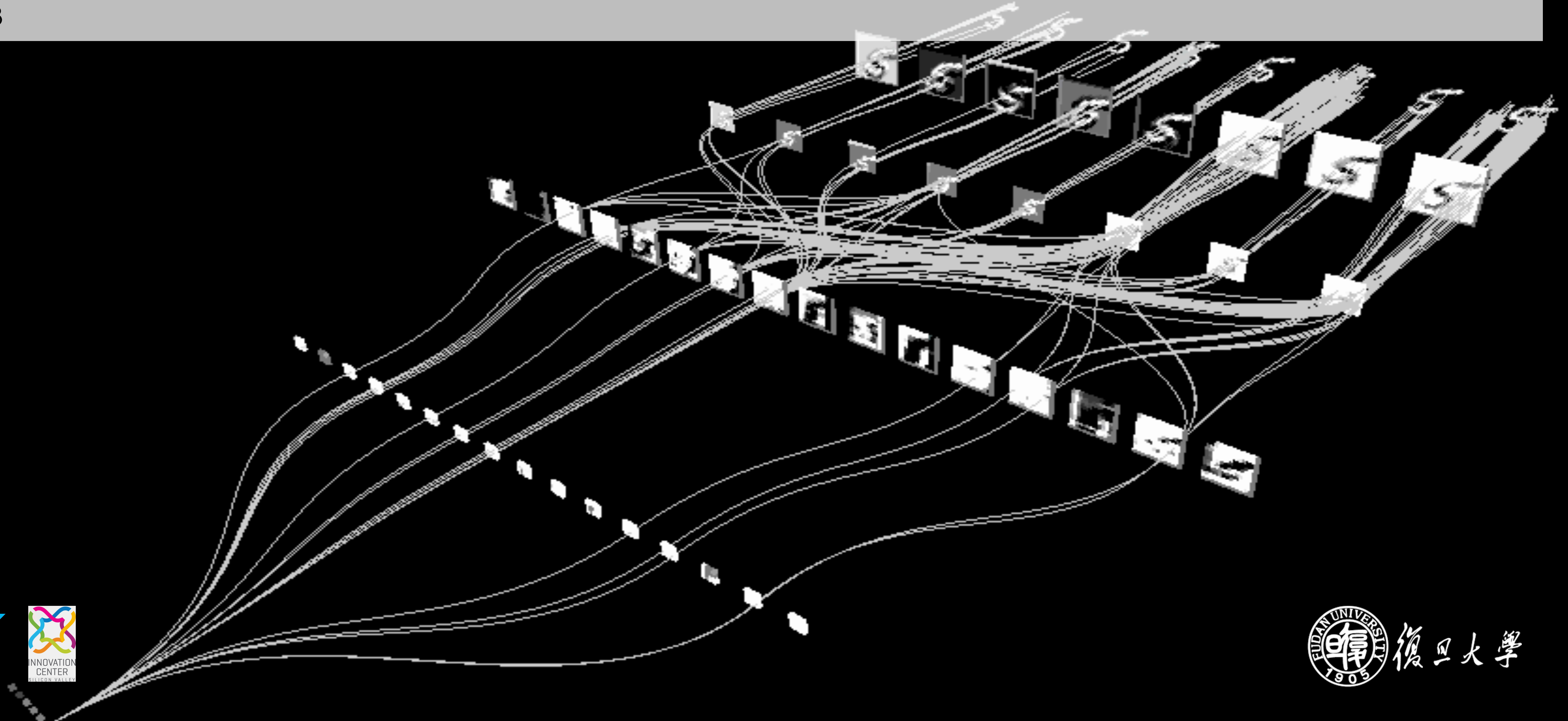
数据驱动的人工智能（3b）卷积神经网络

Data Driven Artificial Intelligence

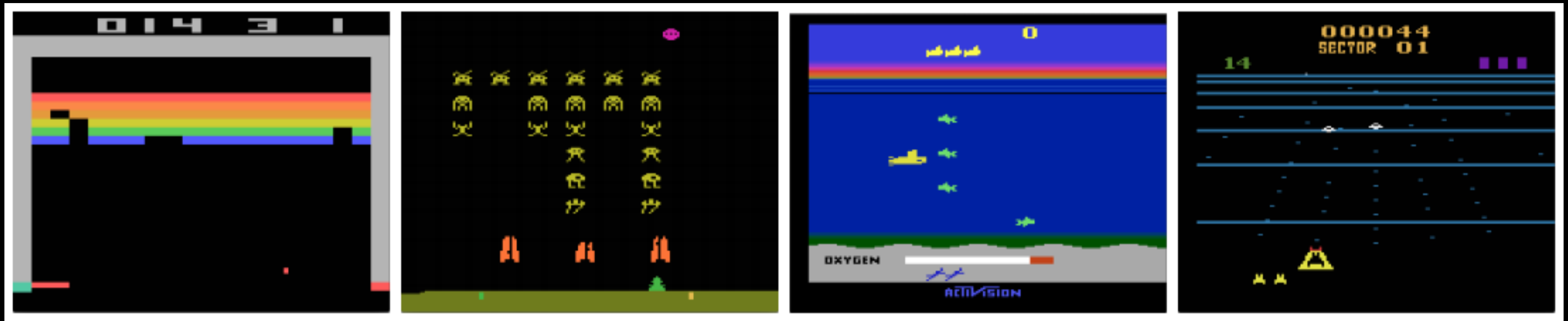
邬学宁 SAP硅谷创新中心

2017 / 03



日程

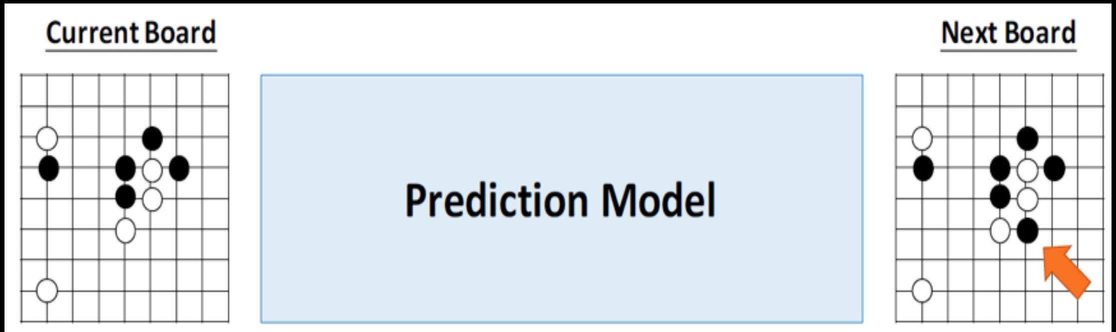
Convolution Neural Network

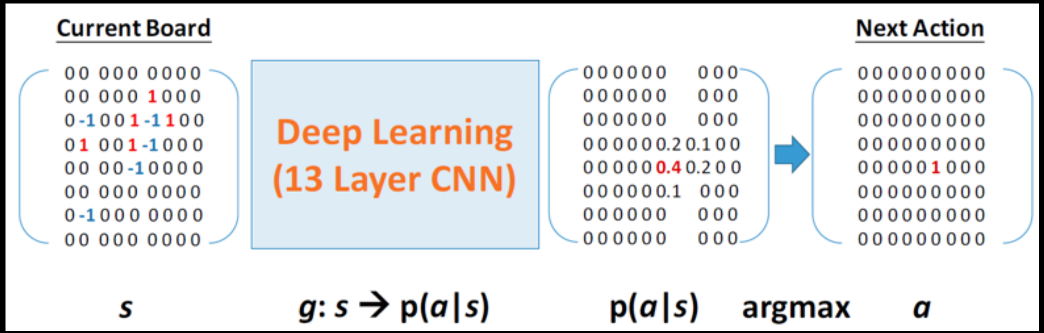


Playing Atari with Deep Reinforcement Learning.
Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Alex Graves, Ioannis Antonoglou, Daan Wierstra, Martin Riedmiller

AlphaGo

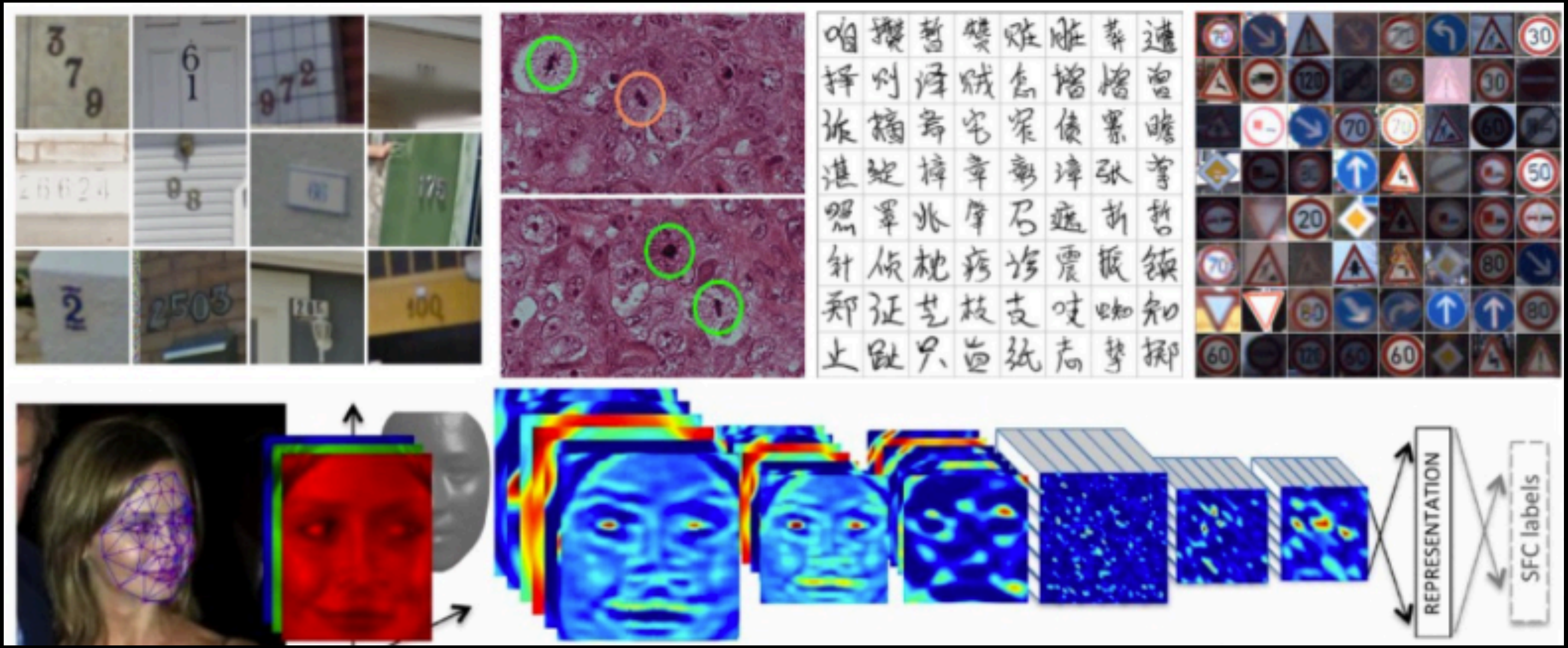
Lee Sedol: 2nd Highest Ranking professional Go player



