Lecture 2: Convolutional Neural Networks

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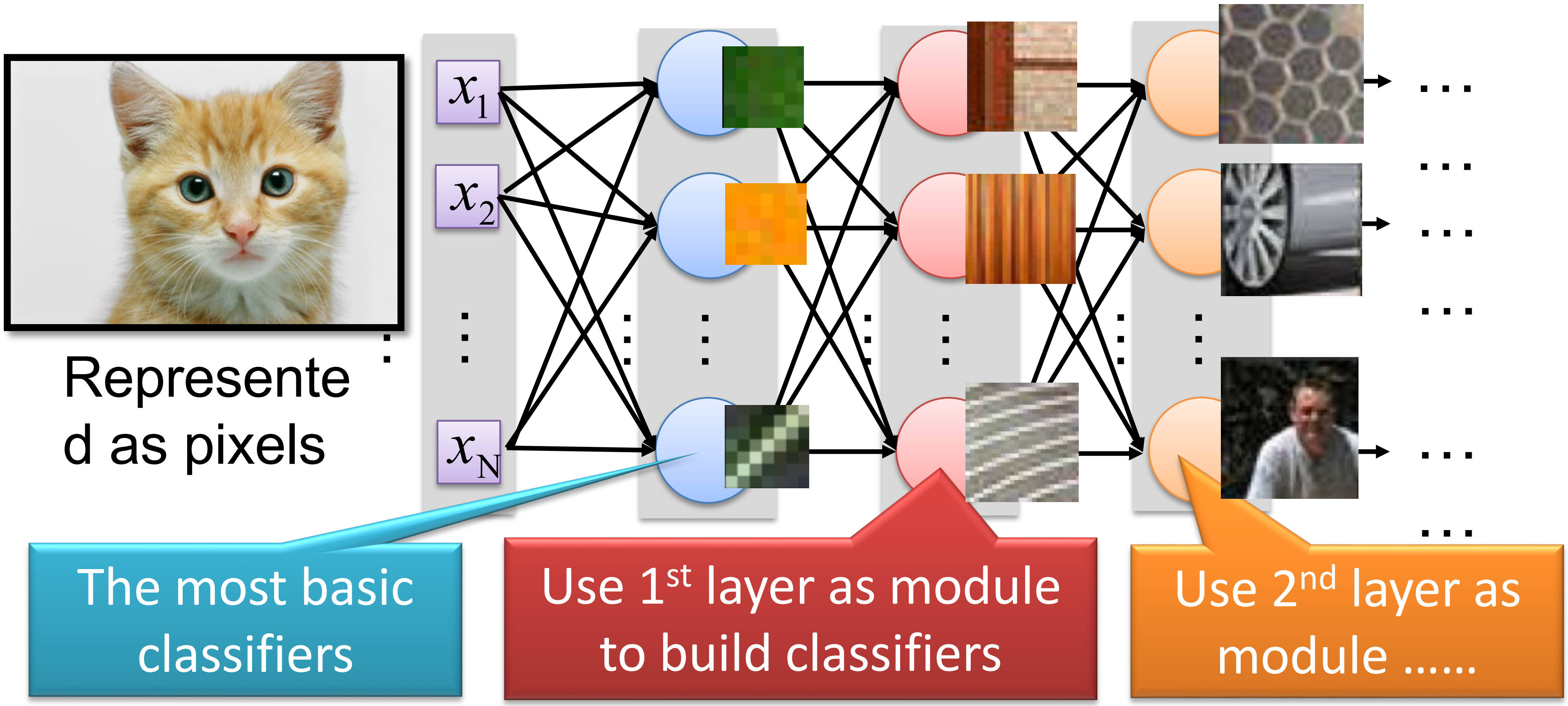
Thanks to the slides from Prof. Hung-Yi Lee in NTU.

Why CNN for Image?

[Zeiler, M. D., *ECCV 2014*]



Can the network be simplified by considering the properties of images?

Why CNN for Image

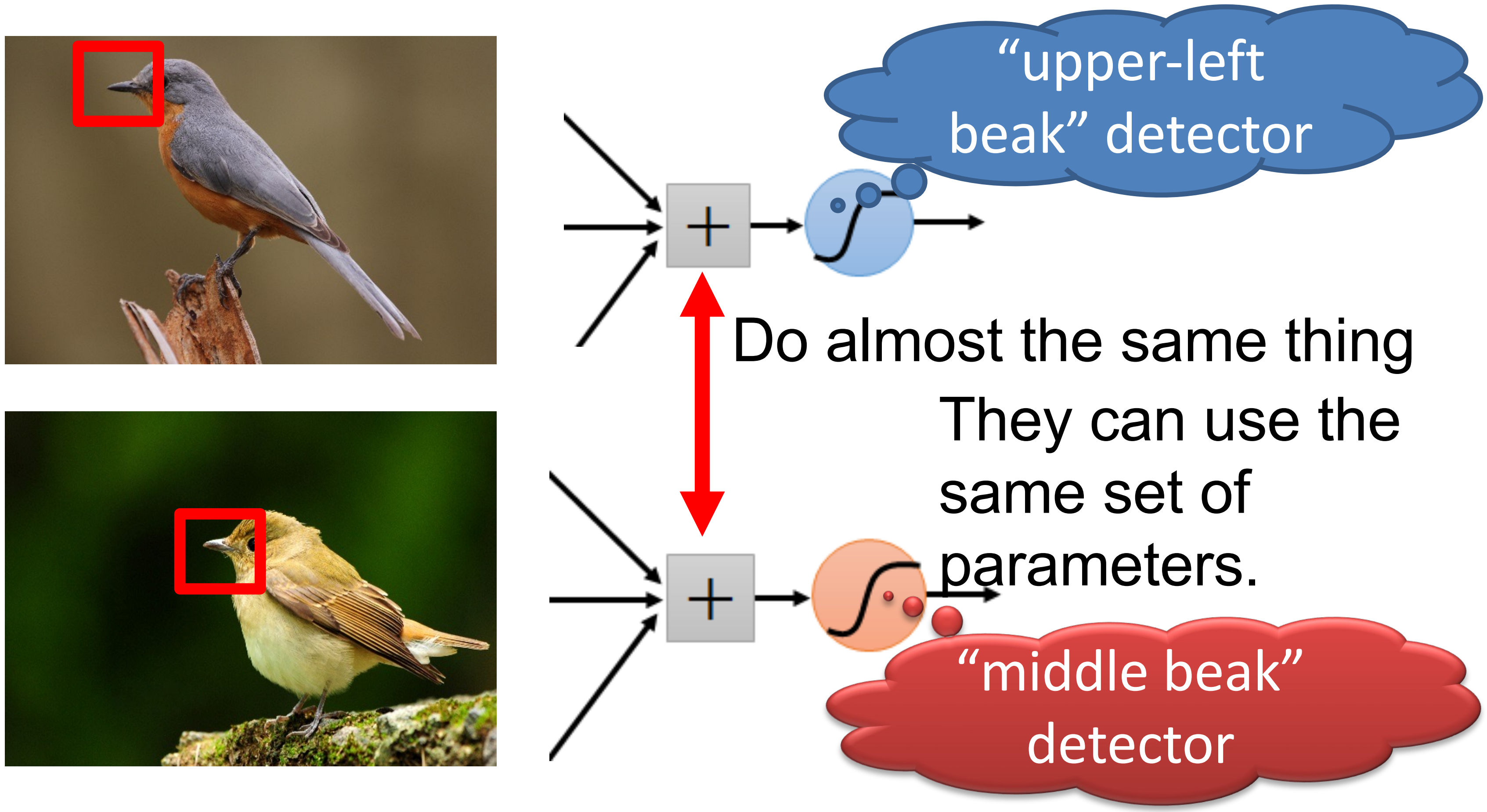
- Some patterns are much smaller than the whole image

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

Connecting to small region with less parameters

Why CNN for Image

- The same patterns appear in different regions.



