

# Convolutional Neural Network

Hung-yi Lee

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

# Why CNN for Image

- Some patterns are much smaller than the whole image

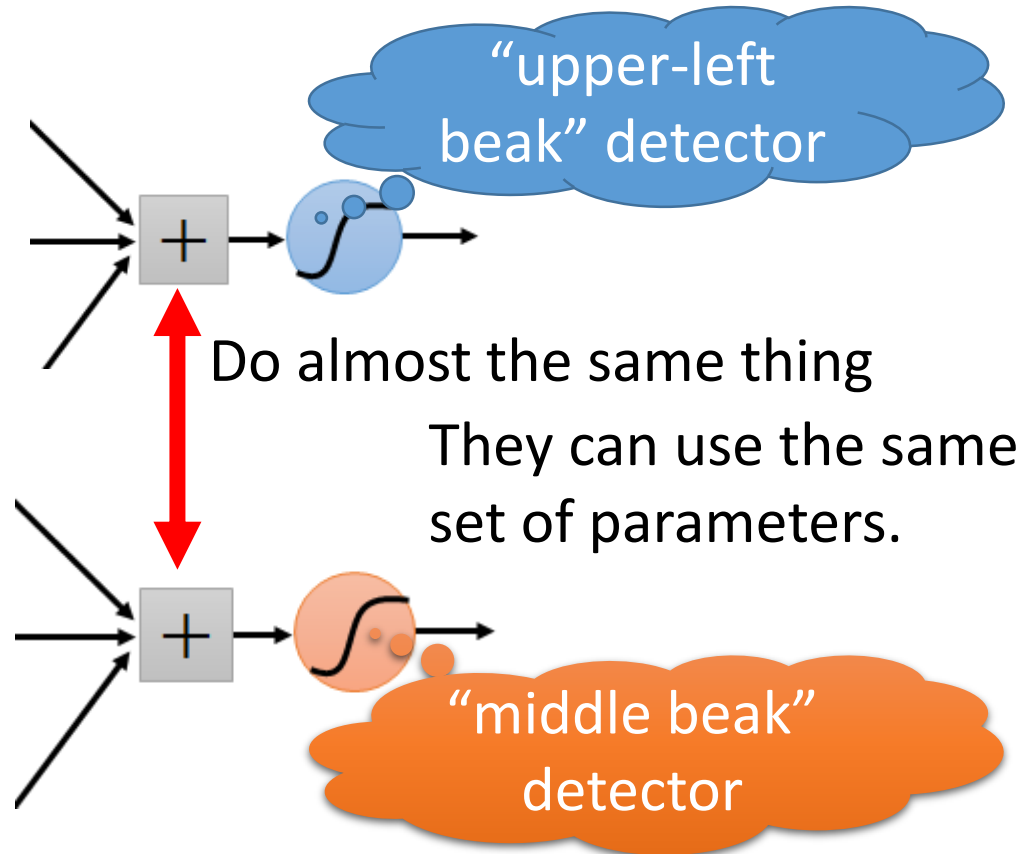
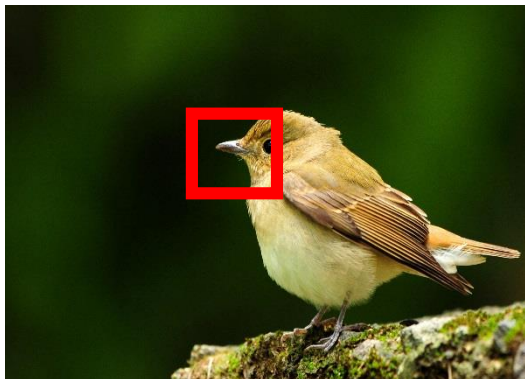
A neuron does not have to see the whole image to discover the pattern.

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

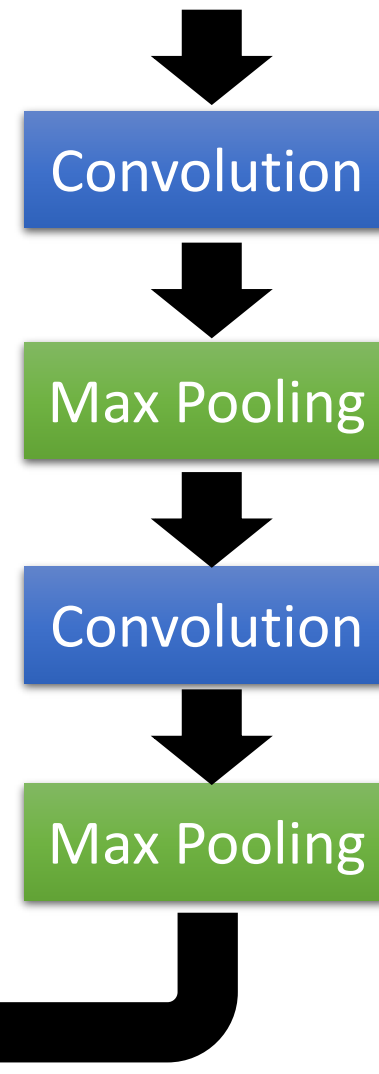
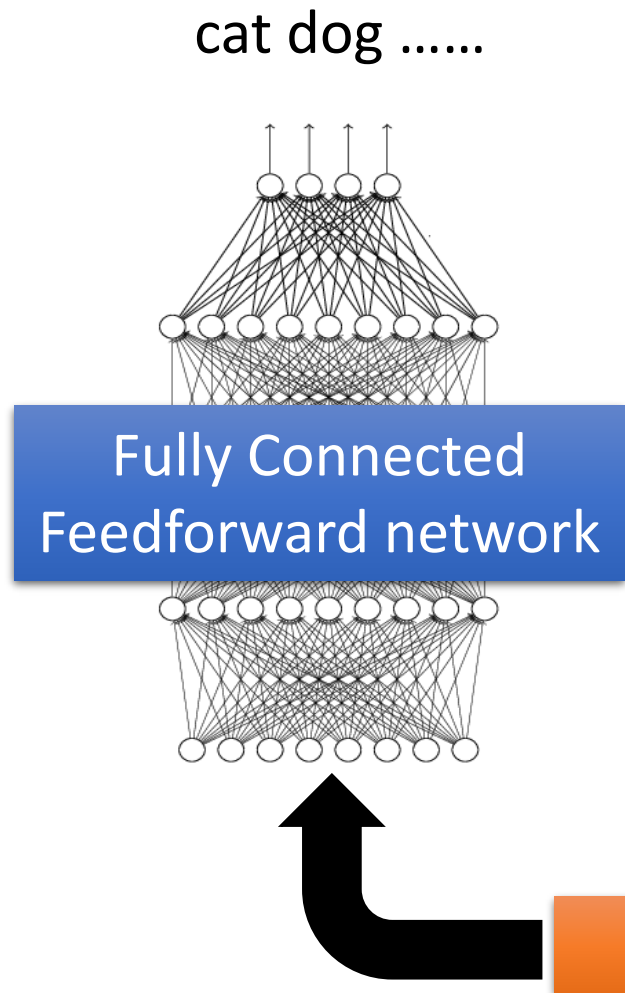


We can subsample the pixels to make image smaller



Less parameters for the network to process the image

# The whole CNN



# The whole CNN

## Property 1

- Some patterns are much smaller than the whole image

## Property 2

- The same patterns appear in different regions.

## Property 3

- Subsampling the pixels will not change the object



Convolution

Max Pooling

Convolution

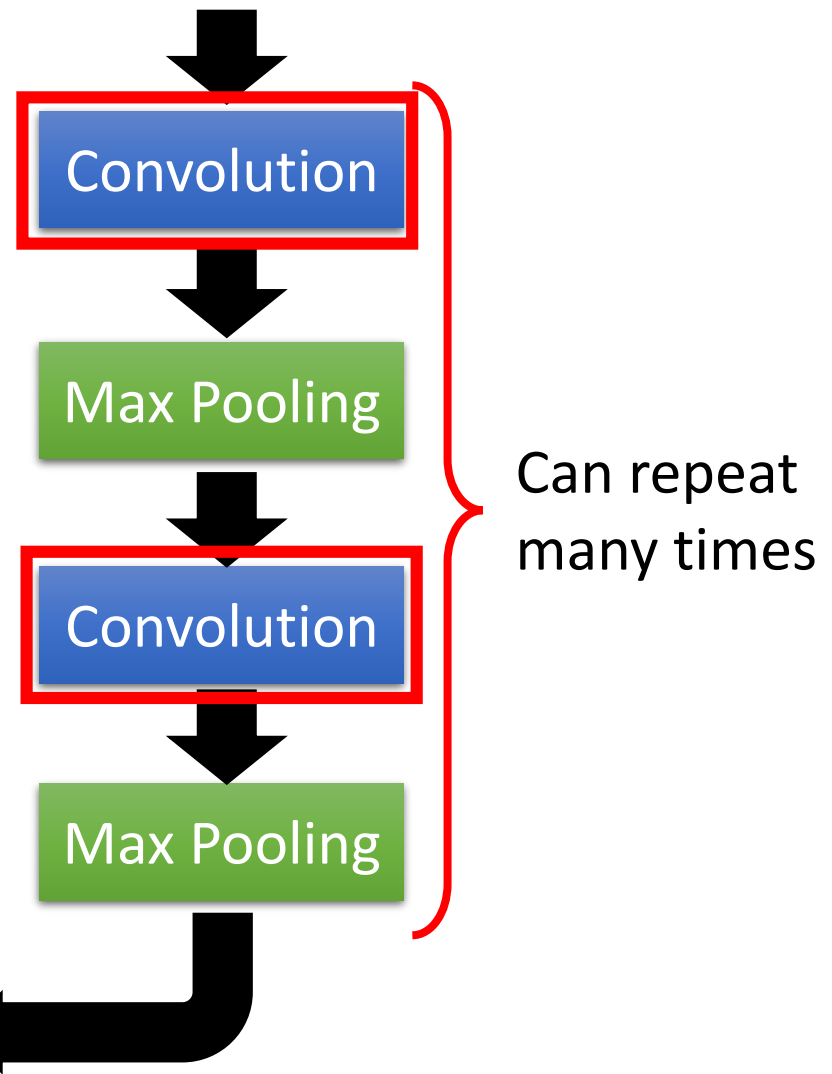
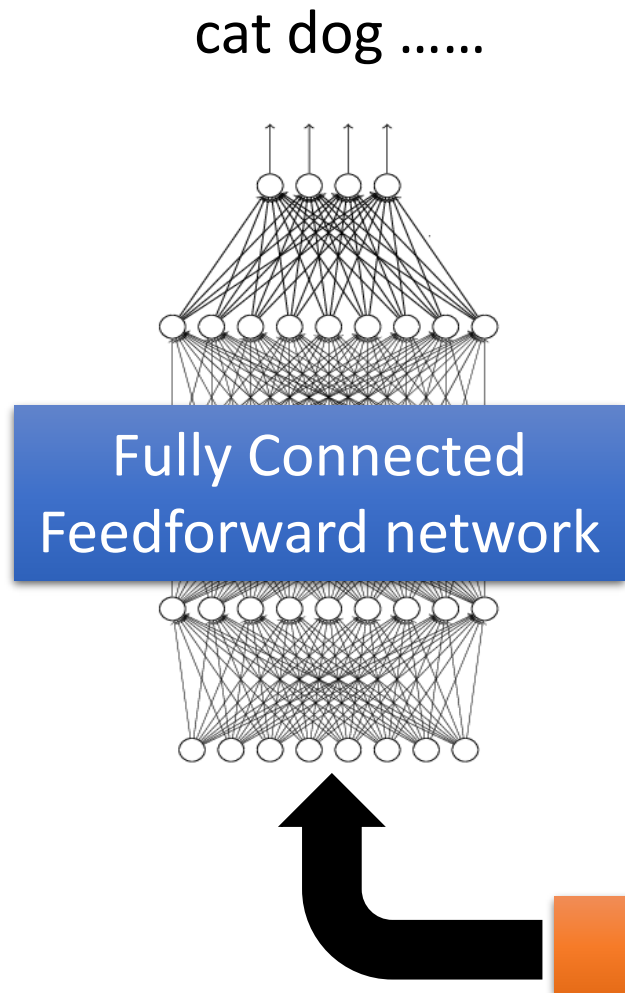
Max Pooling

