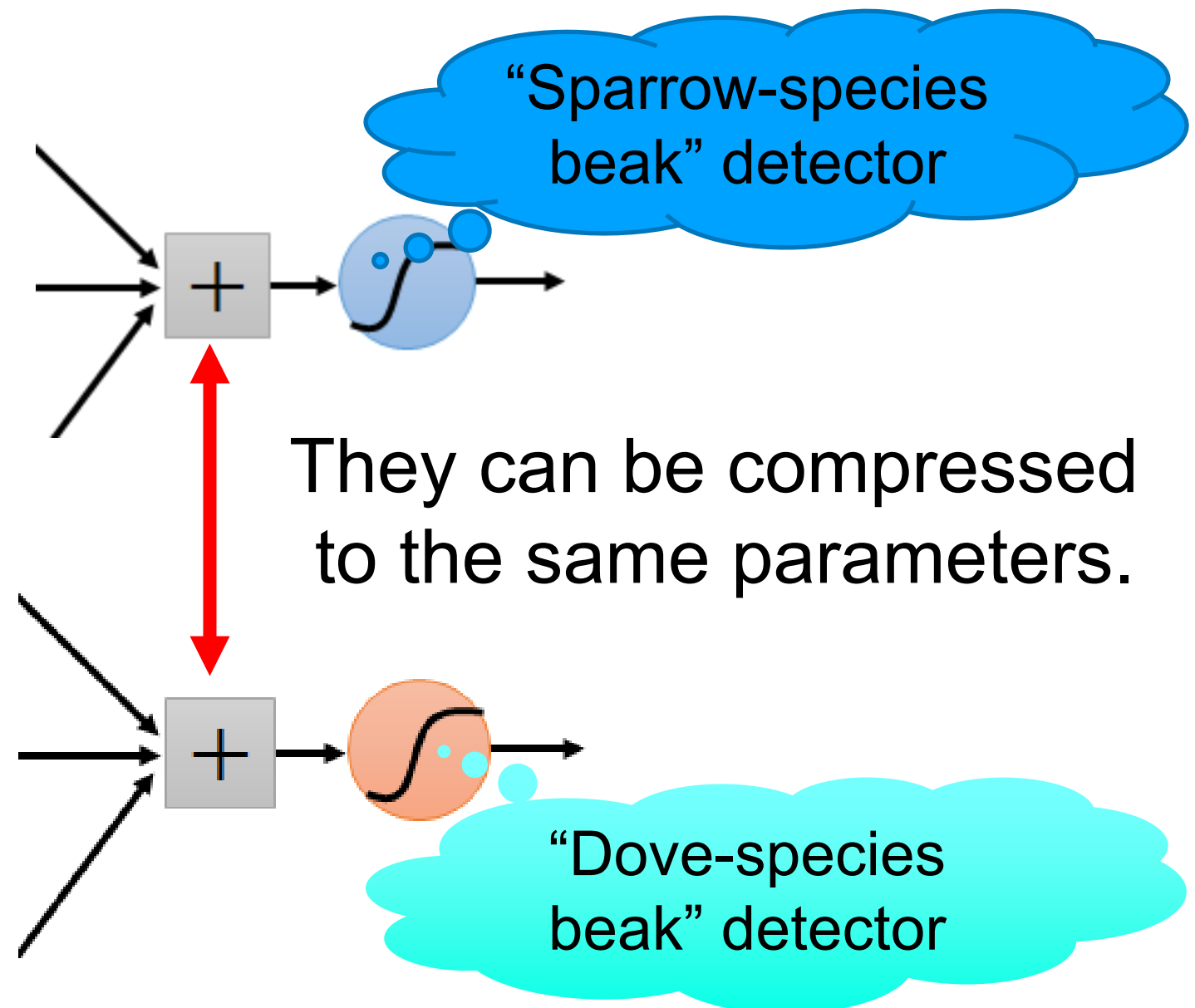
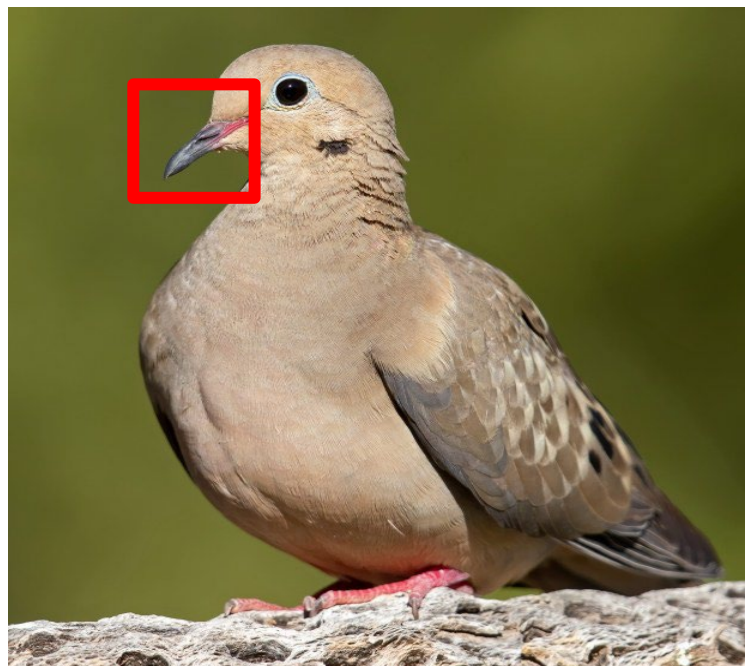
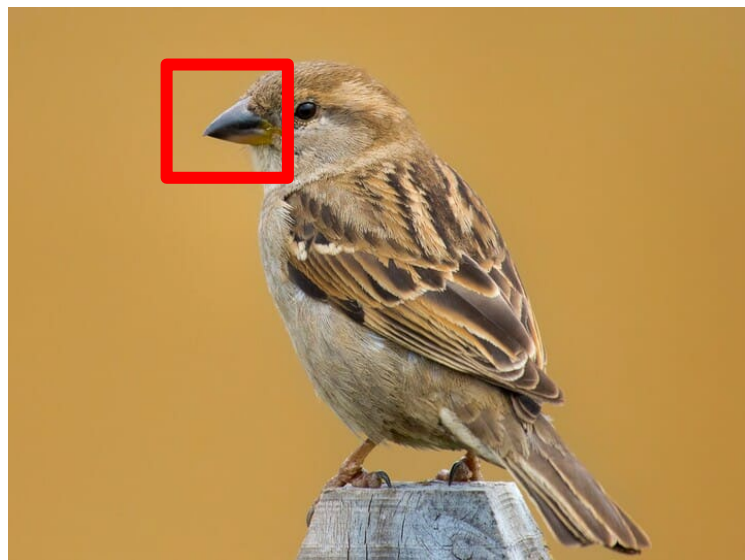
Can represent a small region with fewer parameters





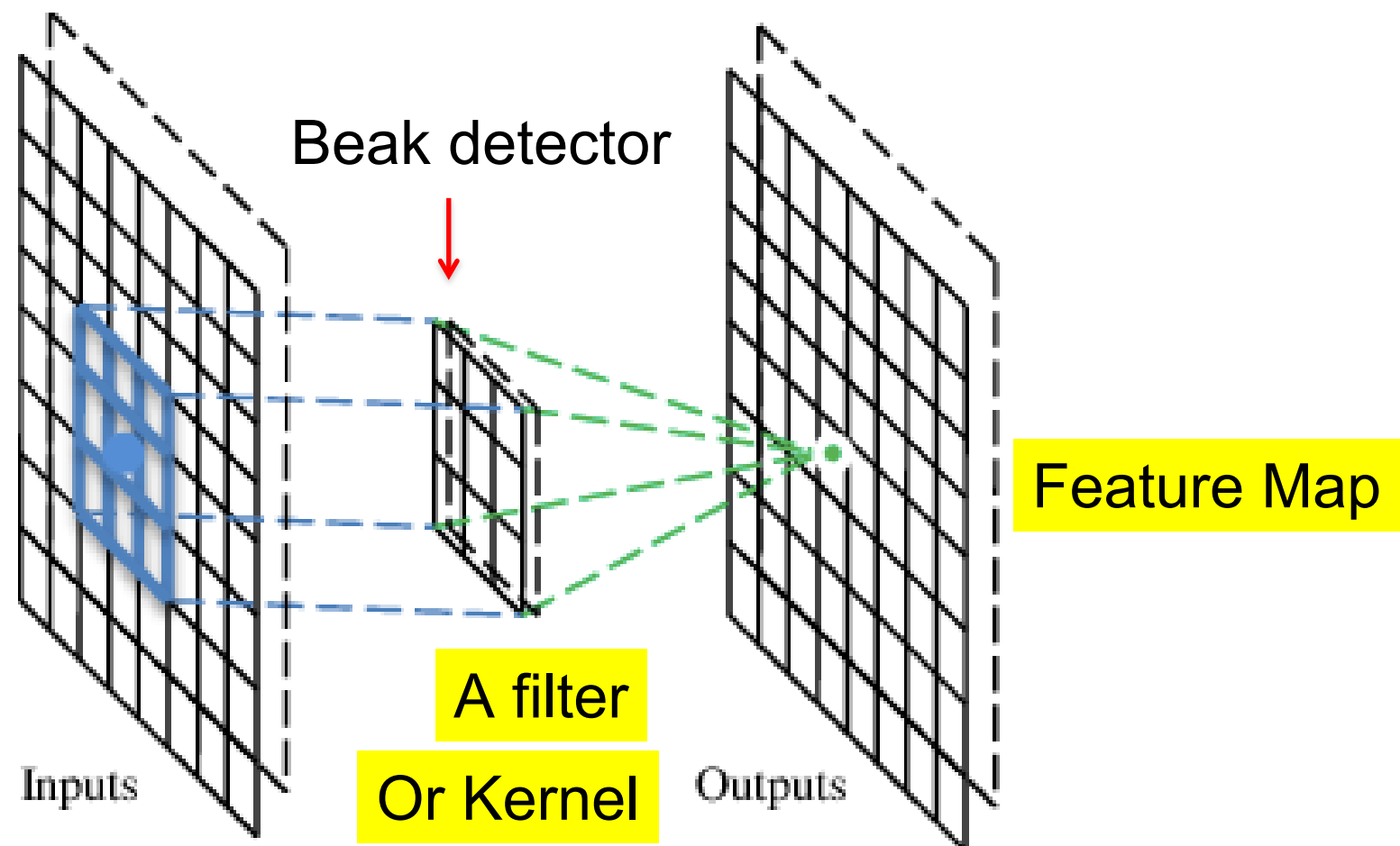
Same pattern appears in different places:  
They can be compressed!