Why CNN for Image

- Subsampling the pixels will not change the object

bird

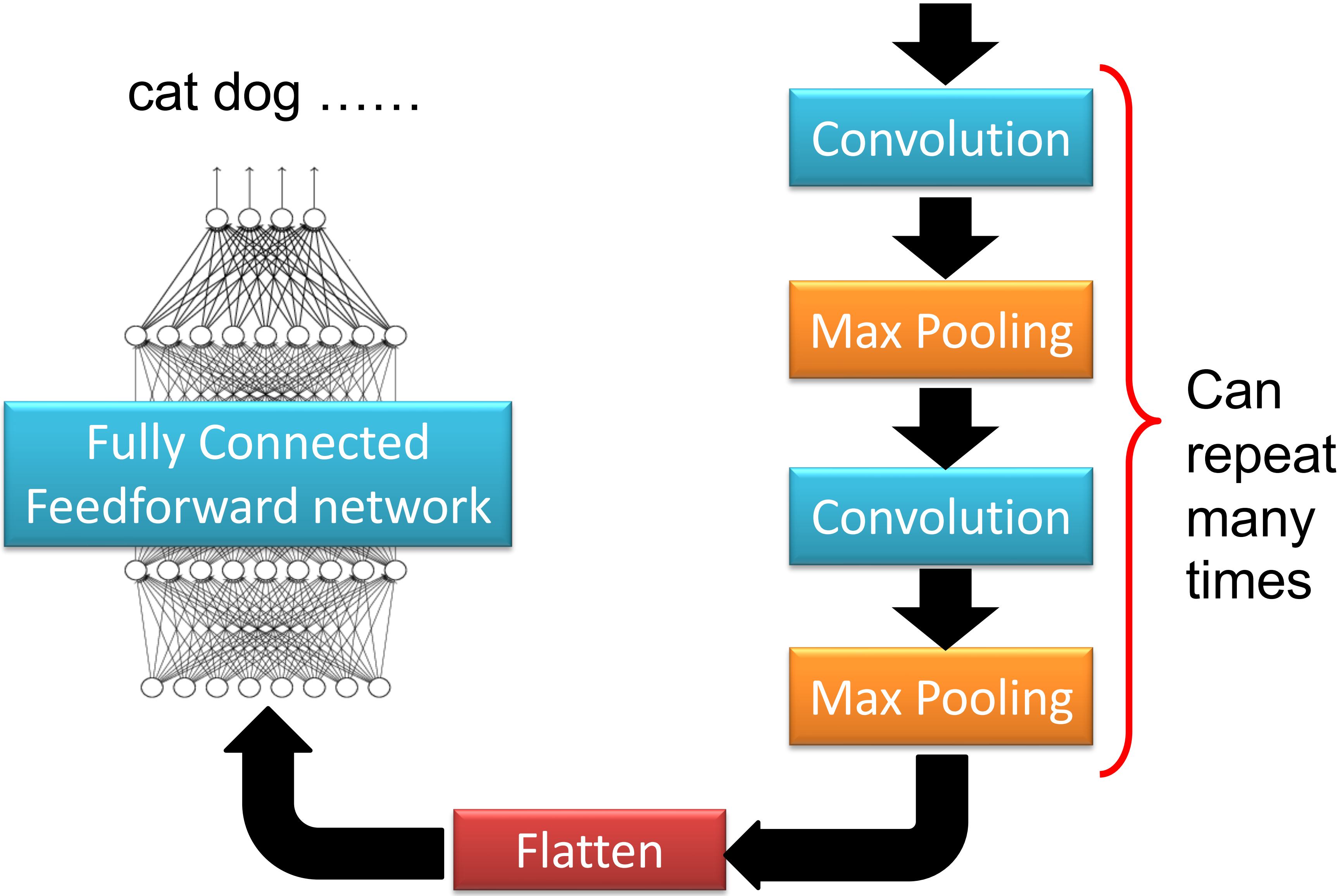
subsampling

bird

We can subsample the pixels to make image smaller

Less parameters for the network to process the image

The whole



Convolution
Max Pooling
Convolution
Max Pooling
Can repeat many times
Flatten
Fully Connected Feedforward network
cat dog ……

The whole

Property 1

- Some patterns are much smaller than the whole

Property 2

- The same patterns appear in different regions.

Property 3

- Subsampling the pixels will not change the object

Convolution

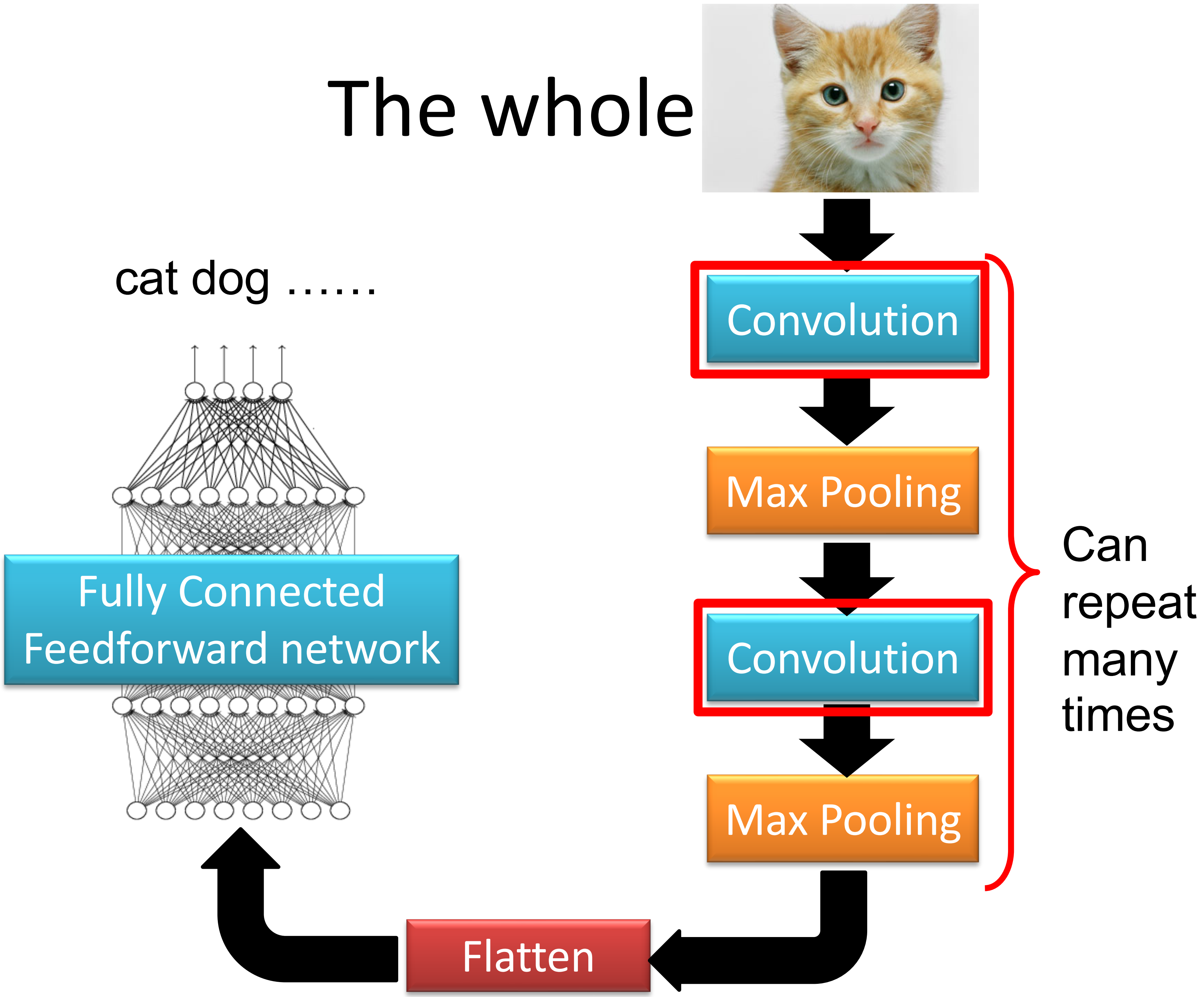
Max Pooling

Convolution

Max Pooling

Can repeat many times

Flatten


The whole
cat dog ……
Convolution
Max Pooling
Convolution
Max Pooling
Can repeat many times
Fully Connected Feedforward network
Flatten

CNN – Convolution

Those 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

Matrix

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

Filter 2

Matrix

⋮ ⋮

Property 1

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

CNN – Convol

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

CNN – Convol

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

Filter 1

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

3 -3

We set stride=1 below

CNN – Convol

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

Property 2

CNN – Convolu

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

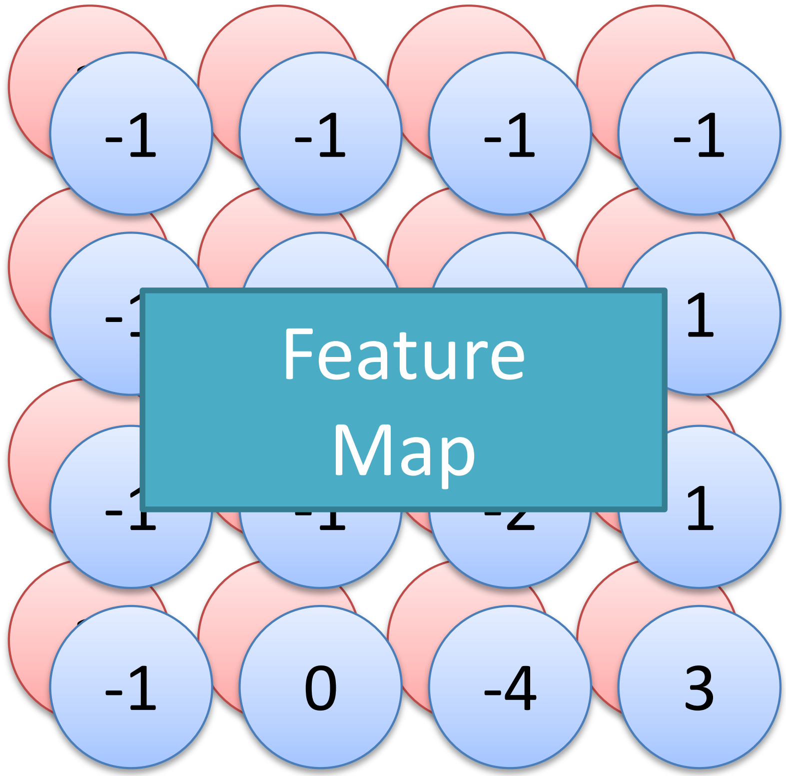
Filter 2

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



4 x 4 image

Animation

0	0	0	0	0	0	0
0	60	113	56	139	85	0
0	73	121	54	84	128	0
0	131	99	70	129	127	0
0	80	57	115	69	134	0
0	104	126	123	95	130	0
0	0	0	0	0	0	0

