

# Convolutional Neural Network

--- Zhongwu xie

# **1 . Types of layers in a convolutional network.**

- -Convolution
- -Pooling
- -Fully connected

# 1 . Dot Product(scalar product)

The dot product of two vectors  $\vec{a} = [a_1, a_2, \dots, a_n]$  and  $\vec{b} = [b_1, b_2, \dots, b_n]$  is defined as:

$$\vec{a} \cdot \vec{b} = \sum_{i=1}^n a_i b_i = a_1 b_1 + a_2 b_2 + \dots + a_n b_n$$

e.g.  $\vec{a} = [1, 3, -5]$ ,  $\vec{b} = [4, -2, -1]$

$$\vec{a} \cdot \vec{b} = [1 \quad 3 \quad -5] \begin{bmatrix} 4 \\ -2 \\ -1 \end{bmatrix} = 1 \times 4 + 3 \times (-2) + (-5) \times (-1) = 3$$

## 2 Convolution in Neural Network

10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0

\*

1	0	-1
1	0	-1
1	0	-1

=

0	30	30	0
0	30	30	0
0	30	30	0
0	30	30	0

10	10	10
10	10	10
10	10	10



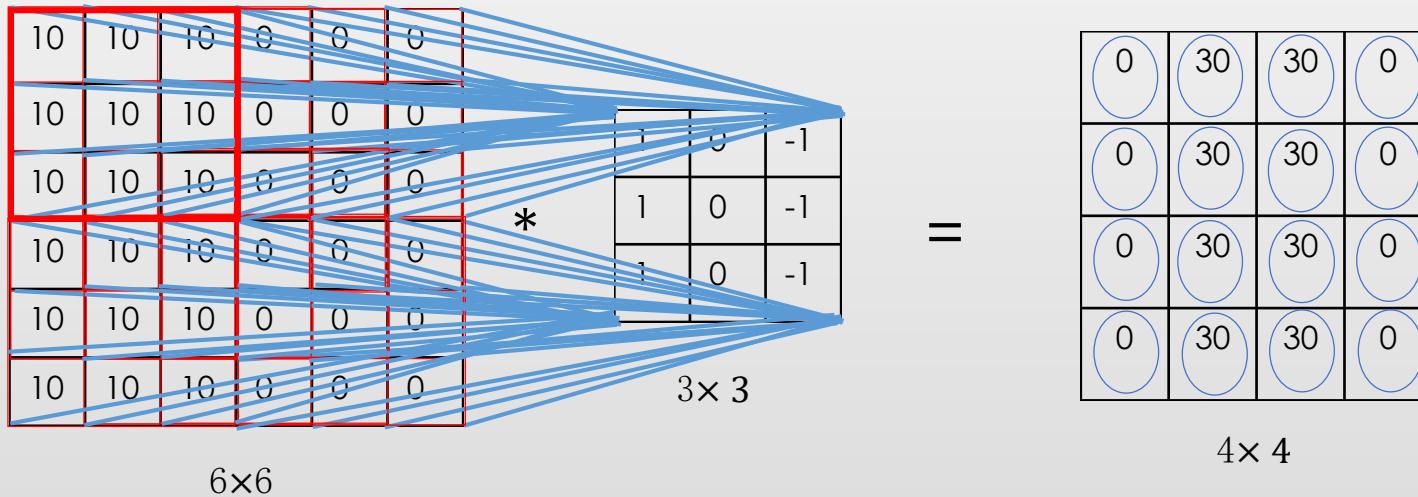
1	0	-1
1	0	-1
1	0	-1

$$10 \times 1 + 10 \times 0 + 10 \times (-1) + 10 \times 1 + 10 \times 0 + 10 \times (-1) + 10 \times 1 + 10 \times 0 + 10 \times (-1) = 0$$

$$= 0$$

Then slide the local receptive field across the entire input image.

## 2.1 Convolution in Neural Network



Notation:

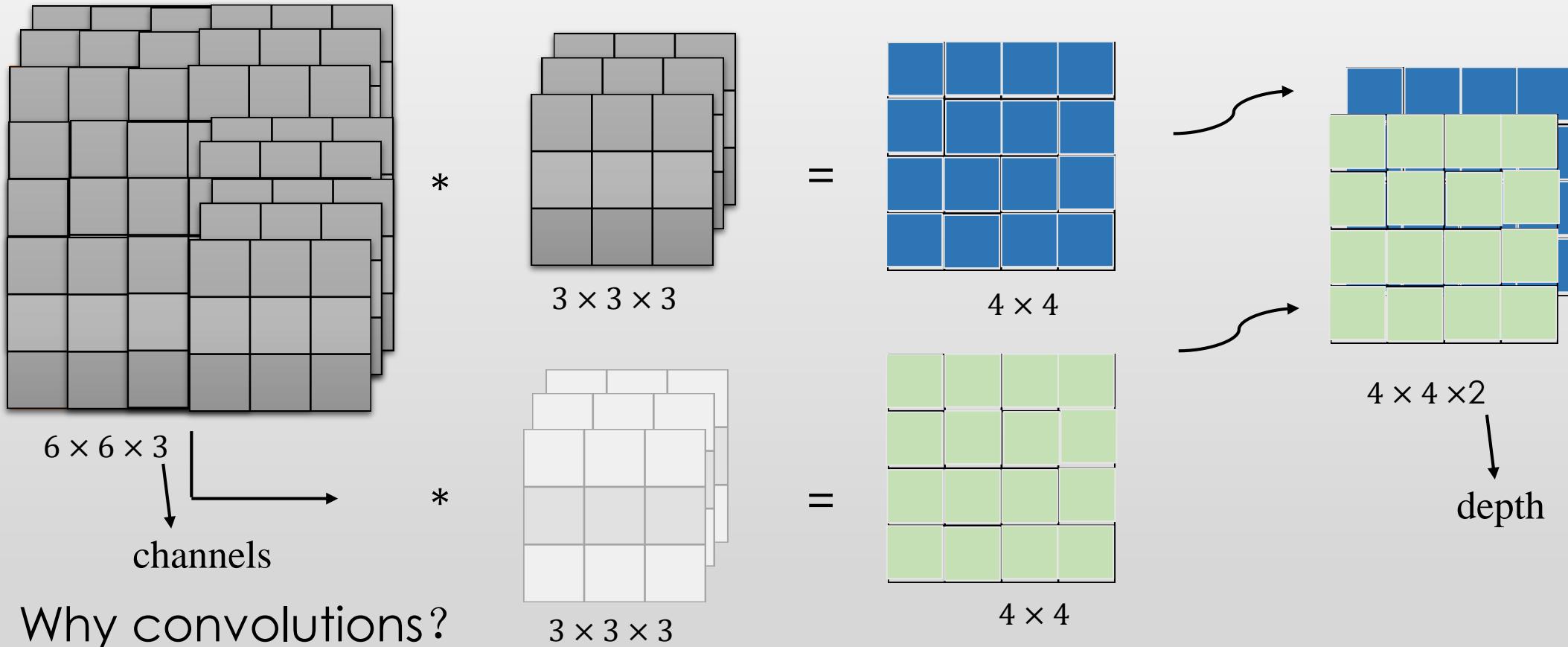
Image:  $n \times n$  filter:  $f \times f$