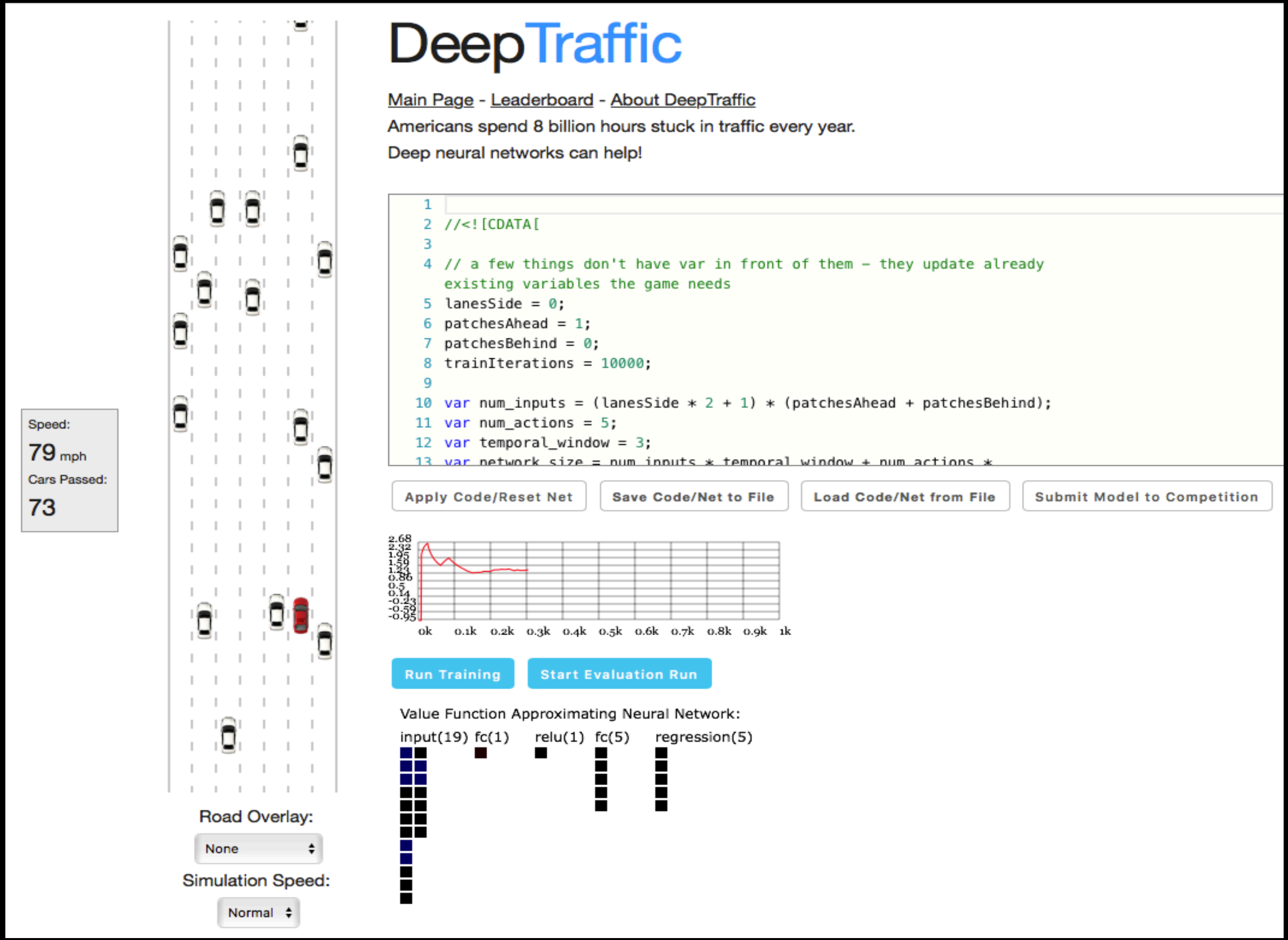


Source : Shane Moon

卷积神经网络应用

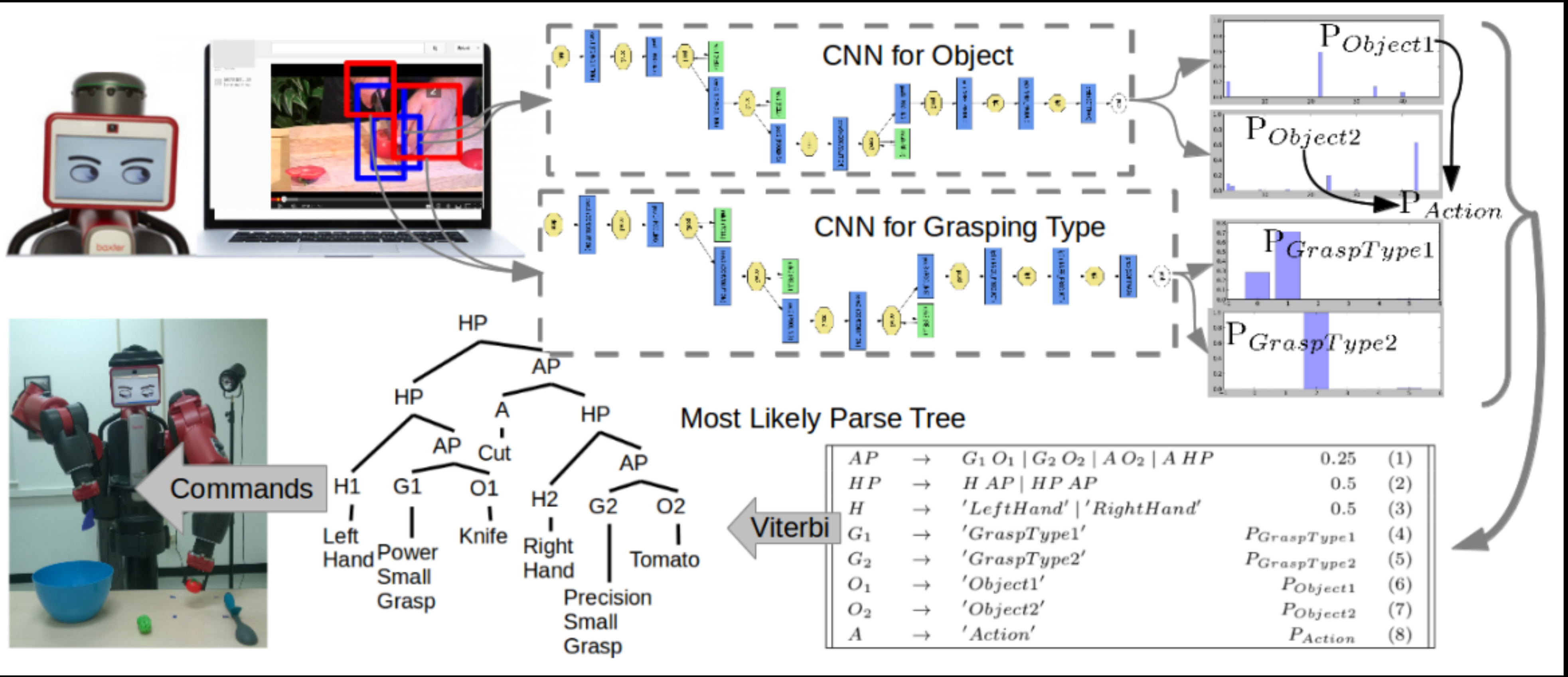


MIT 无人车项目



http://selfdrivingcars.mit.edu/deeptrafficjs/

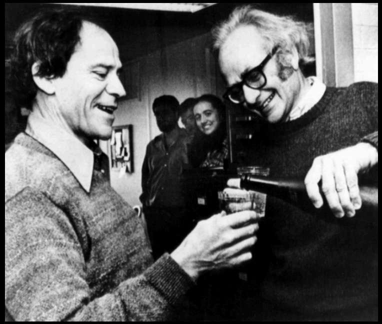
Robot learns manipulation actions by watching videos



Yezhou Yang, Cornelia Fermuller, Yiannis Aloimonos

CNN历史

Hubel & Wiesel



1959

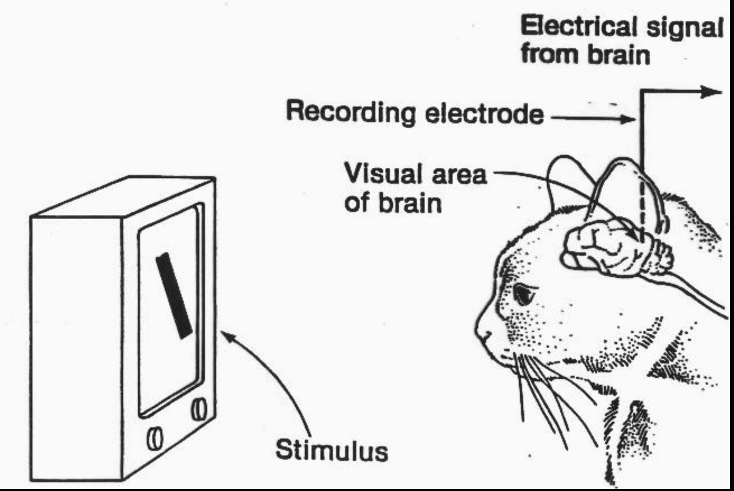
猫视觉皮层单神经元的可视野

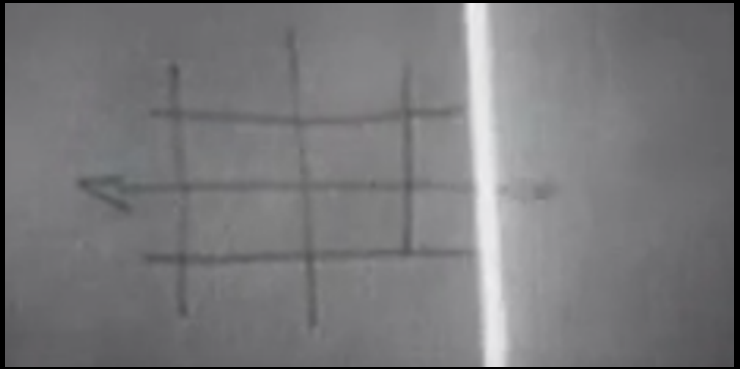
1962

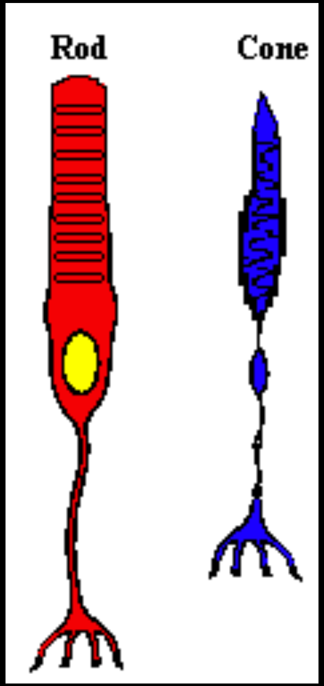
猫视觉神经可视野、双眼交互与功能结构

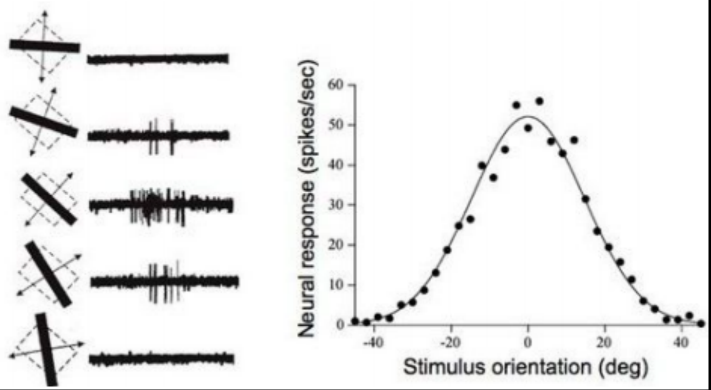
1981

诺贝尔医学奖

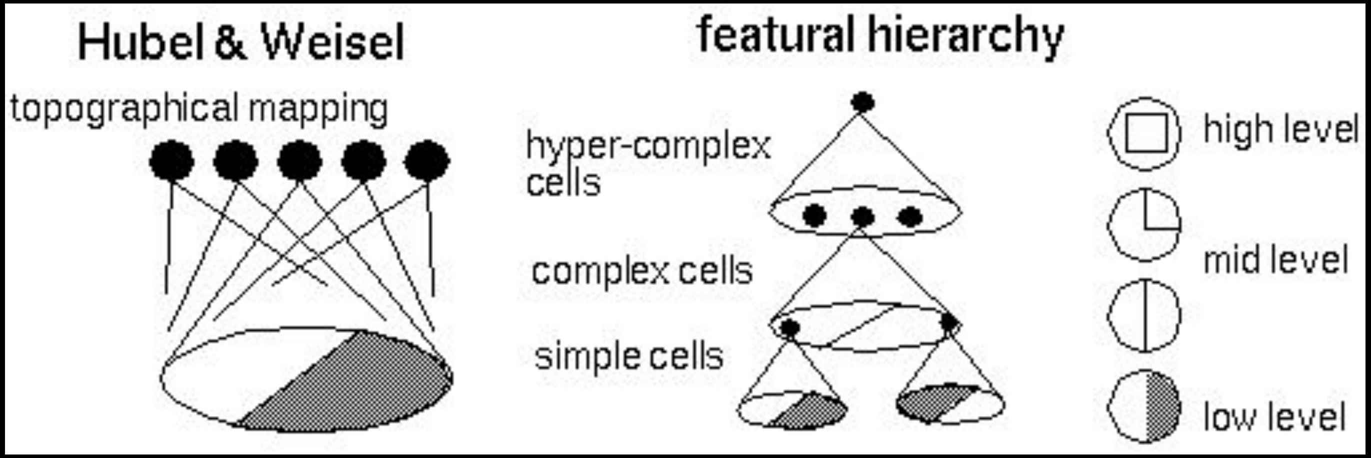






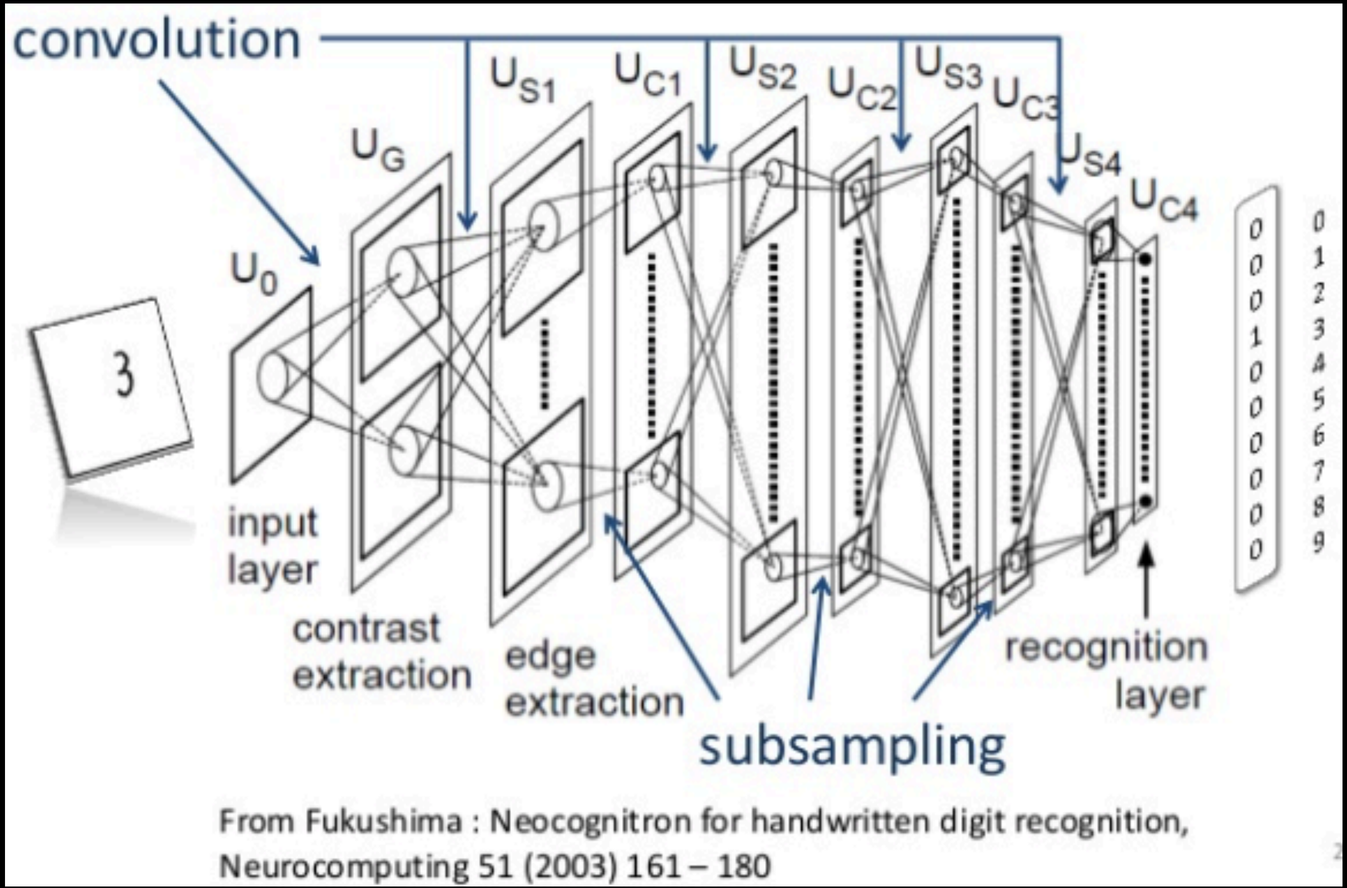


层次结构

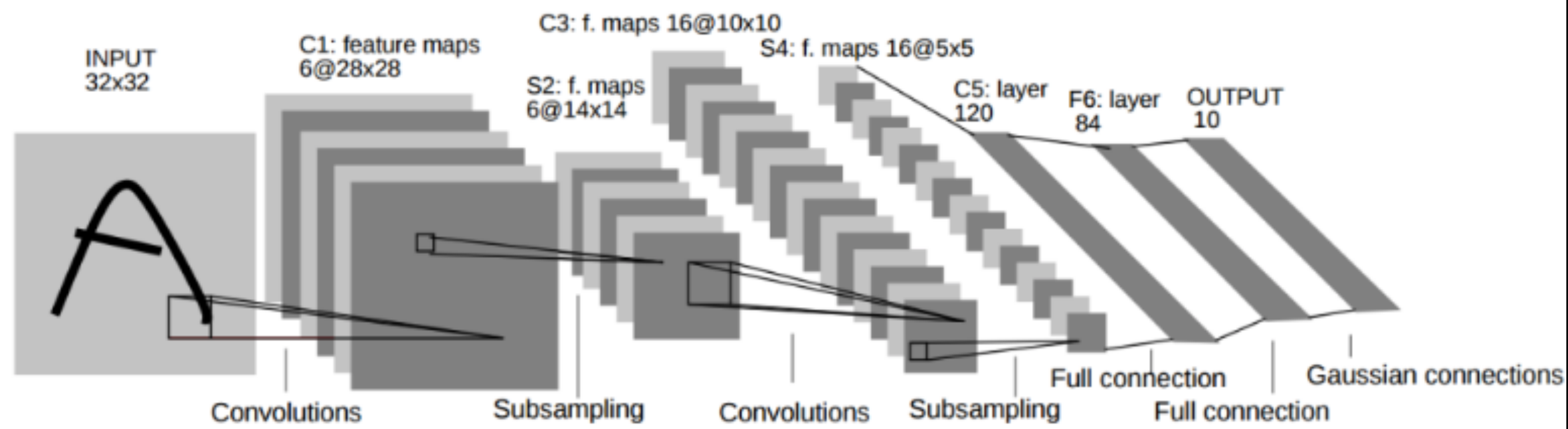


Hubel & Weisel
topographical mapping
featural hierarchy
hyper-complex cells
complex cells
simple cells
high level
mid level
low level