Kernel

0	-1	0
-1	5	-1
0	-1	0

114				

CNN – Colorful image

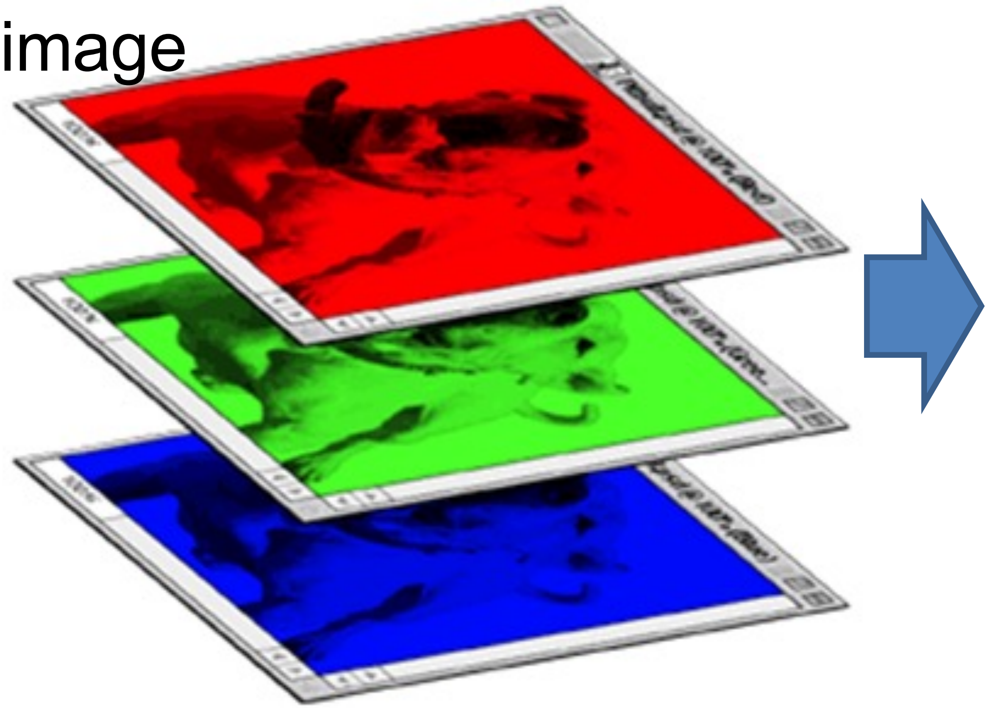
1	-1	-1
-1	1	-1
-1	-1	1

Filter 1

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

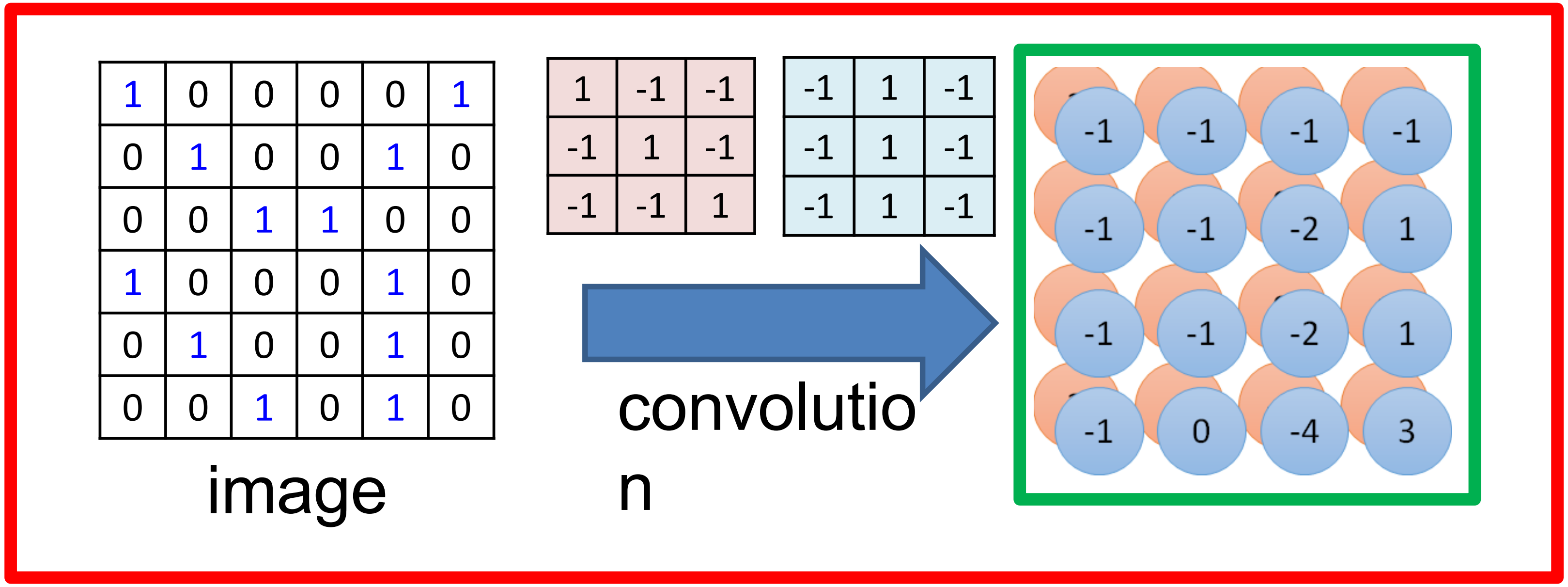
Filter 2

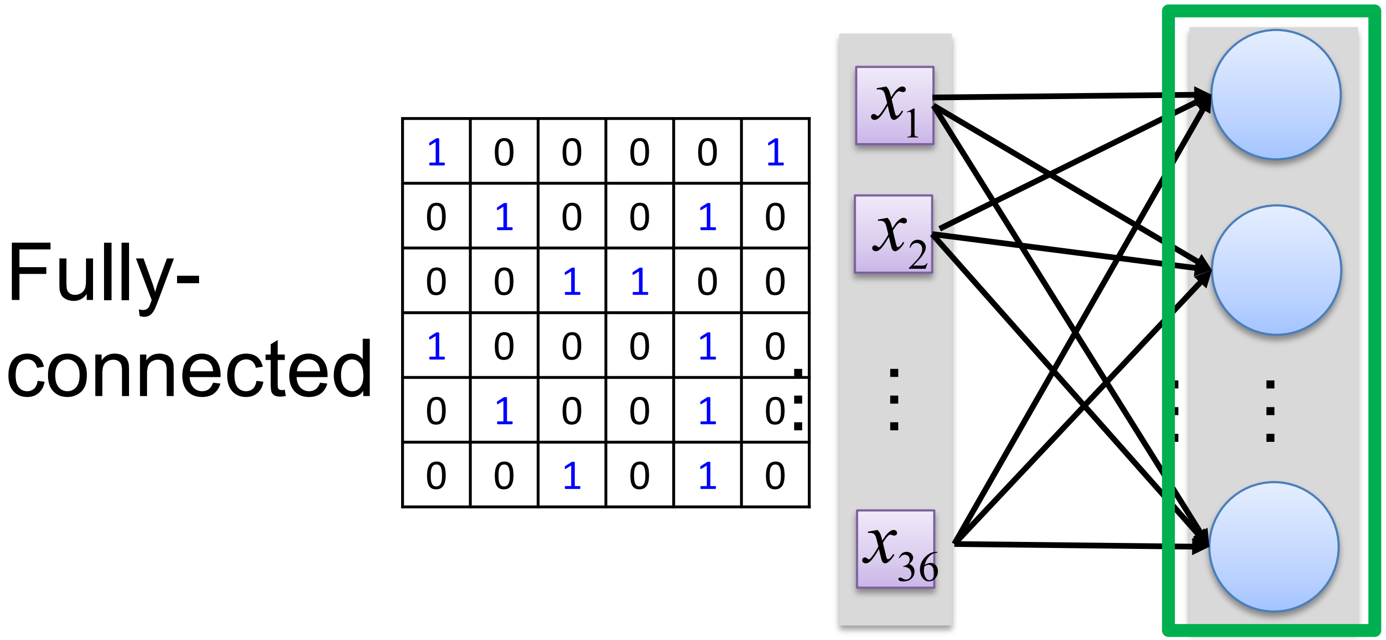
Colorful image

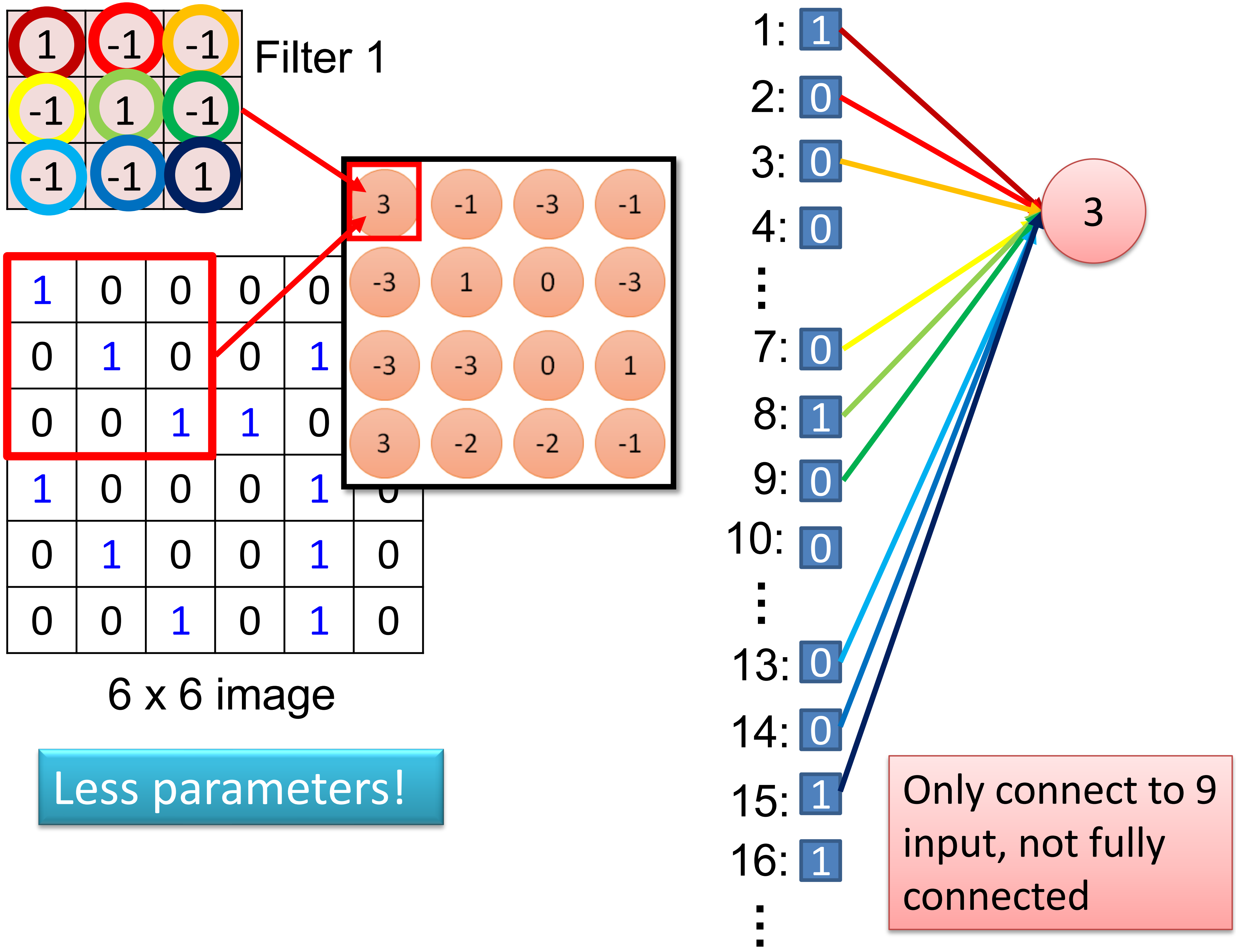


1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

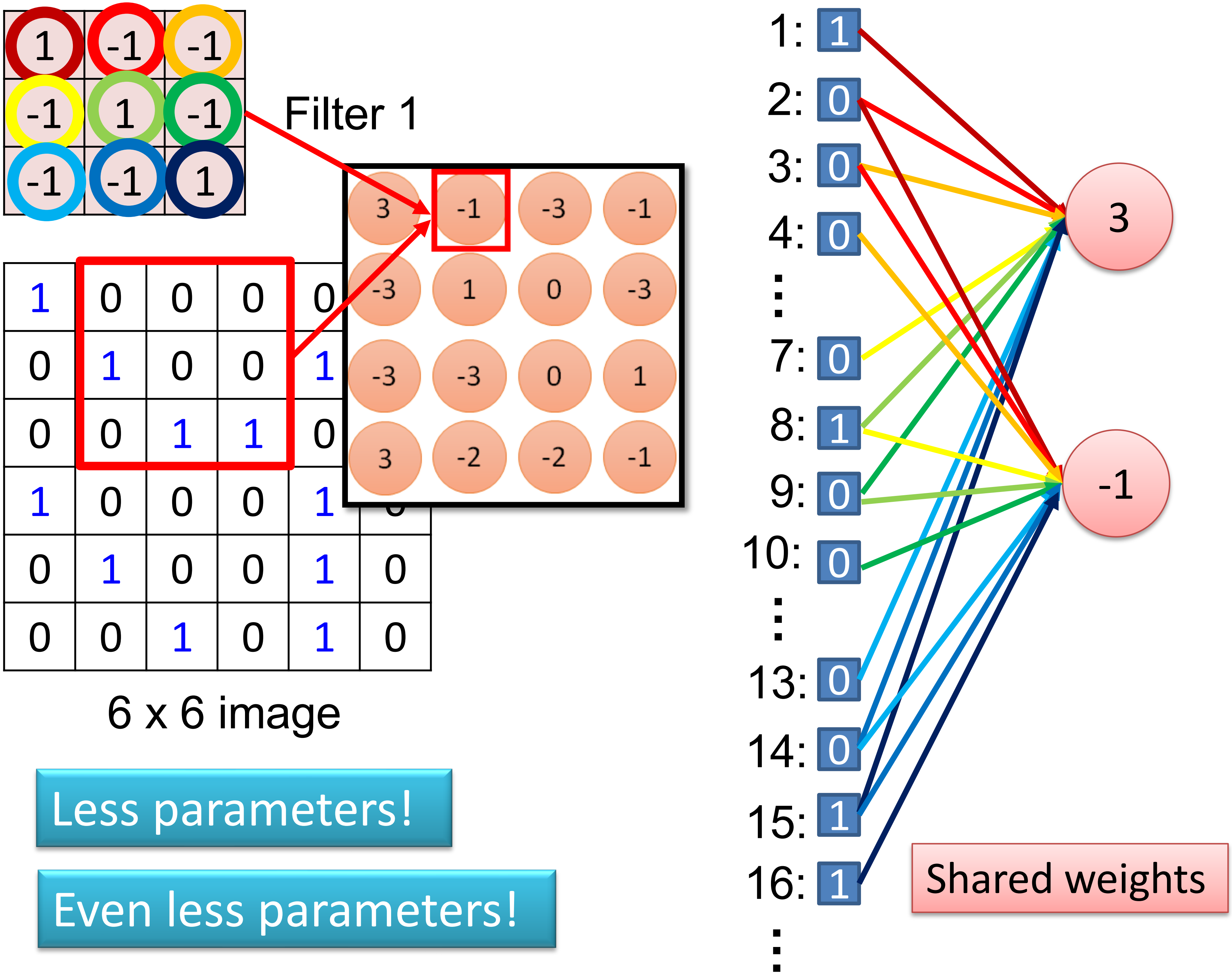
Convolution v.s. Fully Connected