Flatten

Can repeat many times



# The whole CNN



# 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 – Convolution

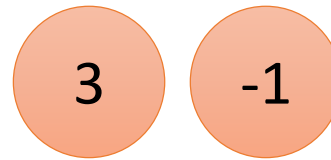
1	-1	-1
-1	1	-1
-1	-1	1

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



# CNN – Convolution

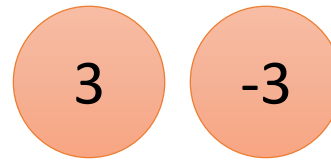
1	-1	-1
-1	1	-1
-1	-1	1

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



We set stride=1 below

# CNN – 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

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

Property 2

# CNN – Convolution

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

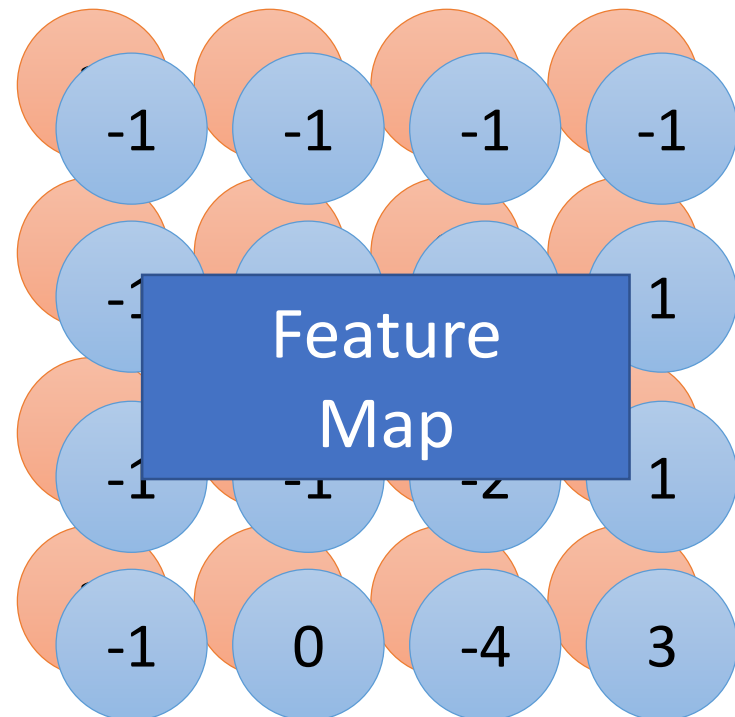
Filter 2

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