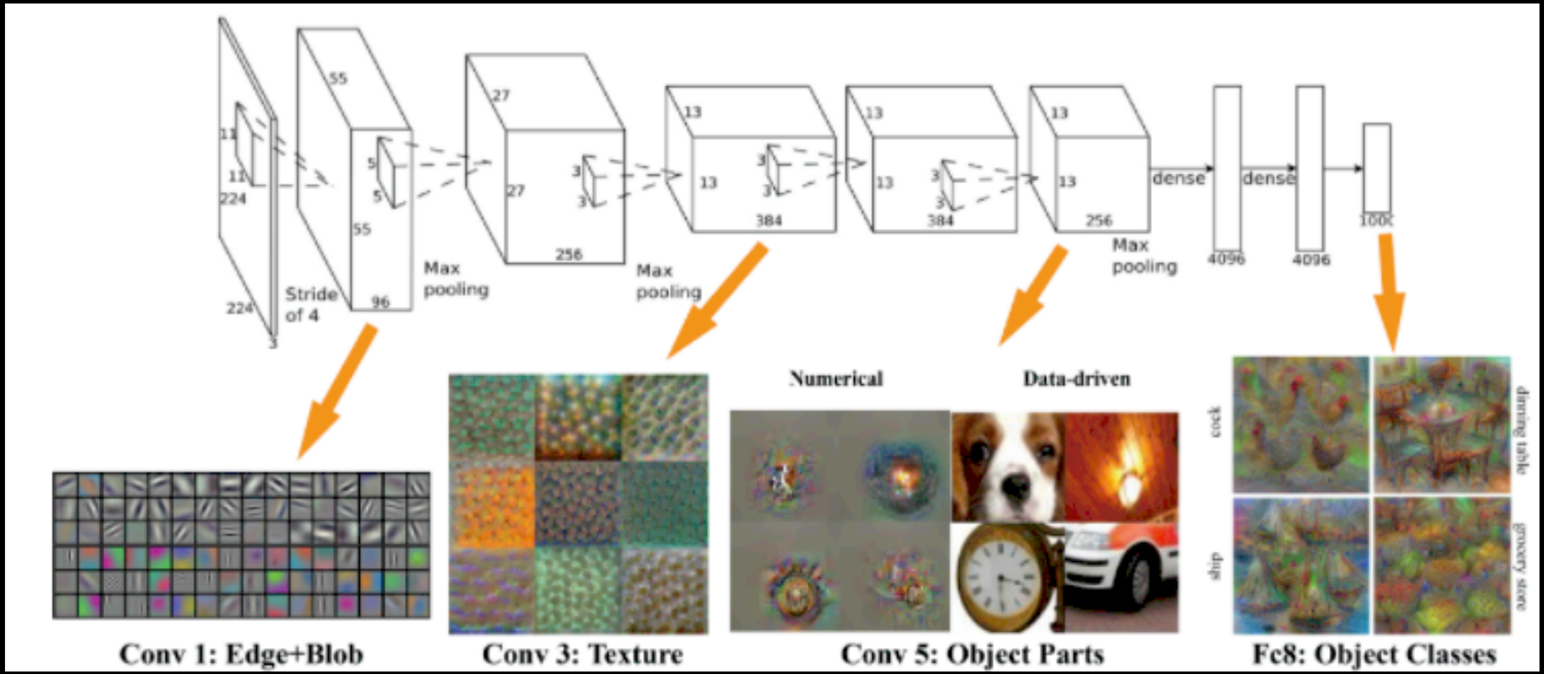
CNN鼻祖：Fukushima(1980) Kunihiko Neocognition



CNN之父：Le Cun, Yan (1998) LeNet-5



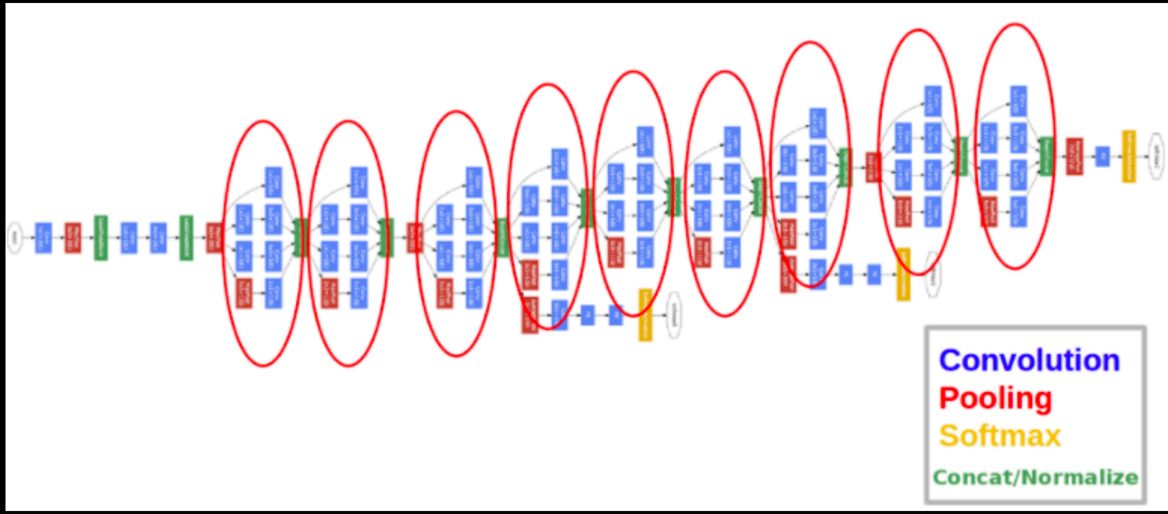
AlexNet (2012)

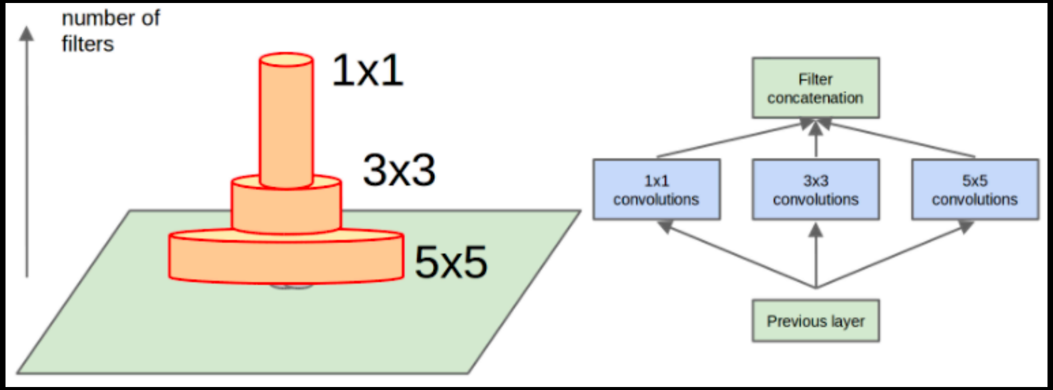


ImageNet Large Scale Visual Recognition Challenge 2012

params	AlexNet	FLOPs
4M	FC 1000	4M
16M	FC 4096 / ReLU	16M
37M	FC 4096 / ReLU	37M
	Max Pool 3x3s2	
442K	Conv 3x3s1, 256 / ReLU	74M
1.3M	Conv 3x3s1, 384 / ReLU	112M
884K	Conv 3x3s1, 384 / ReLU	149M
	Max Pool 3x3s2	
	Local Response Norm	
307K	Conv 5x5s1, 256 / ReLU	223M
	Max Pool 3x3s2	
	Local Response Norm	
35K	Conv 11x11s4, 96 / ReLU	105M

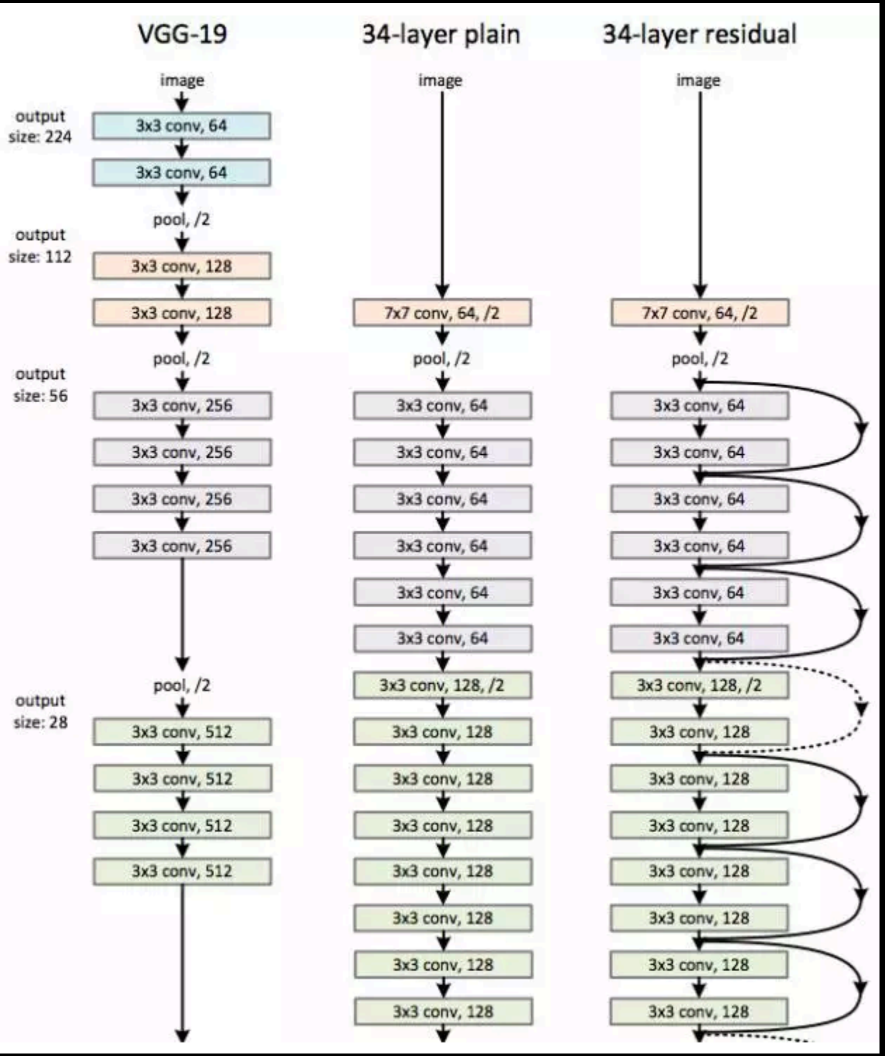
GoogLeNet (2014冠军) Inception / Deep Dream





Inception核心思想：同时使用不同大小的滤波器进行平行卷积，保留对图像高分辨率下的细节。

残差网络 ResNet (ILSVRC 2015冠军)



传统的卷积层 / Pooling层在信息传递时，或多或少会存在信息丢失、损耗等问题。ResNet在某种程度上解决了这个问题，通过直接将输入信息绕道传到输出，保持了信息的完整性，整个网络则只需学习输入、输出差别的那一部分，简化学习目标和难度。

ILSVRC 记录

2015 ResNet (ILSVRC'15) 3.57

Year	Codename	Error (percent)	99.9% Conf Int
2014	**GoogLeNet**	**6.66**	**6.40 - 6.92**
2014	VGG	7.32	7.05 - 7.60
2014	MSRA	8.06	7.78 - 8.34
2014	AHoward	8.11	7.83 - 8.39
2014	DeeperVision	9.51	9.21 - 9.82
2013	Clarifai†	11.20	10.87 - 11.53
2014	CASIAWS†	11.36	11.03 - 11.69
2014	Trimps†	11.46	11.13 - 11.80
2014	Adobe†	11.58	11.25 - 11.91
2013	**Clarifai**	**11.74**	**11.41 - 12.08**
2013	NUS	12.95	12.60 - 13.30
2013	ZF	13.51	13.14 - 13.87
2013	AHoward	13.55	13.20 - 13.91
2013	OverFeat	14.18	13.83 - 14.54
2014	Orange†	14.80	14.43 - 15.17
2012	SuperVision†	15.32	14.94 - 15.69
2012	**SuperVision**	**16.42**	**16.04 - 16.80**
2012	ISI	26.17	25.71 - 26.65
2012	VGG	26.98	26.53 - 27.43
2012	XRCE	27.06	26.60 - 27.52
2012	UvA	29.58	29.09 - 30.04