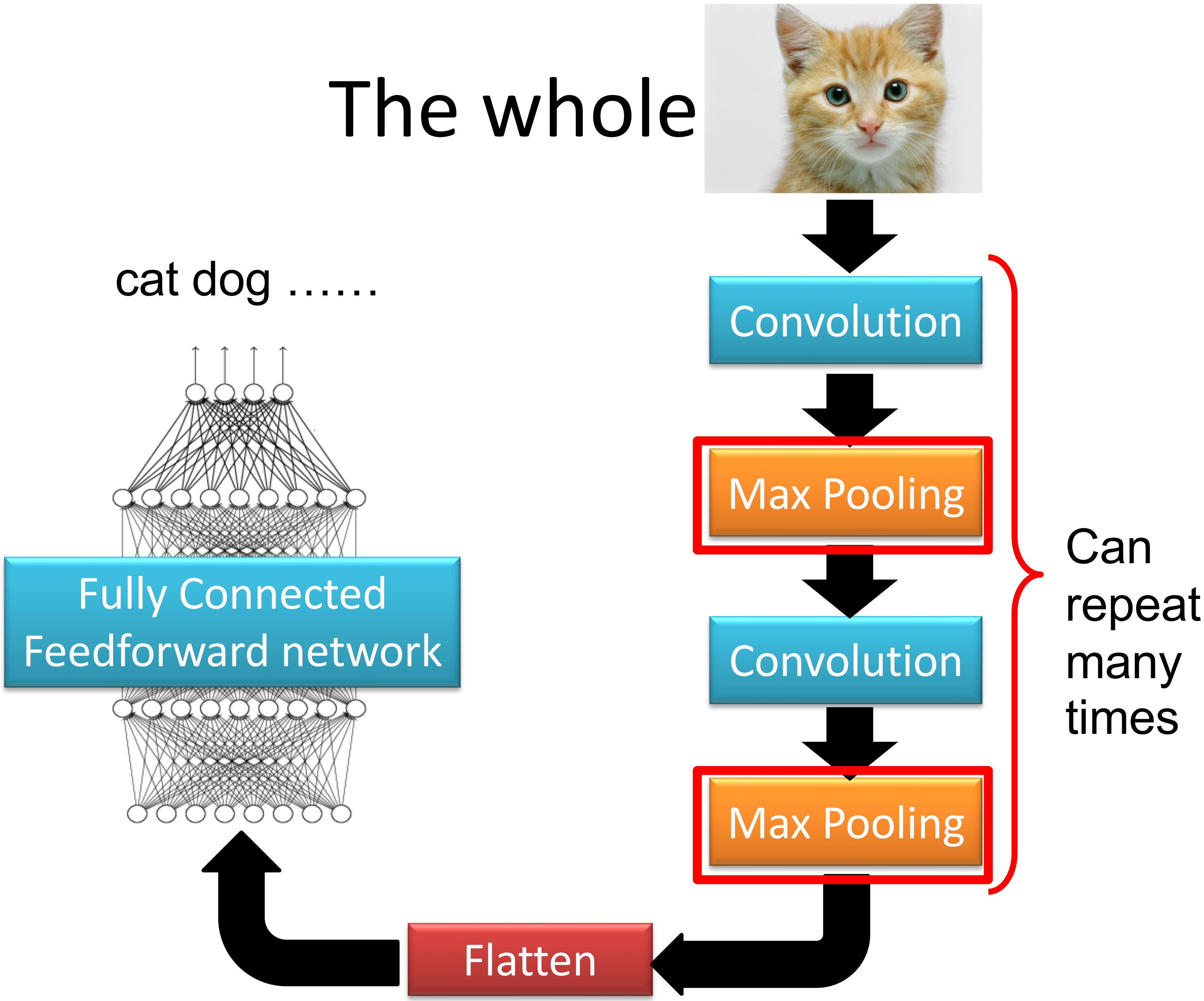






Filter 1
6 x 6 image
Less parameters!
1: 1
2: 0
3: 0
4: 0
7: 0
8: 1
9: 0
10: 0
13: 0
14: 0
15: 1
16: 1
3
Only connect to 9 input, not fully connected


Filter 1
6 x 6 image
Less parameters!
Even less parameters!
1: 1
2: 0
3: 0
4: 0
7: 0
8: 1
9: 0
10: 0
13: 0
14: 0
15: 1
16: 1
3
-1
Shared weights


The whole
cat dog ……
Fully Connected
Feedforward network
Convolution
Max Pooling
Convolution
Max Pooling
Can
repeat
many
times
Flatten