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

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

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

⋮ ⋮

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

# Convolution

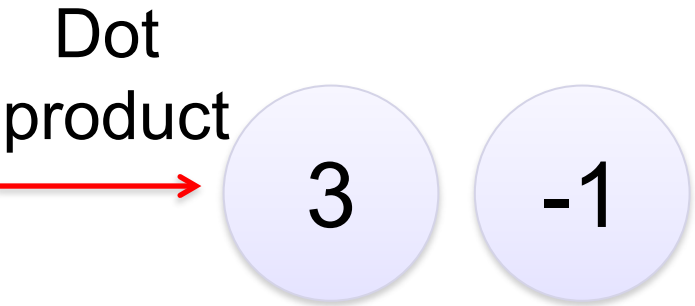
stride=1

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





# Convolution

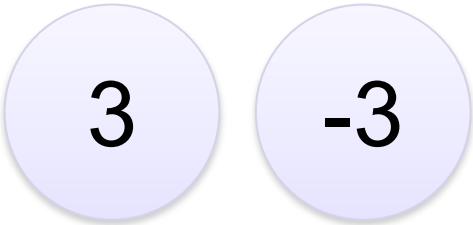
If stride=2

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

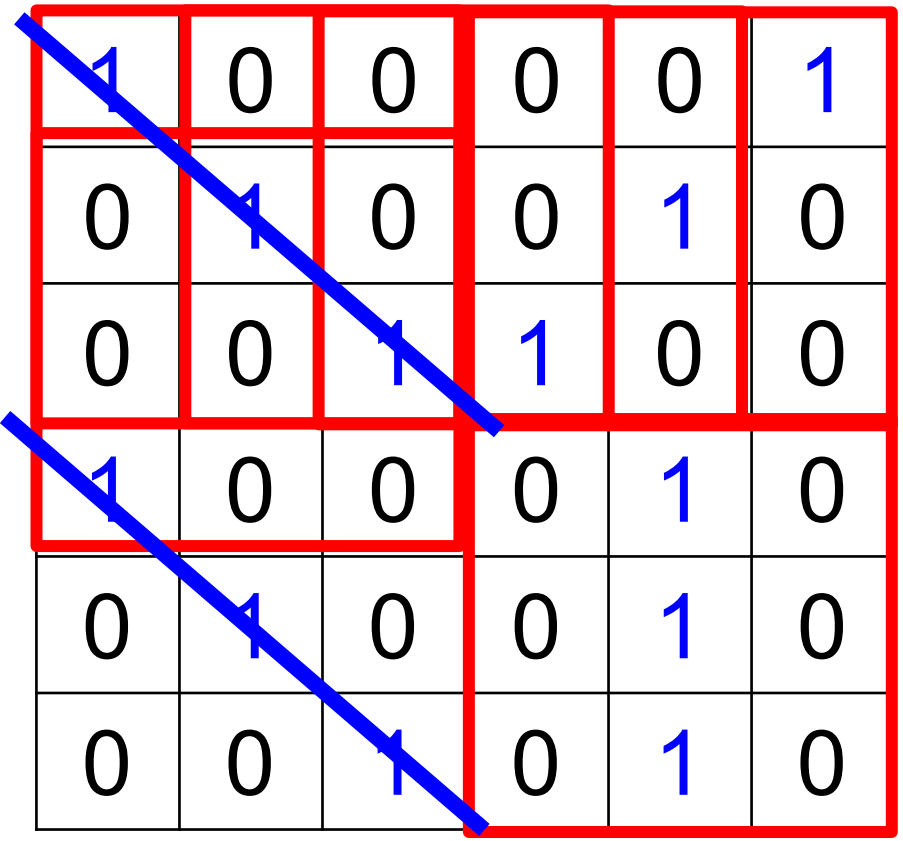
1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

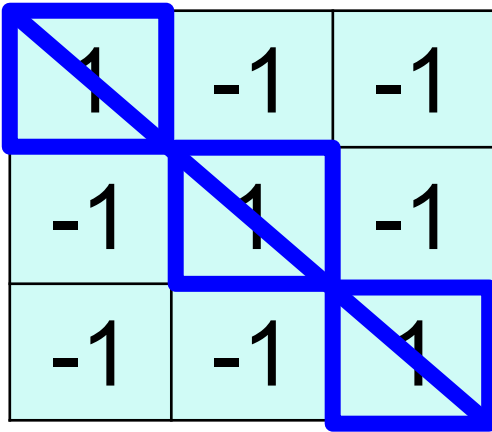


# Convolution

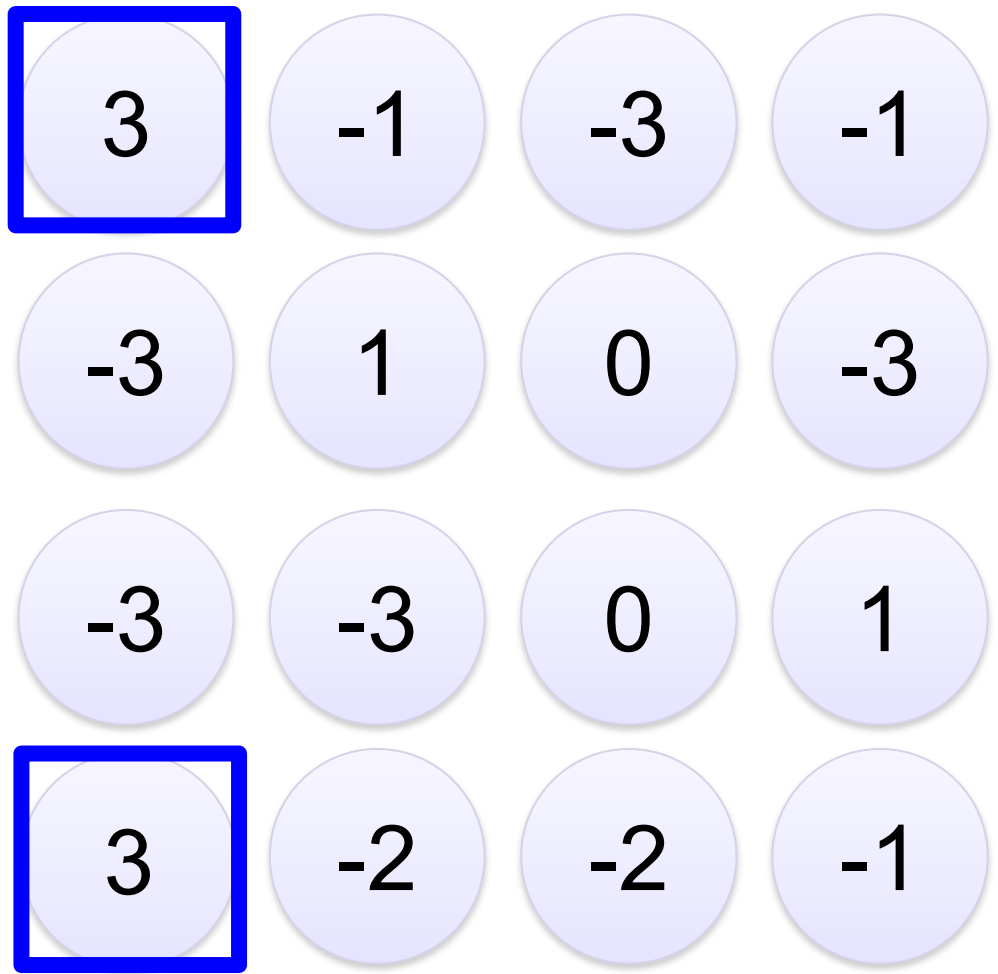
stride=1



6 x 6 image



Filter 1





# Convolution

stride=1

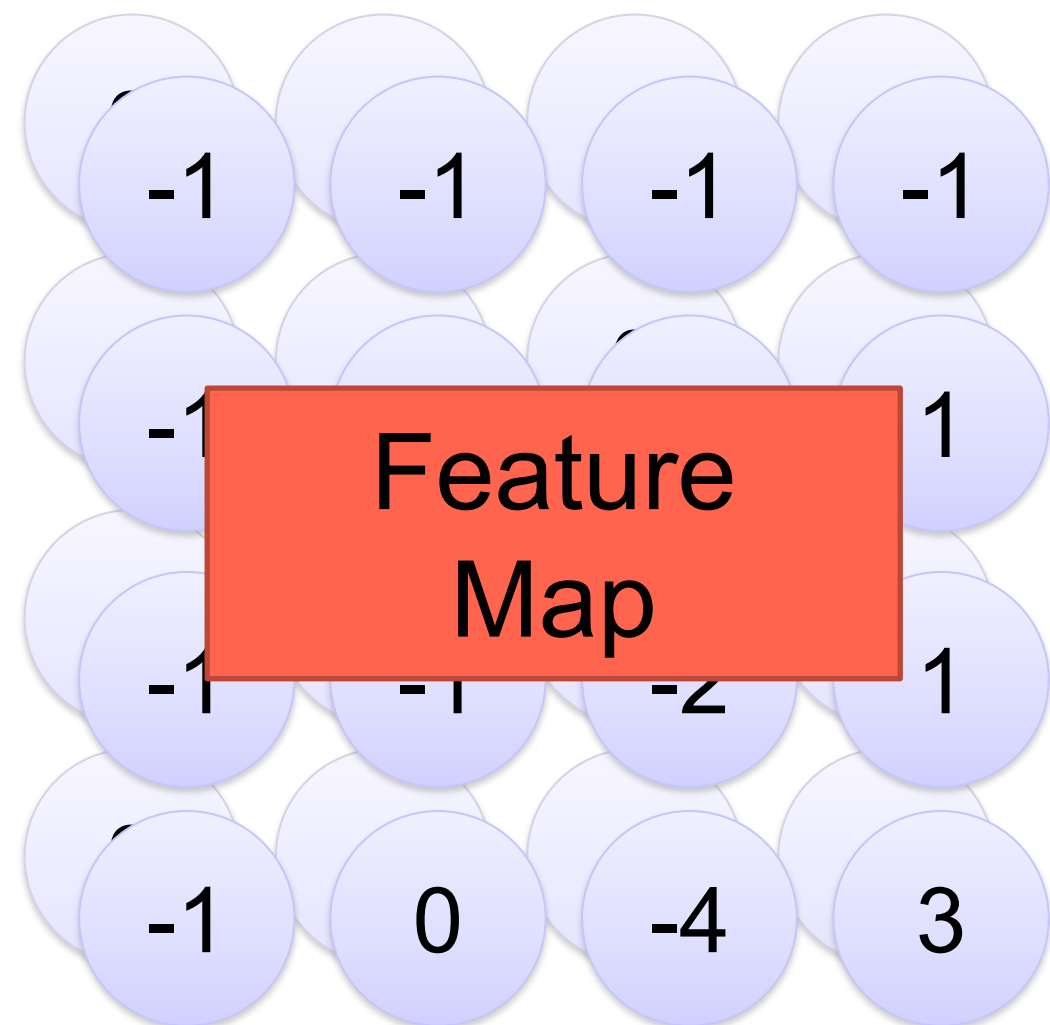
1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

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

sub-matrix  $\begin{bmatrix} 1 & 0 & 0 & \dots & \dots & \dots \end{bmatrix}_{1 \times 27} = \text{Sub}$  sub.f = IR

filter  $\begin{bmatrix} 1 & -1 & -1 & \dots & \dots & \dots \end{bmatrix}_{1 \times 27} = f$

The image displays three overlapping windows, each showing a different color channel of a grayscale image. The top window shows the red channel, the middle window shows the green channel, and the bottom window shows the blue channel. Each window has a standard Mac OS-style title bar with a red close button, a yellow maximize button, and a green minimize button. The windows are slightly offset from each other, creating a 3D effect.