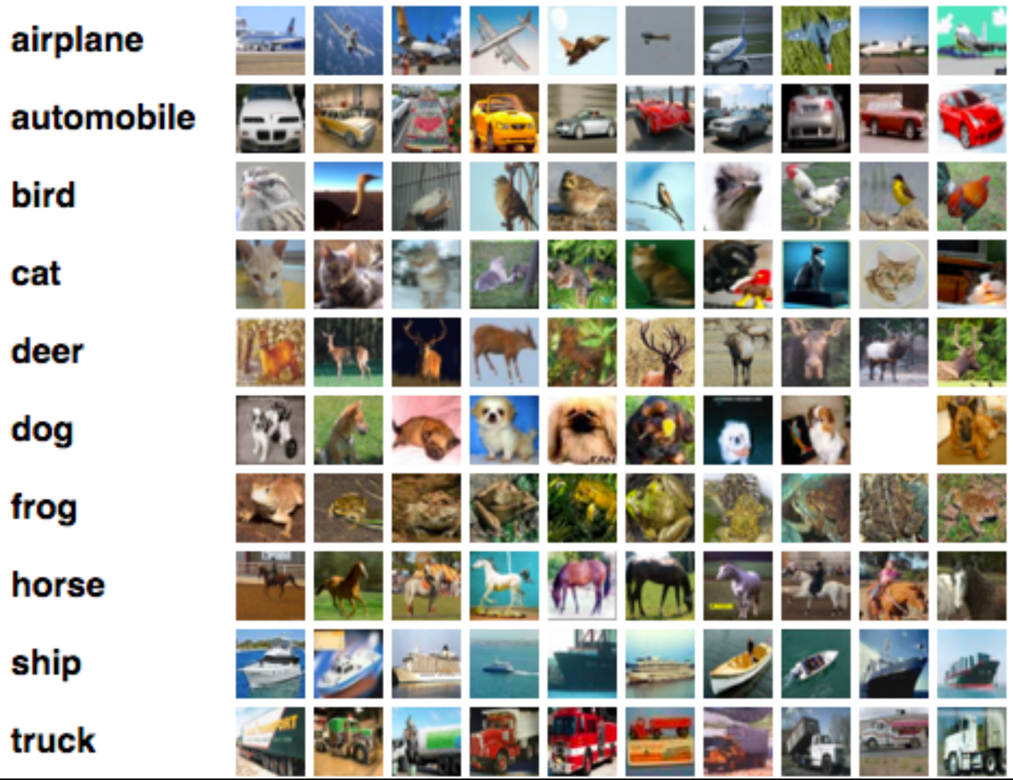
Microsoft ResNet, a 152 layers network

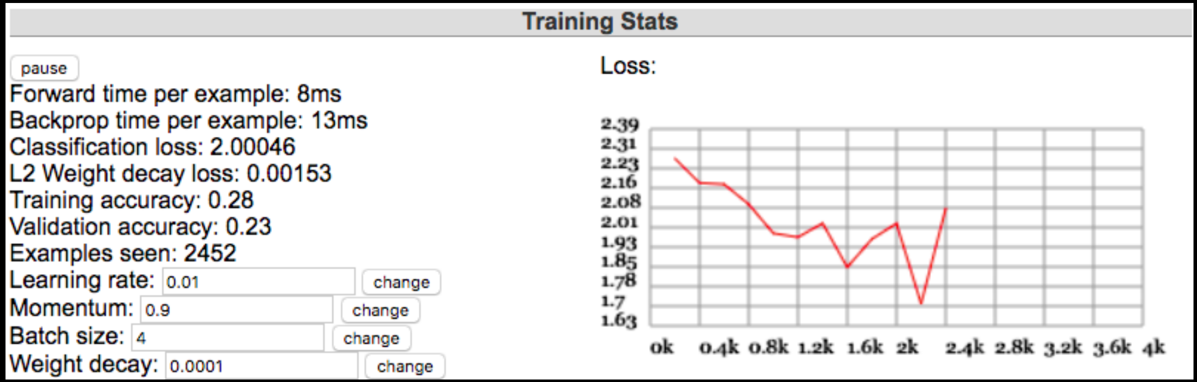
GoogLeNet, 22 layers network

U. of Toronto, SuperVision, a 7 layers network

human error is around *5.1%* on a subset

ConvNet CIFAR-10





http://[Stanford CIFAR10 ConvNetJS Demo]()

Convolutional Neural Network

问题：

在MNIST数据集上，Softmax虽然可达到约90%的正确率，但是把32x32的平面图像压扁成784x1的矢量真的好吗？

缺点：

- 图像的2维特征不能很好的表达
- Statistical Invariance
- RGB颜色数据与对象识别无关，灰度即可*

充分利用数据的特点，可以进一步提升准确率。

了解数据结构有助于机器学习

如何对像素数据建模？

输入RGB数据还是灰度数据？

充分利用数据的特点，可以进一步提升准确率。

Statistical Invariance

Weight Sharing

Statistical Invariance

There once was a Kitten named Locke Ness, after the greatest Kitten monster.

A Kitten plays with a ball of yarn while his brother creeps around a Kitten lying in the sunlight.