padding : p stride : s

Then output:

$$\left\lfloor \frac{n+2p-f}{s} + 1 \right\rfloor \times \left\lfloor \frac{n+2p-f}{s} + 1 \right\rfloor$$

## 2.2 Multiple filters



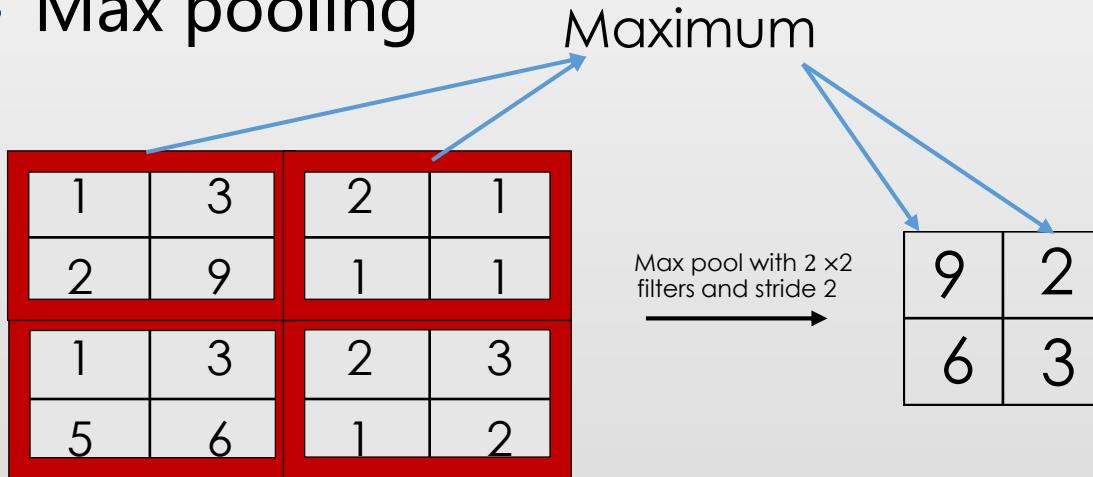
Why convolutions?

---Parameter sharing

---Sparsity of connections

### 3 . Pooling layers ---Shrinking the image stack

- Max pooling

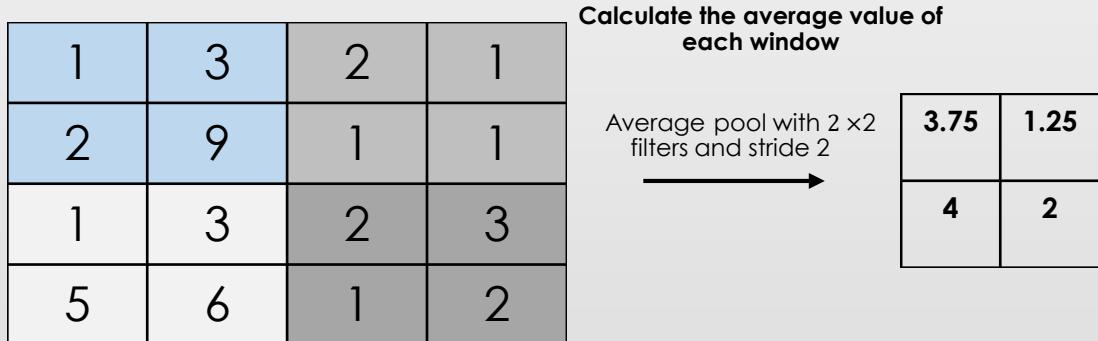


Pooling:

- 1.Pick a window size(usually 2 or 3)
- 2.Pick a stride(usually 2)
- 3.Walk your window across your filtered images.
- 4.From each window , take the maximum value.