The diagram shows a 3x3 grid of light blue squares with black borders. The grid contains the following values:

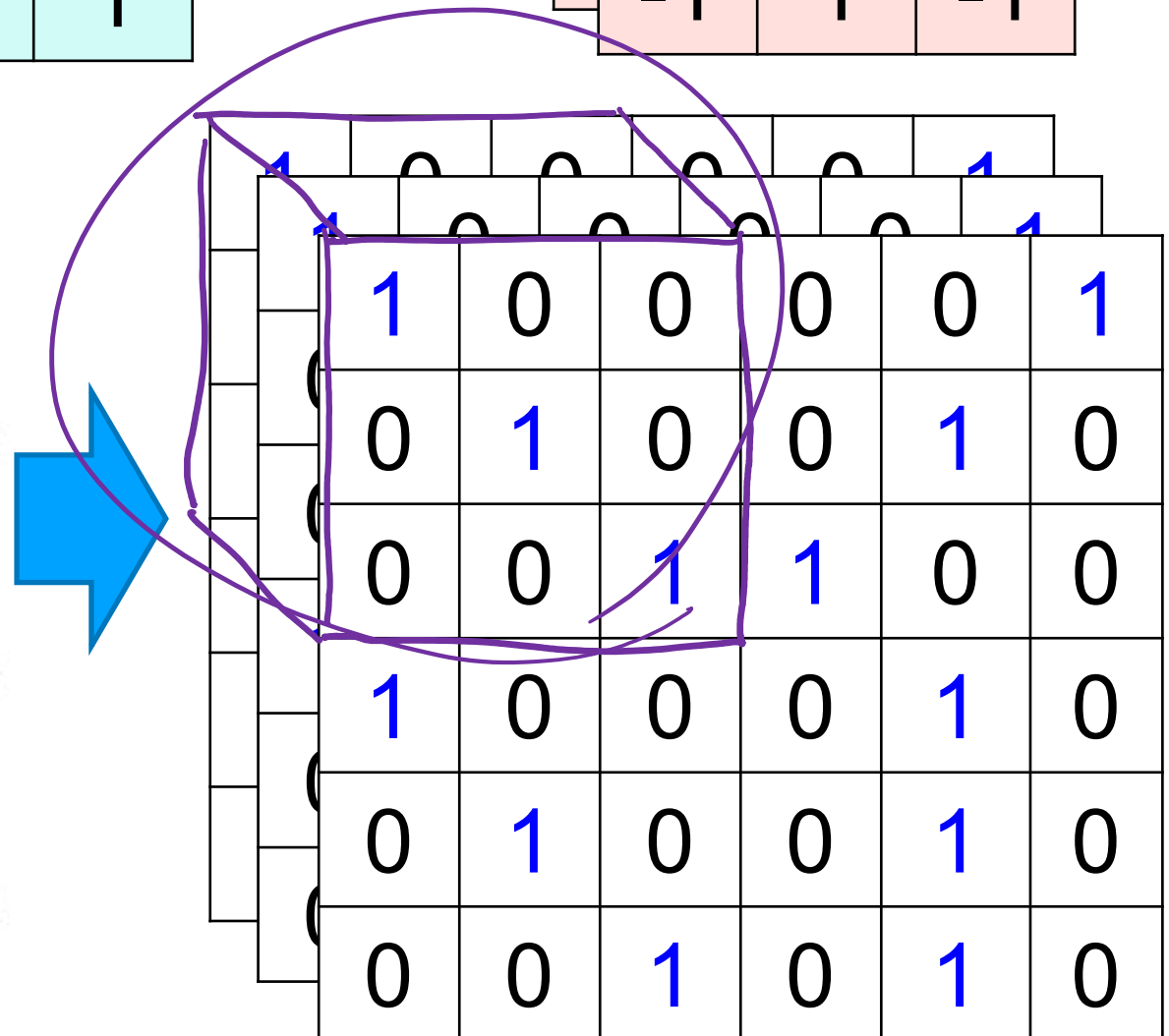
1	-1	-1
-1	1	-1
-1	-1	1

Behind this grid, two more identical 3x3 grids are visible, offset to the top-left and top-right, suggesting a sequence of operations or a larger pattern.

A diagram showing a 3x3 grid of cells. The cells are arranged in three rows and three columns. The values in the cells are as follows:

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

The grid is surrounded by a light pink border. A purple arc is visible at the bottom left corner of the grid.