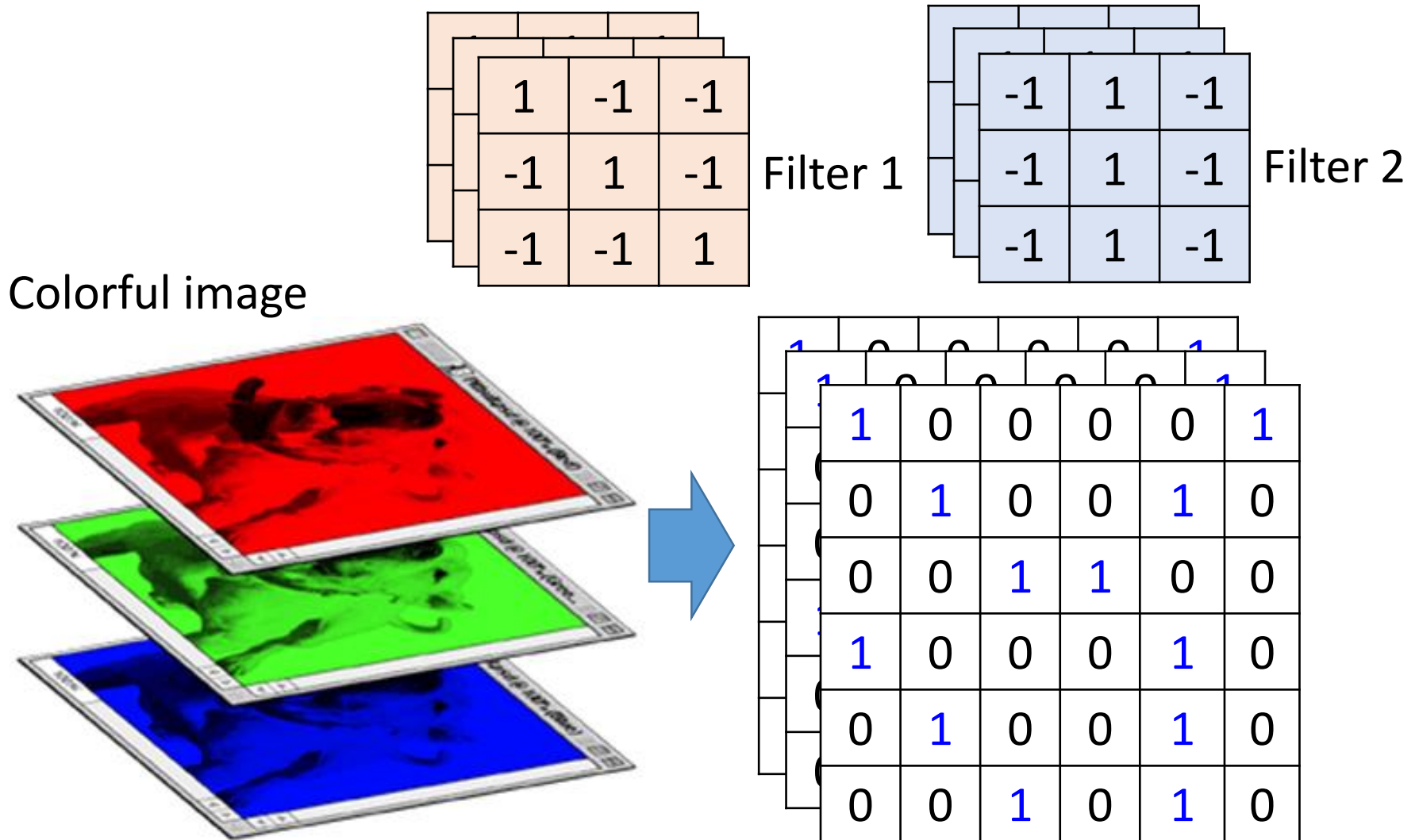
6 x 6 image

Do the same process for every filter

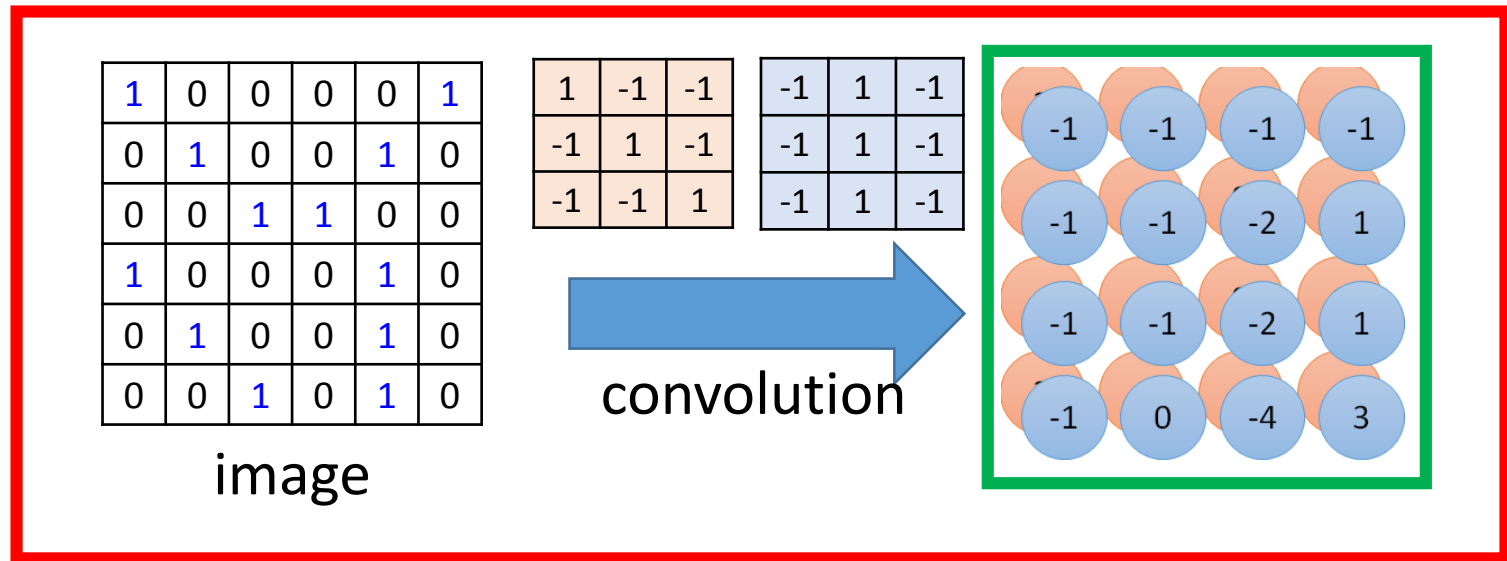


4 x 4 image

# CNN – Colorful image

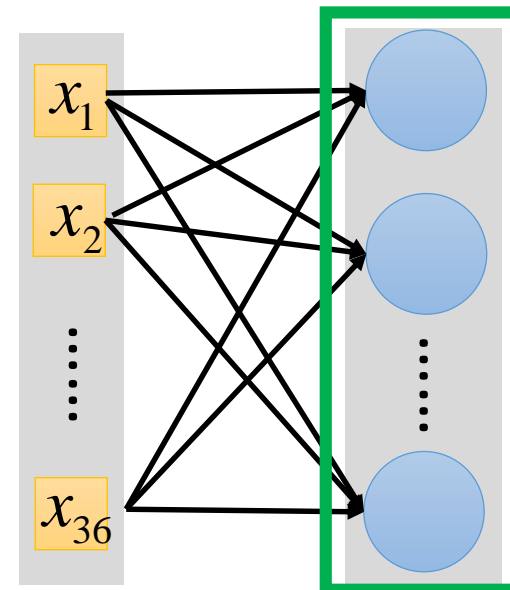


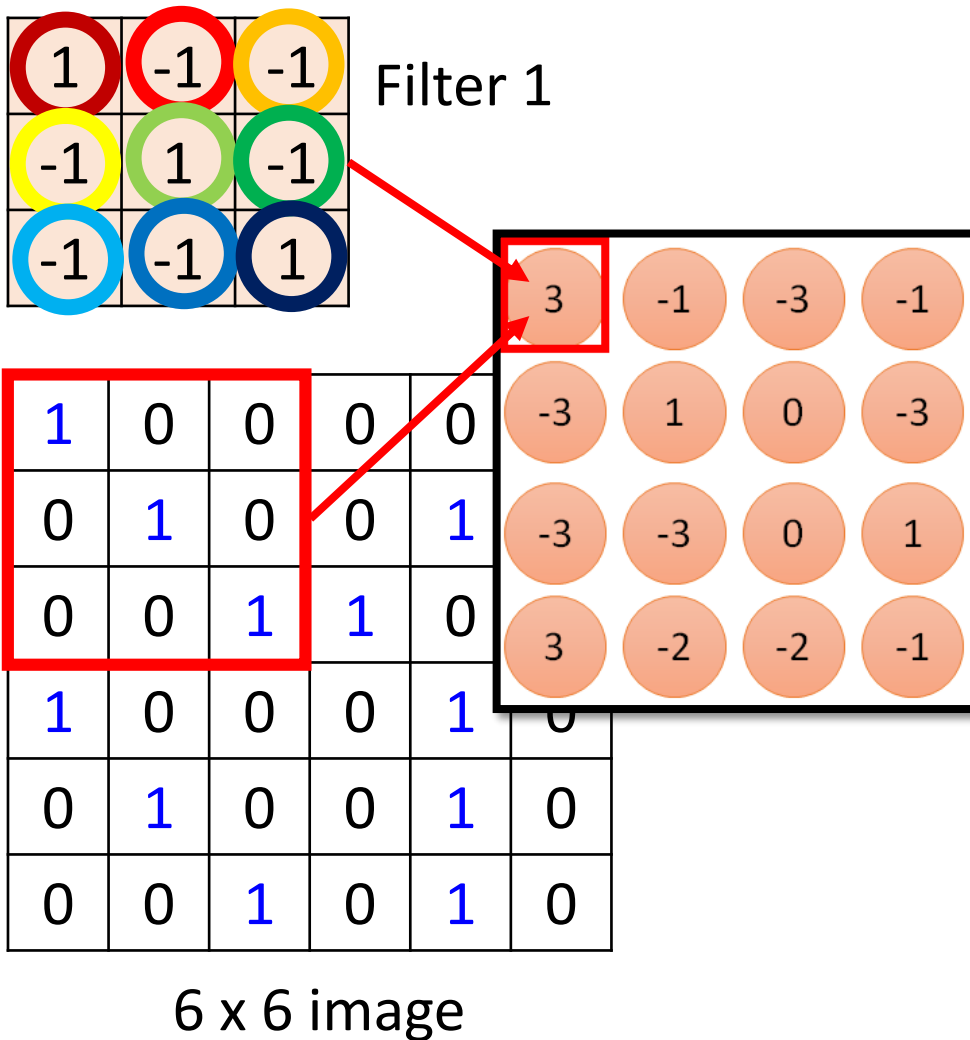
# Convolution v.s. Fully Connected



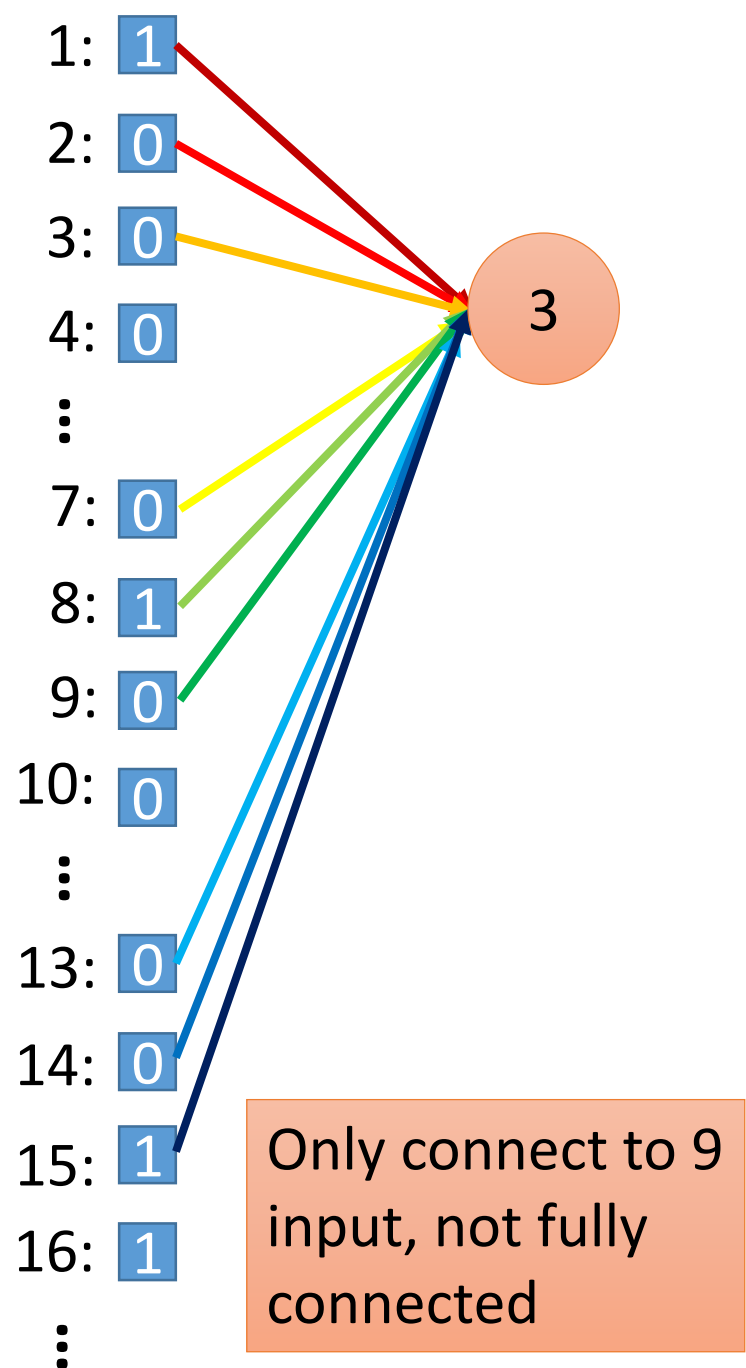
Fully-  
connected

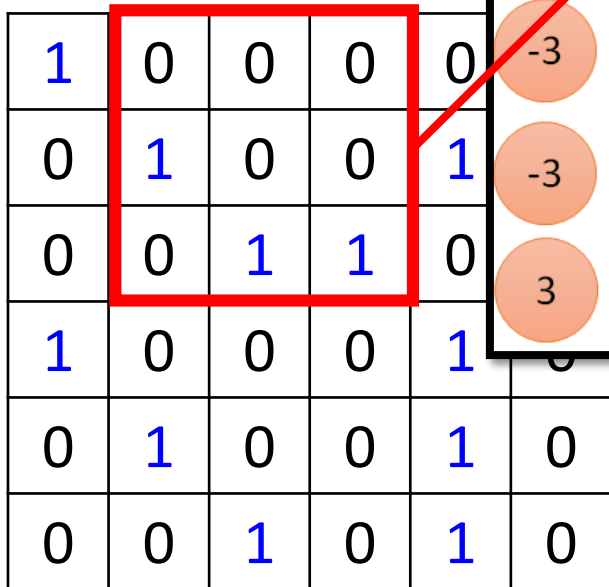
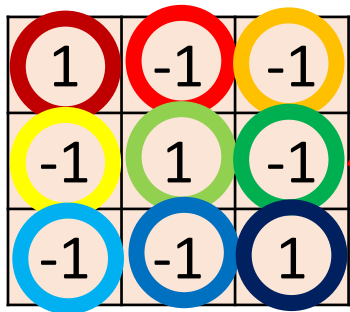
1	0	0	0	0	1
0	1	0	0	1	0
0	0	1	1	0	0
1	0	0	0	1	0
0	1	0	0	1	0
0	0	1	0	1	0



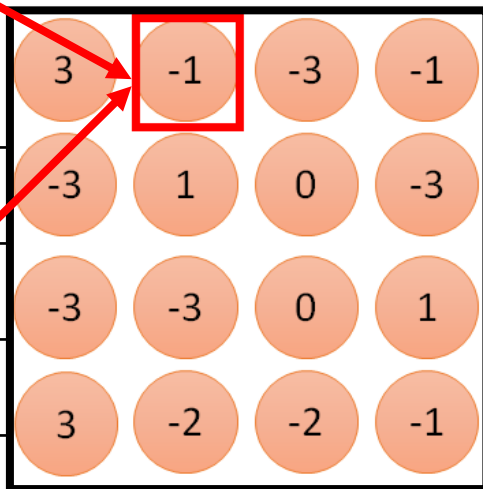


Less parameters!



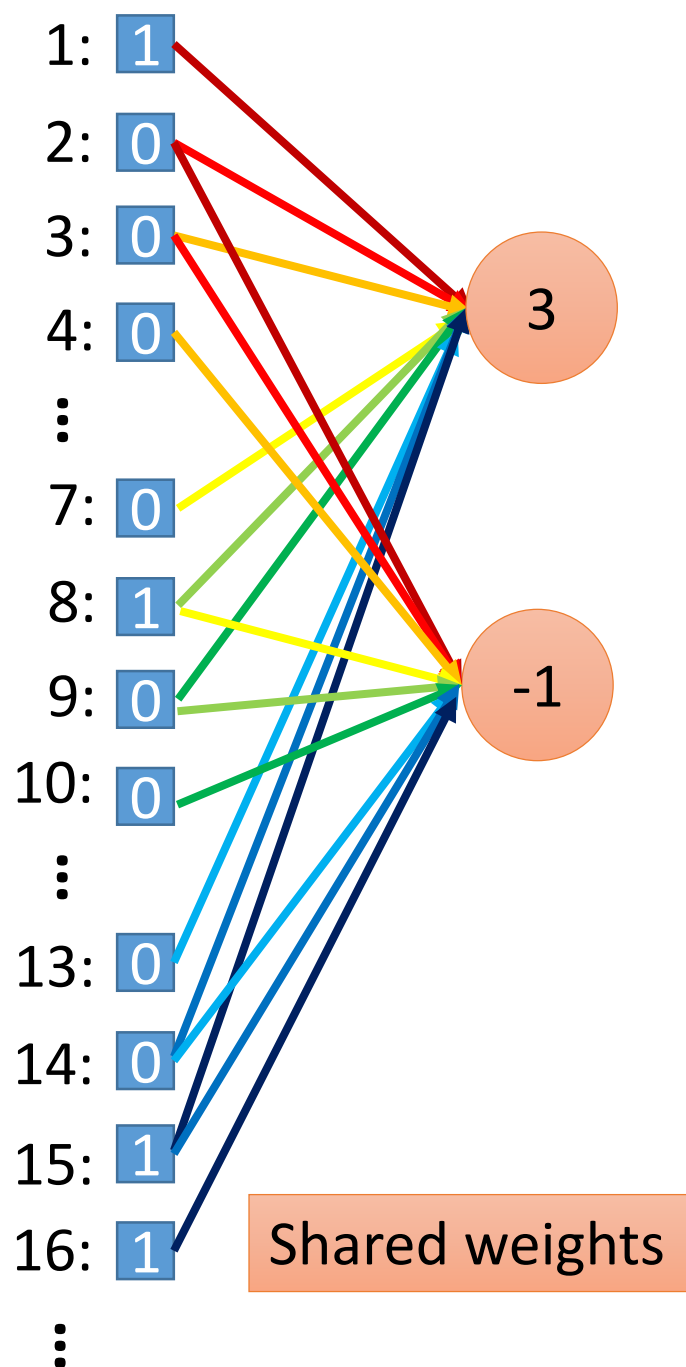


6 x 6 image



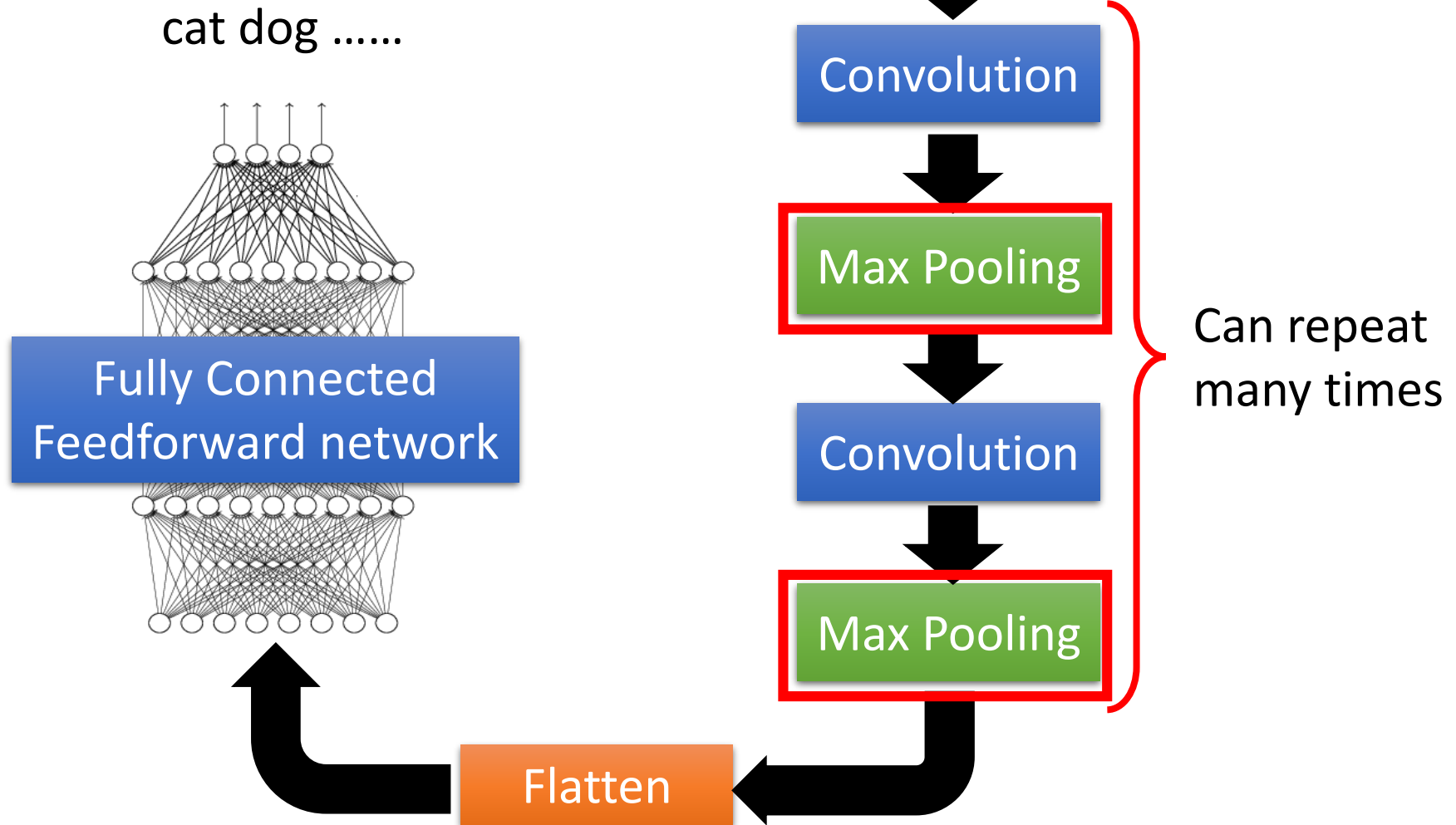
Less parameters!

Even less parameters!