## 3 . Pooling layers ---Shrinking the image stack

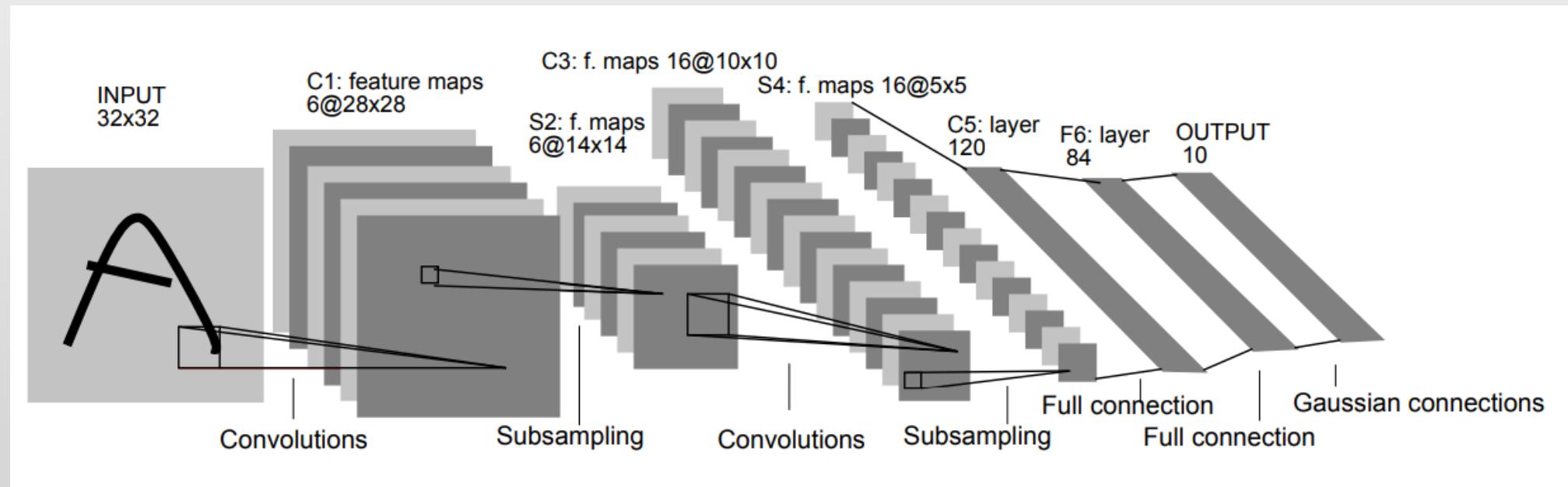
- Average pooling



- Remove the redundancy information of convolutional layer .
  - By having less spatial information you gain computation performance
  - Less spatial information also means less parameters, so less chance to over-fit
  - You get some translation invariance.

### 3 . Full connection layer

The CNNs help extract certain features from the image , then fully connected layer is able to generalize from these features into the output-space.

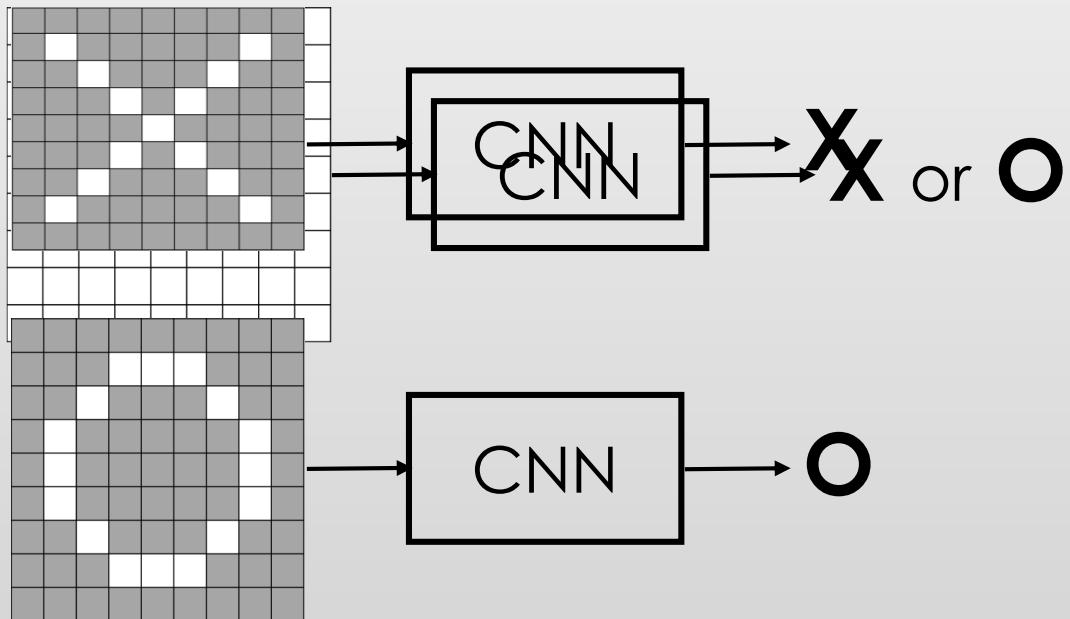


[LeCun et al.,1998.Gradient-based learning applied to document recognition.]