# Convolution v.s. 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

image

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

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

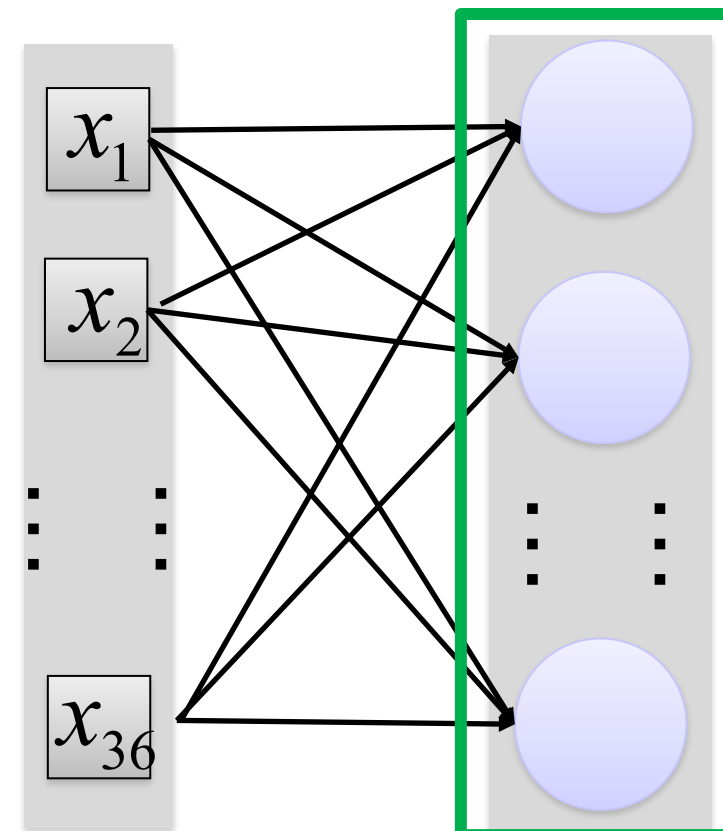


convolution

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

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

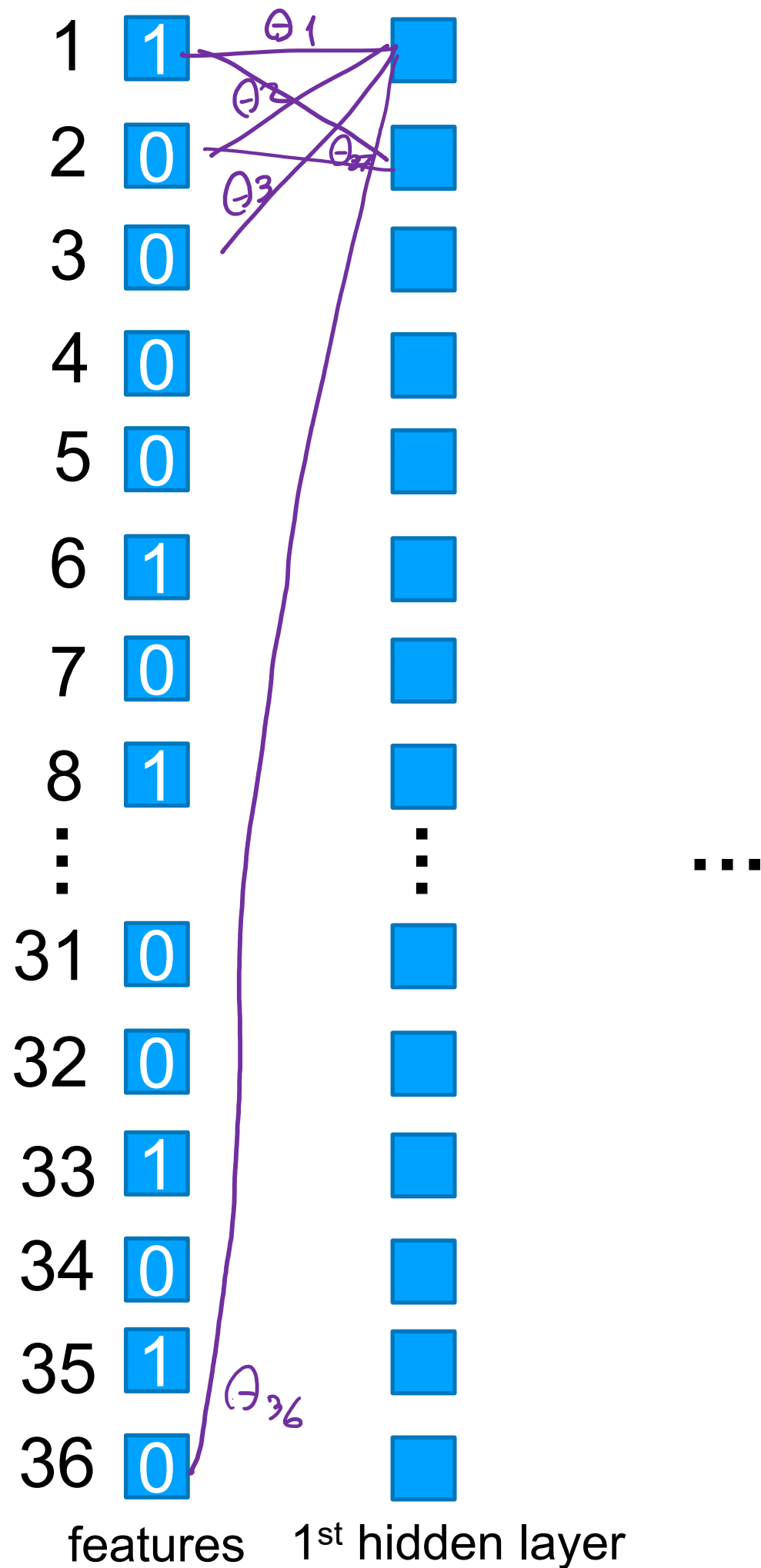


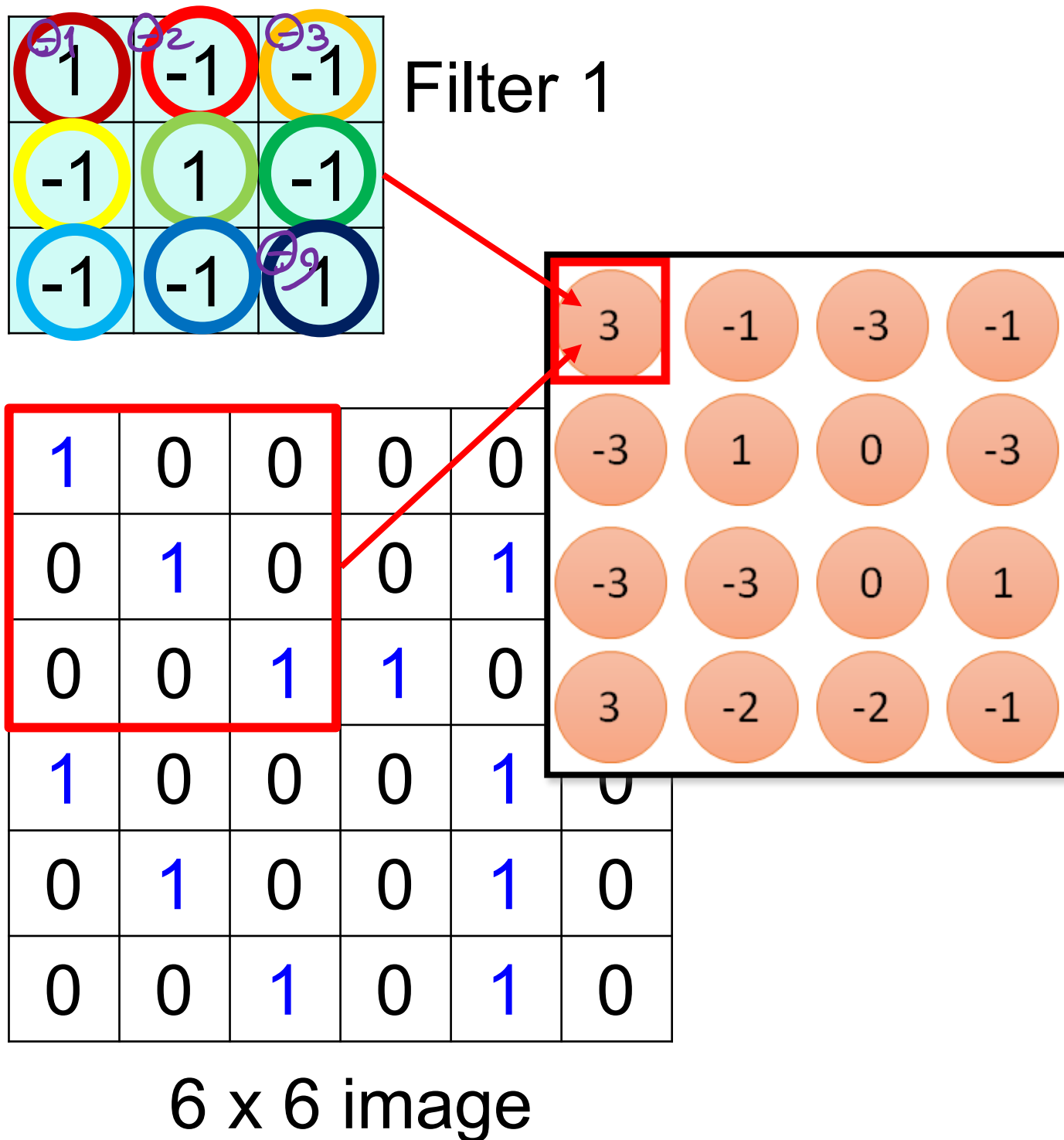


Conventional  
Fully Connected  
layers  
(FC layers)

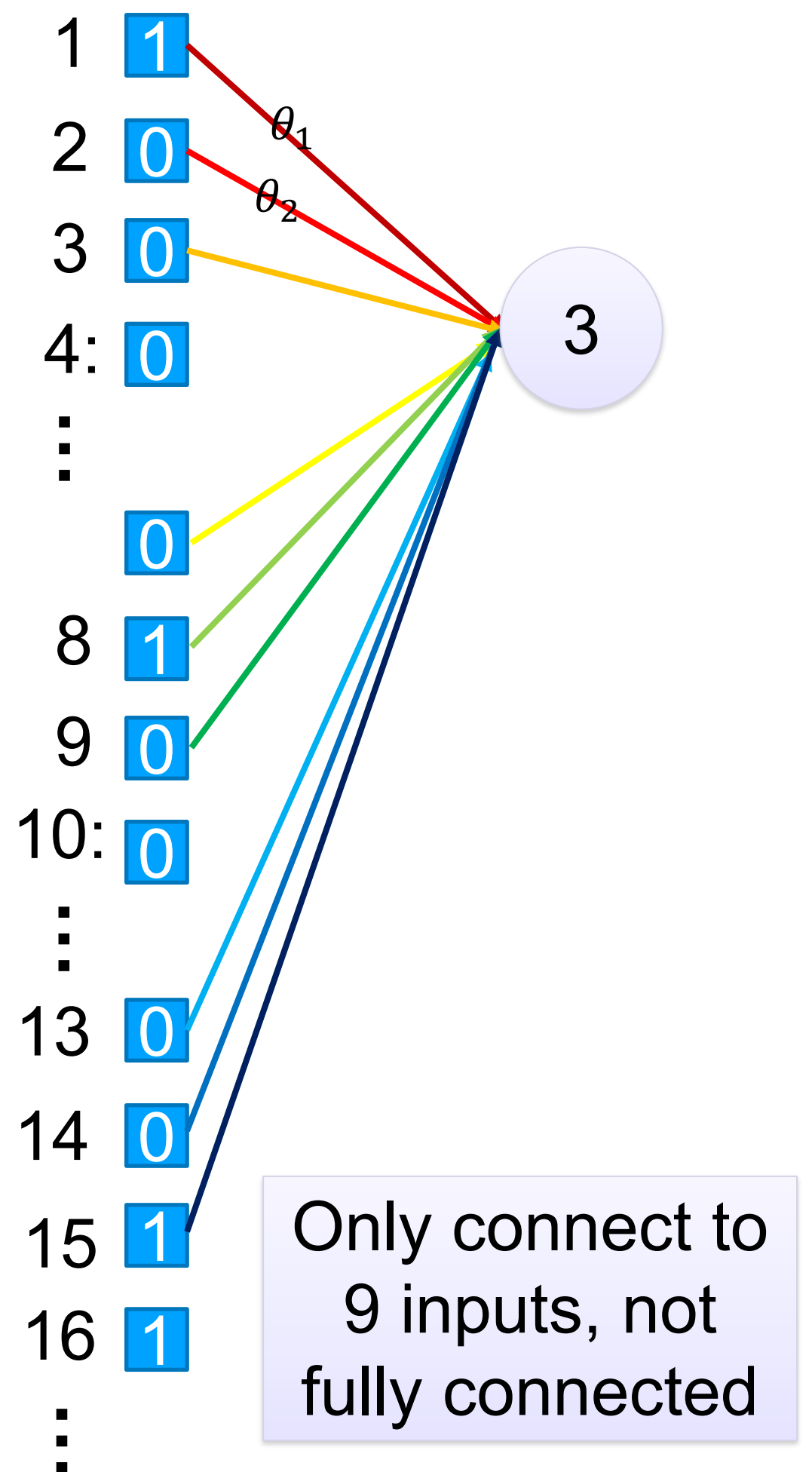
1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

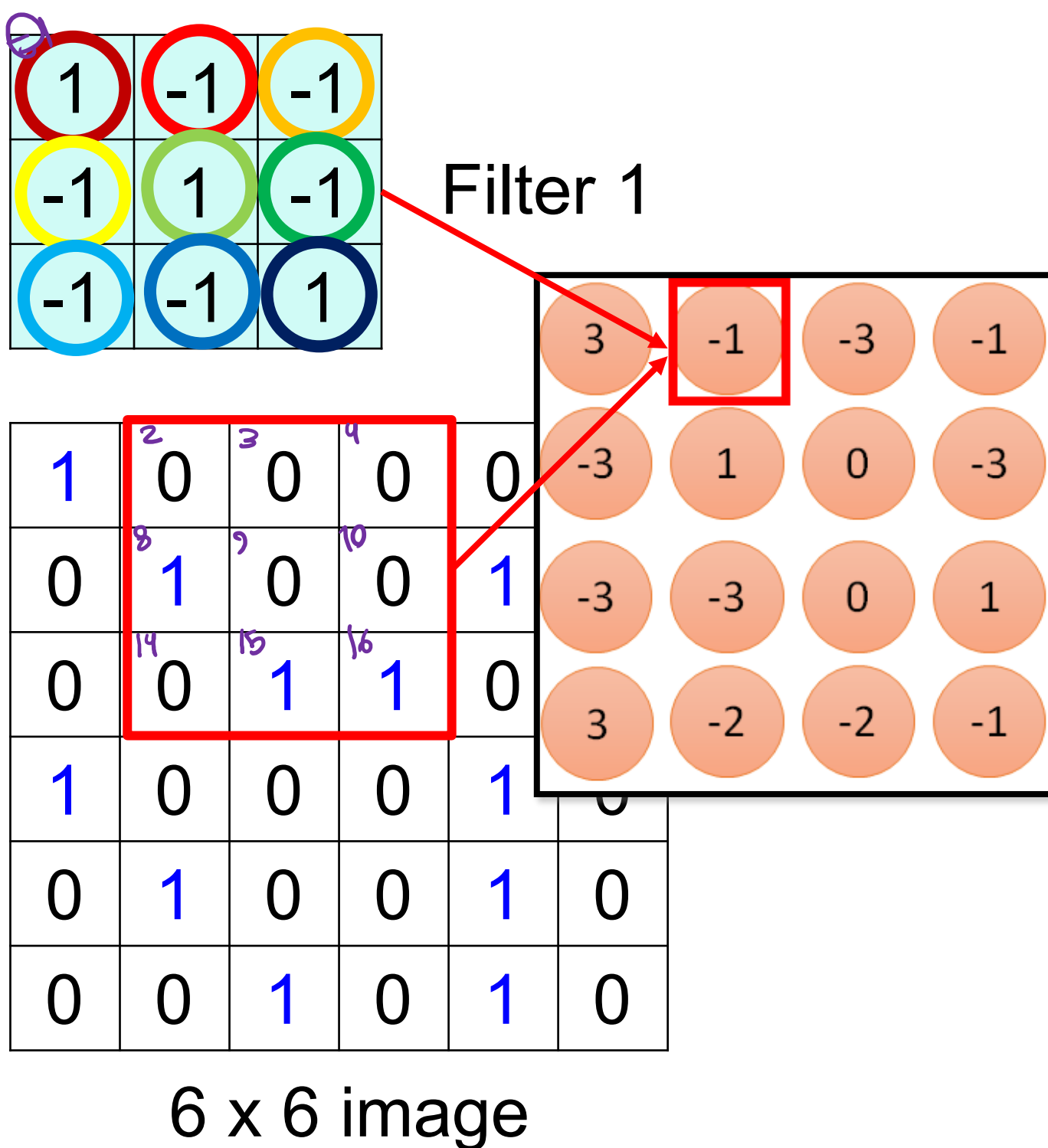
6 x 6 image





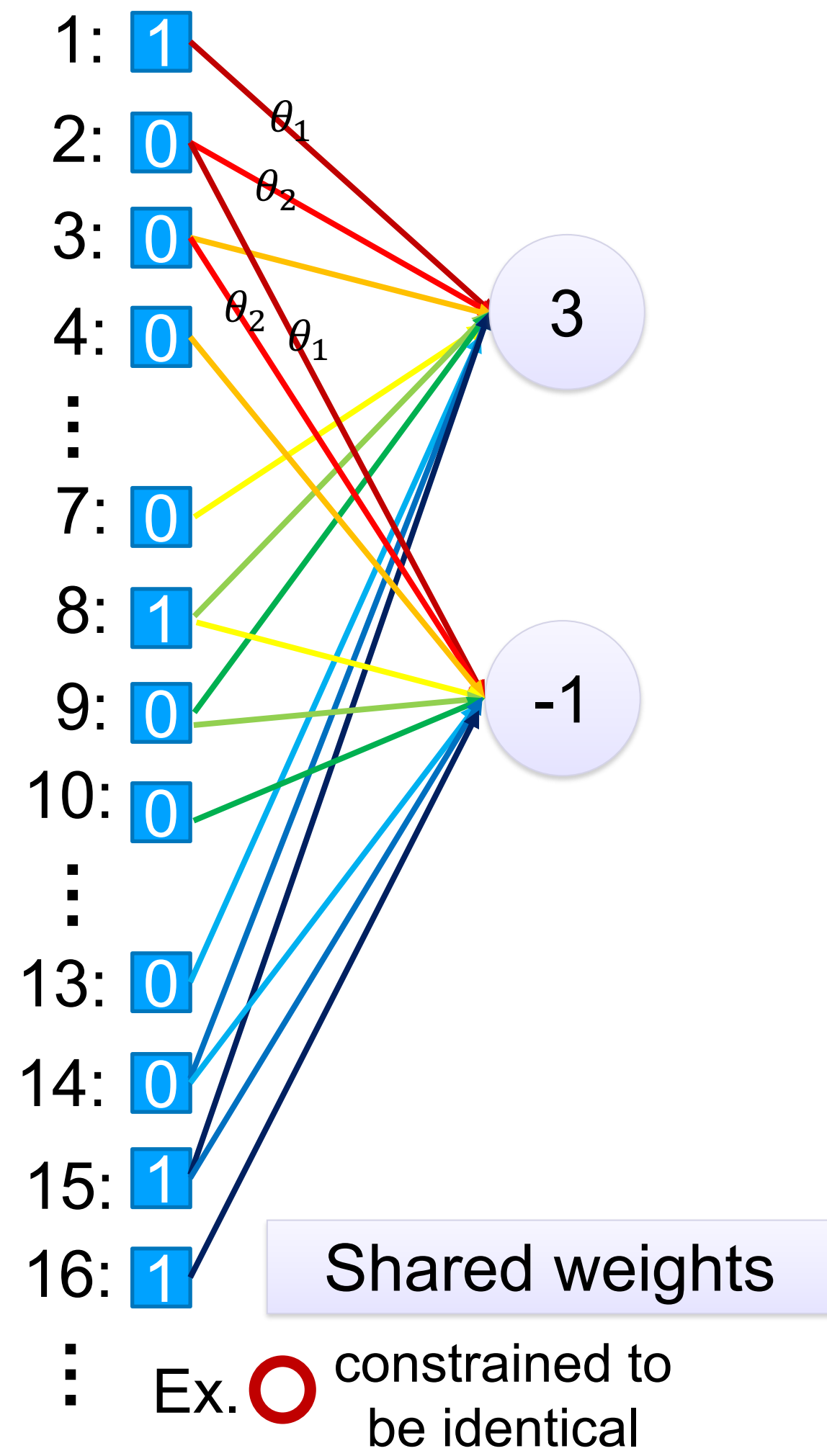
fewer parameters!