# The whole CNN



# 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

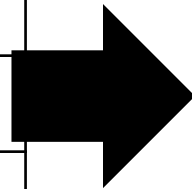
3	-1	-3	-1
-3	1	0	-3
-3	-3	0	1
3	-2	-2	-1

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

# 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

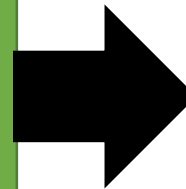
6 x 6 image



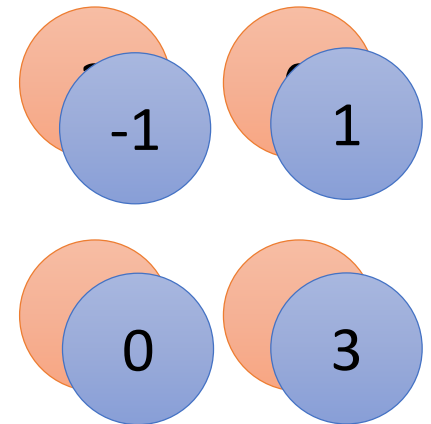
Conv



Max  
Pooling



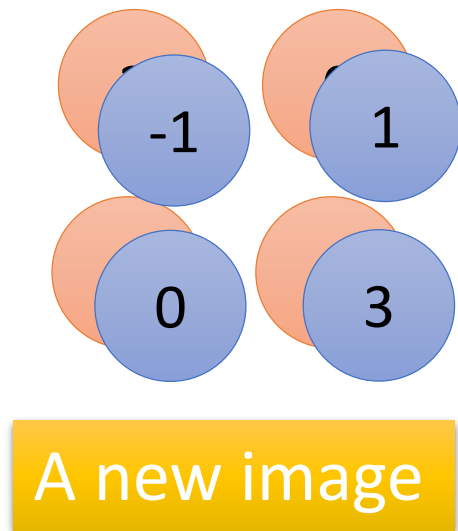
New image  
but smaller



2 x 2 image

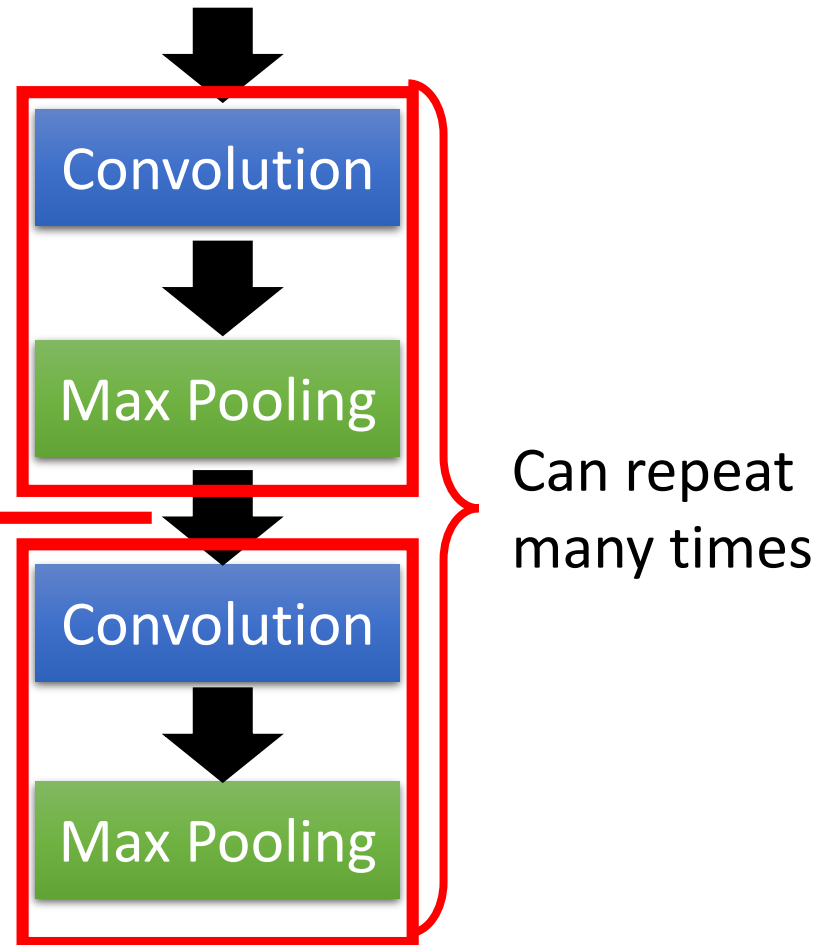
Each filter  
is a channel

# The whole CNN



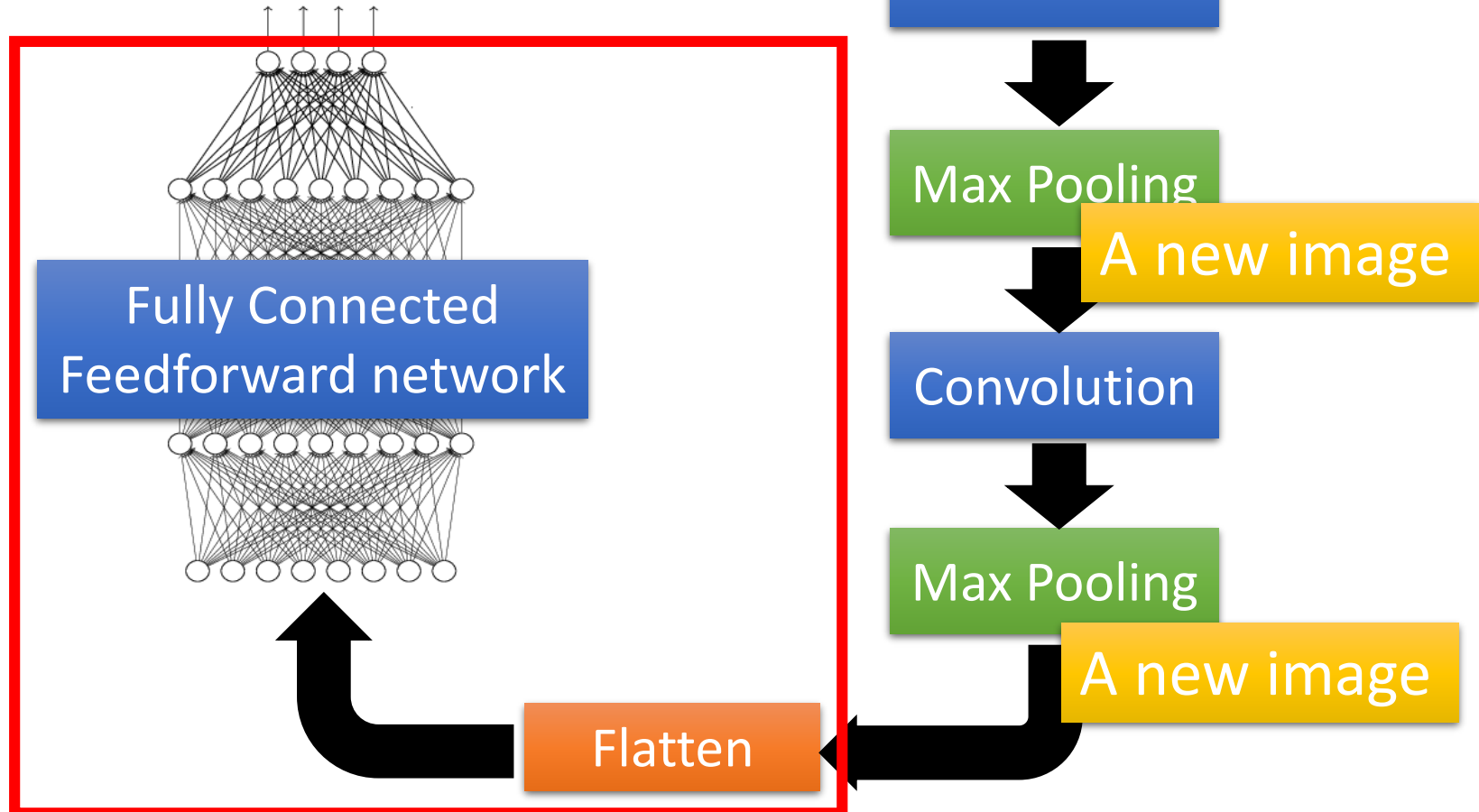
Smaller than the original image

The number of the channel is the number of filters

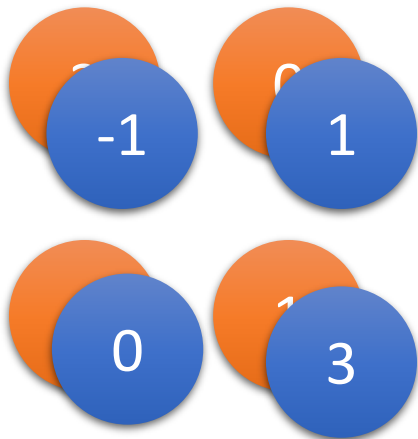


# The whole CNN

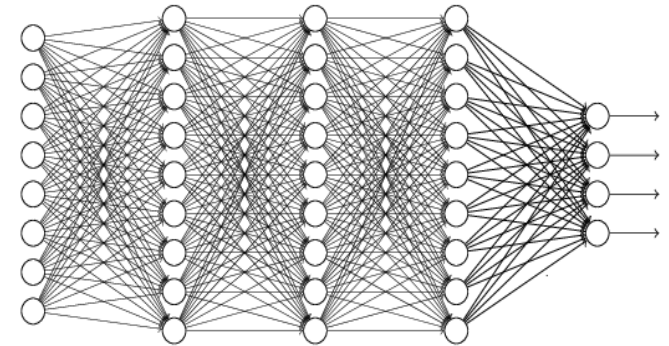
cat dog .....