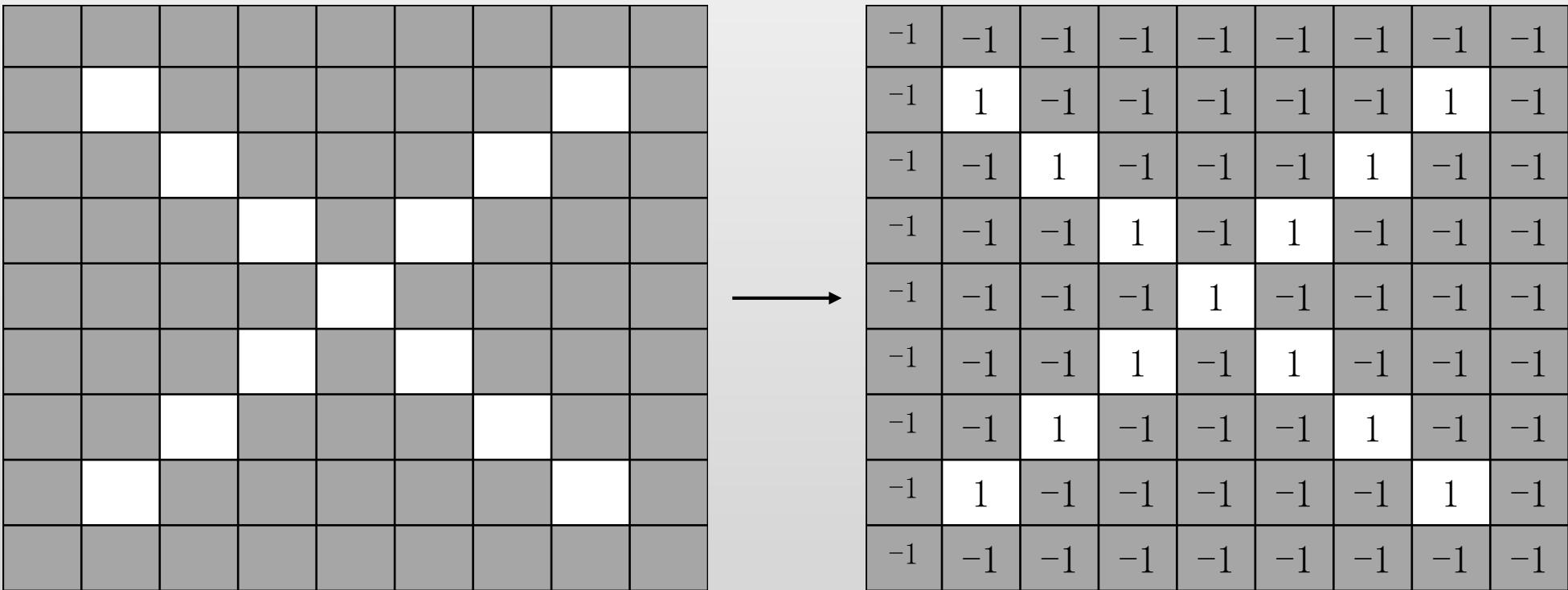
## 4 . For example

Say whether a picture is of an X or O.