Fewer parameters

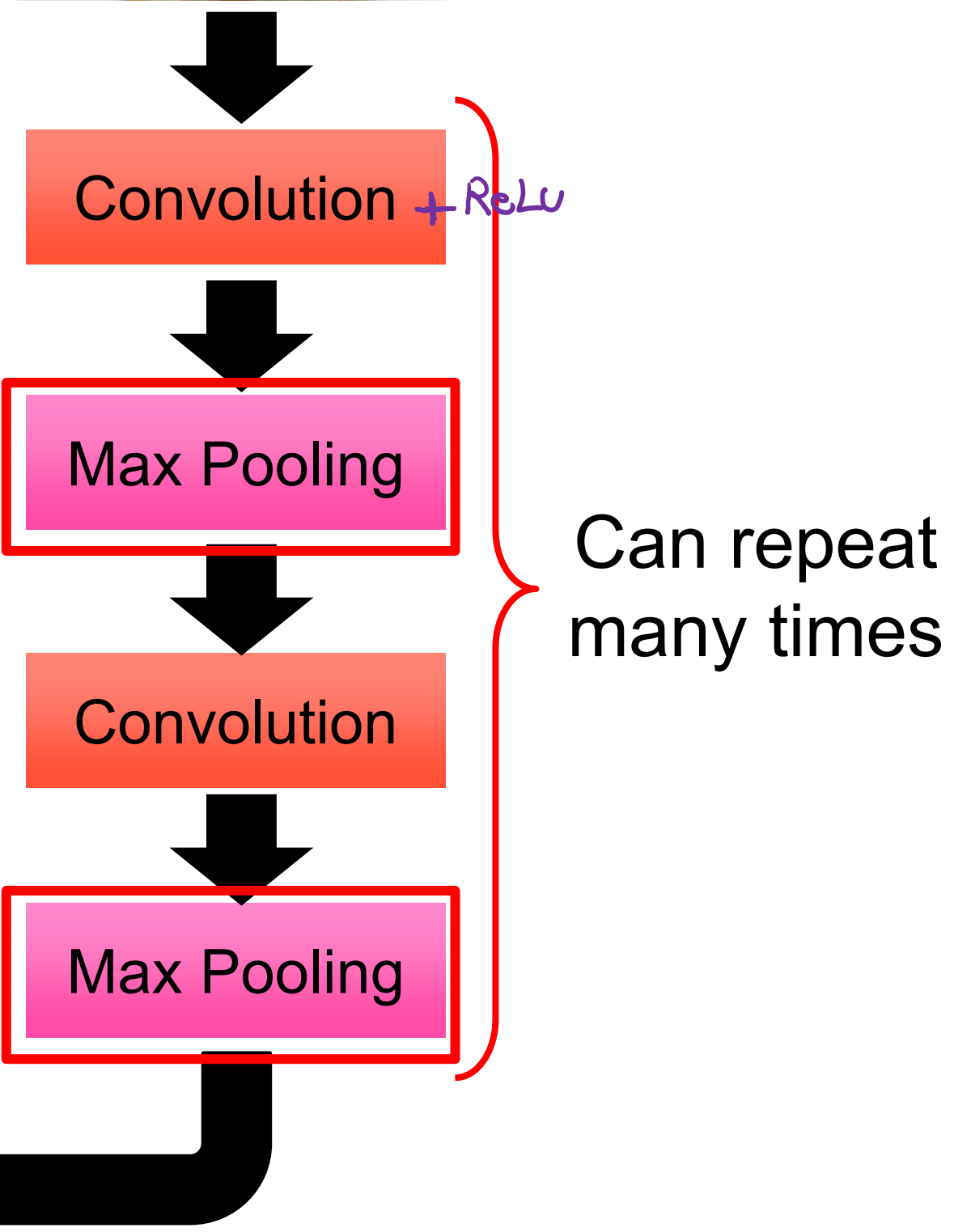
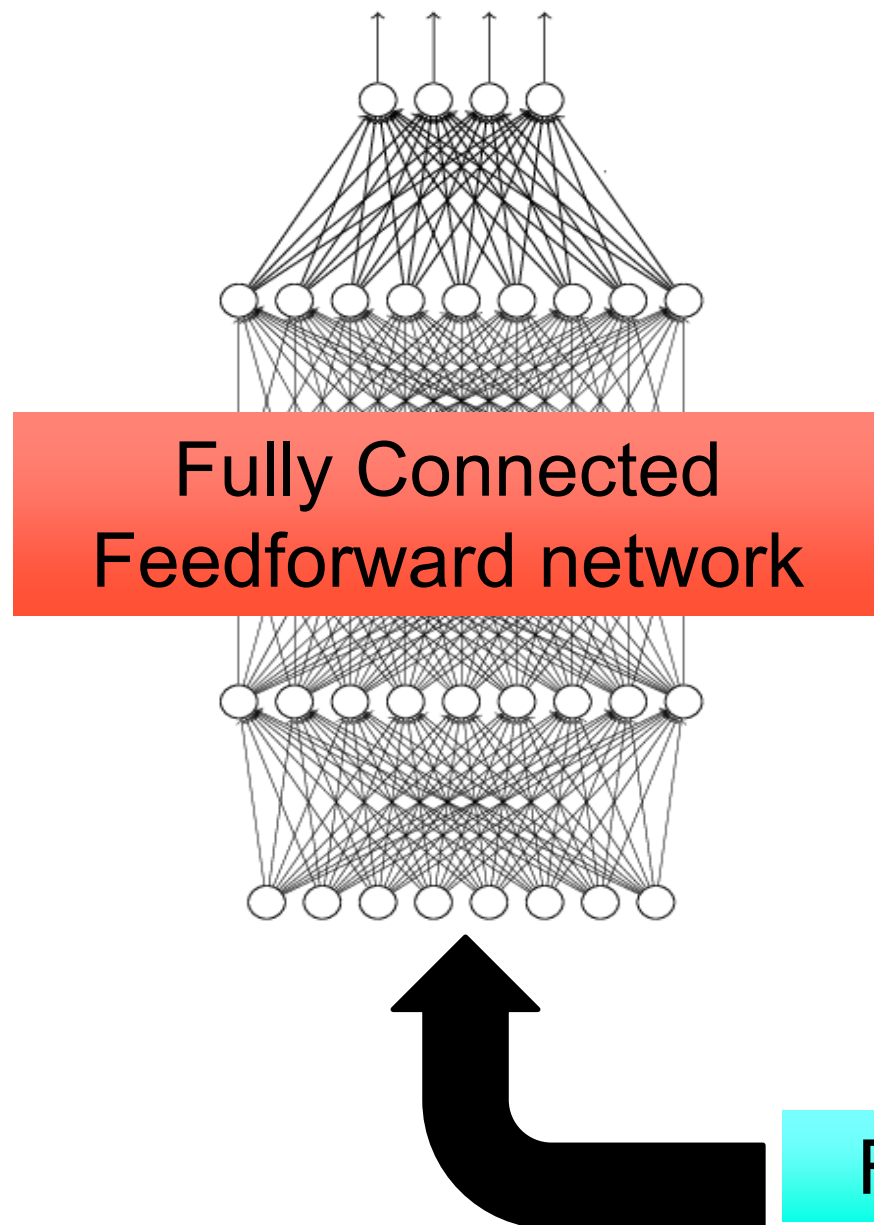
Even fewer parameters





# The whole CNN

cat dog .....



# 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

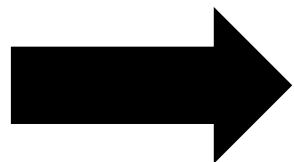


Subsampling



bird

We can subsample the pixels to make image smaller



fewer parameters to characterize the image



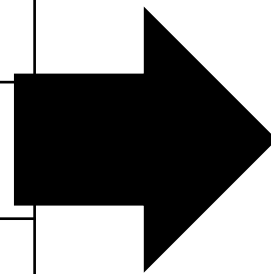
# A CNN compresses a fully connected network in three ways:

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

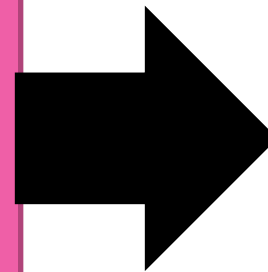
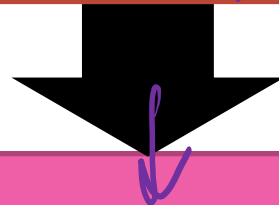
# Max Pooling

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

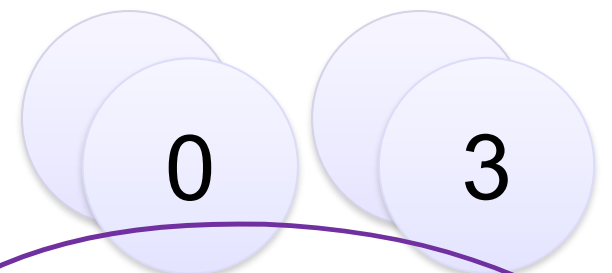
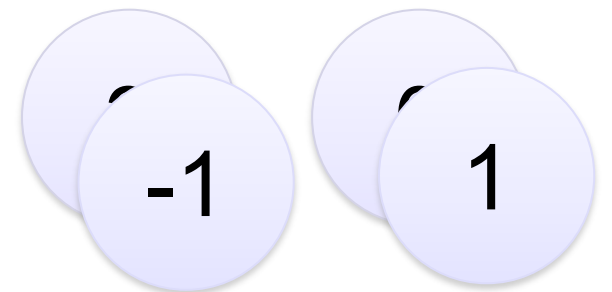
6 x 6 image