# Flatten



Flatten



Fully Connected  
Feedforward network

# 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

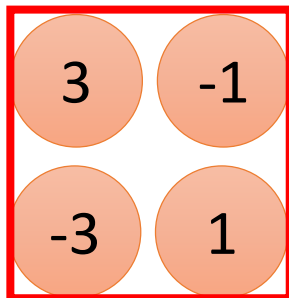
-1	1	-1
-1	1	-1
-1	1	-1

..... 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

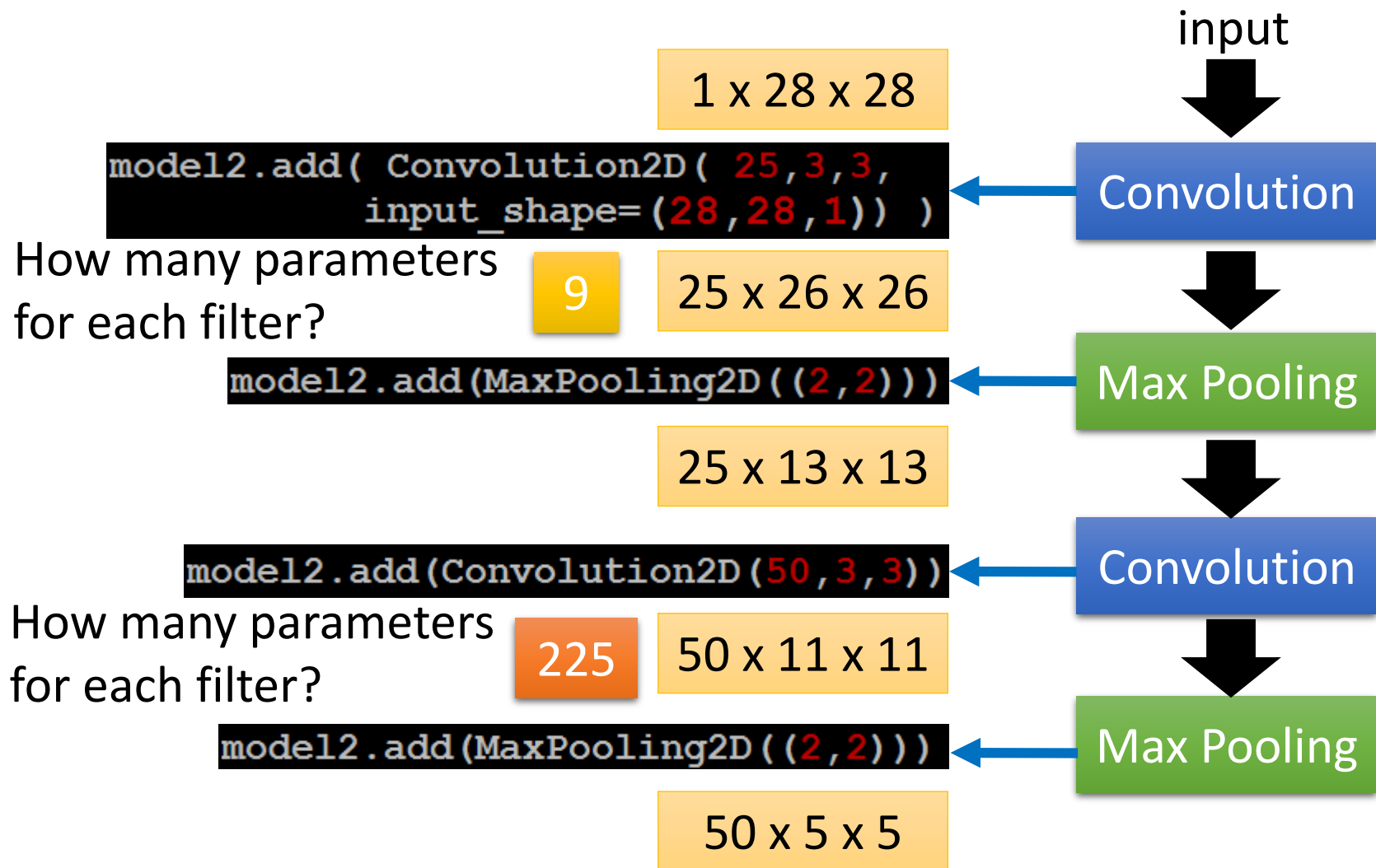
Max Pooling

Convolution

Max Pooling

## CNN in Keras

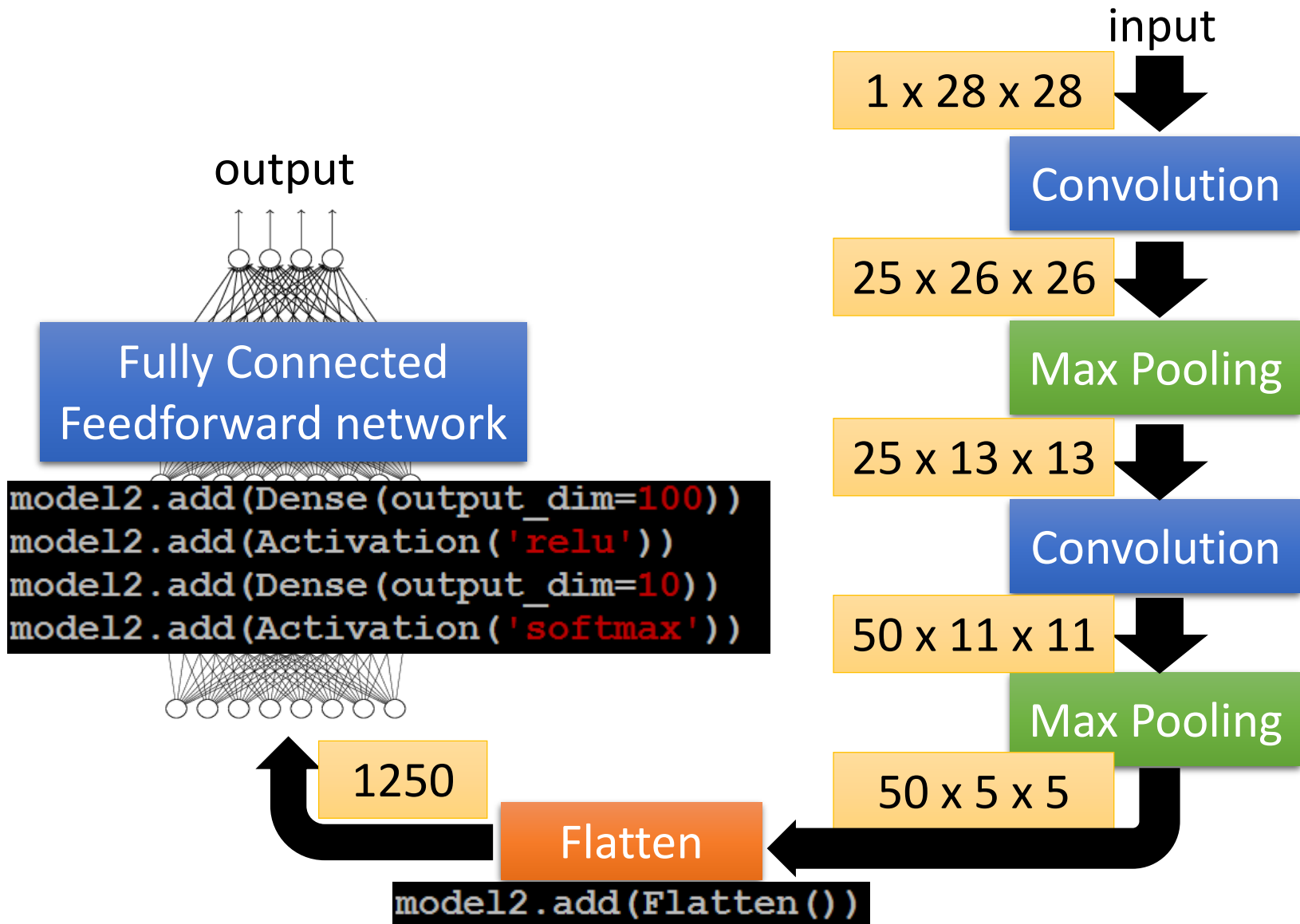
Only modified the *network structure* and *input format (vector -> 3-D tensor)*





# CNN in Keras

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



# Live Demo

# What does machine learn?

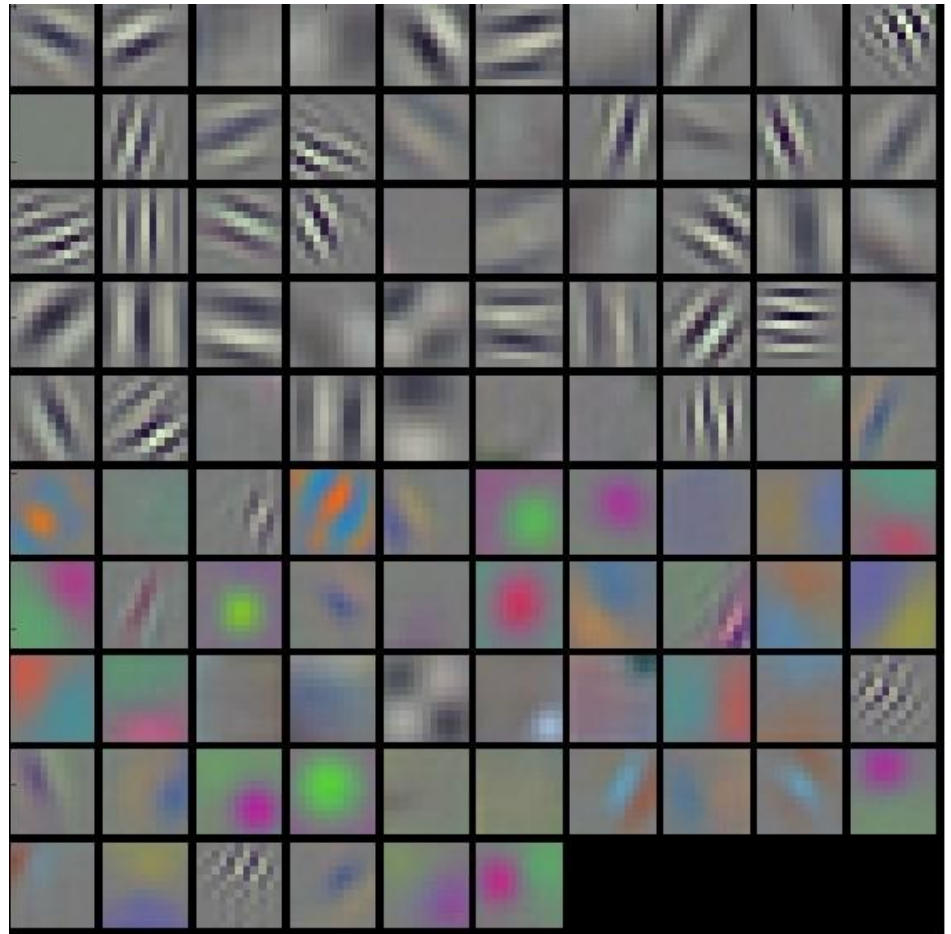


<http://newsneakernews.wpengine.netdna-cdn.com/wp-content/uploads/2016/11/rihanna-puma-creeper-velvet-release-date-02.jpg>

# First Convolution Layer

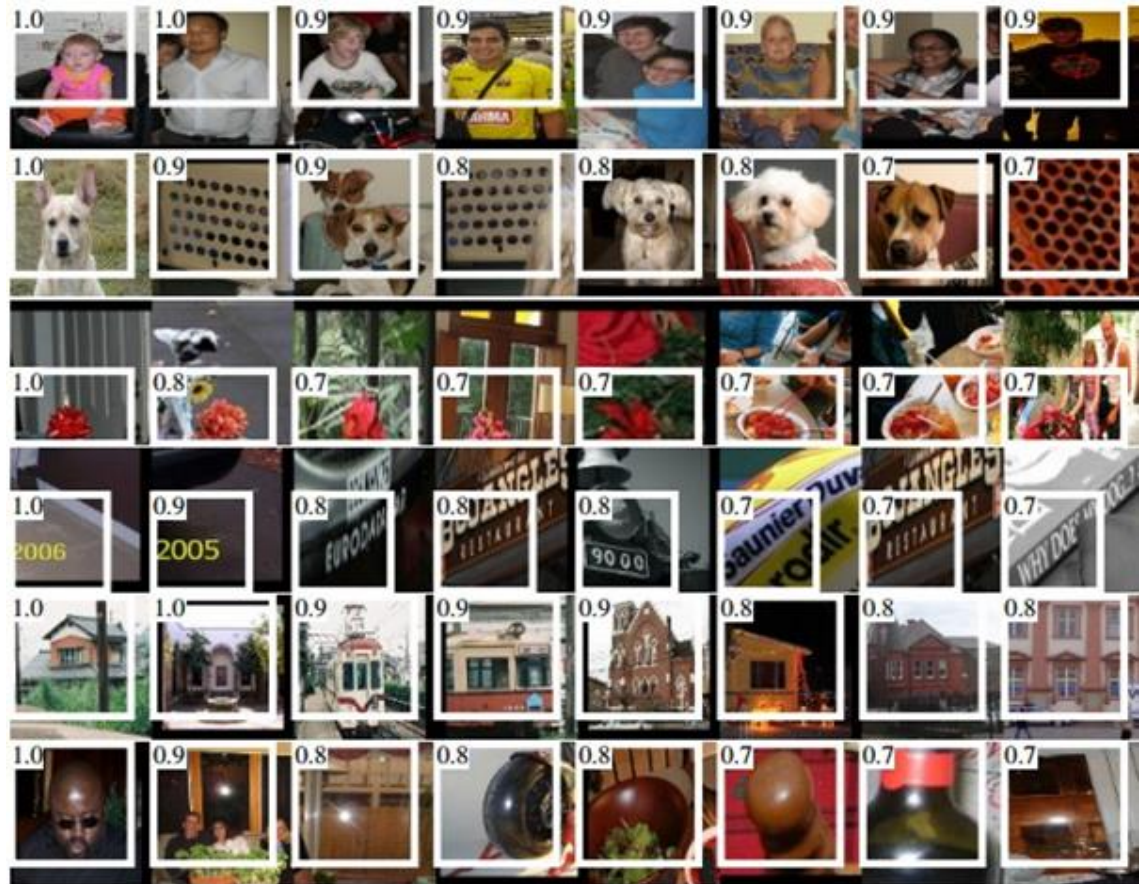
- Typical-looking filters on the trained first layer

11 x 11  
(AlexNet)



# How about higher layers?

- Which images make a specific neuron activate



Ross Girshick, Jeff  
Donahue, Trevor  
Darrell, Jitendra Malik, “Rich  
feature hierarchies for accurate  
object detection and semantic  
segmentation”, CVPR, 2014