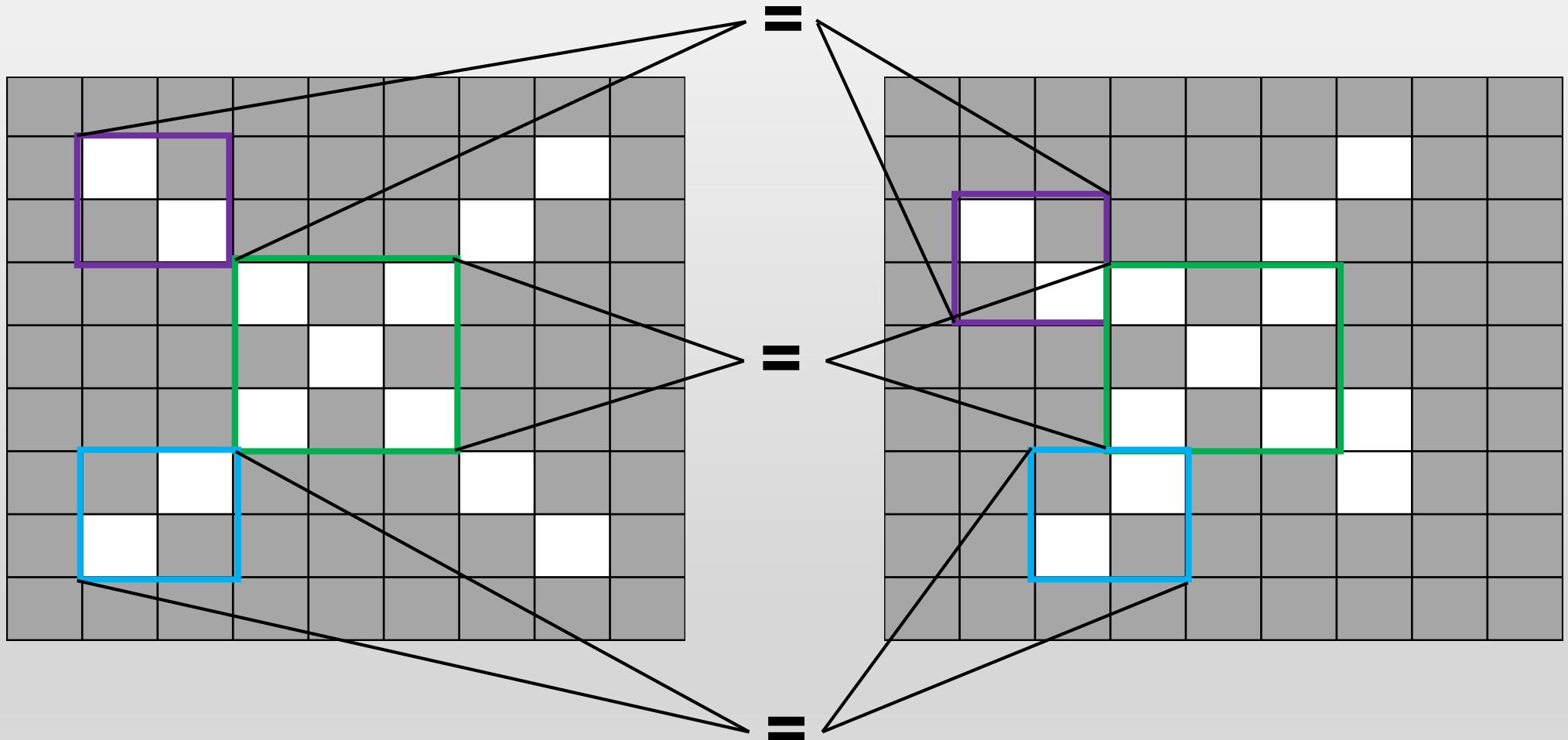
A two-dimensional array of pixels



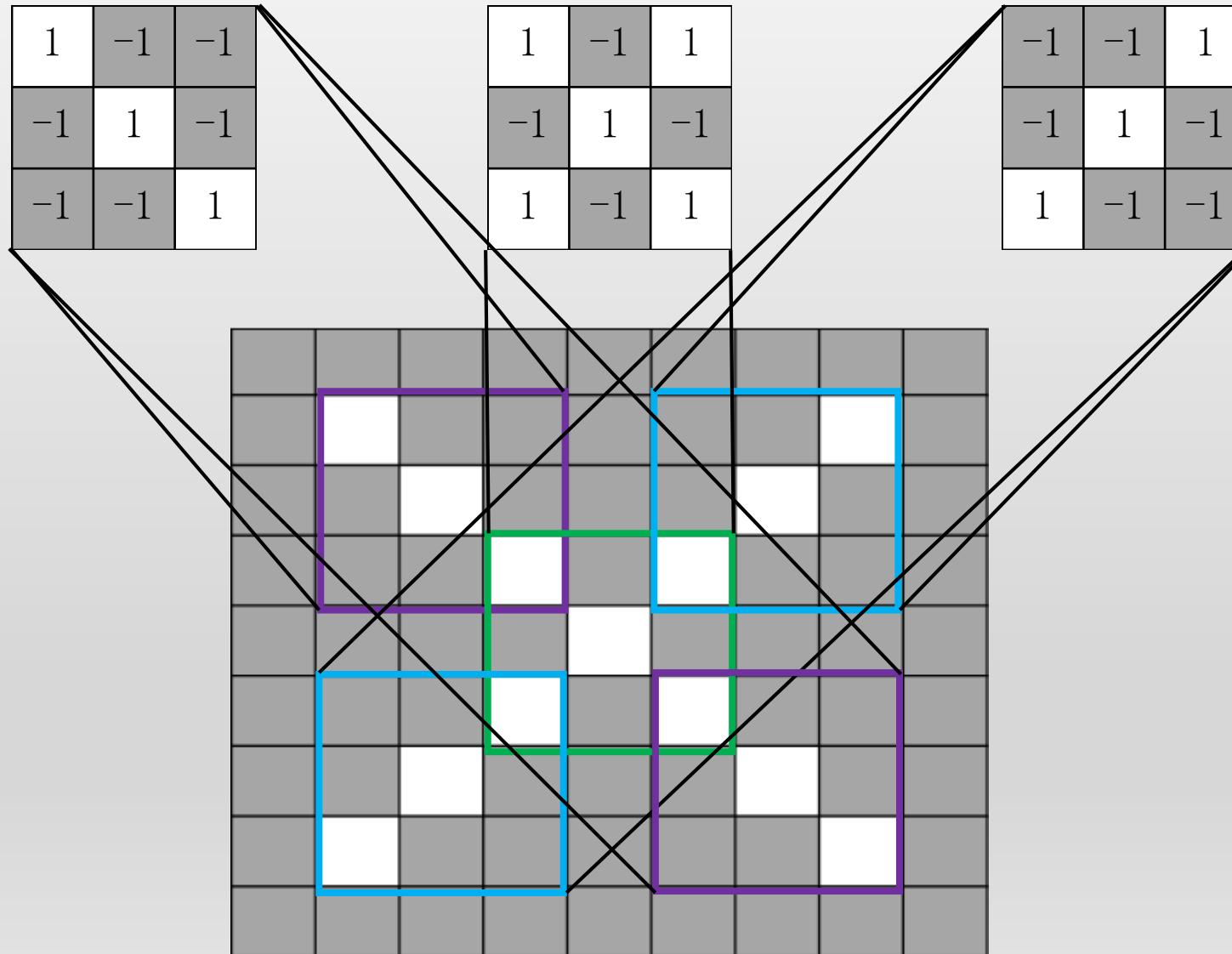
# 4 . 1 What the computer see



## 4 . 1 ConvNets match pieces of the image



## 4 . 1 Features match pieces of the image



## 4 . Filtering : The math behind the match

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

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

$9 \times 9$

7	-1	1	3	5	-1	3
-1	9	-1	3	-1	1	-1
1	-1	9	-3	1	-1	5
3	3	-3	5	-3	3	3
5	-1	1	3	9	-1	1
-1	1	-1	3	-1	9	-1
3	-1	5	3	1	-1	7