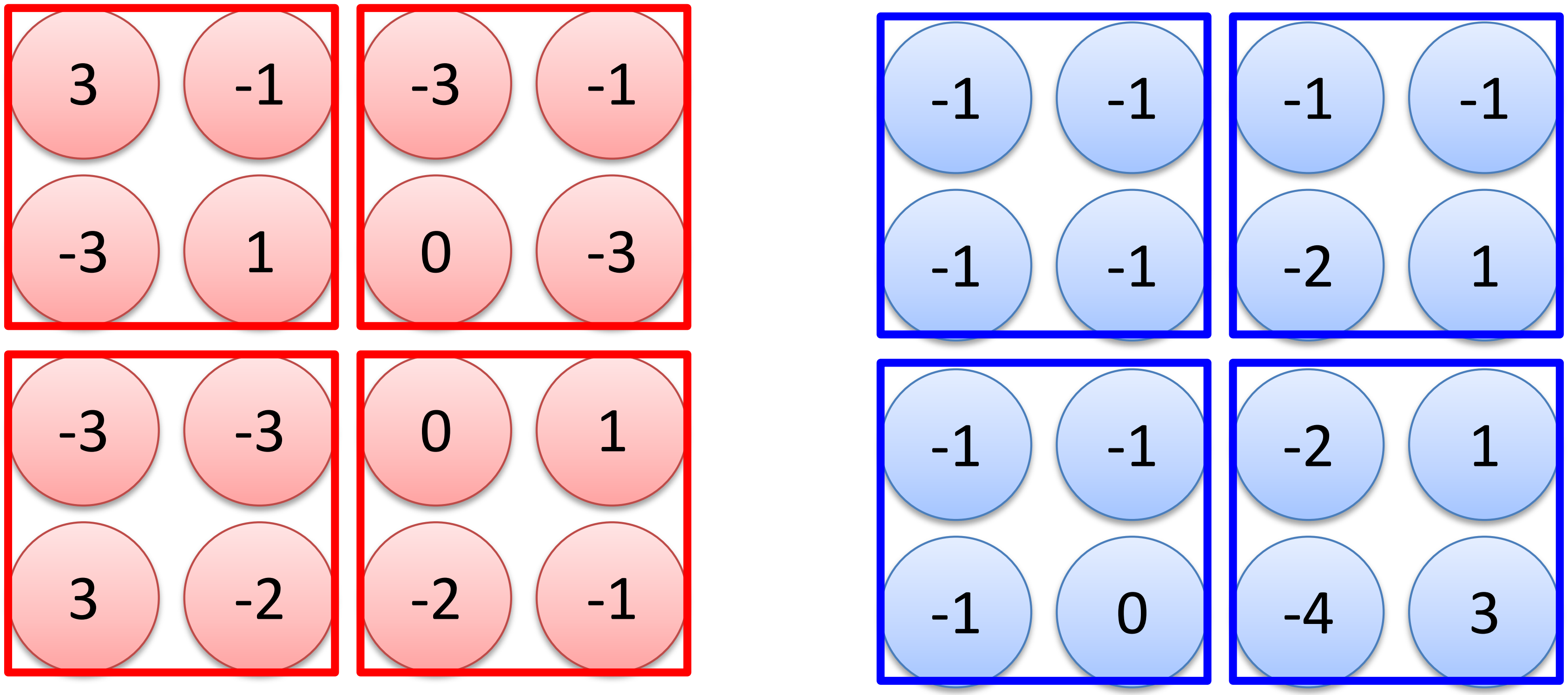
CNN – Max Pooling

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

Filter 1

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

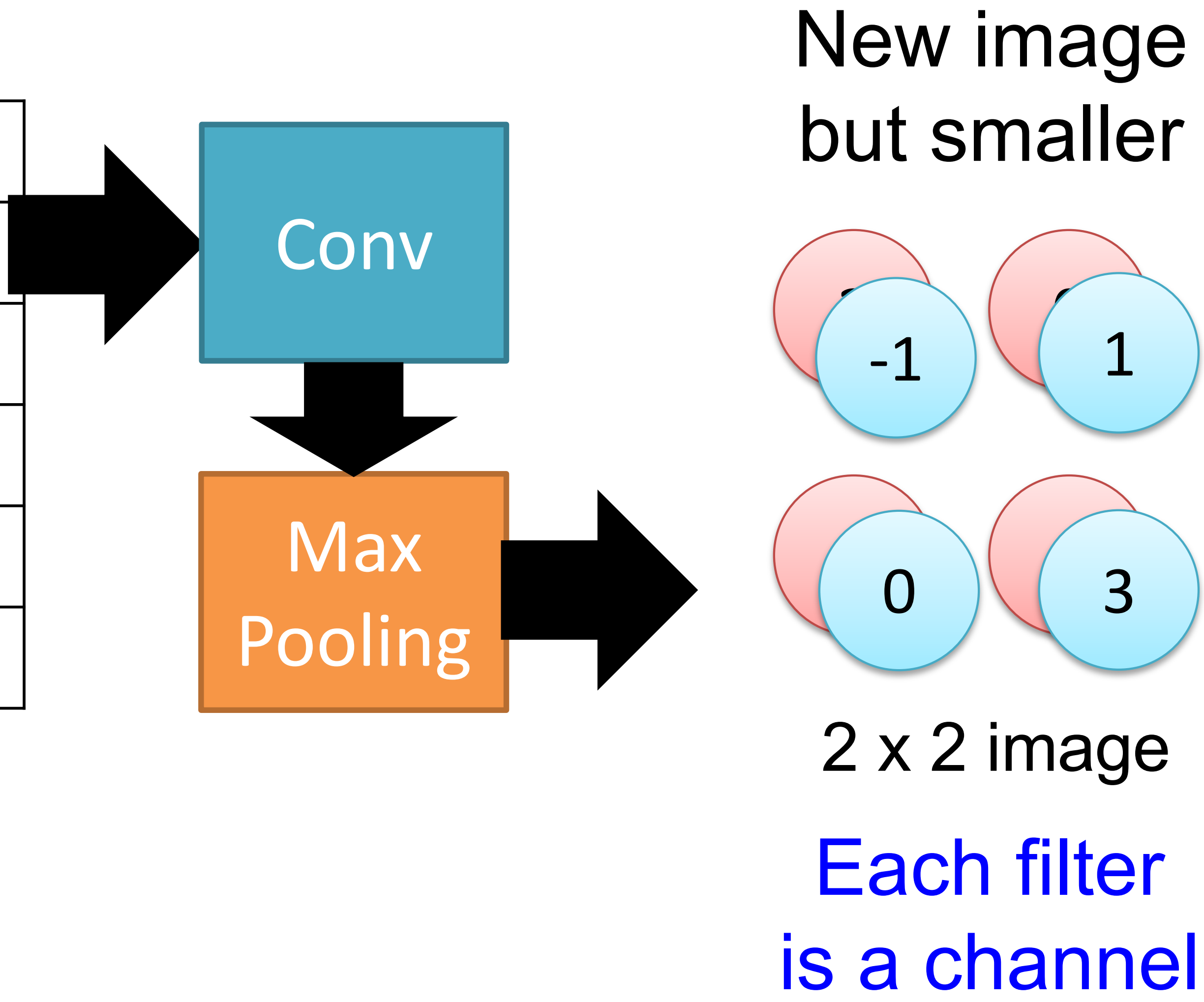
Filter 2



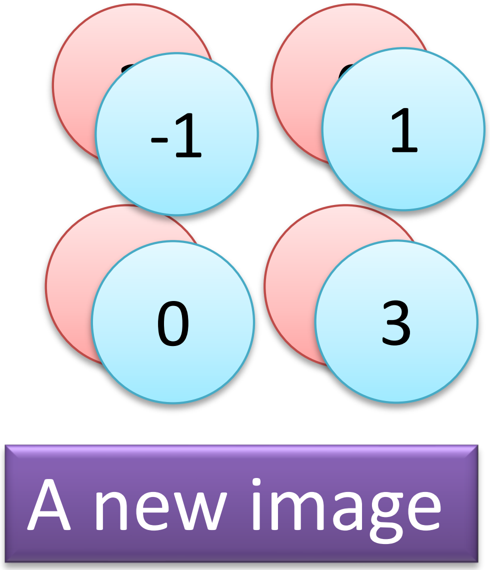
CNN – Max Pooling

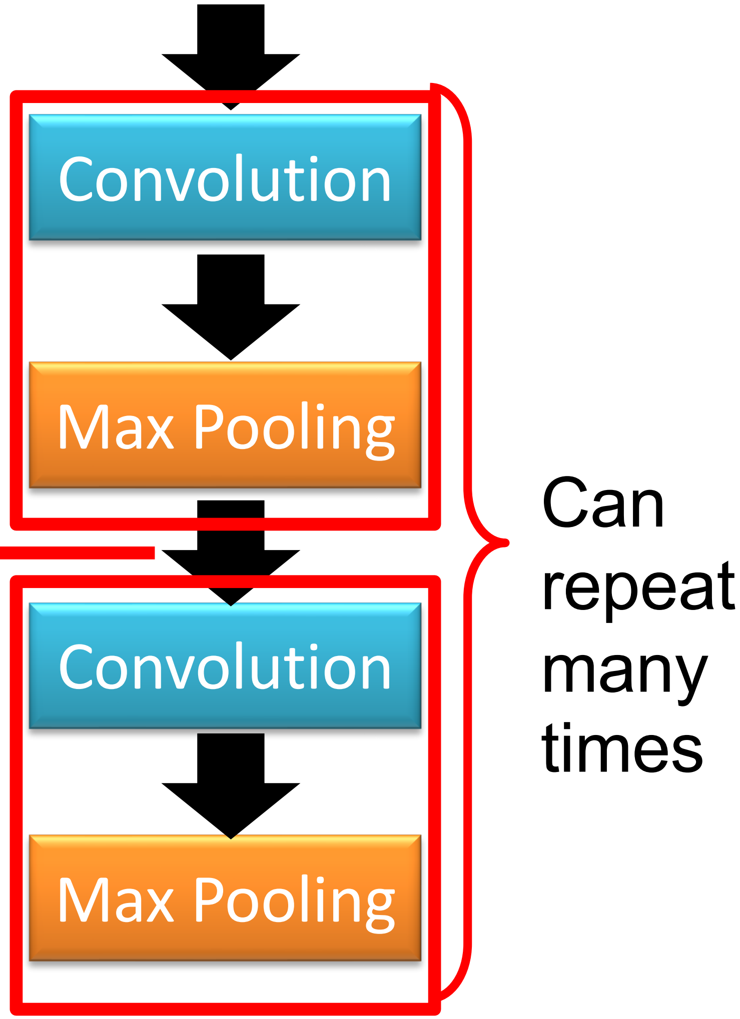
1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0