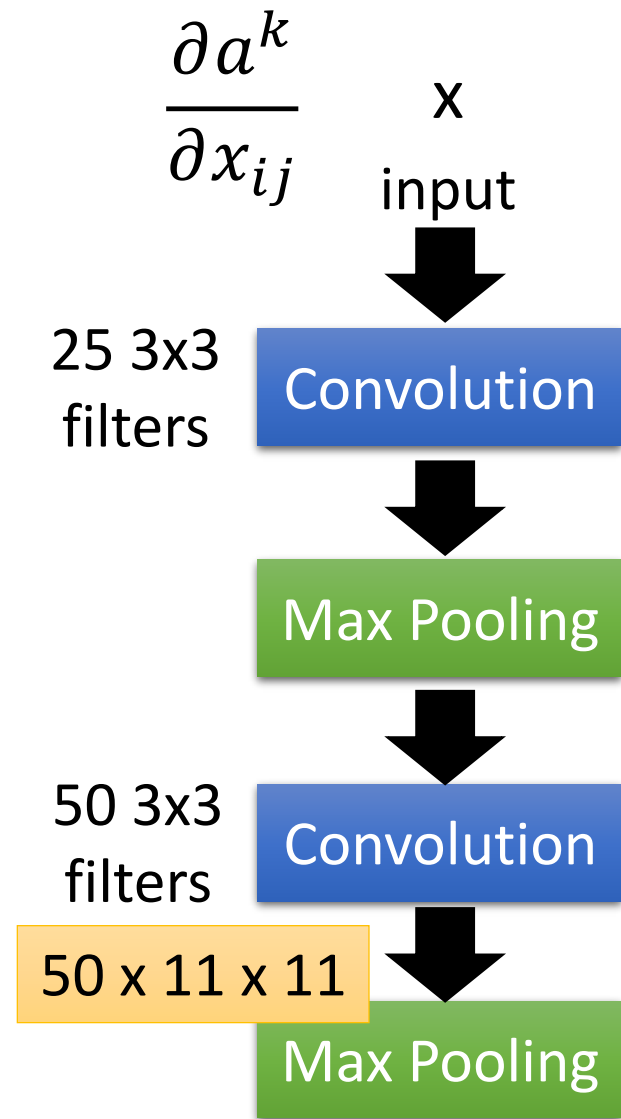
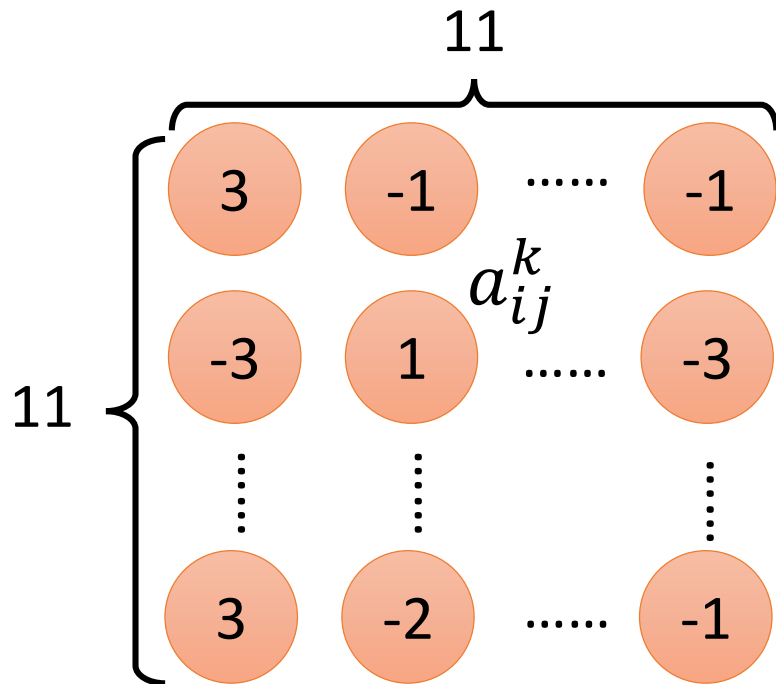
# What does CNN learn?

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)



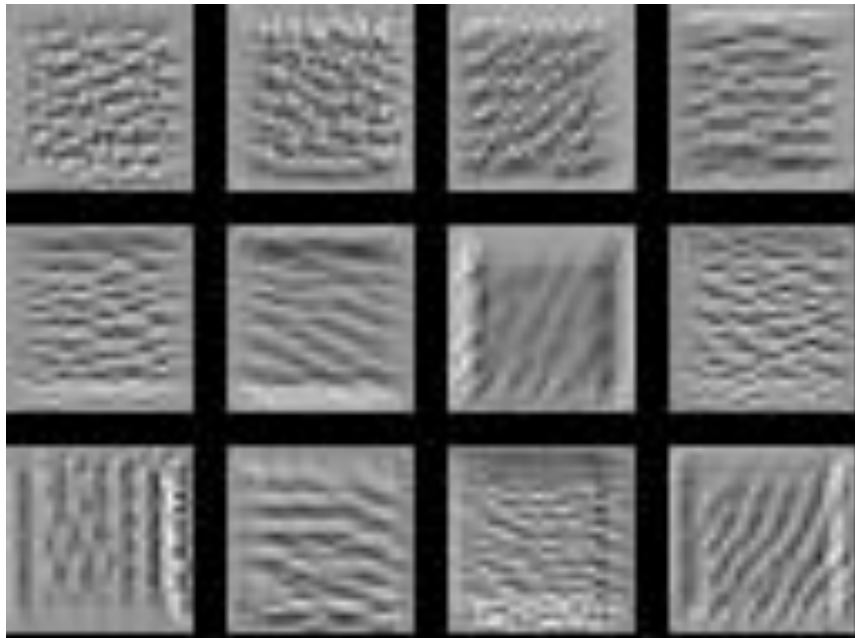
## What does CNN learn?

The output of the k-th filter is a 11 x 11 matrix.

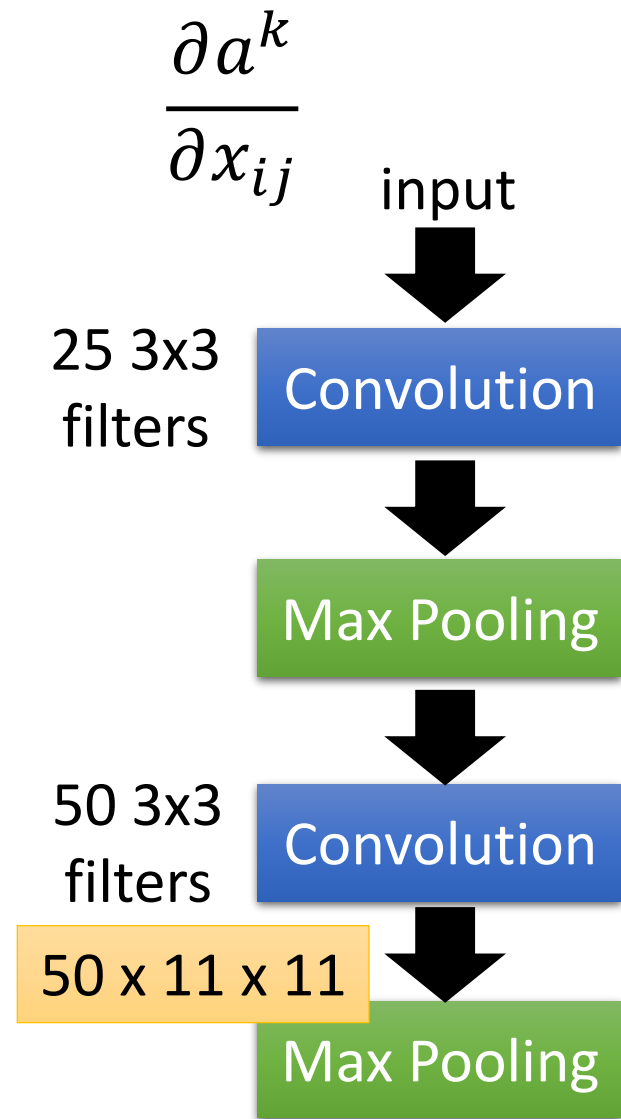
Degree of the activation of the k-th filter:

$$a^k = \sum_{i=1}^{11} \sum_{j=1}^{11} a_{ij}^k$$

$x^* = \arg \max_x a^k$  (gradient ascent)



For each filter

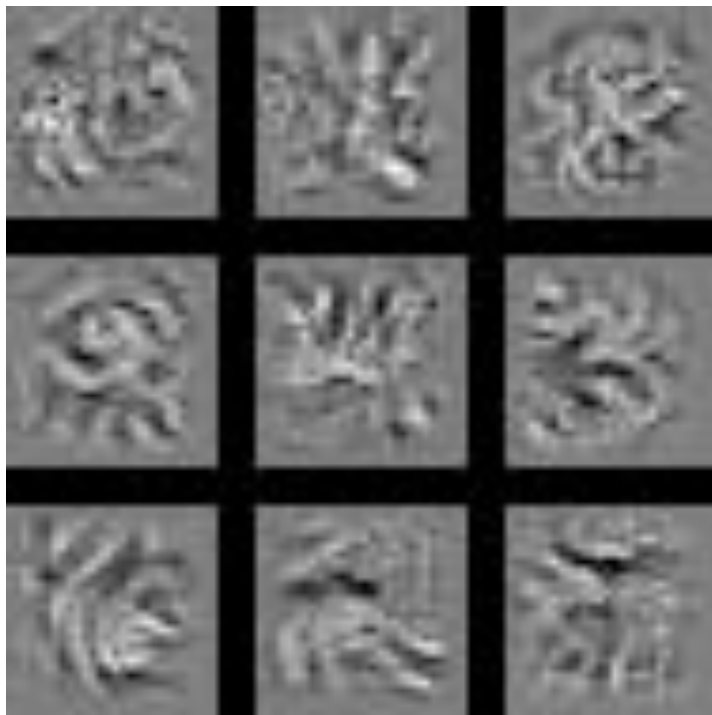




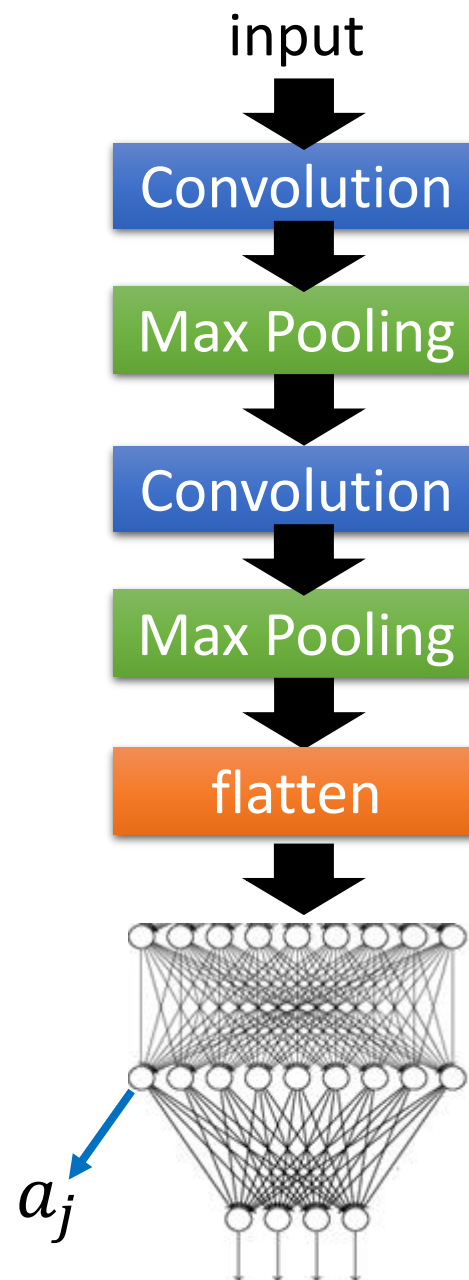
# What does CNN learn?

Find an image maximizing the output of neuron:

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



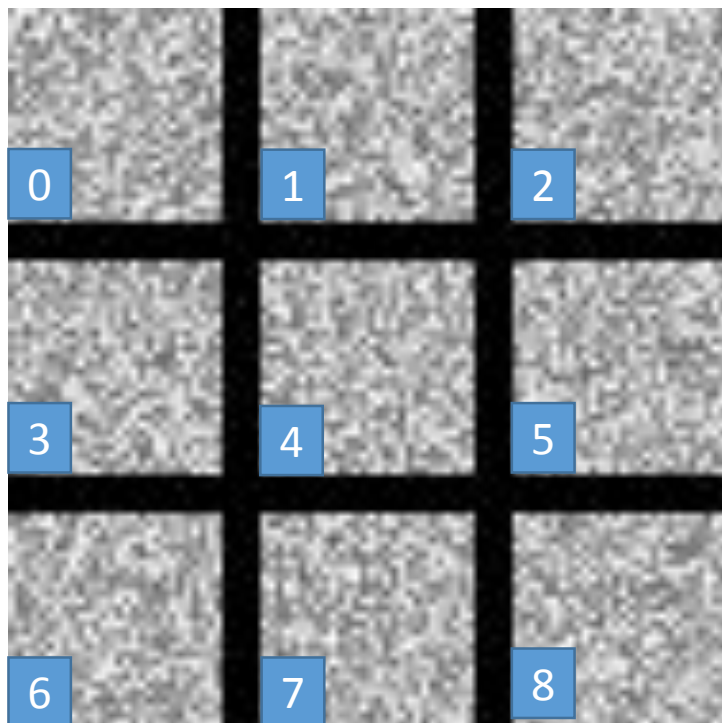
Each figure corresponds to a neuron





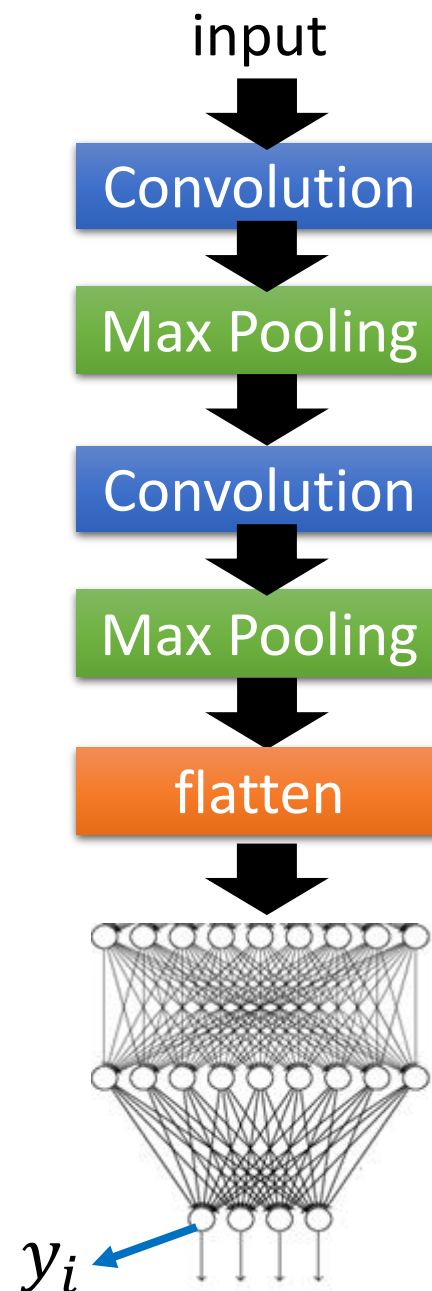
# What does CNN learn?