$7 \times 7$

## 4 . Filtering : The math behind the match

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

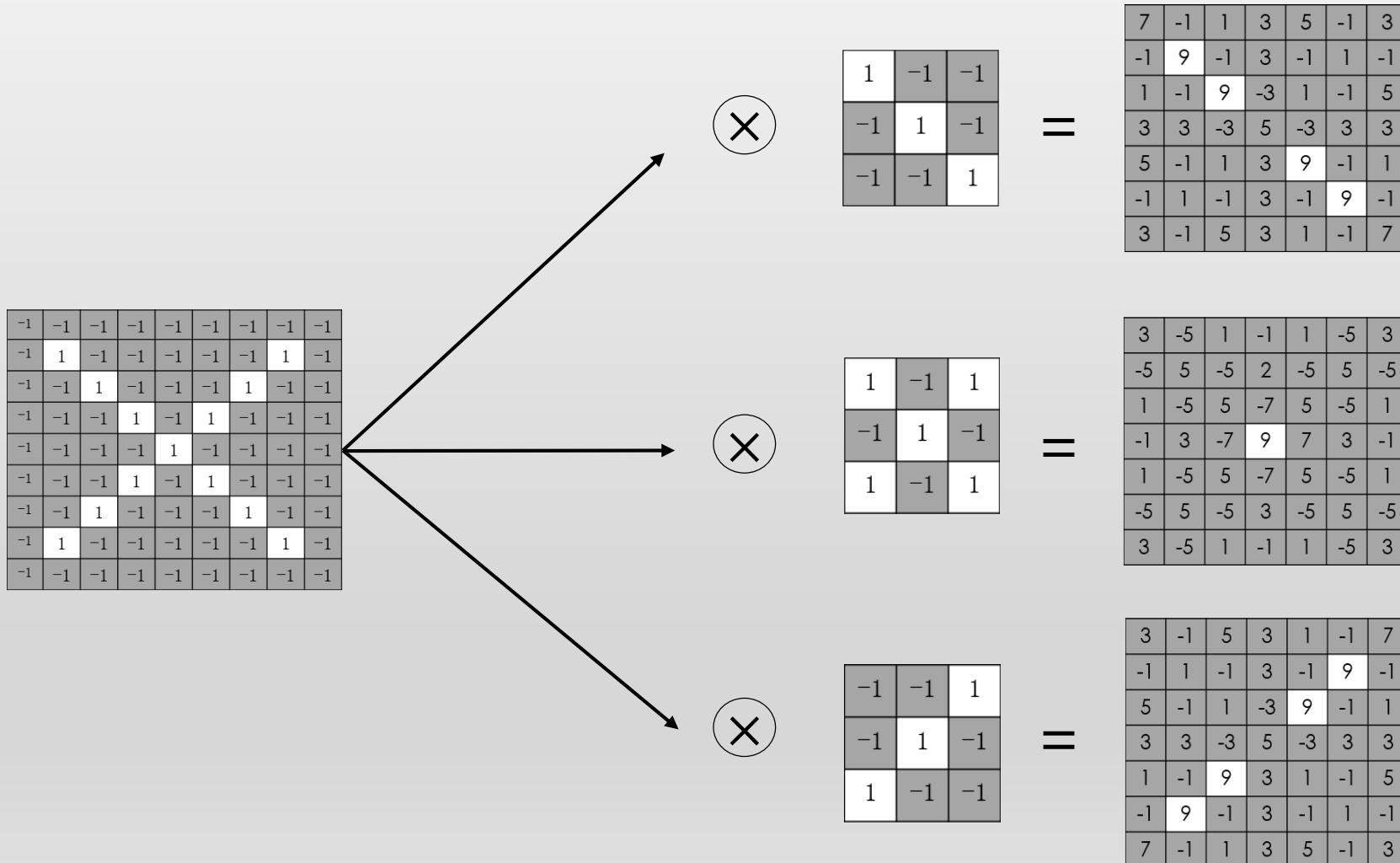


1	-1	-1
-1	1	-1
-1	-1	1

=

7	-1	1	3	5	-1	3
-1	9	-1	3	-1	1	-1
1	-1	9	-3	1	-1	5
3	3	-3	5	-3	3	3
5	-1	1	3	9	-1	1
-1	1	-1	3	-1	9	-1
3	-1	5	3	1	-1	7

## 4 . Filtering : The math behind the match

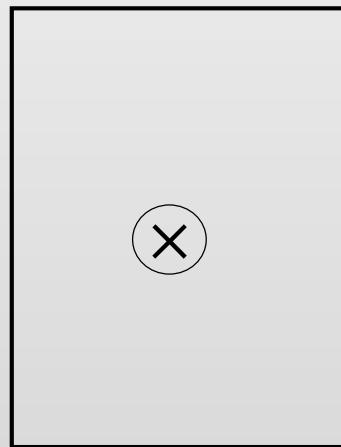


## 4 . Convolution layer

---One image becomes a stack of filtered images

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

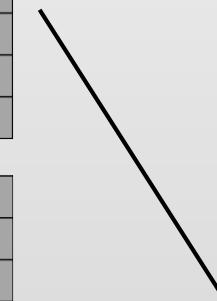
$9 \times 9$



7	-1	1	3	5	-1	3
-1	9	-1	3	-1	1	-1
1	-1	9	-3	1	-1	5
3	3	-3	5	-3	3	3
5	-1	1	3	9	-1	1
-1	1	-1	3	-1	9	-1
3	-1	5	3	1	-1	7

3	-5	1	-1	1	-5	3
-5	5	-5	2	-5	5	-5
1	-5	5	-7	5	-5	1
-1	3	-7	9	7	3	-1
1	-5	5	-7	5	-5	1
-5	5	-5	3	-5	5	-5
3	-5	1	-1	1	-5	3

3	-1	5	3	1	-1	7
-1	1	-1	3	-1	9	-1
5	-1	1	-3	9	-1	1
3	3	-3	5	-3	3	3
1	-1	9	3	1	-1	5
-1	9	-1	3	-1	1	-1
7	-1	1	3	5	-1	3



7	-1	1	3	5	-1	3
3	-5	1	-1	1	-5	3
3	-1	5	3	1	-1	7
-1	1	-1	3	-1	9	-1
5	-1	1	-3	9	-1	1
3	3	-3	5	-3	3	3
1	-1	9	3	1	-1	5

$7 \times 7 \times 3$

depth

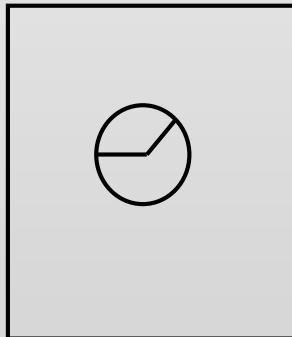
## 4 . Relu layer

A stack of images becomes a stack of images with no negative values.

7	-1	1	3	5	-1	3
-1	9	-1	3	-1	1	-1
1	-1	9	-3	1	-1	5
3	3	-3	5	-3	3	3
5	-1	1	3	9	-1	1
-1	1	-1	3	-1	9	-1
3	-1	5	3	1	-1	7

3	-5	1	-1	1	-5	3
-5	5	-5	2	-5	5	-5
1	-5	5	-7	5	-5	1
-1	3	-7	9	7	3	-1
1	-5	5	-7	5	-5	1
-5	5	-5	3	-5	5	-5
3	-5	1	-1	1	-5	3

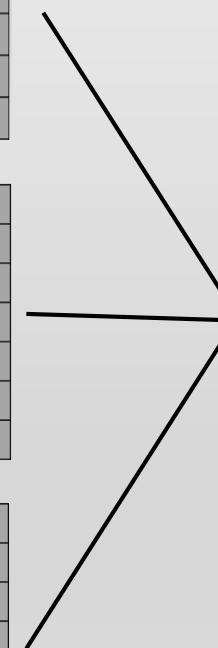
3	-1	5	3	1	-1	7
-1	1	-1	3	-1	9	-1
5	-1	1	-3	9	-1	1
3	3	-3	5	-3	3	3
1	-1	9	3	1	-1	5
-1	9	-1	3	-1	1	-1
7	-1	1	3	5	-1	3



7	0	1	3	5	0	3
0	9	0	3	0	1	0
1	0	9	0	1	0	5
3	3	0	5	0	3	3
5	0	1	3	9	0	1
0	1	0	3	0	9	0
3	0	5	3	1	0	7

3	0	1	0	1	0	3
0	5	0	2	0	5	0
1	0	5	0	5	0	1
0	3	0	9	7	3	0
1	0	5	0	5	0	1
0	5	0	3	0	5	0
3	0	1	0	1	0	3