6 x 6 image



The whole

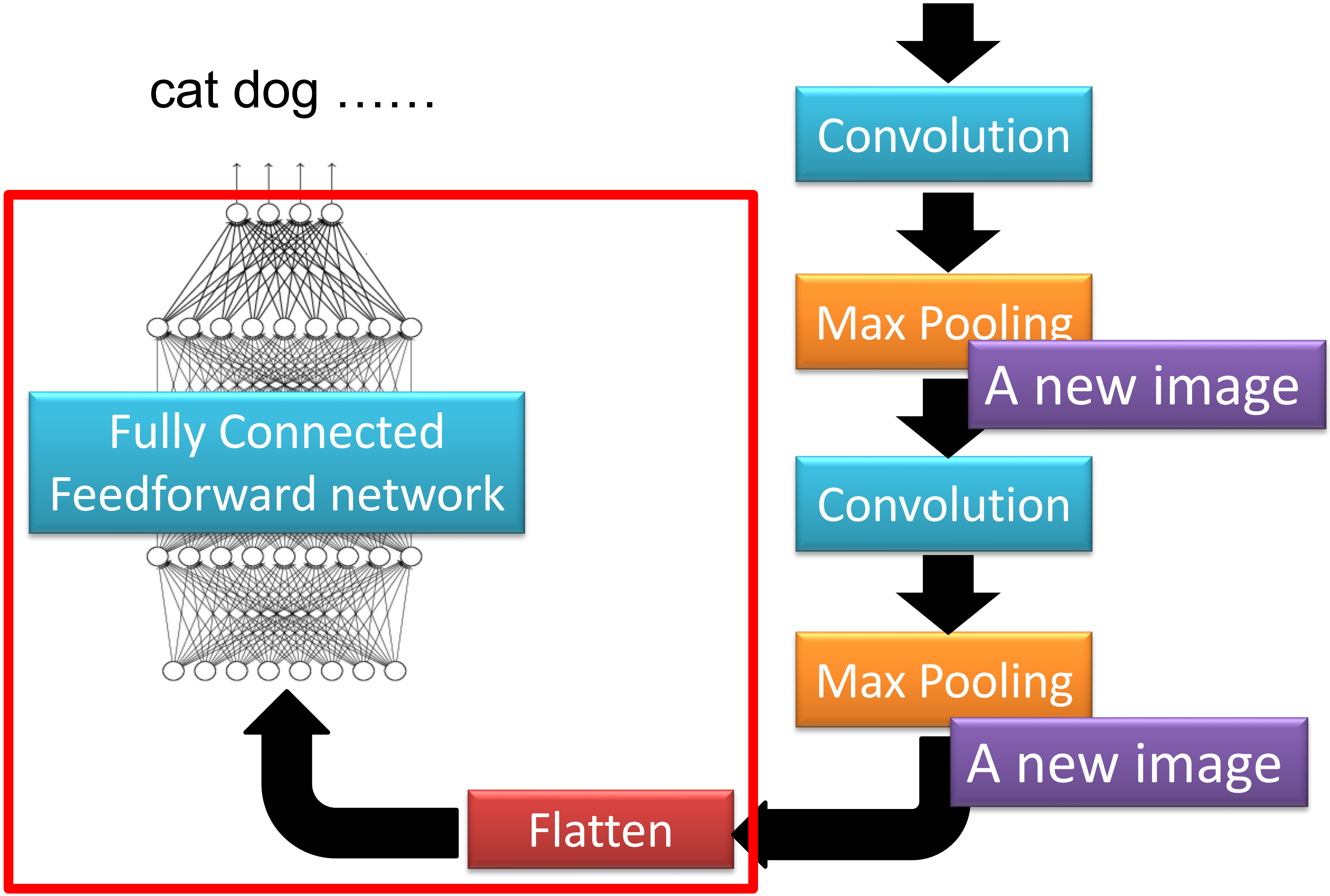


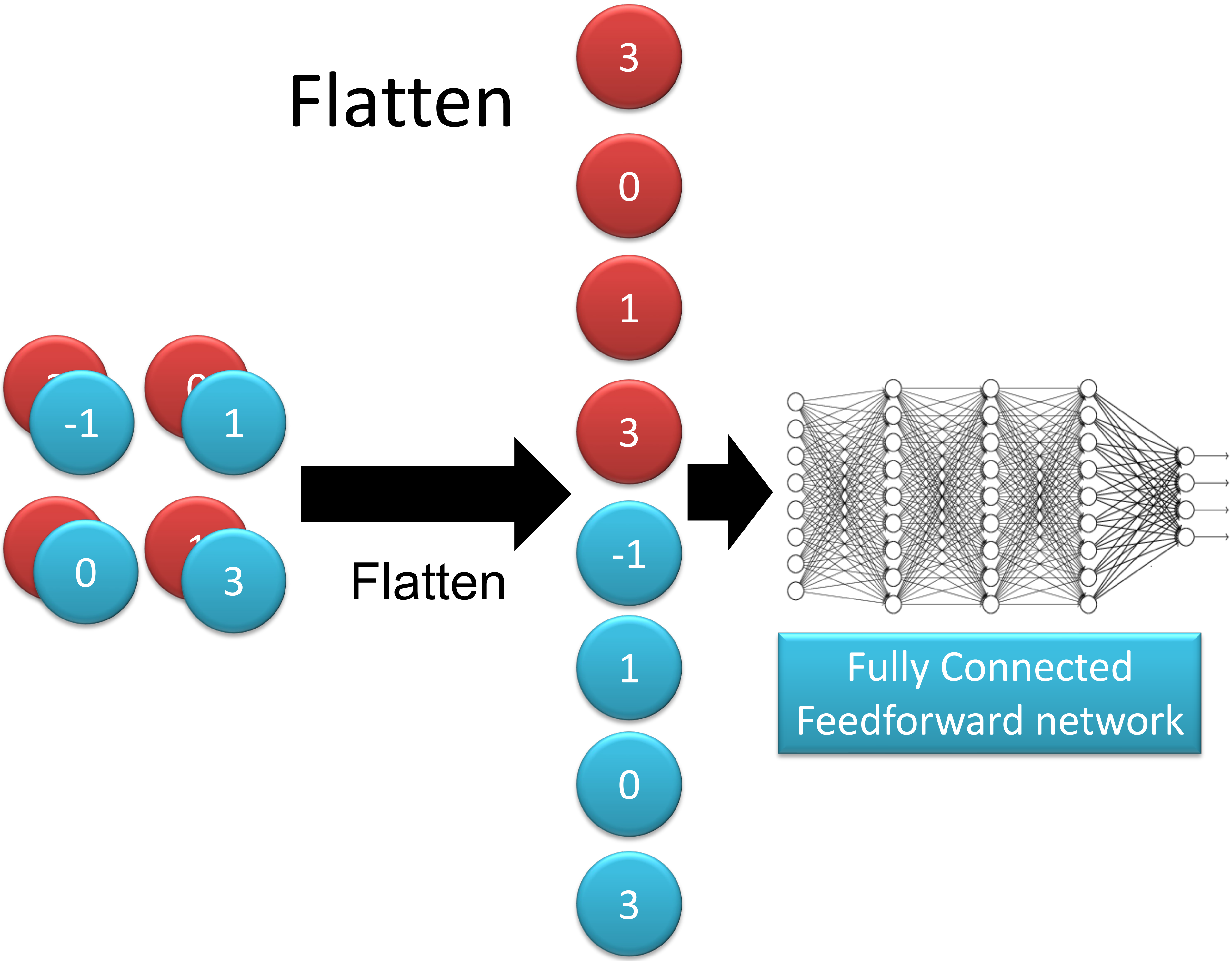


Smaller than the original image

The number of the channel is the number of filters

The whole


cat dog ……
Convolution
Max Pooling
A new image
Convolution
Max Pooling
A new image
Flatten
Fully Connected
Feedforward network