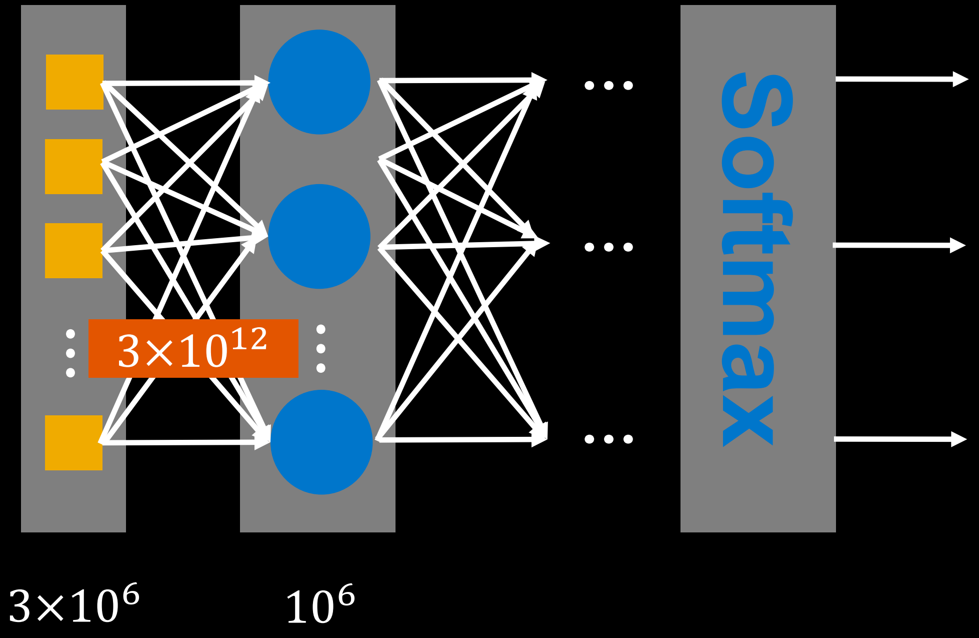
Udacity

Embedding

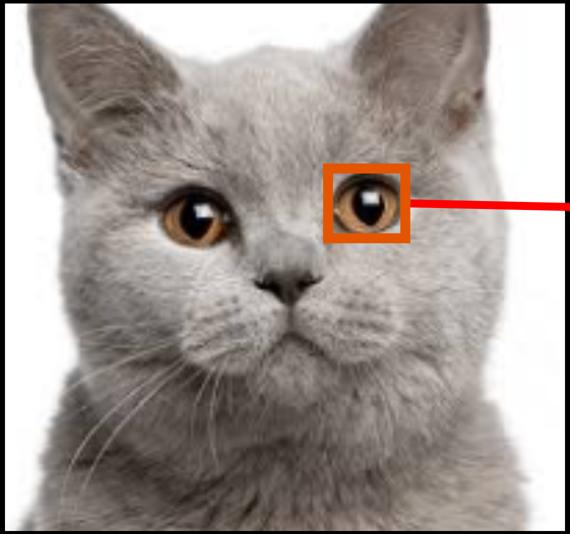
首层全连接导致网络参数过多

1000

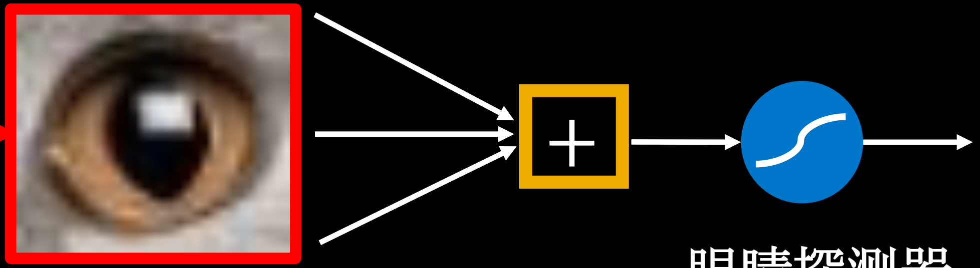
1000



一些模式比图像要小得多



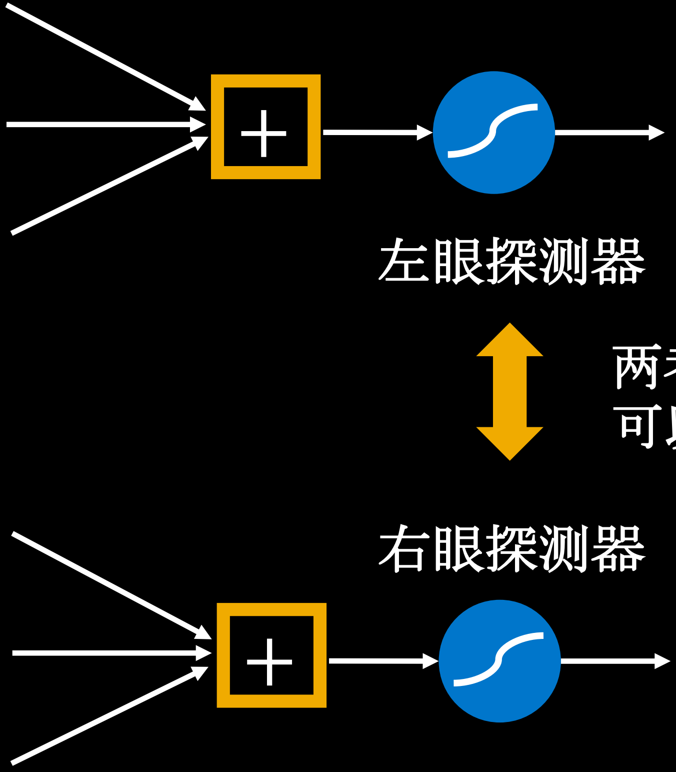
一个神经元无需连接整个图像的所有像素，以发现模式（Pattern）



眼睛探测器

可连接至较小范围，参数更少

类似的模式出现在图像的不同区域



两者的功能几乎相同，
可以共享同一套权重

下采样像素不会改变对象

Subsampling

下采样像素使图像更小，处理图像时所需的网络参数更少

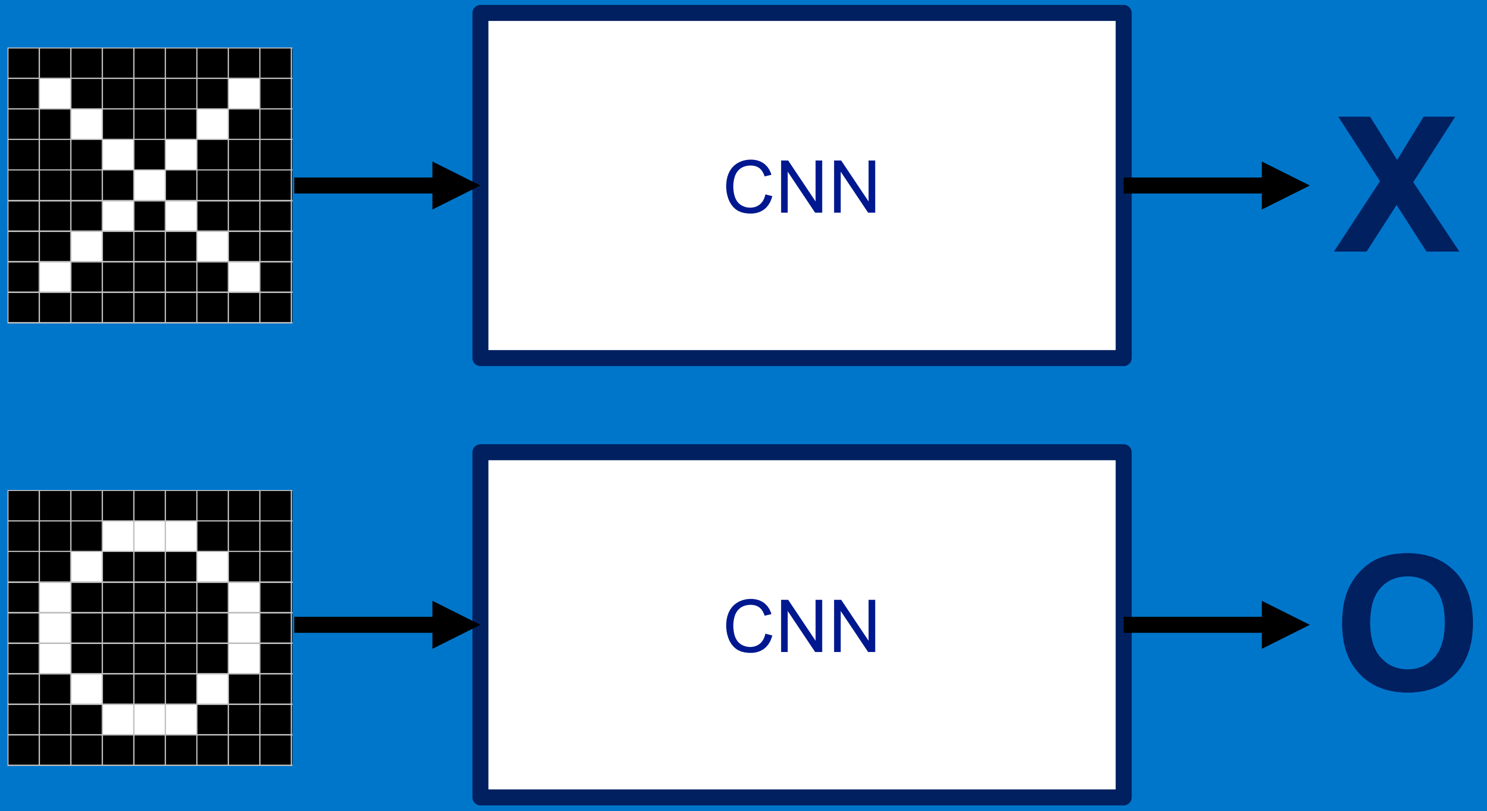
A toy ConvNet: X’s and O’s

Says whether a picture is of an X or an O

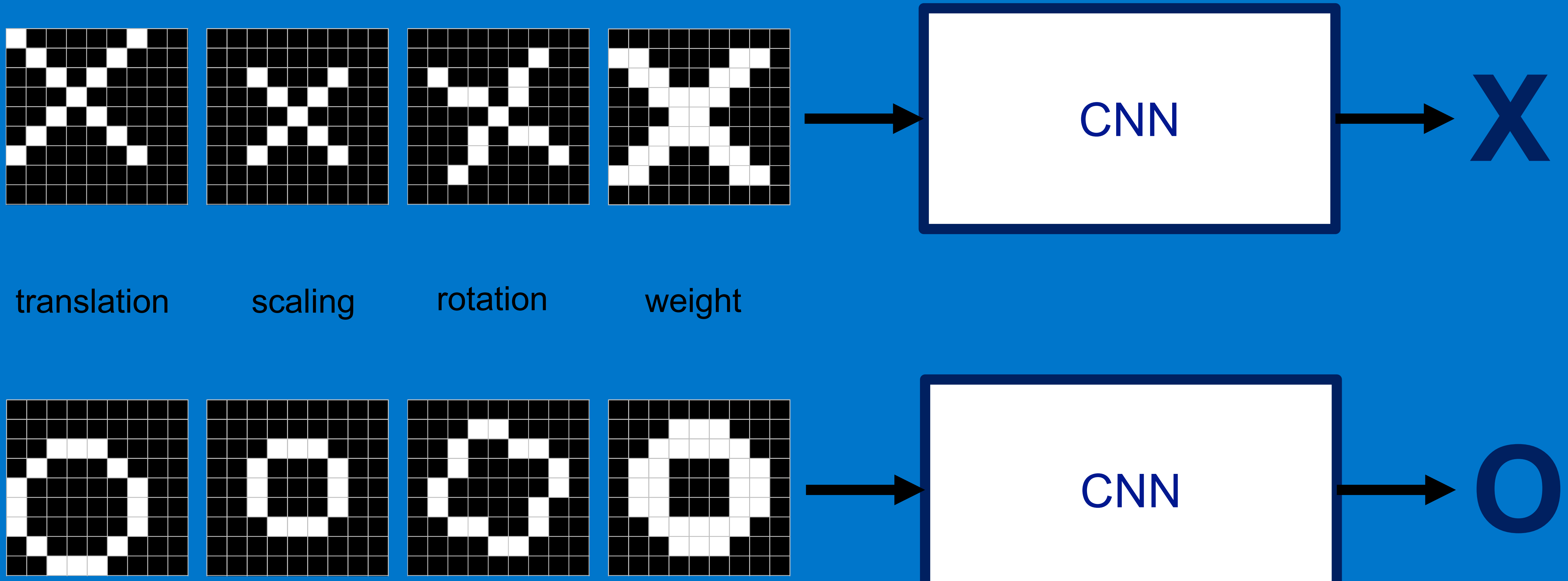
A two-dimensional
array of pixels

Coutesy to: Brandon Rohrer

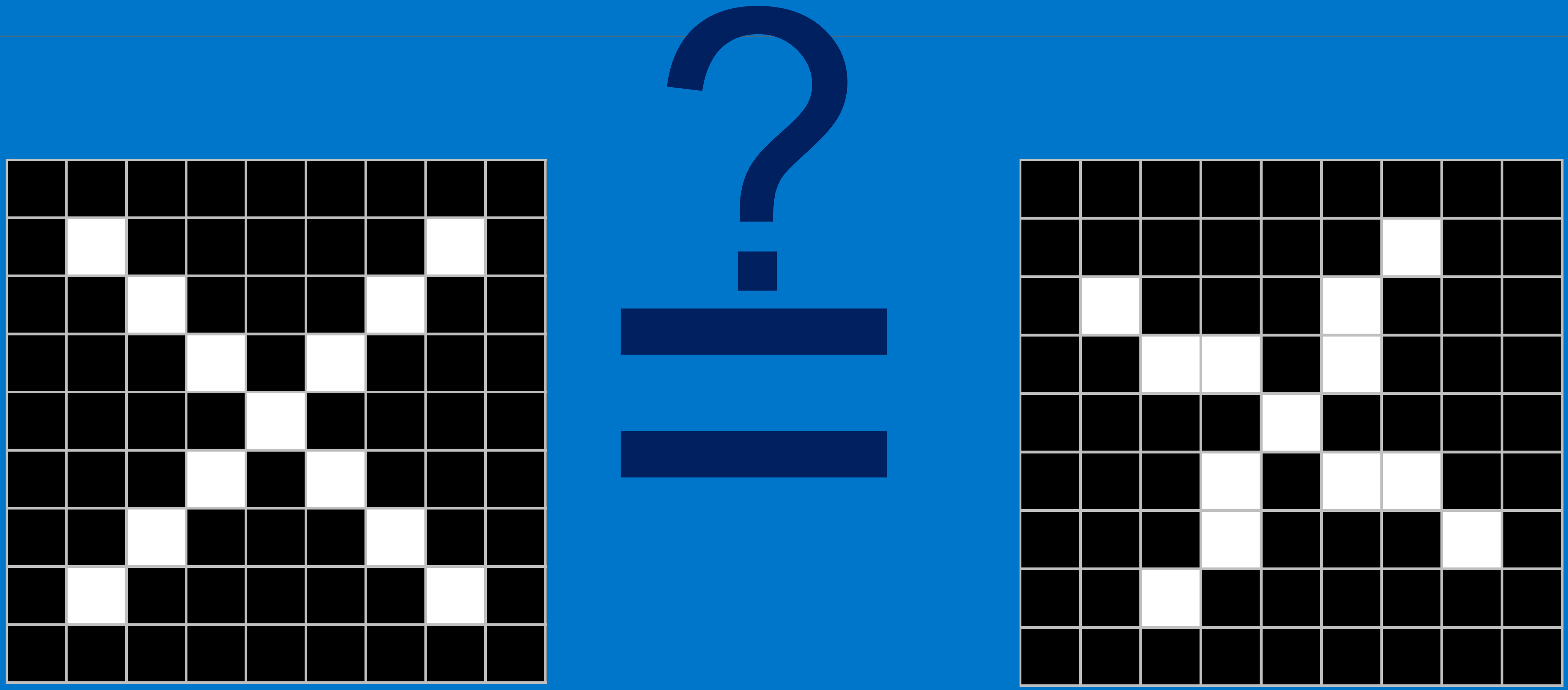
For example



Trickier cases



Deciding is hard



What computers see

-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

$$\stackrel{?}{=}$$

-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

What computers see

-1	-1	-1	-1	-1	-1	-1	-1	-1
-1	X	-1	-1	-1	-1	X	X	-1
-1	X	X	-1	-1	X	X	-1	-1
-1	-1	X	1	-1	1	-1	-1	-1
-1	-1	-1	-1	1	-1	-1	-1	-1
-1	-1	-1	1	-1	1	X	-1	-1
-1	-1	X	X	-1	-1	X	X	-1
-1	X	X	-1	-1	-1	-1	X	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

Computers are literal

-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

$\neq$

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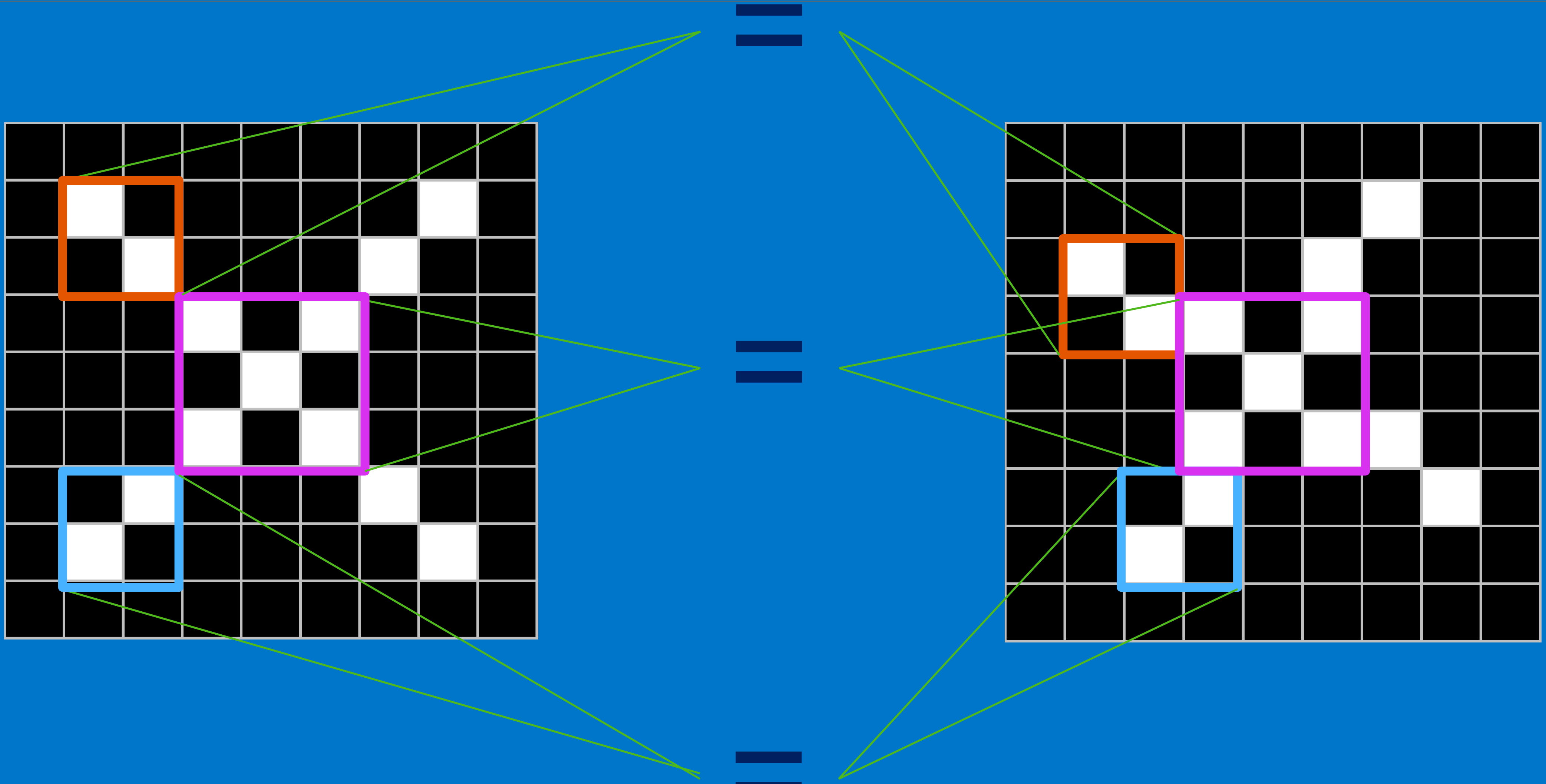
-1	-1	-1	1	-1	1	1	-1	-1
-1	-1	-1	1	-1	-1	-1	1	-1
-1	-1	1	-1	-1	-1	-1	-1	-1
-1	-1	-1	-1	-1	-1	-1	-1	-1