$$x^* = \arg \max_x y^i \quad \text{Can we see digits?}$$



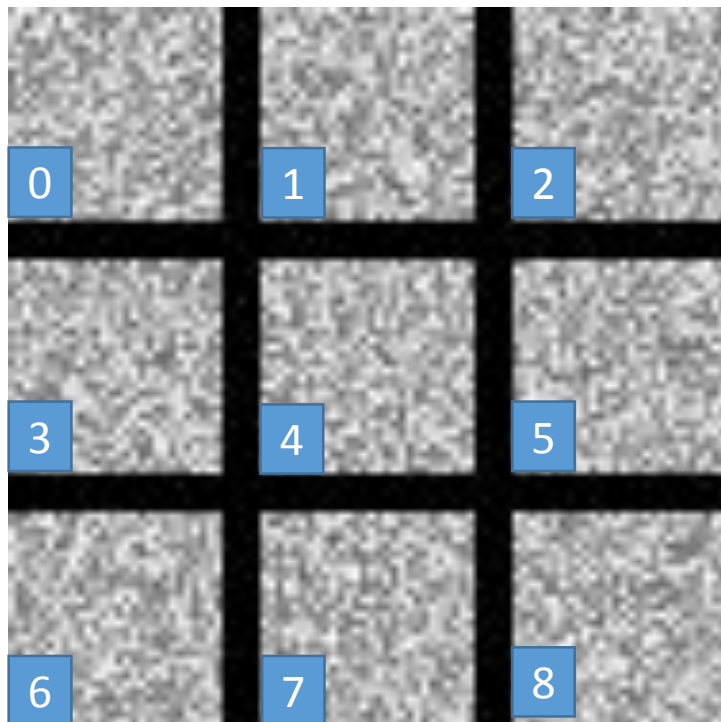
Deep Neural Networks are Easily Fooled

<https://www.youtube.com/watch?v=M2lebCN9Ht4>



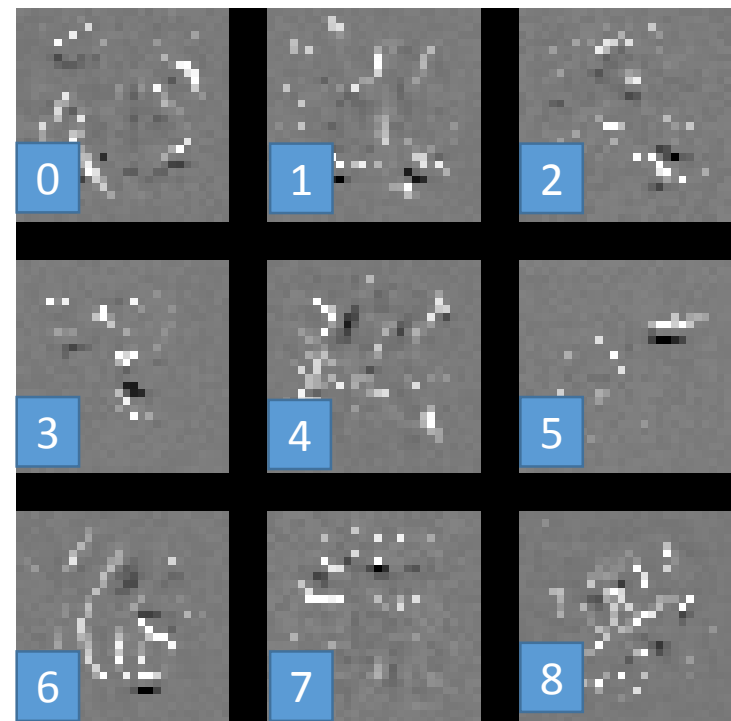
# What does CNN learn?

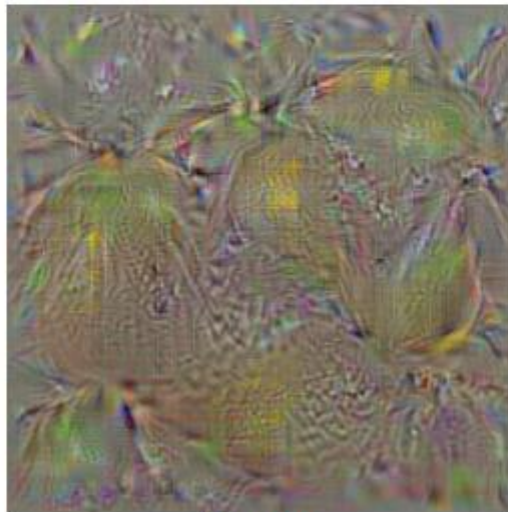
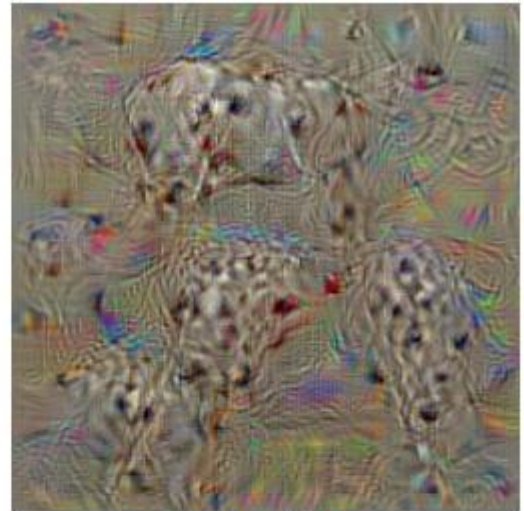
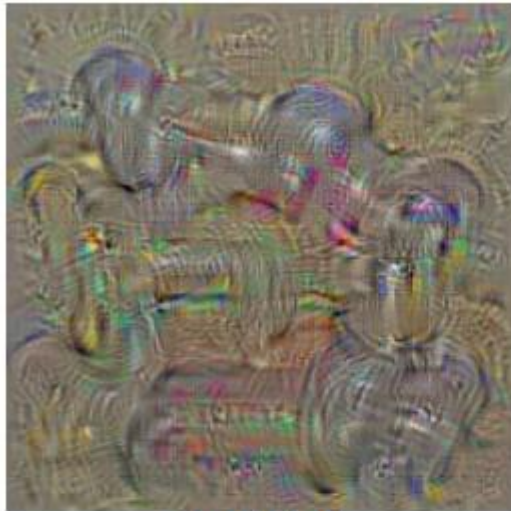
$$x^* = \arg \max_x y^i$$



Over all  
pixel values

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





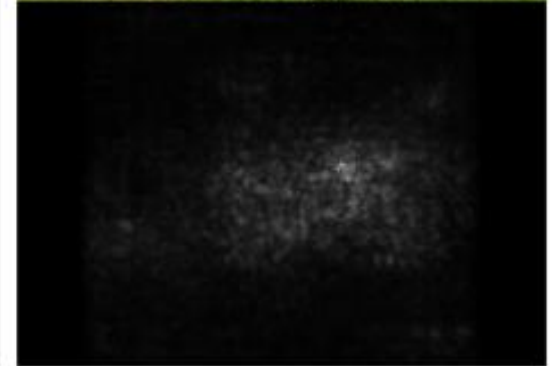
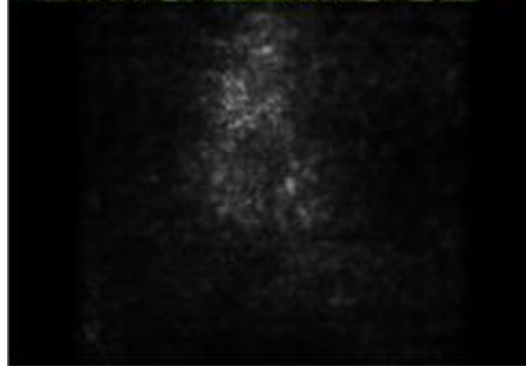
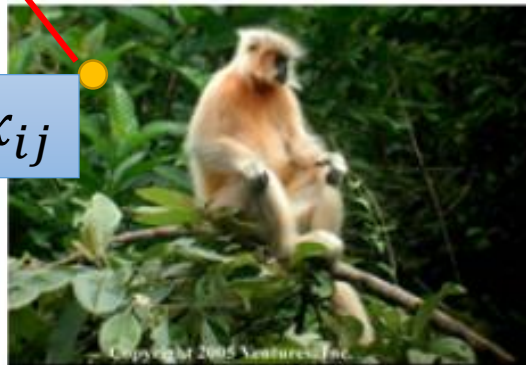
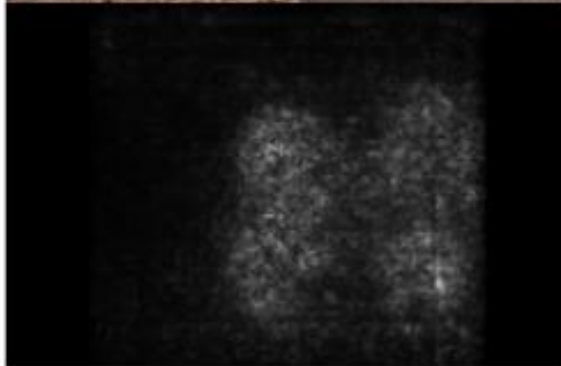
Karen Simonyan, Andrea Vedaldi, Andrew Zisserman, "Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps", ICLR, 2014

$$\left| \frac{\partial y_k}{\partial x_{ij}} \right|$$

$y_k$ : the predicted class of the model



Pixel  $x_{ij}$



Karen Simonyan, Andrea Vedaldi, Andrew Zisserman, "Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps", ICLR, 2014



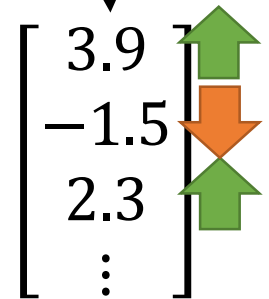


Reference: Zeiler, M. D., & Fergus, R. (2014). Visualizing and understanding convolutional networks. In *Computer Vision—ECCV 2014* (pp. 818-833)

# Deep Dream



- Given a photo, machine adds what it sees .....





# Deep Dream

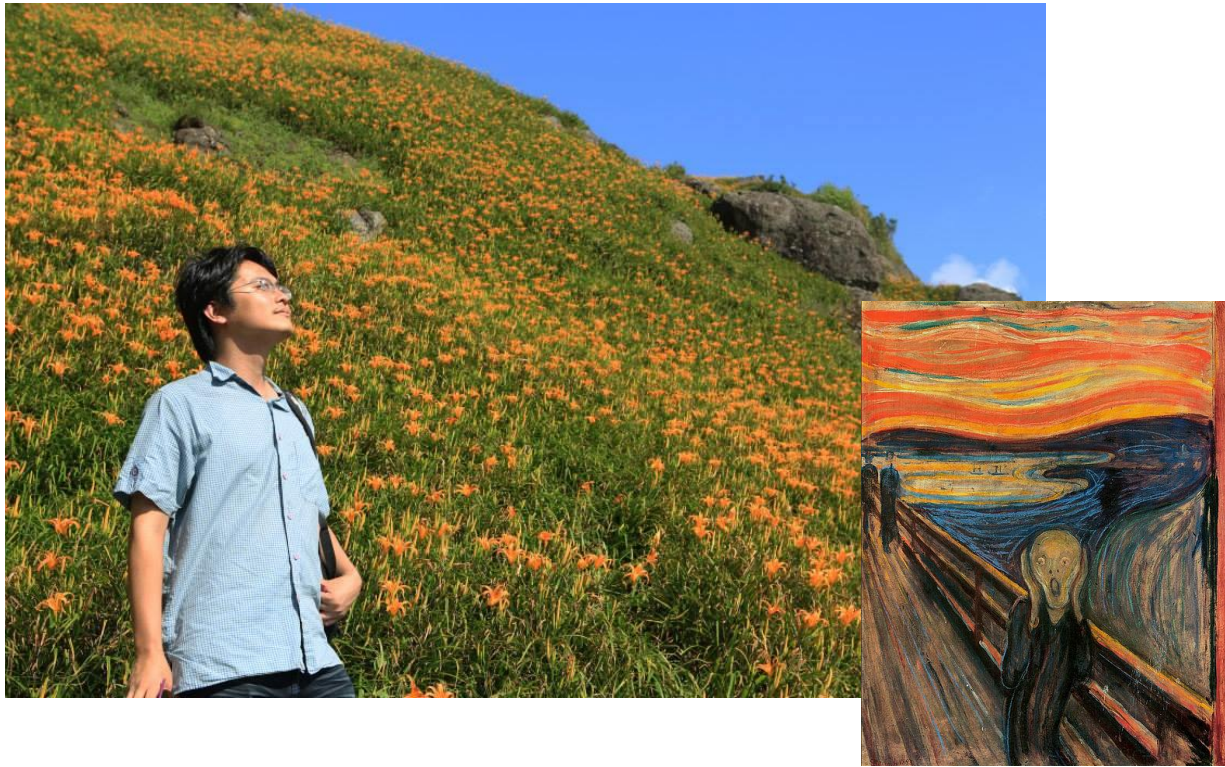
- Given a photo, machine adds what it sees .....