+ ReLU



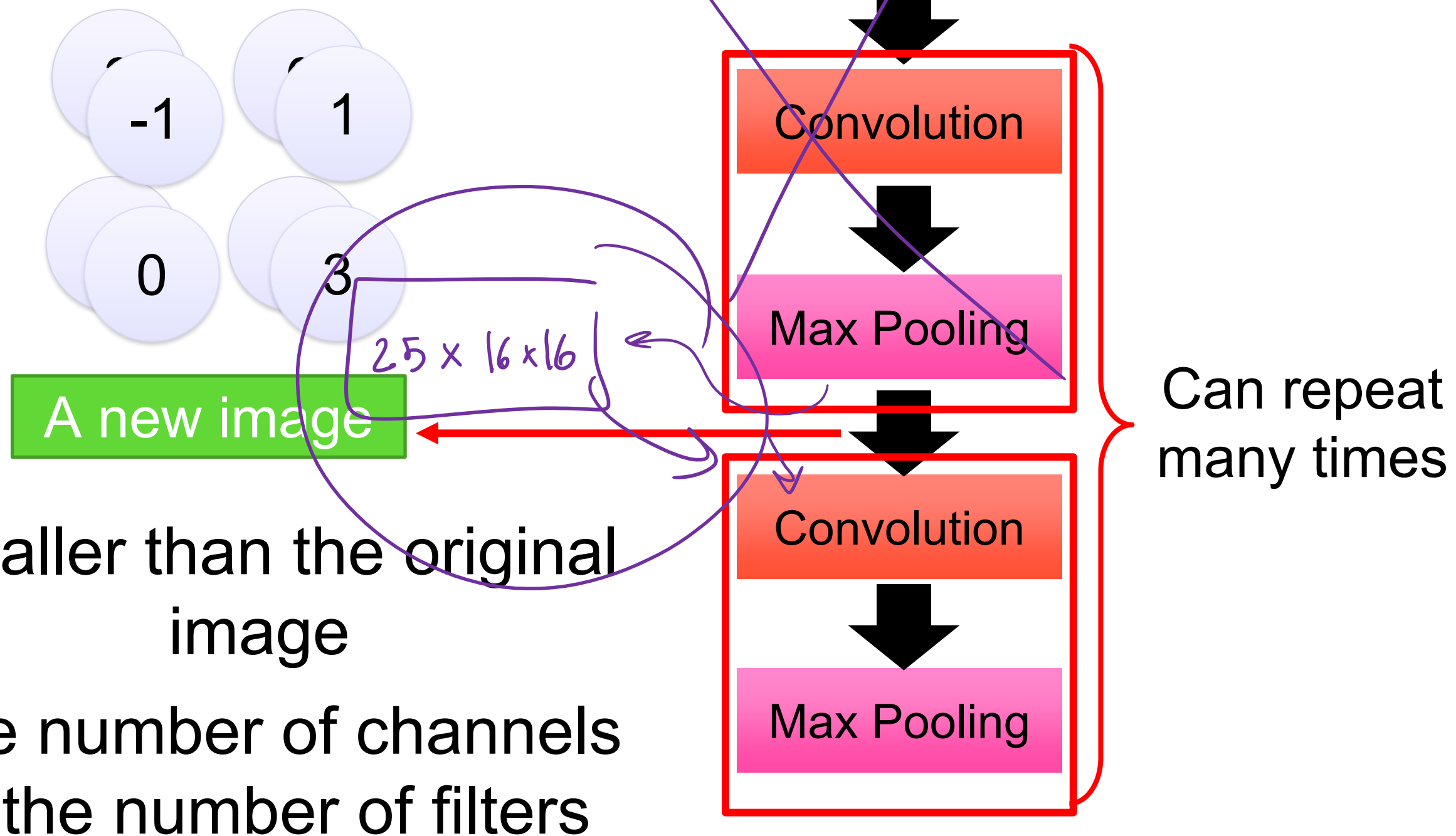
New image  
but smaller



2 x 2 image

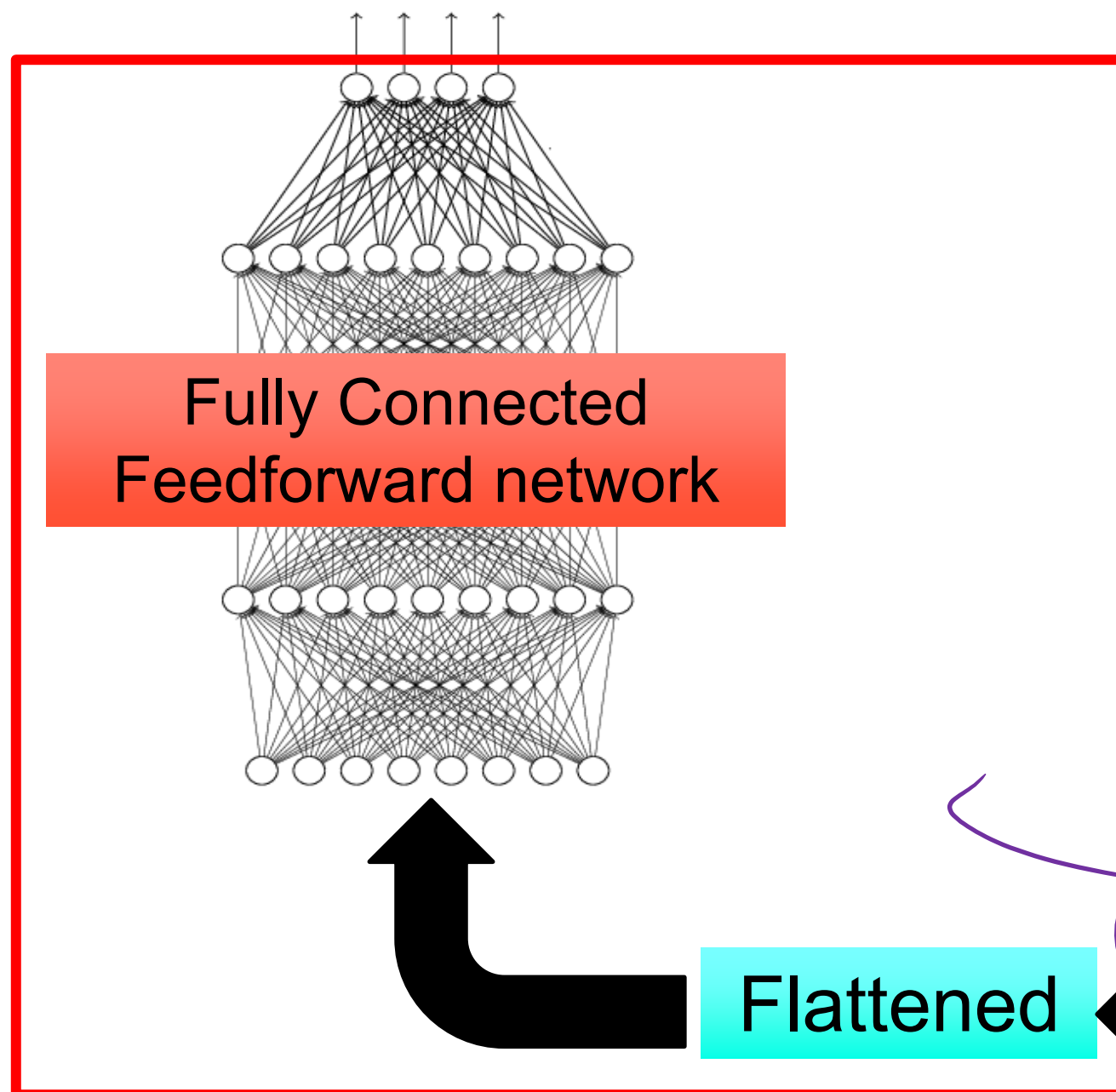
Each filter  
is a channel

# The whole CNN



# The whole CNN

cat dog .....



Convolution

Max Pooling

A new image

Convolution

Max Pooling

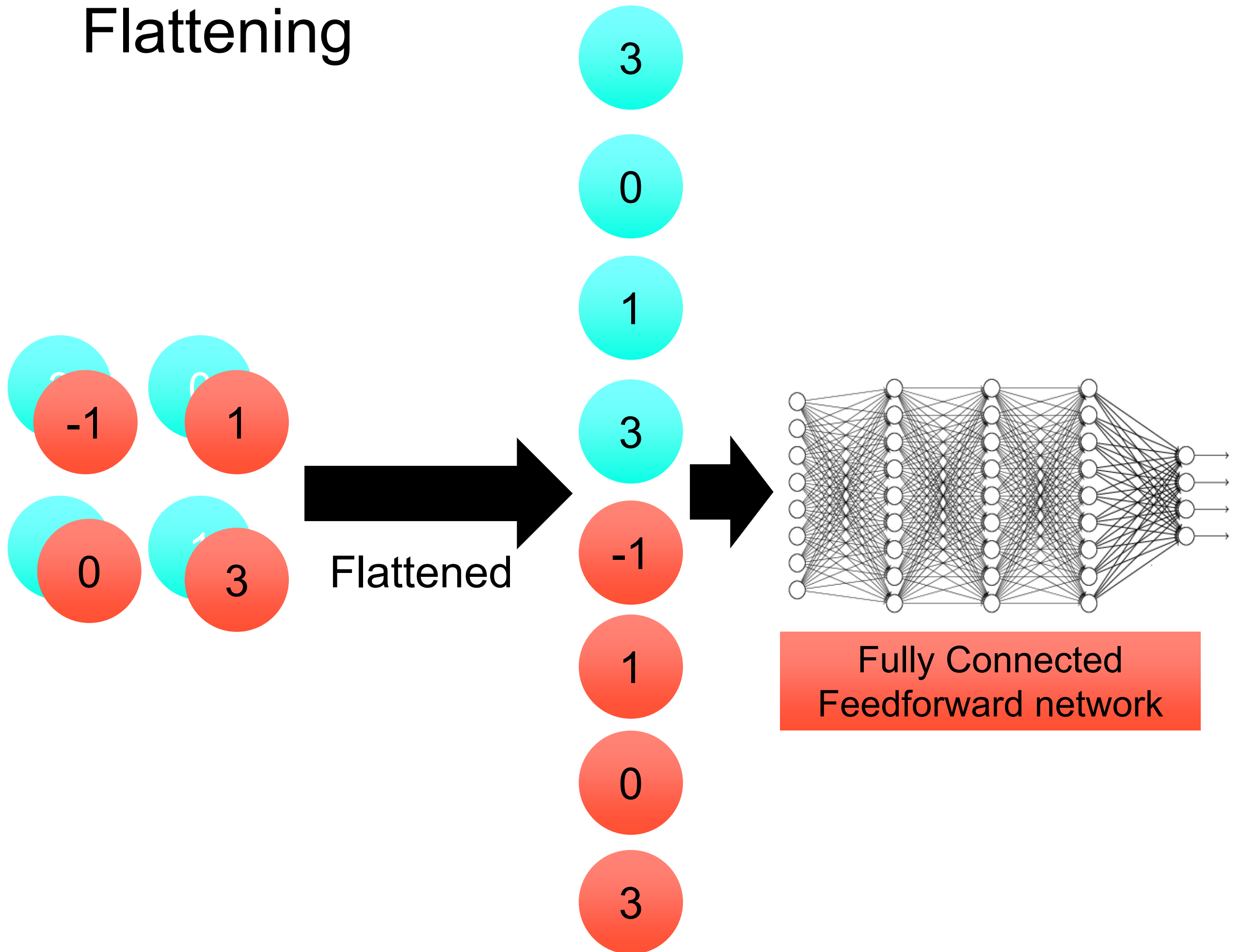
$5 \times 10 \times 10$

A new image

Flattened



# Flattening



# CNN in Keras

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

```
model2.add( Convolution2D( 25,3,3,  
                           input_shape=(28,28,1)) )
```