ConvNets match pieces of the image



Features match pieces of the image

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

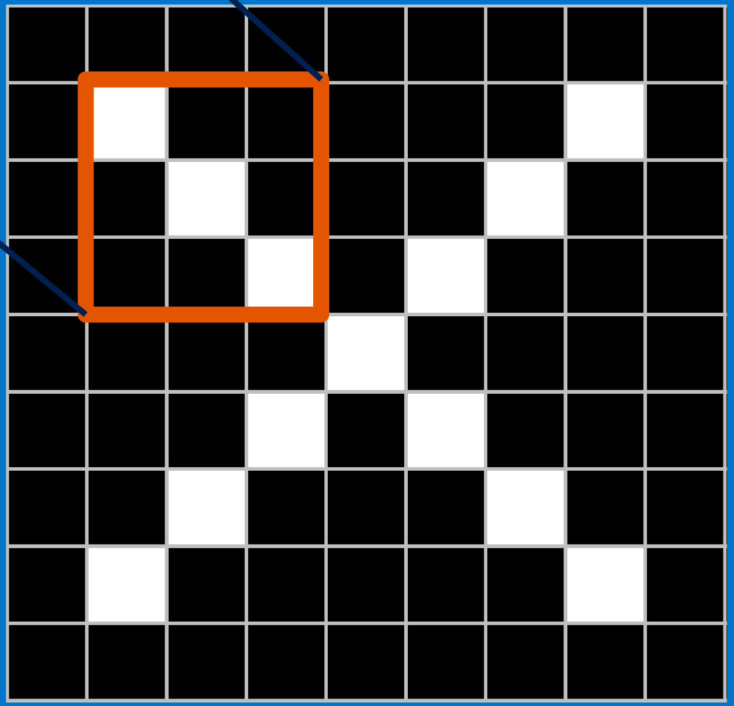
1	-1	1
-1	1	-1
1	-1	1

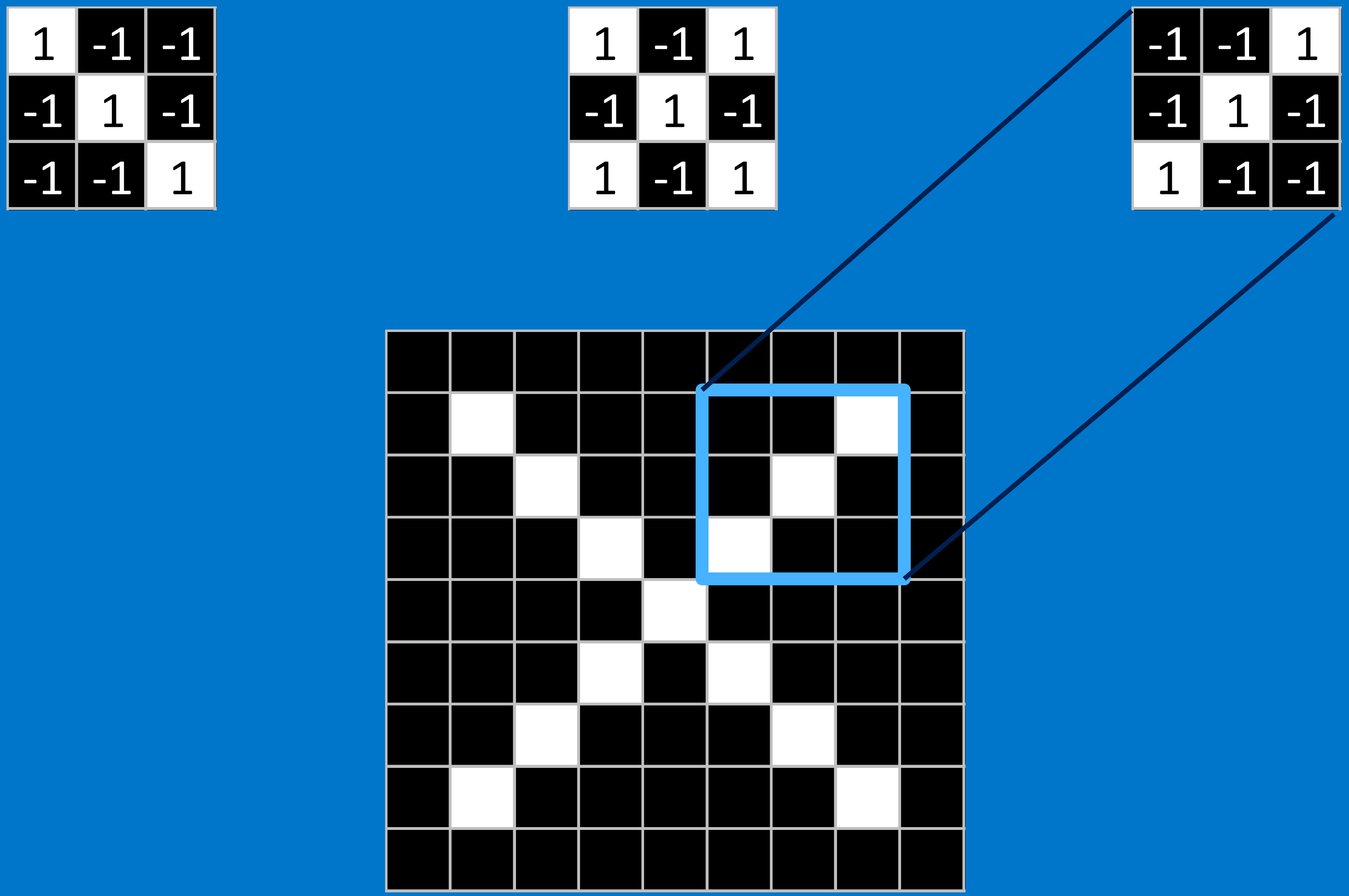
-1	-1	1
-1	1	-1
1	-1	-1

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

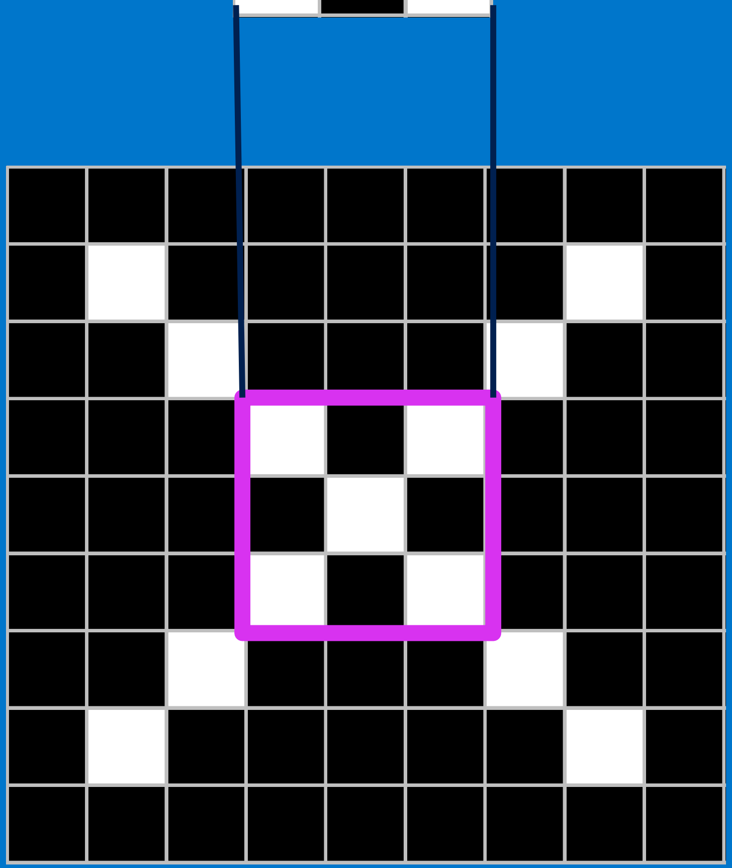



1 -1 -1
-1 1 -1
-1 -1 1
1 -1 1
-1 1 -1
1 -1 1
-1 -1 1
-1 1 -1
1 -1 -1

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

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

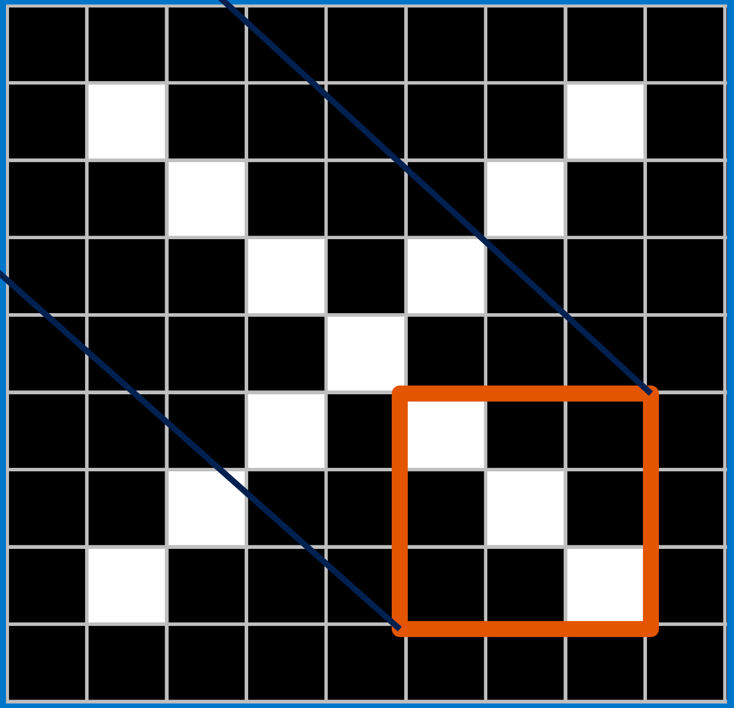
-1	-1	1
-1	1	-1
1	-1	-1



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

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

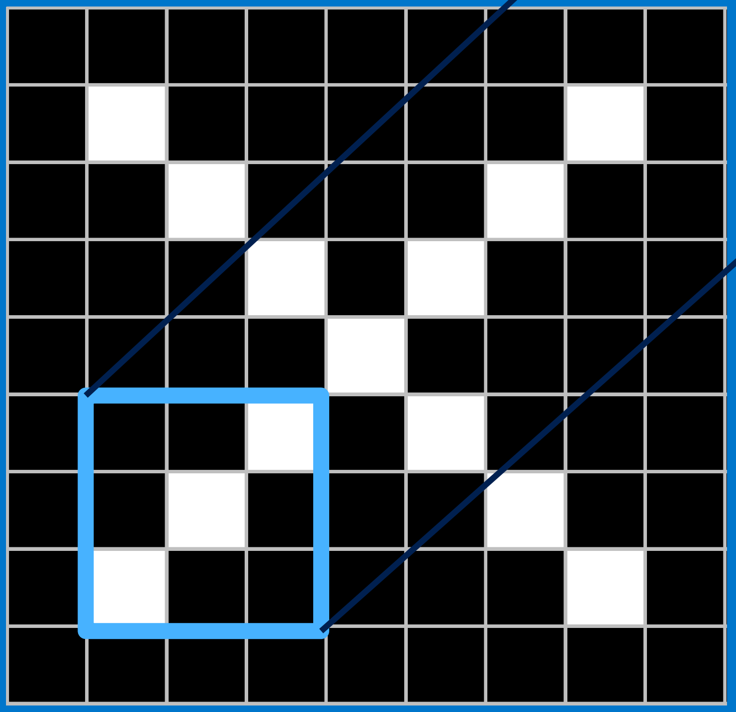
-1	-1	1
-1	1	-1
1	-1	-1



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



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

Filtering: The math behind the match

1. Line up the feature and the image patch.
2. Multiply each image pixel by the corresponding feature pixel.
3. Add them up.
4. Divide by the total number of pixels in the feature.