3	0	5	3	1	0	7
0	1	0	3	0	9	0
5	0	1	0	9	0	1
3	3	0	5	0	3	3
1	0	9	3	1	0	5
0	9	0	3	0	1	0
7	0	1	3	5	0	3



7	0	1	3	5	0	3
3	0	1	0	1	0	3
3	0	5	3	1	0	7
0	1	0	3	0	9	0
5	0	1	0	9	0	1
3	3	0	5	0	3	3
1	0	9	3	1	0	5
0	9	0	3	0	1	0
7	0	1	3	5	0	3

$7 \times 7 \times 3$

## 4 . Pooling layer

---A stack of images becomes a stack of smaller images

7	0	1	3	5	0	3	
0	9	0	3	0	1	0	
1	0	9	0	1	0	5	
3	3	0	5	0	3	3	
5	0	1	3	9	0	1	
0	1	0	3	0	9	0	
3	0	5	3	1	0	7	

3	0	1	0	1	0	3
0	5	0	2	0	5	0
1	0	5	0	5	0	1
0	3	0	9	7	3	0
1	0	5	0	5	0	1
0	5	0	3	0	5	0
3	0	1	0	1	0	3

3	0	5	3	1	0	7
0	1	0	3	0	9	0
5	0	1	0	9	0	1
3	3	0	5	0	3	3
1	0	9	3	1	0	5
0	9	0	3	0	1	0
7	0	1	3	5	0	3

$7 \times 7$

2  $\times$  2 filters and stride 2  
Max pooling



9	3	5	3
3	9	3	5
5	3	9	1
3	5	1	7

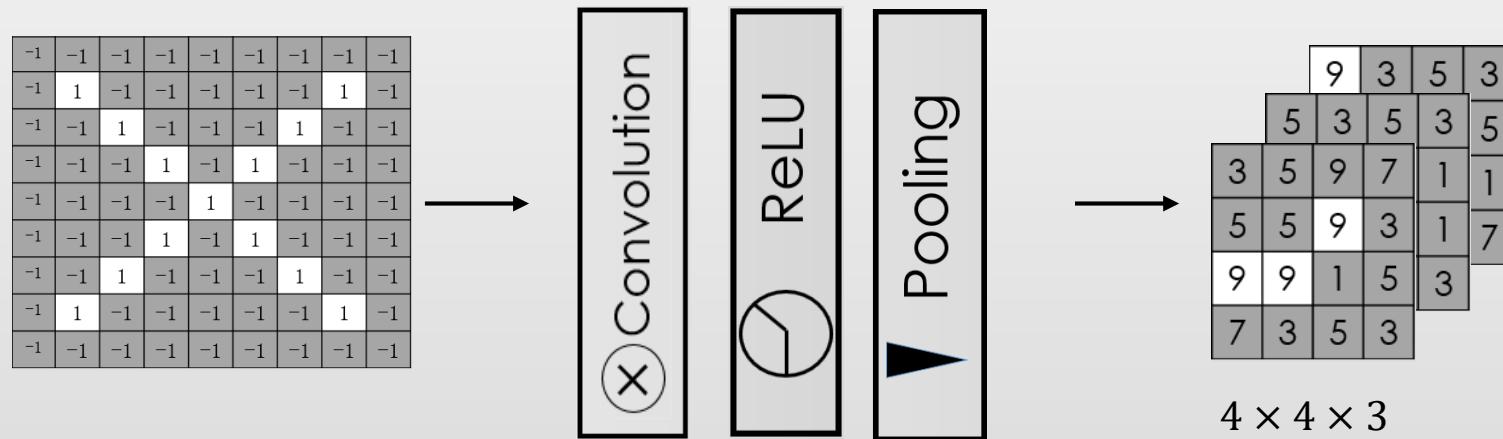
5	3	5	3
3	9	5	1
5	5	5	1
3	1	1	3

3	5	9	7
5	5	9	3
9	9	1	5
7	3	5	3

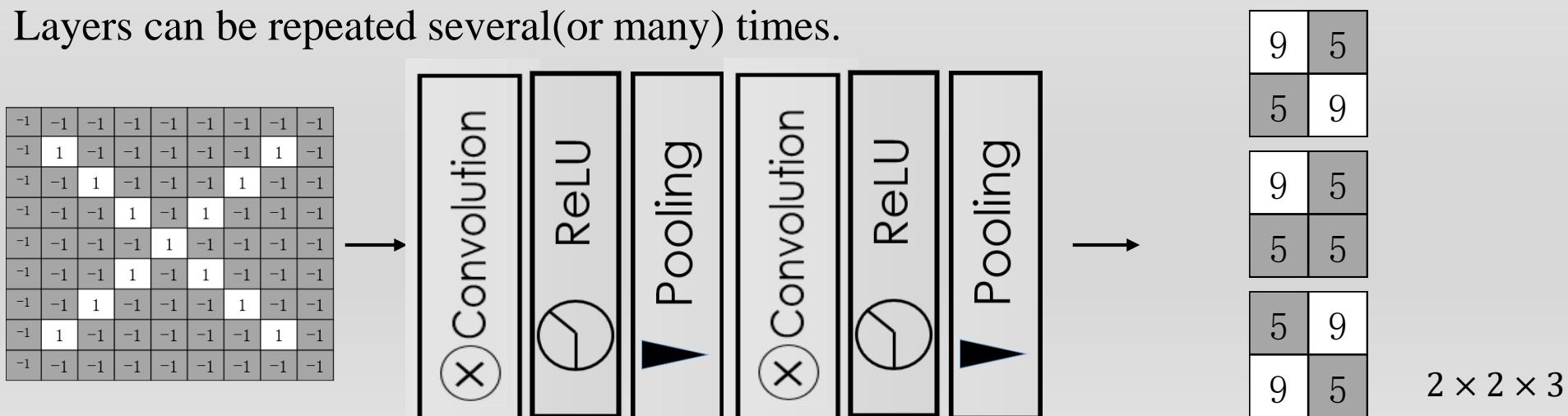
$4 \times 4$

## 4 . Layers get stacked

The output of one becomes the input of the next.