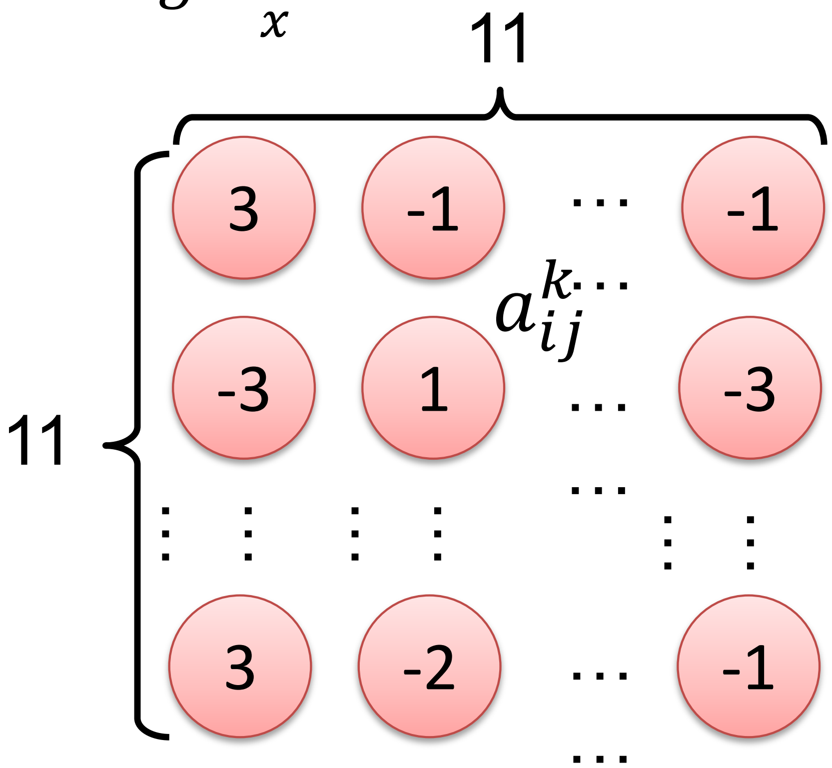

Flatten
-1
1
0
3
Flatten
3
0
1
3
-1
1
0
3
Fully Connected
Feedforward network

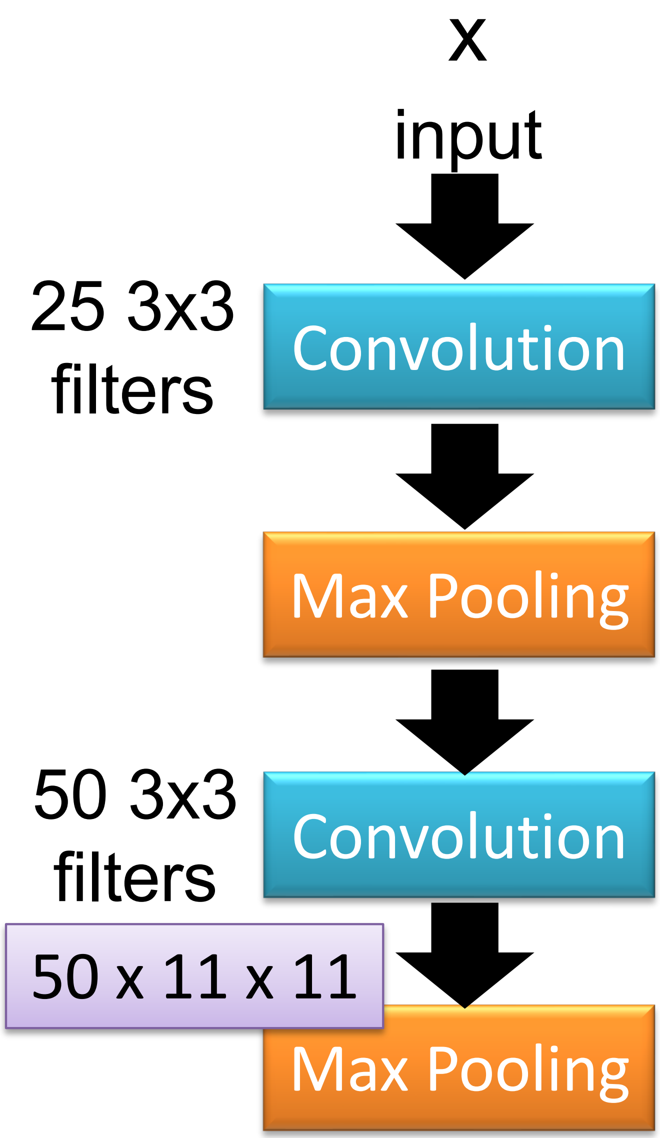
What does CNN learn?

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)





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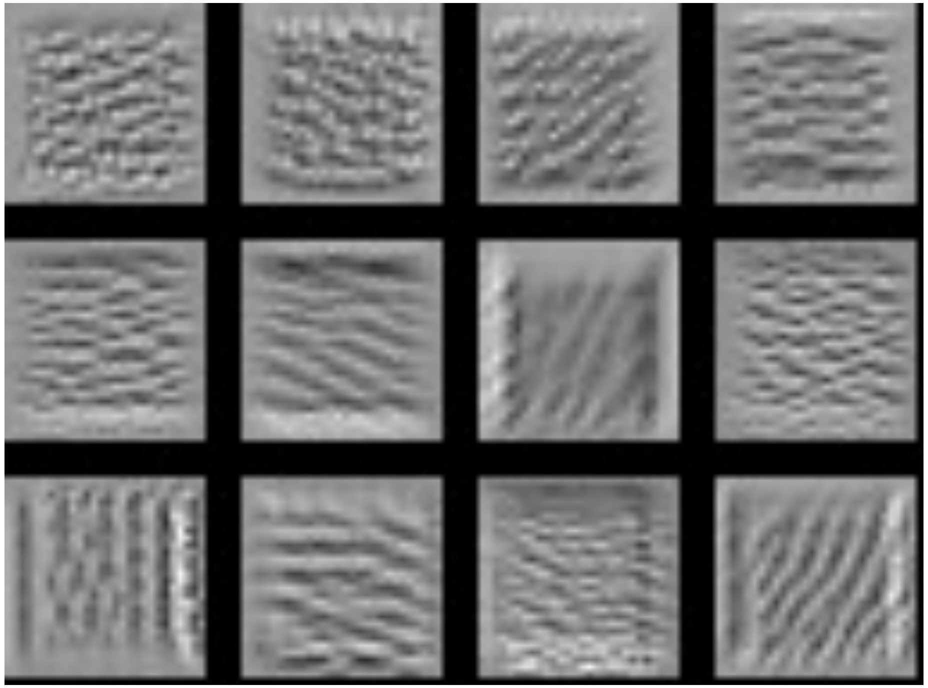
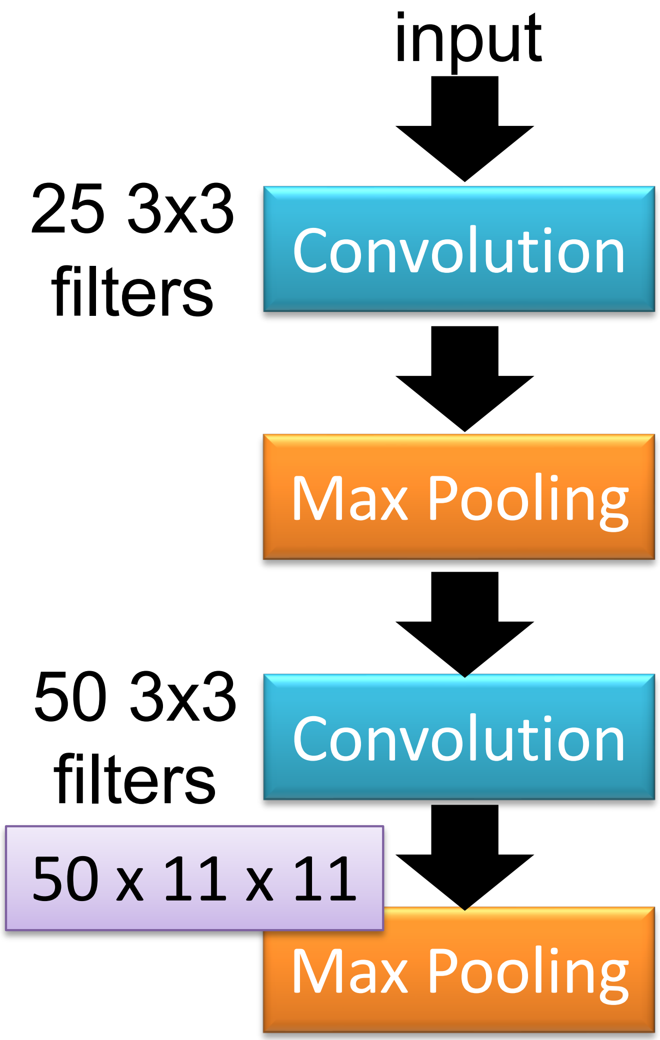


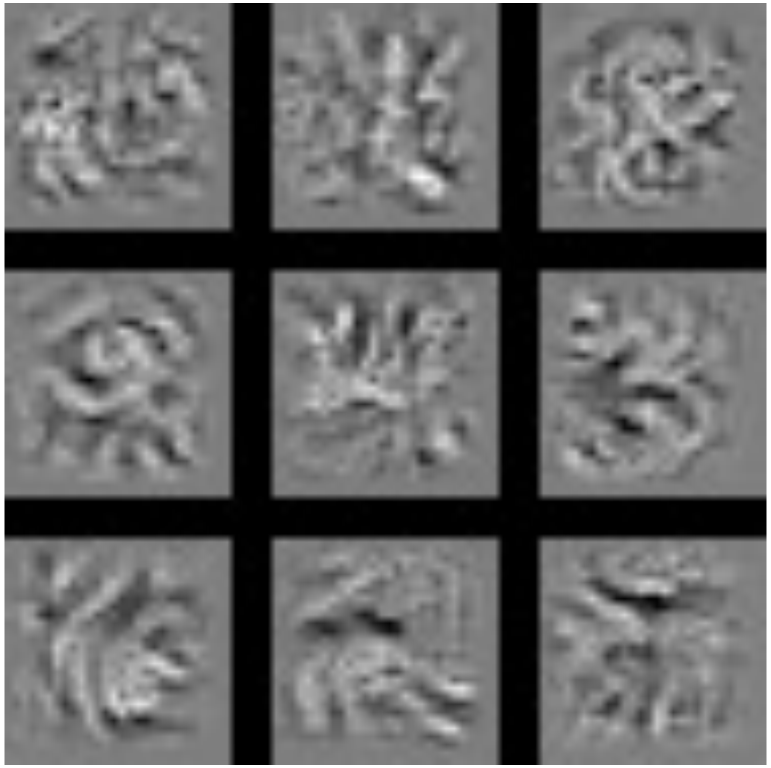
For each filter



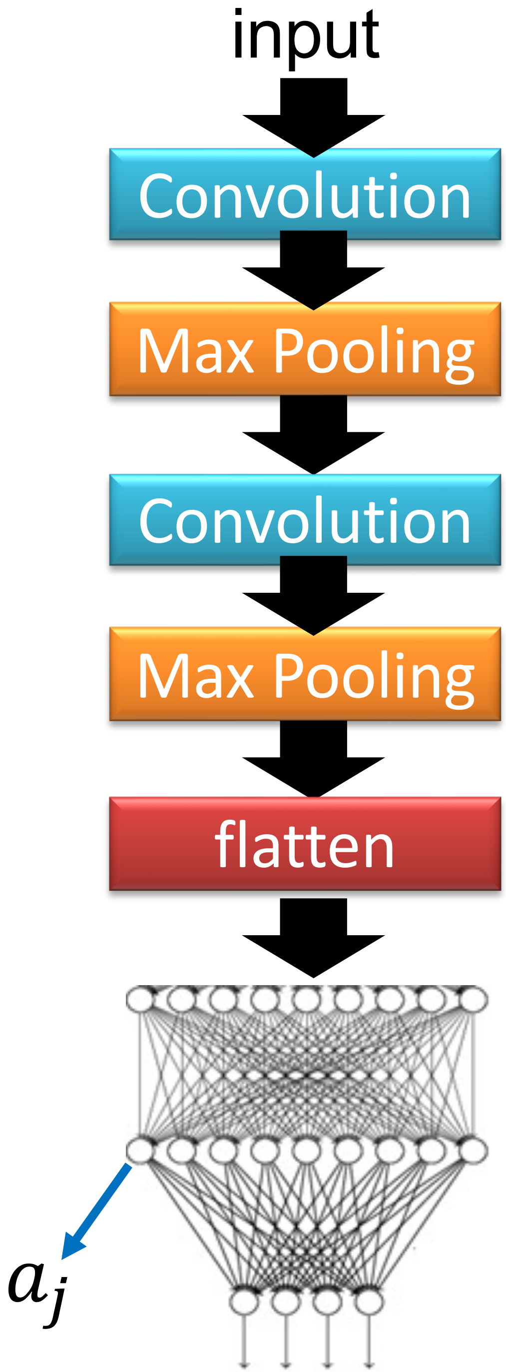
What does CNN learn?