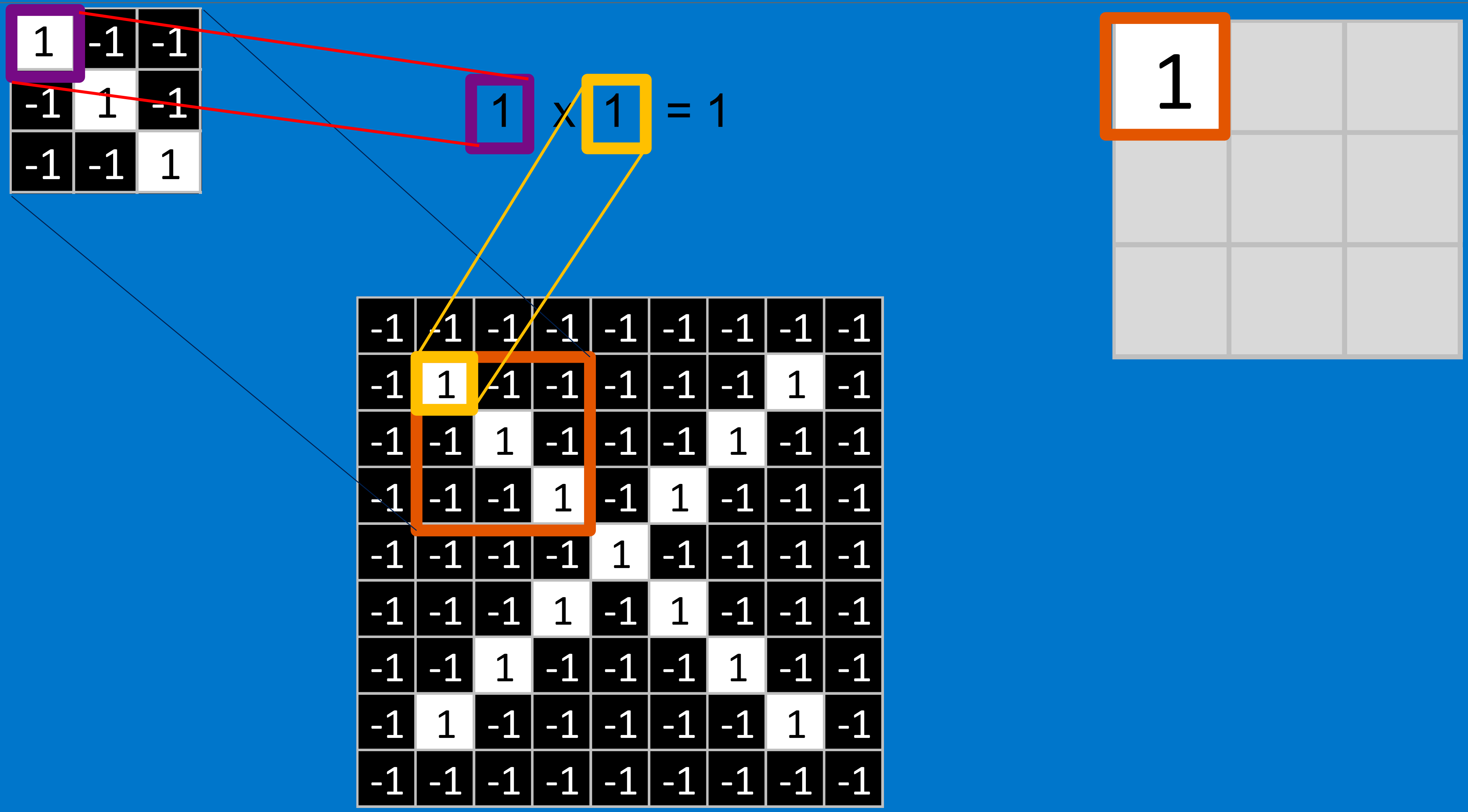
Filtering: The math behind the match

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

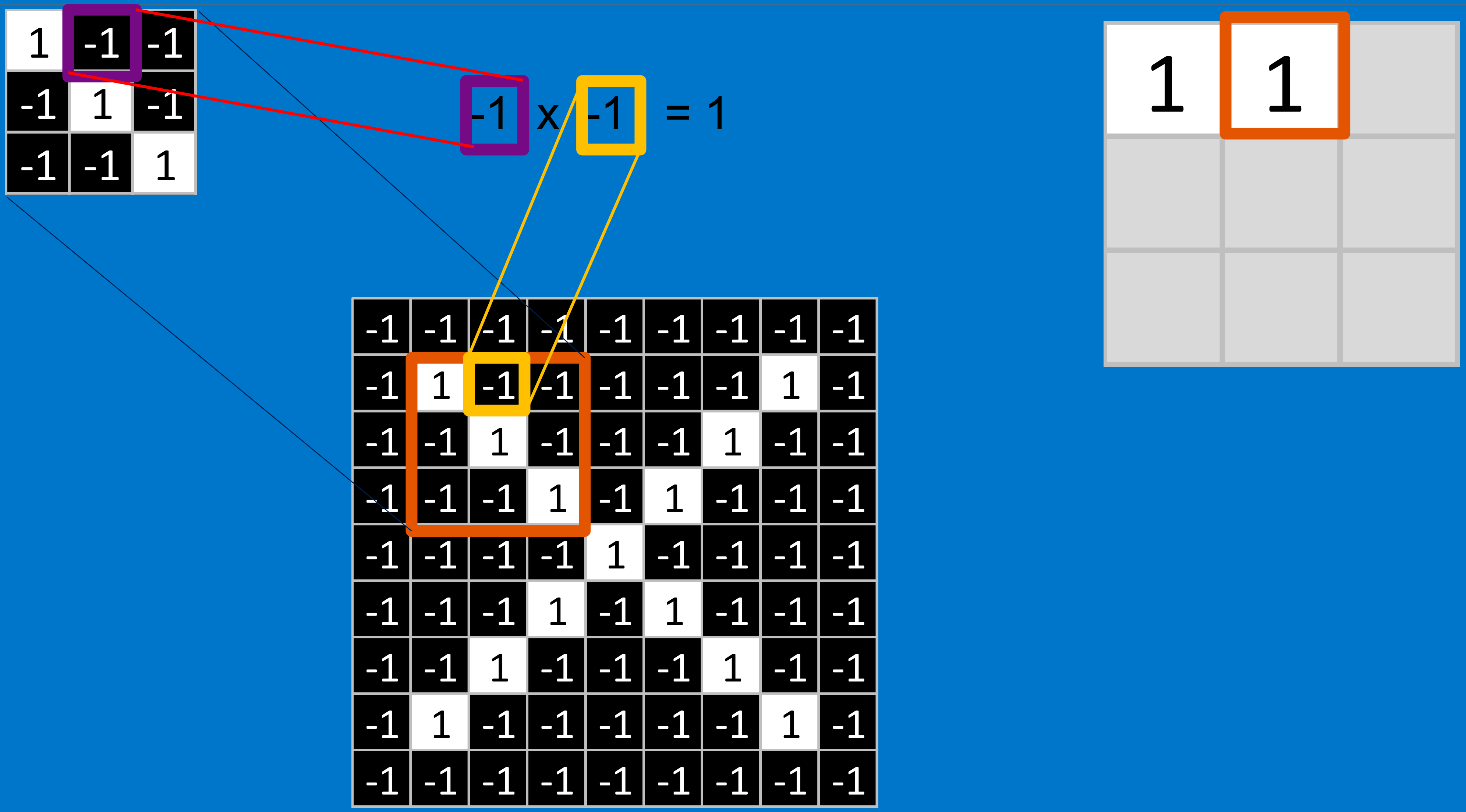
$\boxed{1} \times \boxed{1} = 1$

-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

Filtering: The math behind the match



Filtering: The math behind the match



Filtering: The math behind the match

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

$$\boxed{-1} \times \boxed{-1} = 1$$

-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

Filtering: The math behind the match

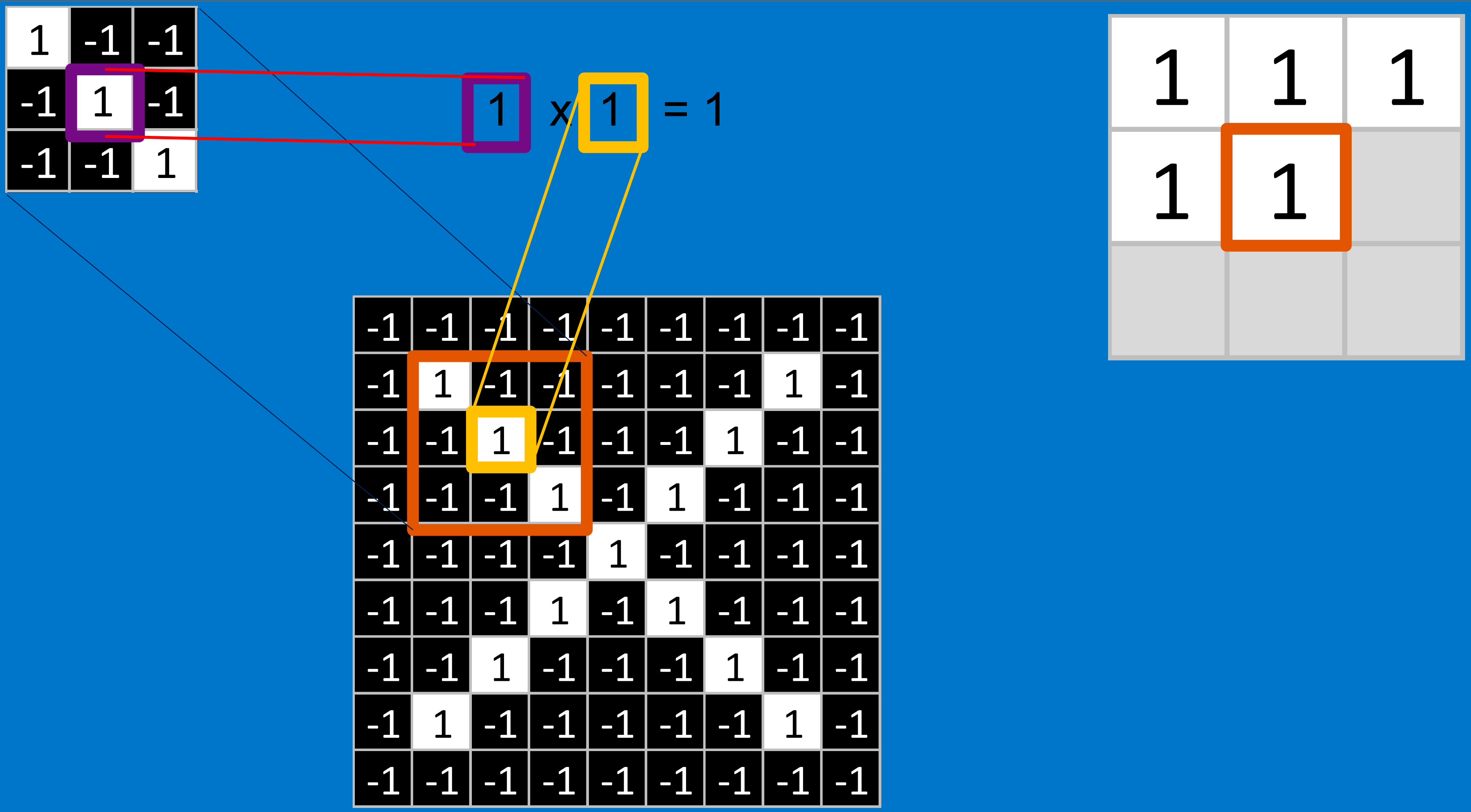
1	-1	-1
-1	1	-1
-1	-1	1

$$-1 \times -1 = 1$$

-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		

Filtering: The math behind the match



Filtering: The math behind the match

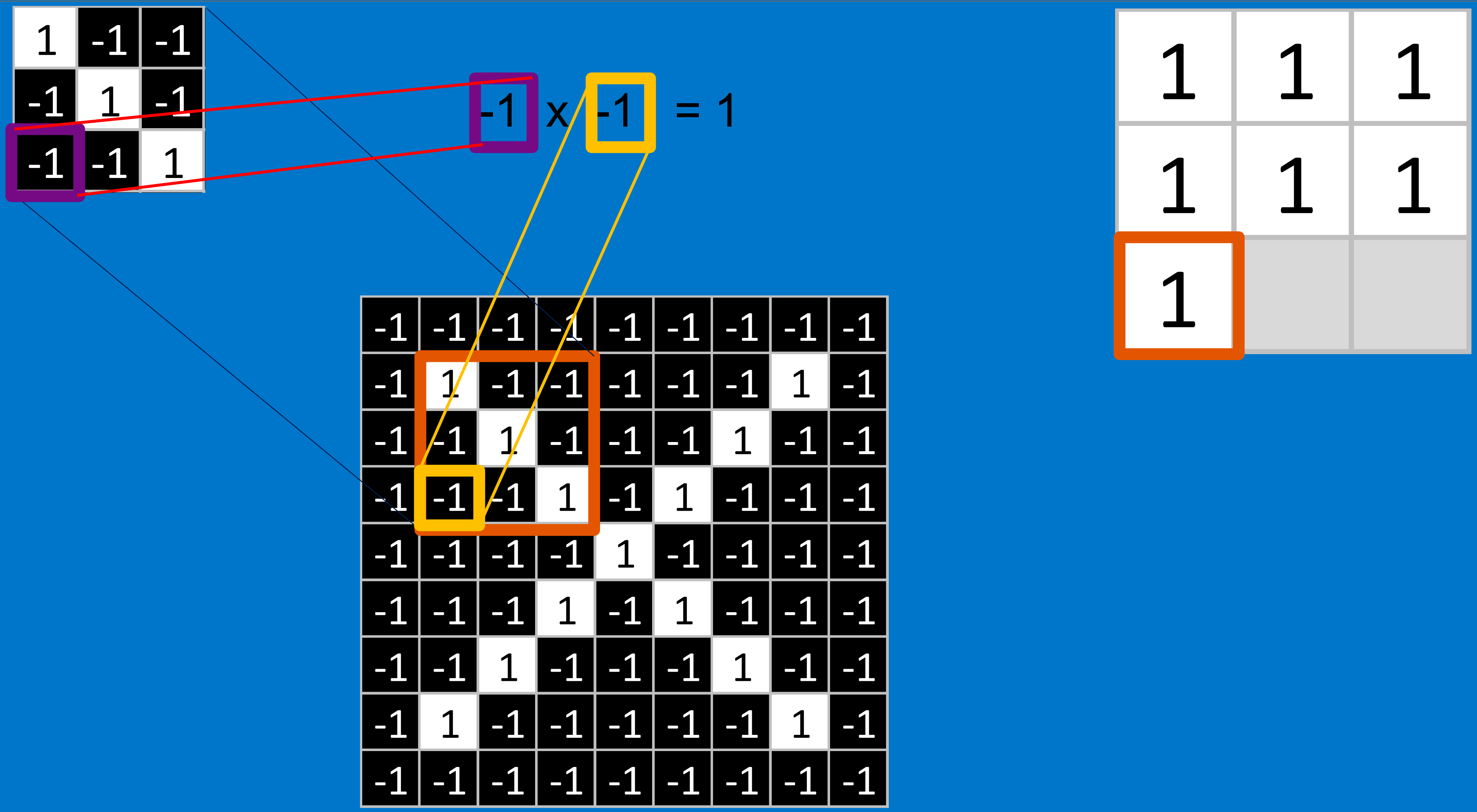
1	-1	-1
-1	1	-1
-1	-1	1

$-1 \times -1 = 1$

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

Filtering: The math behind the match



Filtering: The math behind the match

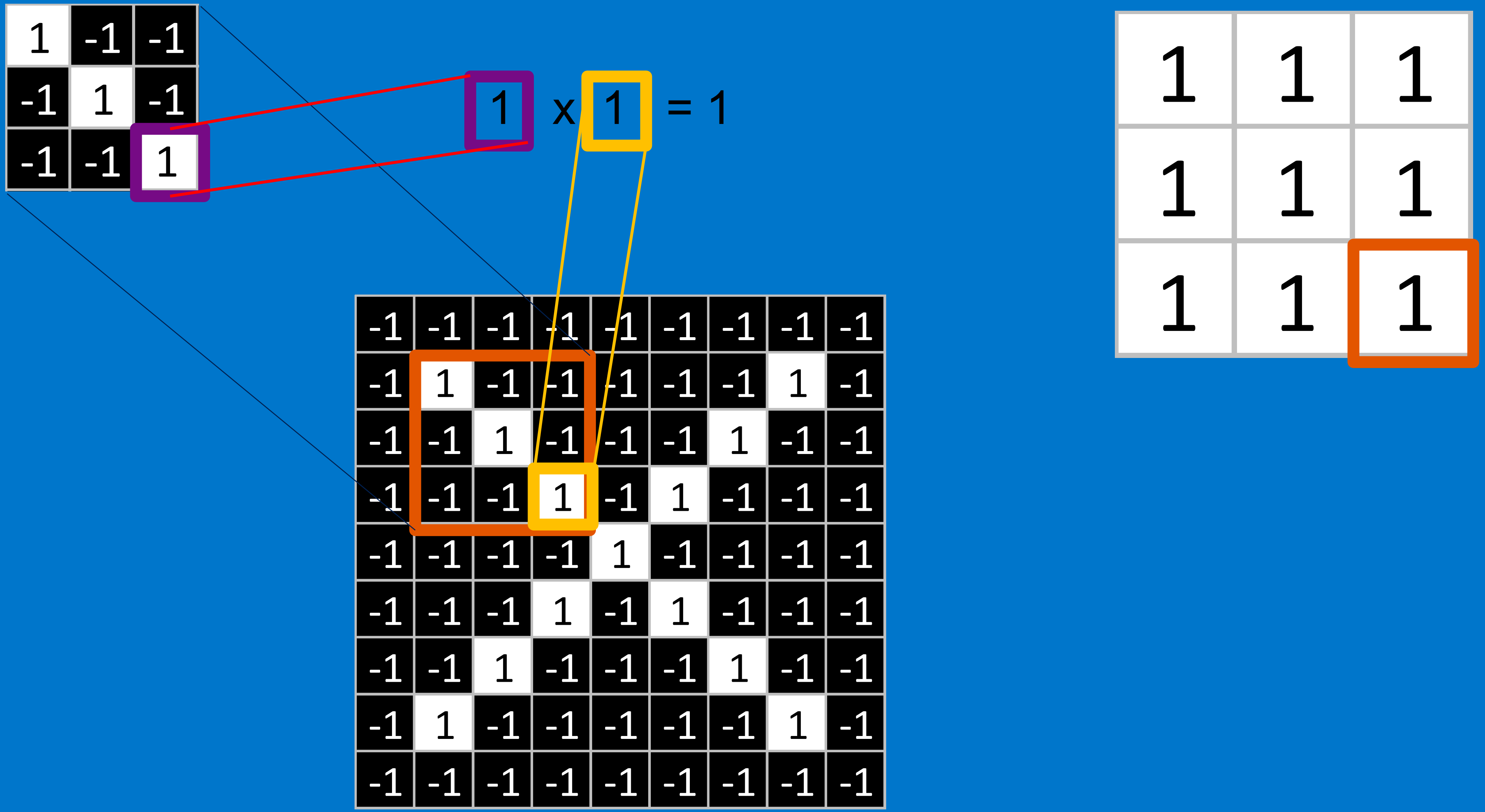
1	-1	-1
-1	1	-1
-1	-1	1

$-1 \times -1 = 1$

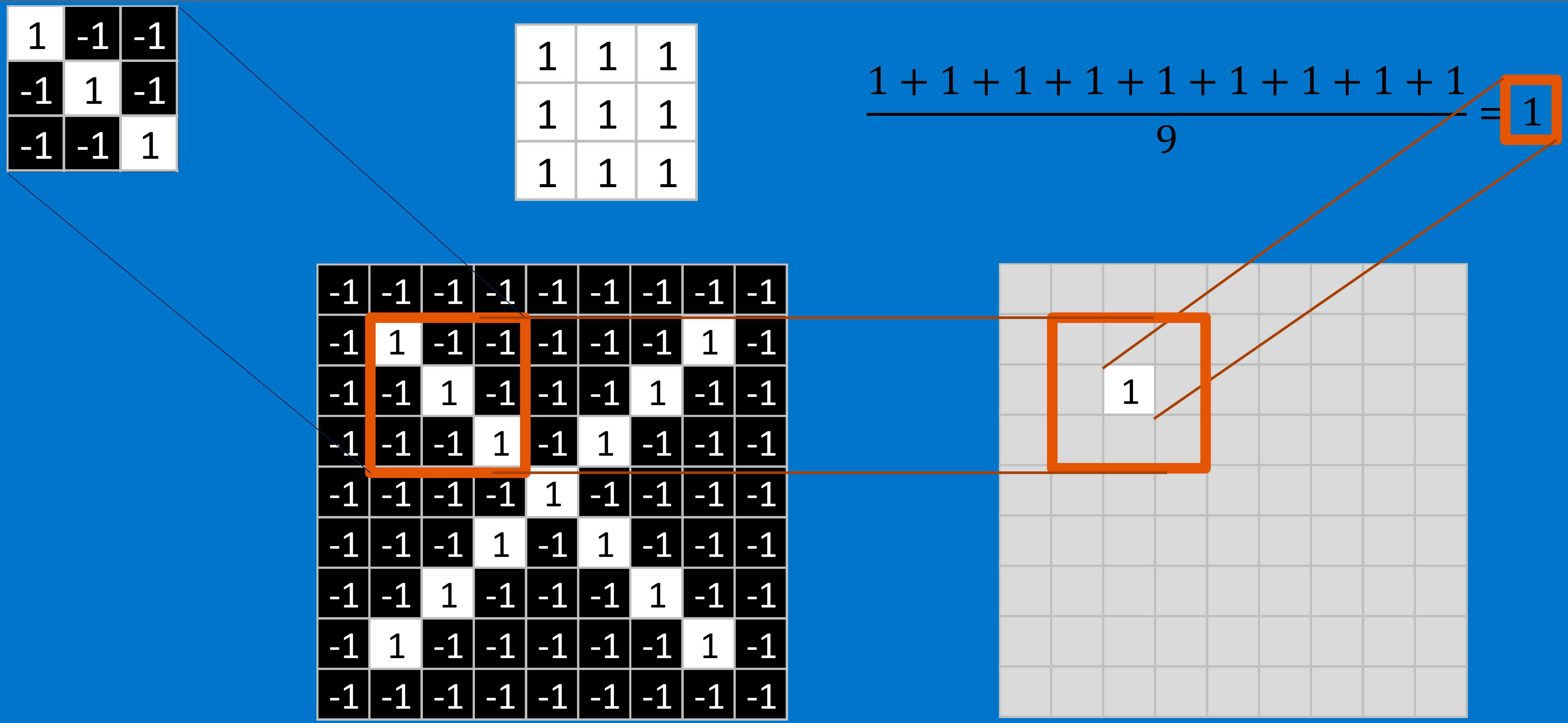
1	1	1
1	1	1
1	1	

-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

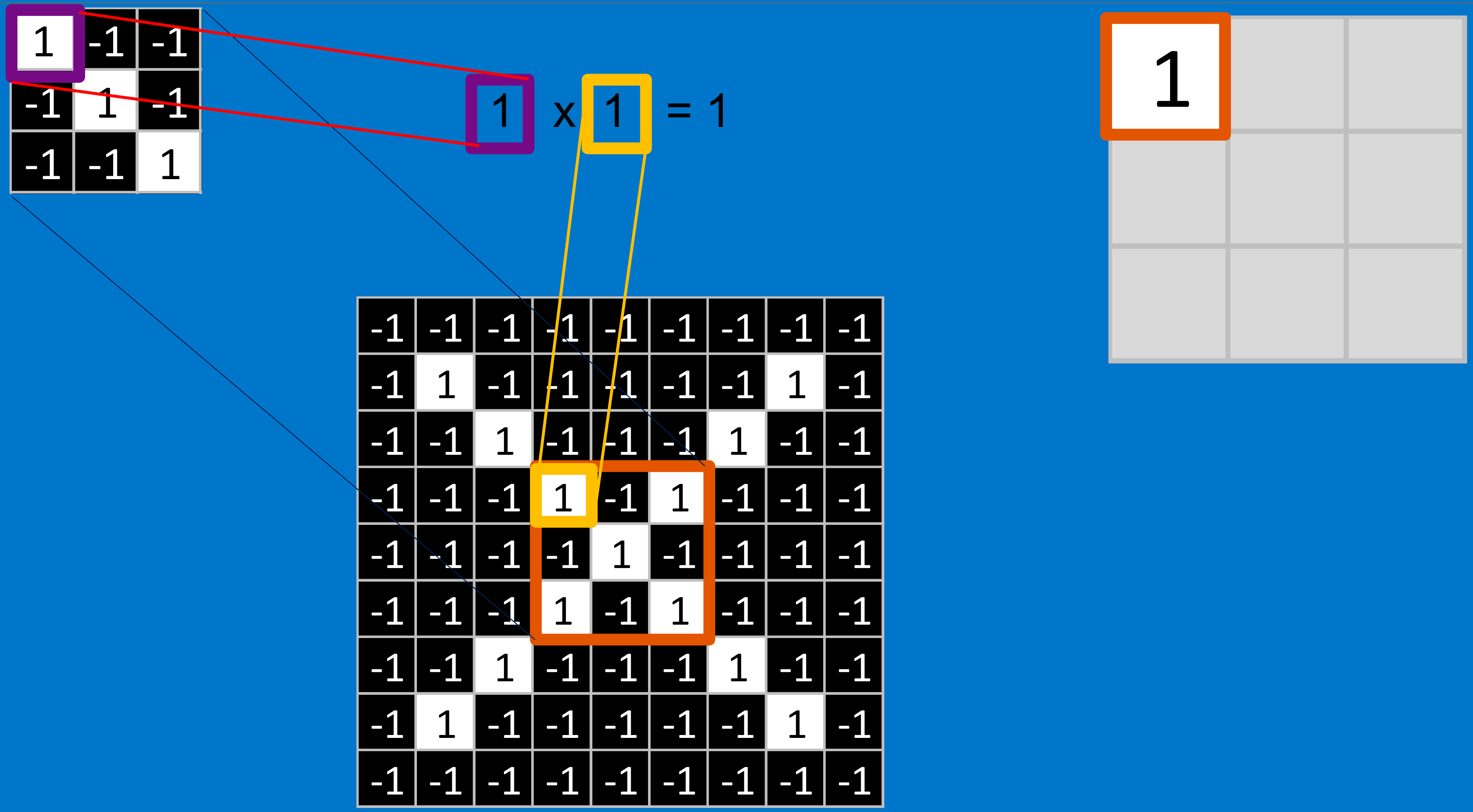
Filtering: The math behind the match



Filtering: The math behind the match



Filtering: The math behind the match



Filtering: The math behind the match

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

$-1 \times 1 = -1$

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

Filtering: The math behind the match

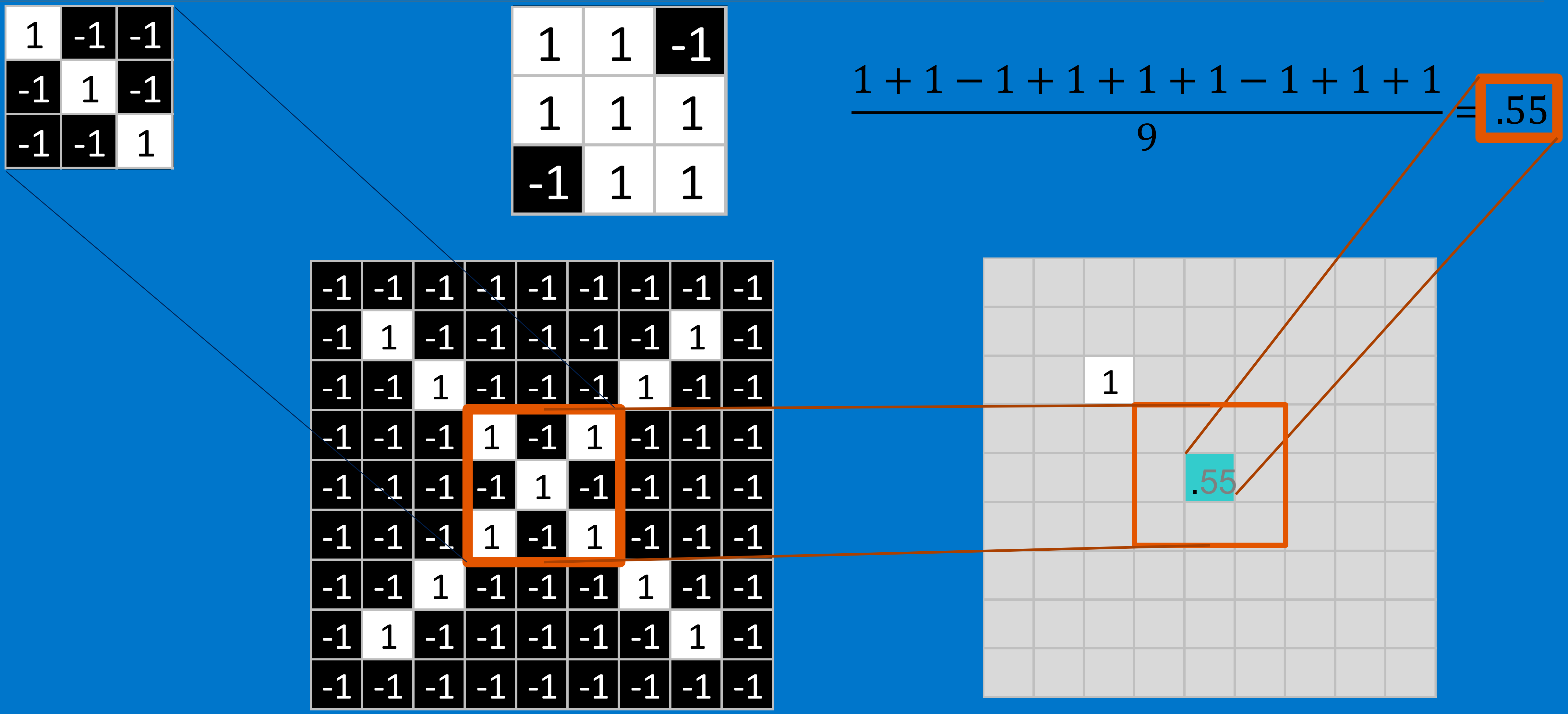
1	-1	-1
-1	1	-1
-1	-1	1

-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

Filtering: The math behind the match

$$\frac{1+1-1+1+1+1-1+1+1}{9} = .55$$



Convolution: Trying every possible 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