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

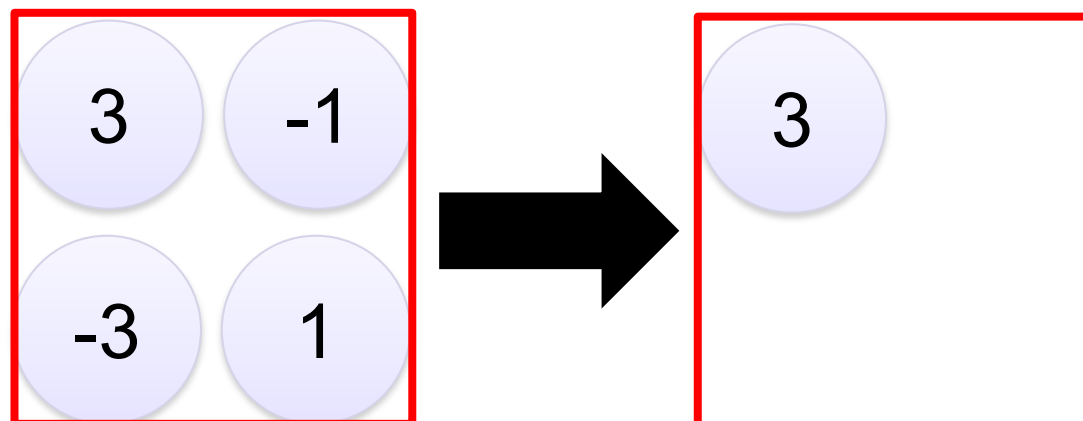
There are  
**25 3x3**  
filters.

Input\_shape = ( 28 , 28 , 1 )

28 x 28 pixels

1: black/white, 3: RGB

```
model2.add(MaxPooling2D((2,2)))
```



input

Convolution

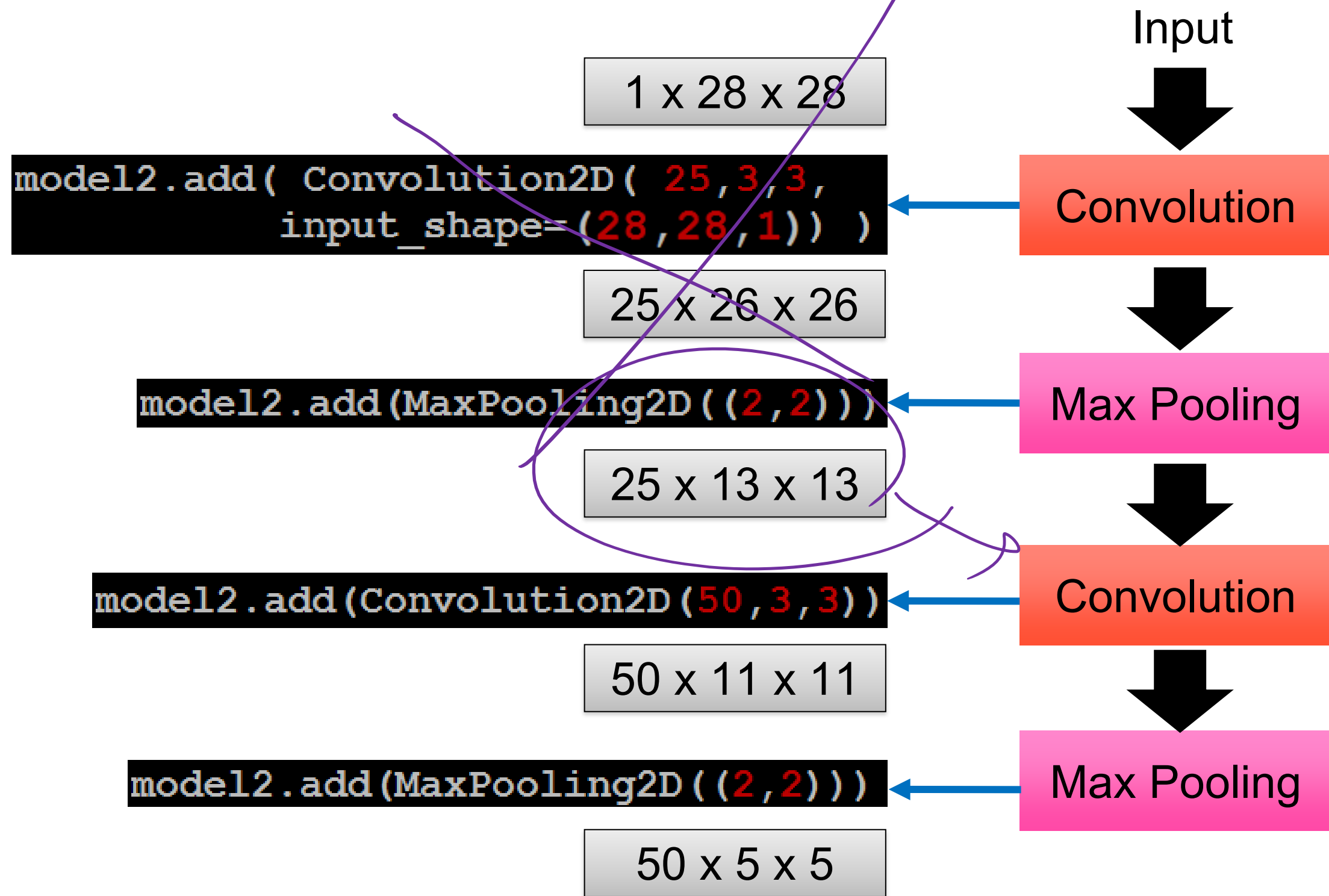
Max Pooling

Convolution

Max Pooling

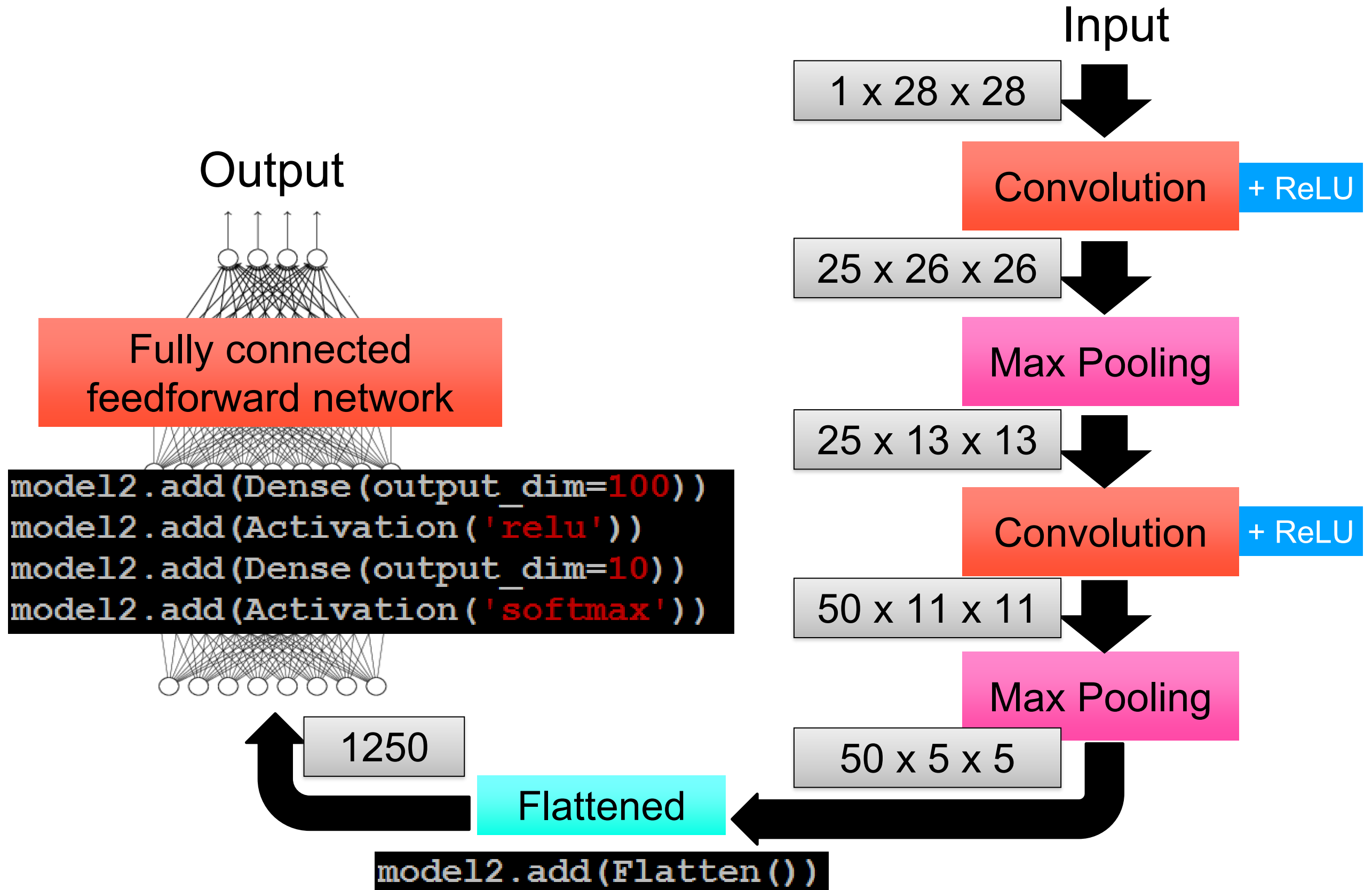
# CNN in Keras

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)