Find an image maximizing the output of neuron:

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



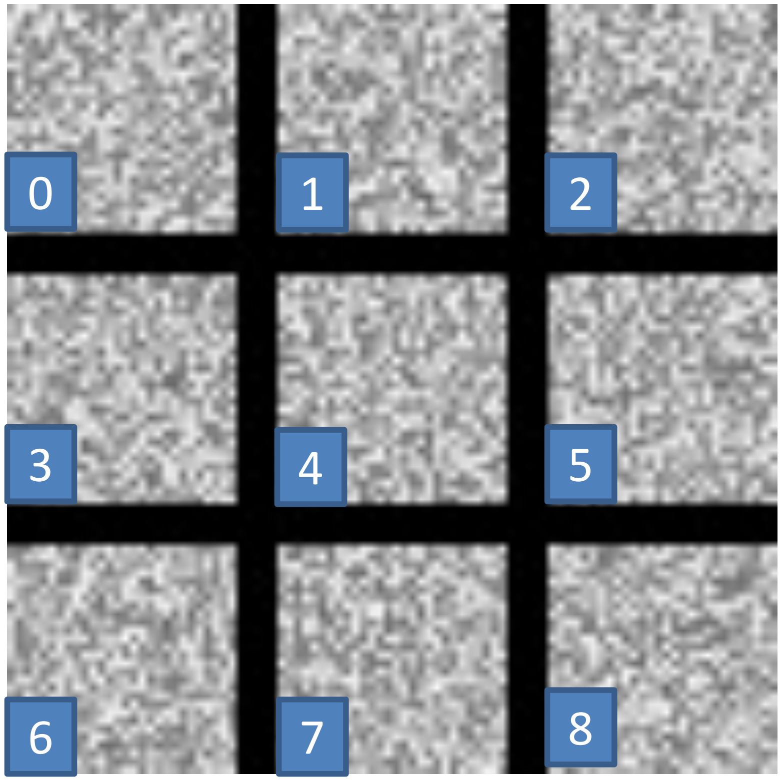
Each figure corresponds to a neuron

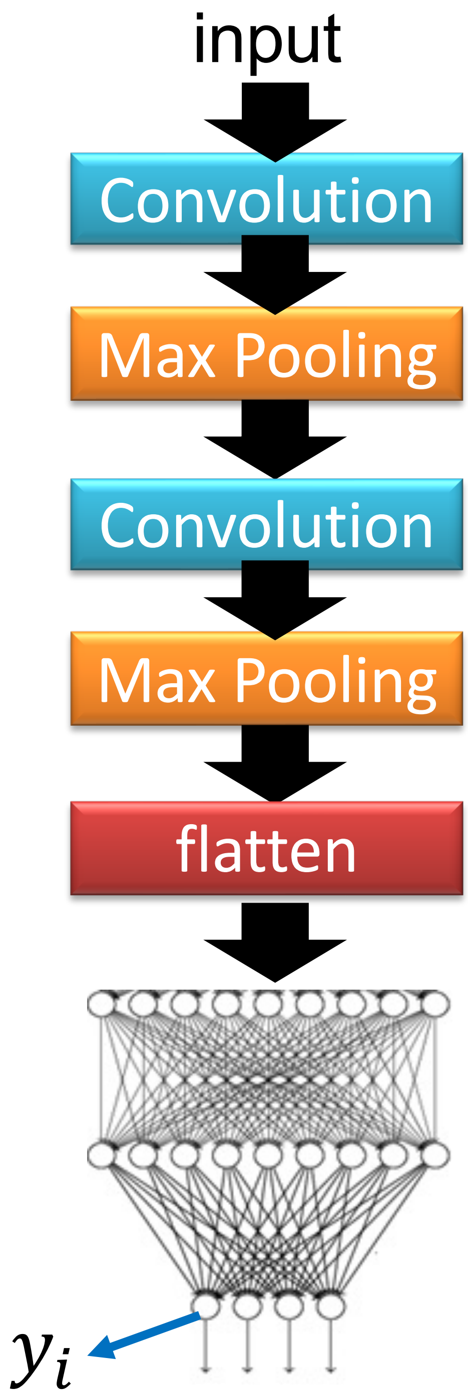


What does CNN learn?

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

Can we see digits?





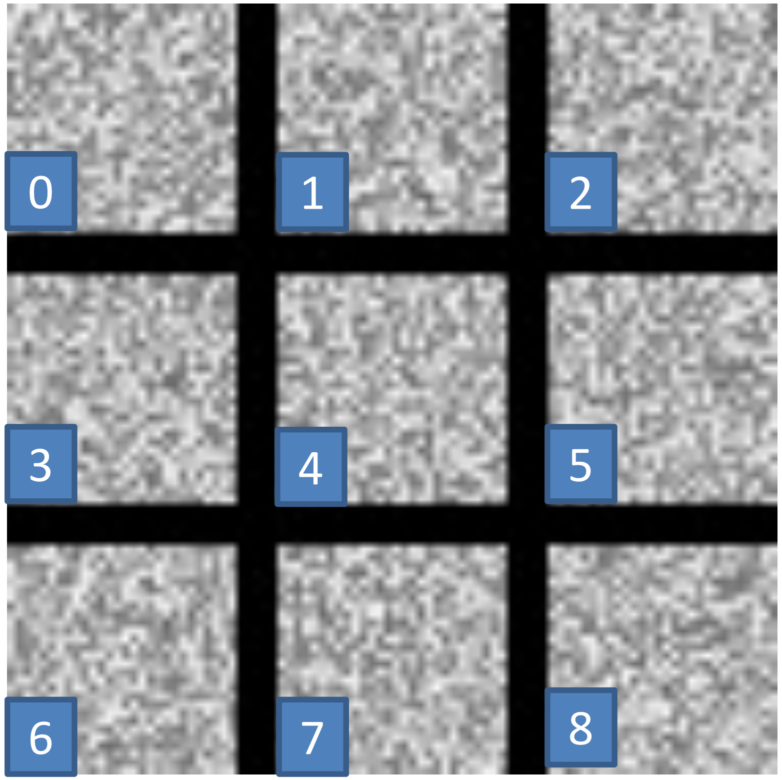
Deep Neural Networks are Easily Fooled

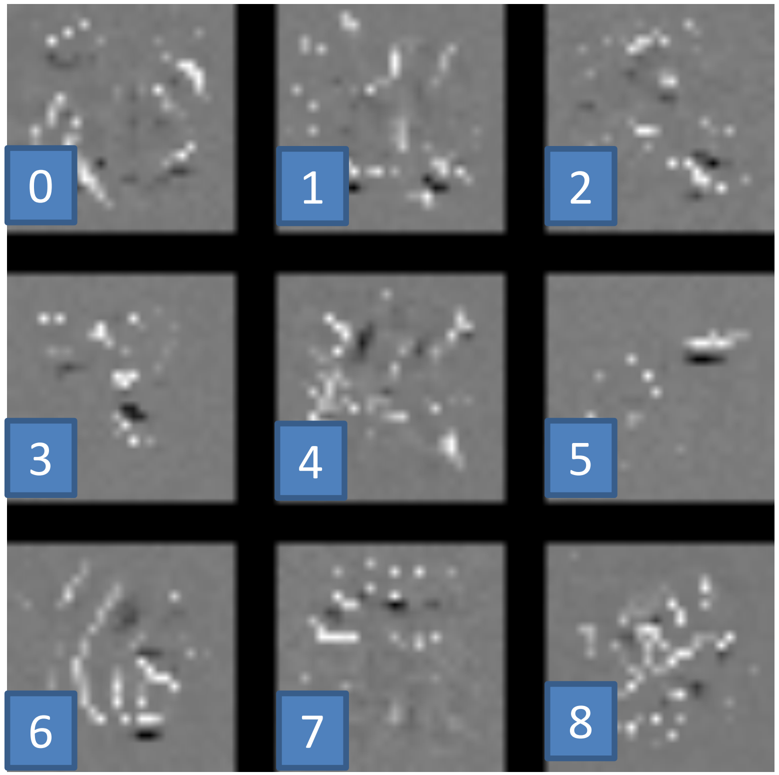
https://www.youtube.com/watch?v=M2IebCN9Ht4

What does CNN learn?

Over all pixel values

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





To learn more ……

- The methods of visualization in these slides
  – https://blog.keras.io/how-convolutional-neural-networks-see-the-world.html
- More about visualization
  – http://cs231n.github.io/understanding-cnn/
- Very cool CNN visualization toolkit
  – http://yosinski.com/deepvis
  – http://scs.ryerson.ca/~aharley/vis/conv/
- The 9 Deep Learning Papers You Need To Know About
  – https://adeshpande3.github.io/adeshpande3.github.io/The-9-Deep-Learning-Papers-You-Need-To-Know-About.html