<http://deepdreamgenerator.com/>

# Deep Style

- Given a photo, make its style like famous paintings



<https://dreamscopeapp.com/>



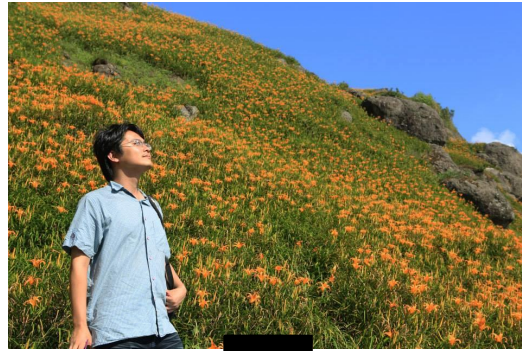
# Deep Style

- Given a photo, make its style like famous paintings



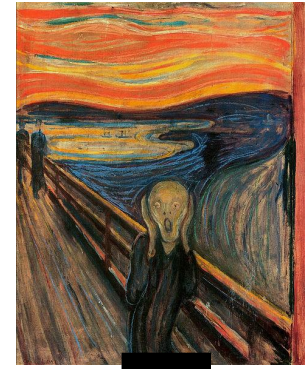
<https://dreamscopeapp.com/>

# Deep Style



CNN

content



CNN

style

A Neural  
Algorithm of  
Artistic Style

<https://arxiv.org/abs/1508.06576>



CNN

?

# More Application: Playing Go



Black: 1  
white: -1  
none: 0



Network



Next move  
(19 x 19  
positions)

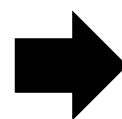
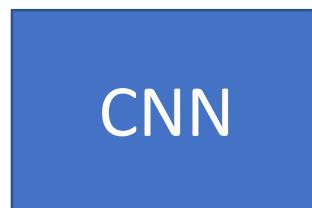
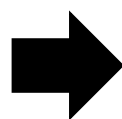
19 x 19 vector

Fully-connected feedforward  
network can be used

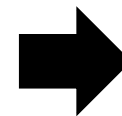
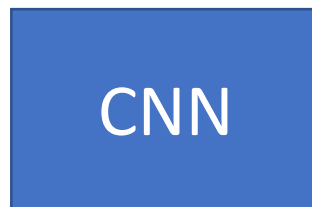
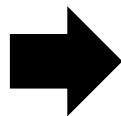
But CNN performs much better.

# More Application: Playing Go

Training: record of previous plays 黒: 5之五 → 白: 天元 → 黒: 五之5 ...



Target:  
“天元” = 1  
else = 0



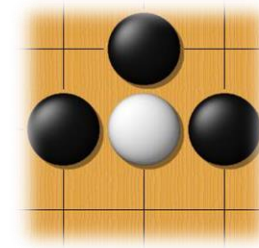
Target:  
“五之5” = 1  
else = 0



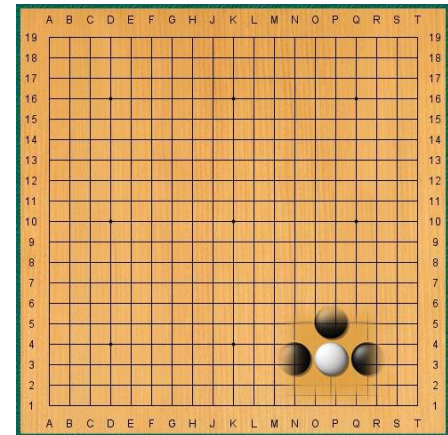
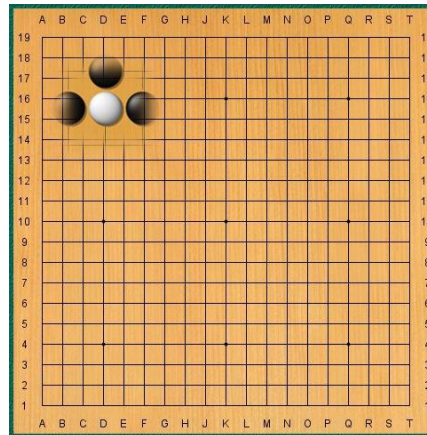
# Why CNN for playing Go?

- 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 playing Go?

- Subsampling the pixels will not change the object



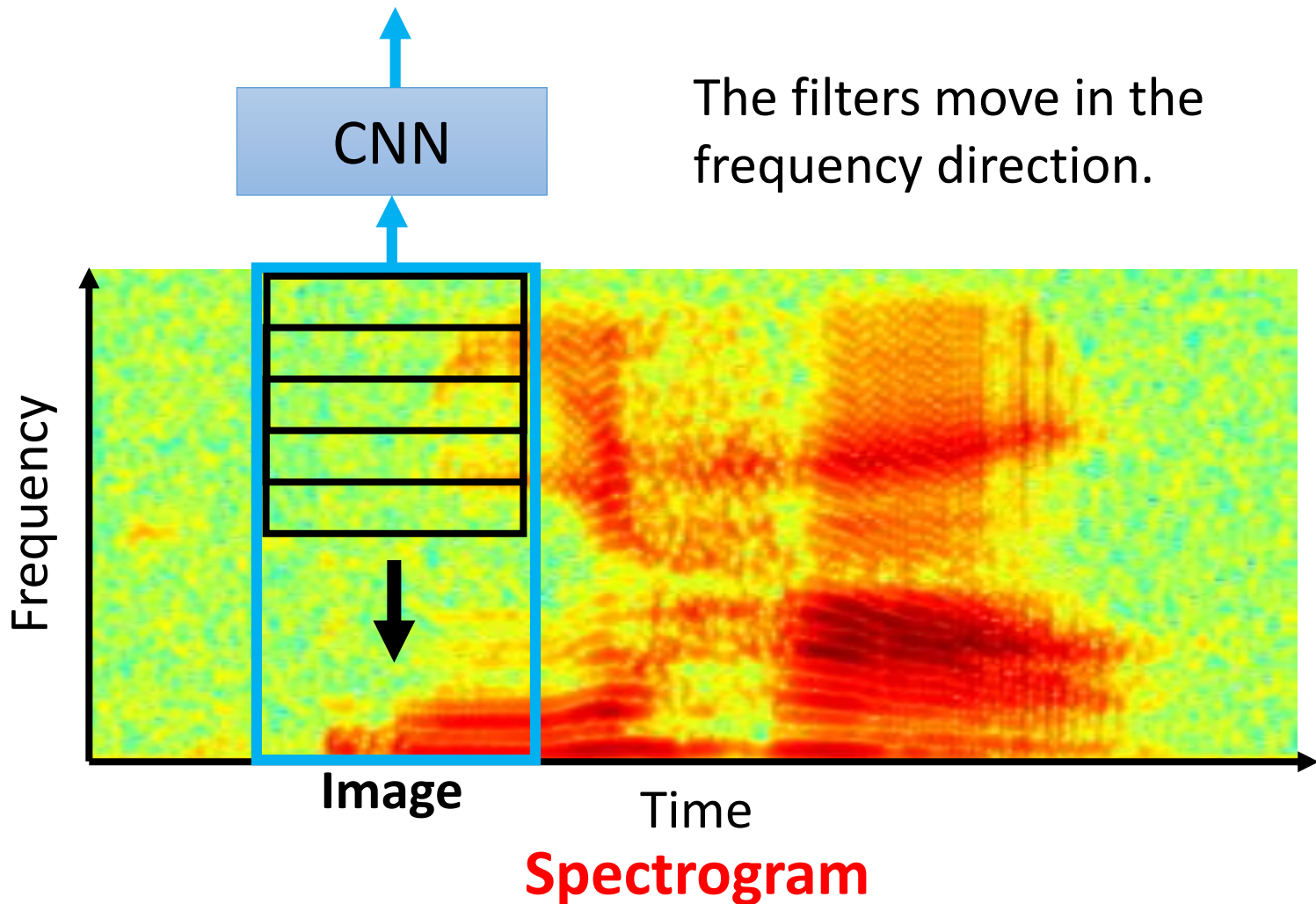
Max Pooling

How to explain this???

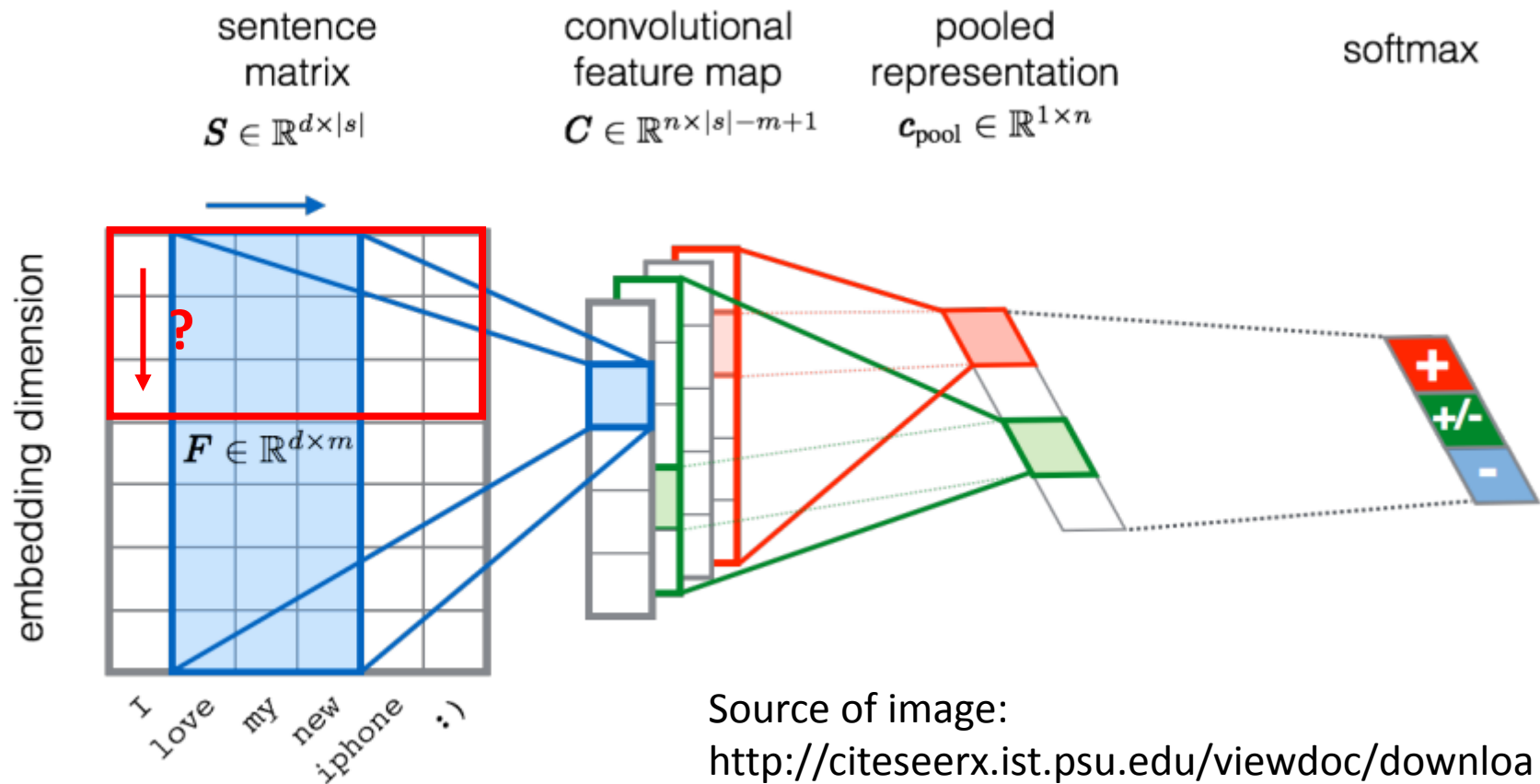
**Neural network architecture.** The input to the policy network is a  $19 \times 19 \times 48$  image stack consisting of 48 feature planes. The first hidden layer zero pads the input into a  $23 \times 23$  image, then convolves  $k$  filters of kernel size  $5 \times 5$  with stride 1 with the input 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

Alpha Go does not use Max Pooling ..... Extended Data Table 3 additionally show the results of training with  $k = 128, 256$  and 384 filters.

# More Application: Speech



# More Application: Text



Source of image:

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



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