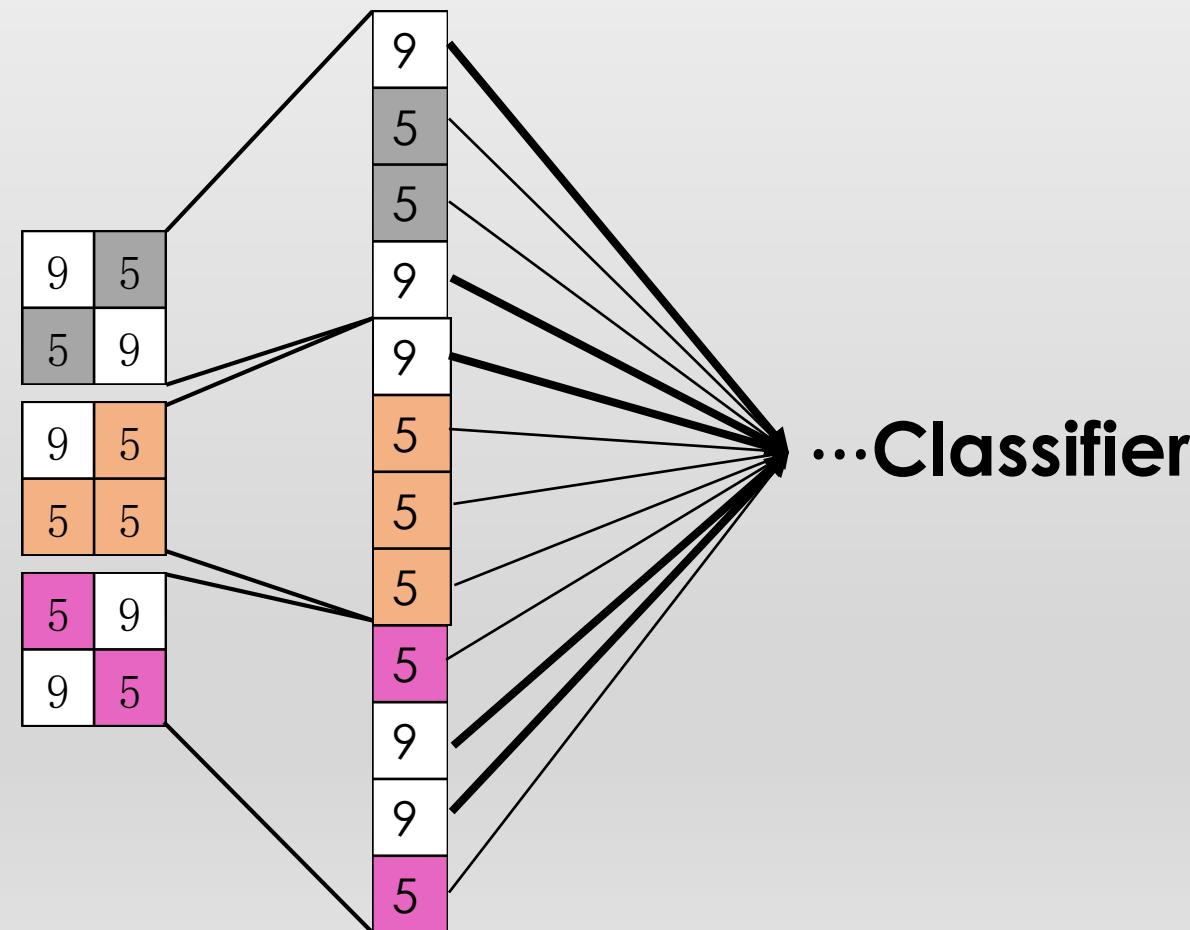


Layers can be repeated several(or many) times.



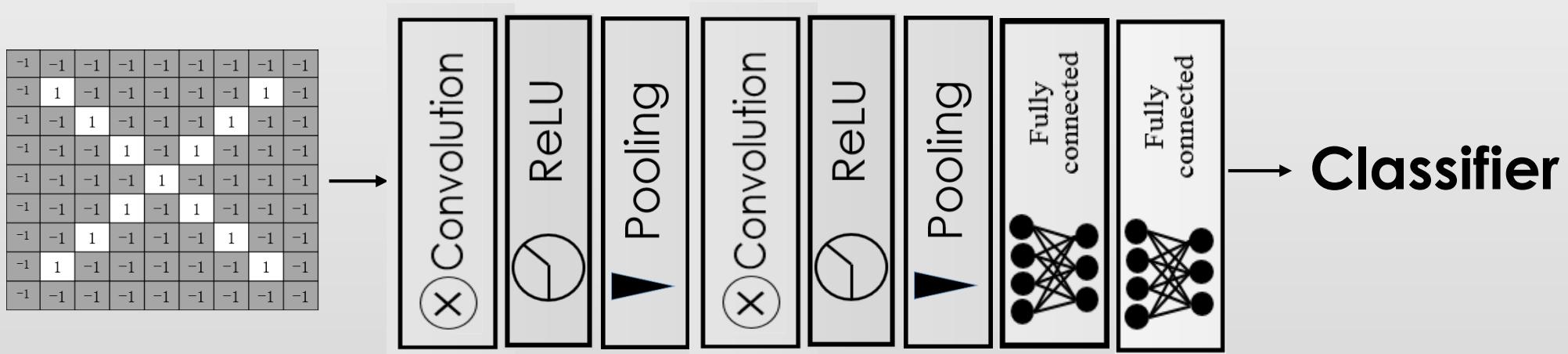
## 4 . Fully connected layer

Every value gets a vote---Vote depends on how strongly a value predicts X or O.



## 4 . Summary: Putting it all together

A set of pixels becomes a set of votes.



# Learning

Q: Where do all the magic numbers come from?

Features in convolutional layers

Voting weights in fully connected layers

A: Backpropagation

**Thank you**