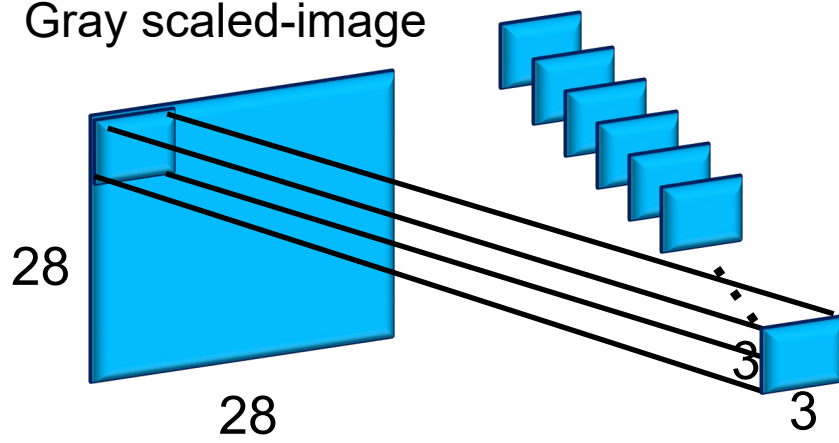
# Number of Parameters

$25 \times 3 \times 3 + 25$  parameters

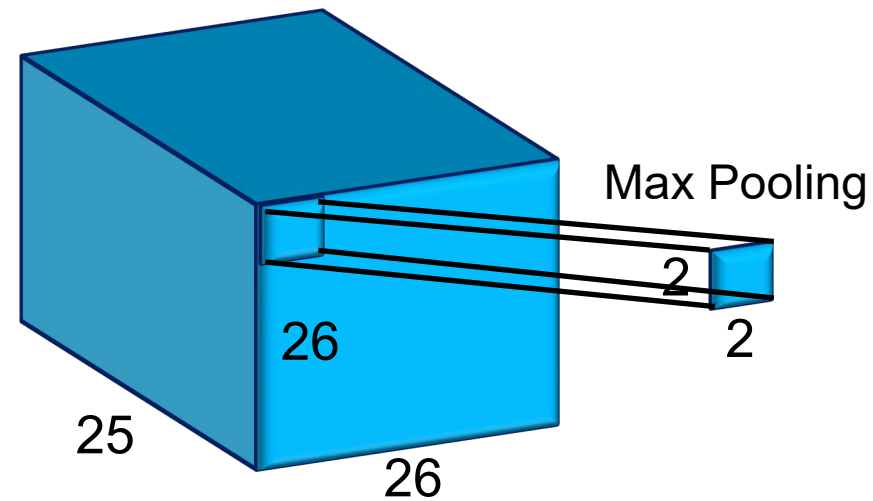
25 filters - Conv1

25:  $3 \times 3$

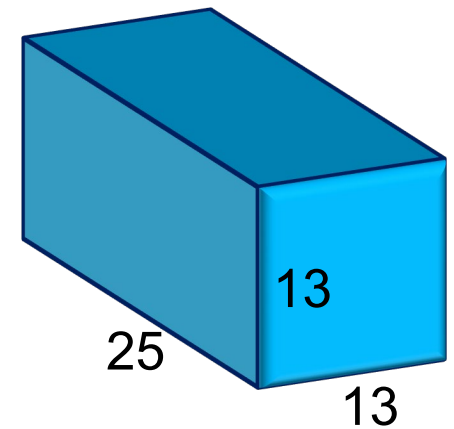
Gray scaled-image



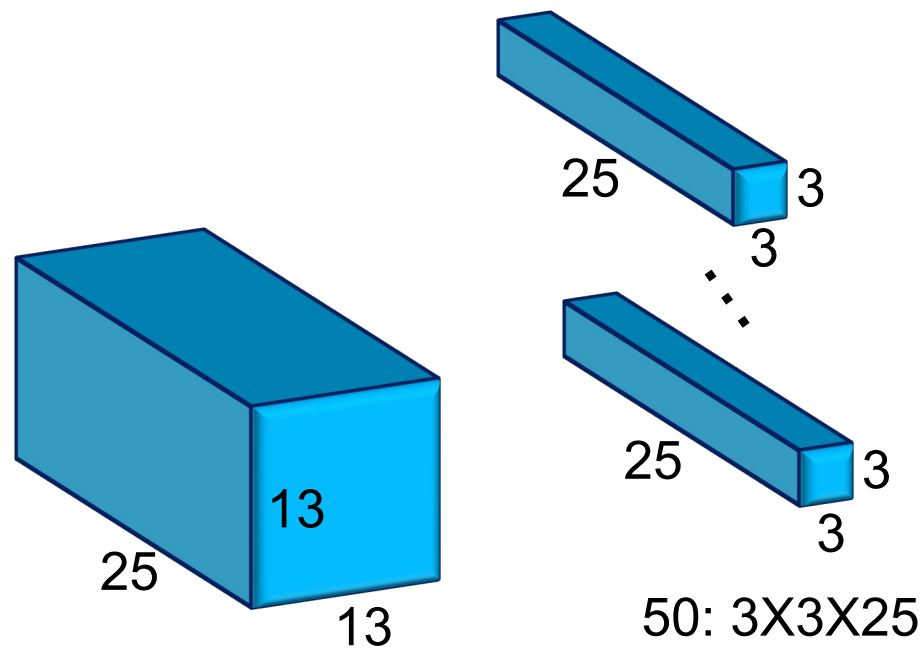
Convolved result for 25 filters



Result after Max Pooling



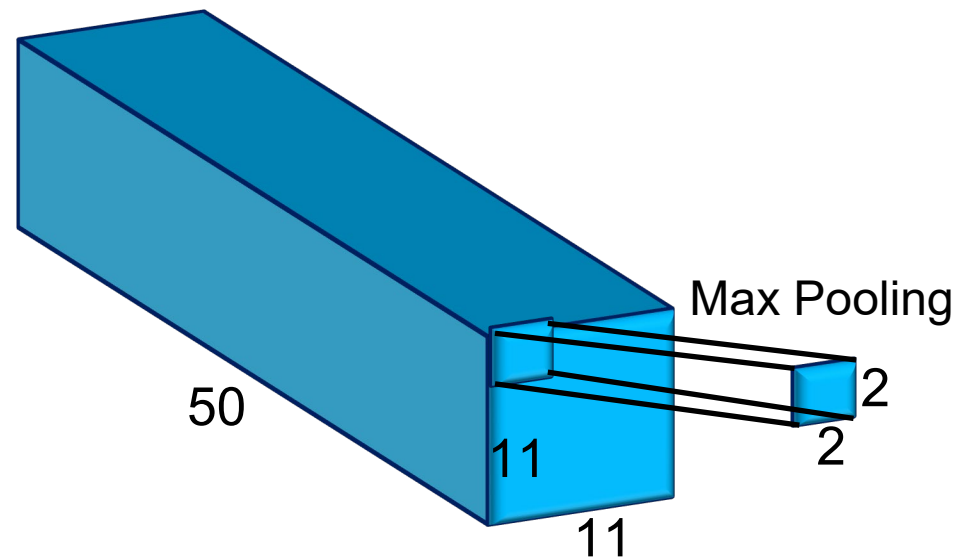
Result after Max Pooling



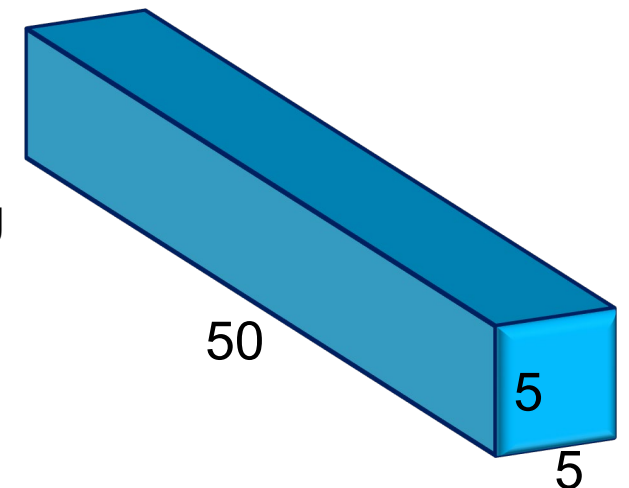
50:  $3 \times 3 \times 25$

50 filters - Conv2

$50 \times 3 \times 3 \times 25 + 50$  parameters

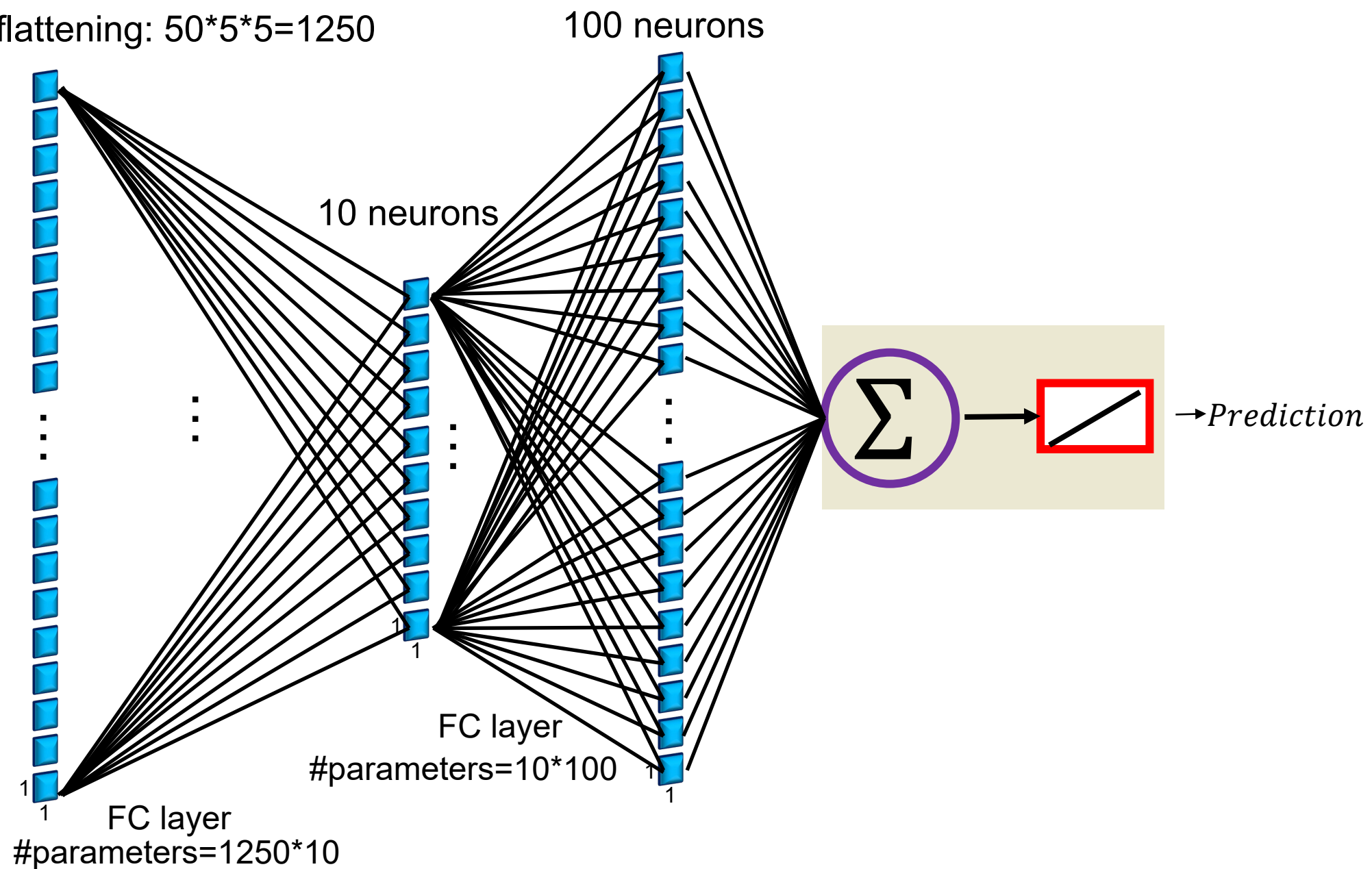
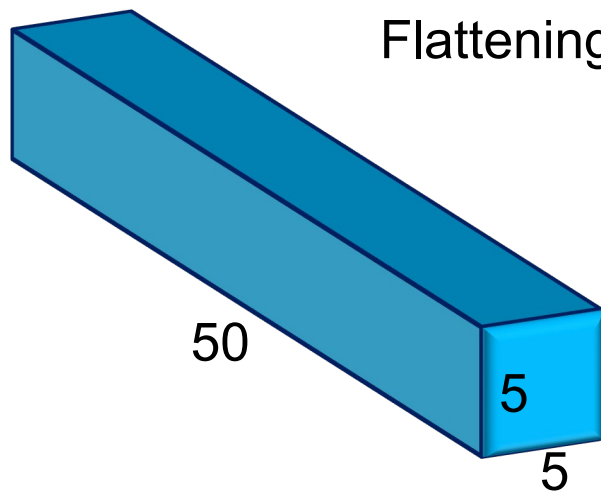


Convolved result for 50 filters



# neurons after flattening:  $50 \times 5 \times 5 = 1250$

Flattening



10 CNN Architecture