0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

Convolution: Trying every possible 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

$\otimes$

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

=

0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

-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

$\otimes$

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

=

0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

-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

$\otimes$

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

=

0.33	-0.55	0.11	-0.11	0.11	-0.55	0.33
-0.55	0.55	-0.55	0.33	-0.55	0.55	-0.55
0.11	-0.55	0.55	-0.77	0.55	-0.55	0.11
-0.11	0.33	-0.77	1.00	-0.77	0.33	-0.11
0.11	-0.55	0.55	-0.77	0.55	-0.55	0.11
-0.55	0.55	-0.55	0.33	-0.55	0.55	-0.55
0.33	-0.55	0.11	-0.11	0.11	-0.55	0.33

-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

$\otimes$

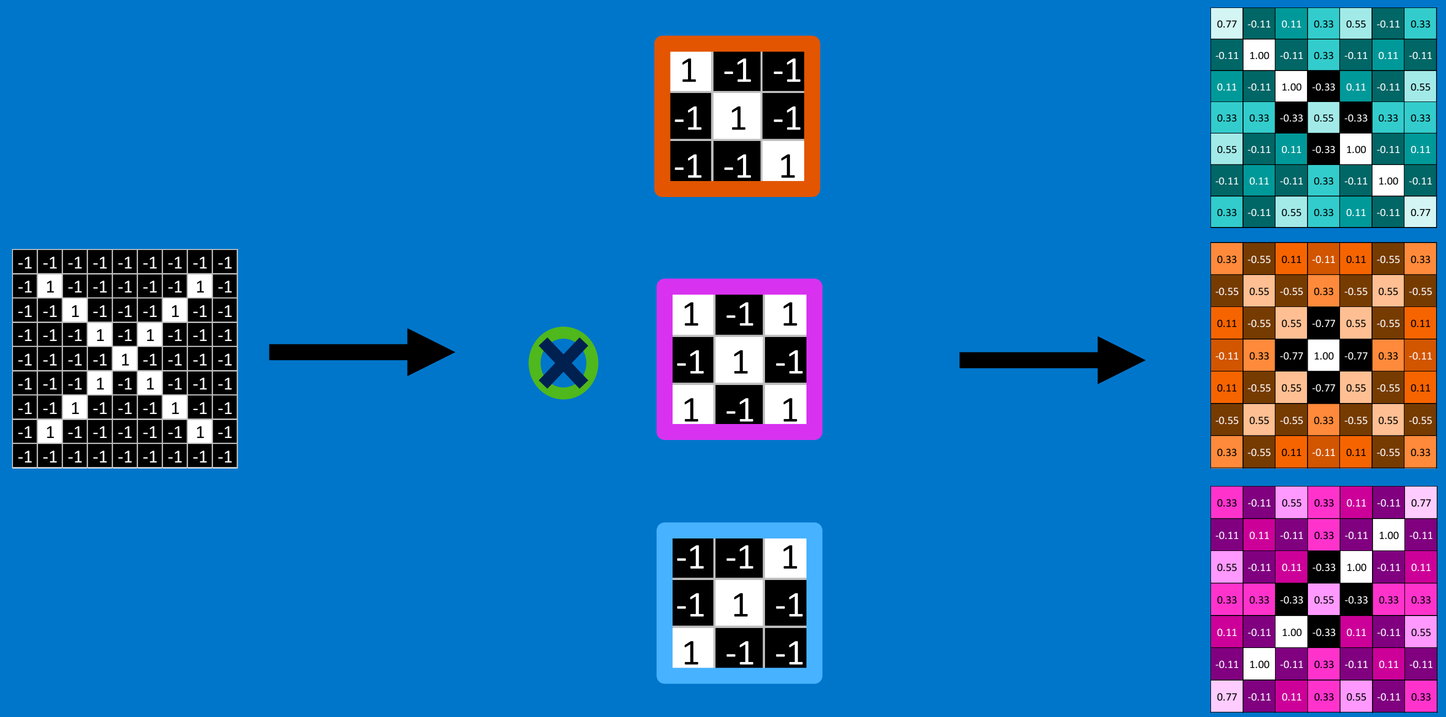
-1	-1	1
-1	1	-1
1	-1	-1

=

0.33	-0.11	0.55	0.33	0.11	-0.11	0.77
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.77	-0.11	0.11	0.33	0.55	-0.11	0.33

Convolution layer

One image becomes a stack of filtered images



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

$\otimes$

0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

0.33	-0.55	0.11	-0.11	0.11	-0.55	0.33
-0.55	0.55	-0.55	0.33	-0.55	0.55	-0.55
0.11	-0.55	0.55	-0.77	0.55	-0.55	0.11
-0.11	0.33	-0.77	1.00	-0.77	0.33	-0.11
0.11	-0.55	0.55	-0.77	0.55	-0.55	0.11
-0.55	0.55	-0.55	0.33	-0.55	0.55	-0.55
0.33	-0.55	0.11	-0.11	0.11	-0.55	0.33

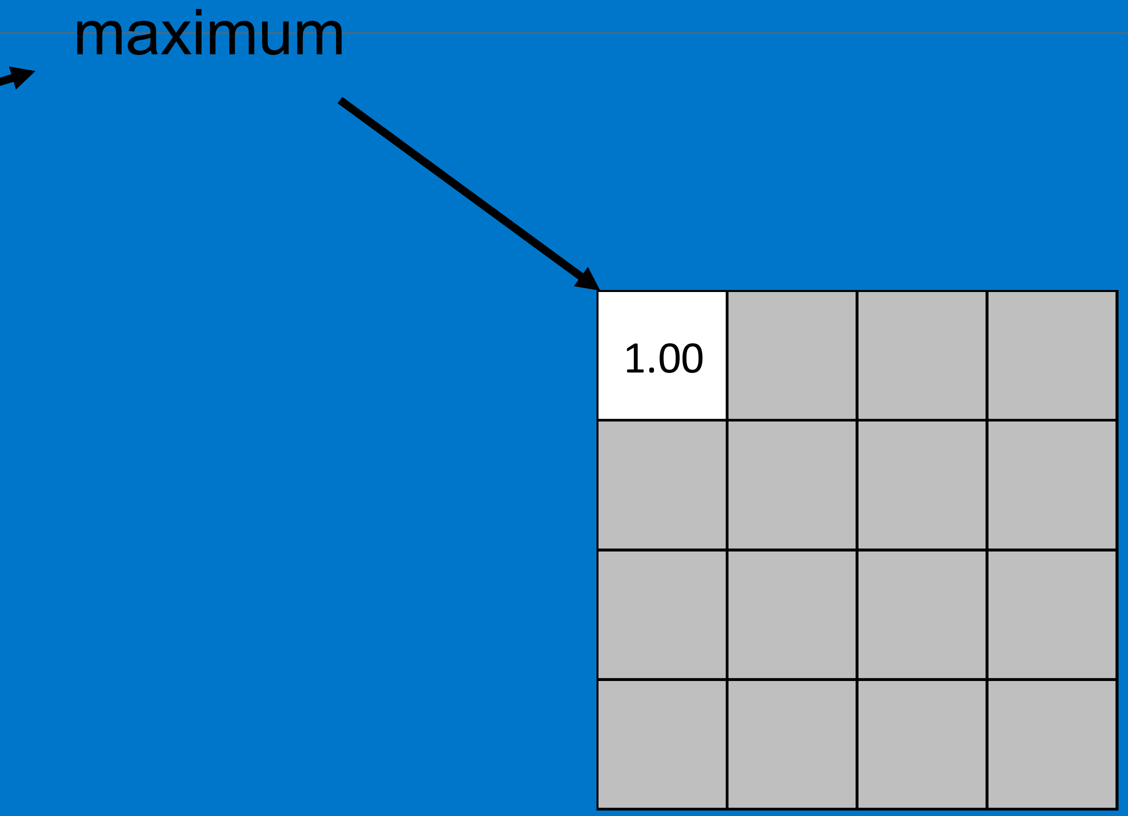
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.77	-0.11	0.11	0.33	0.55	-0.11	0.33

Pooling: Shrinking the image stack

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.

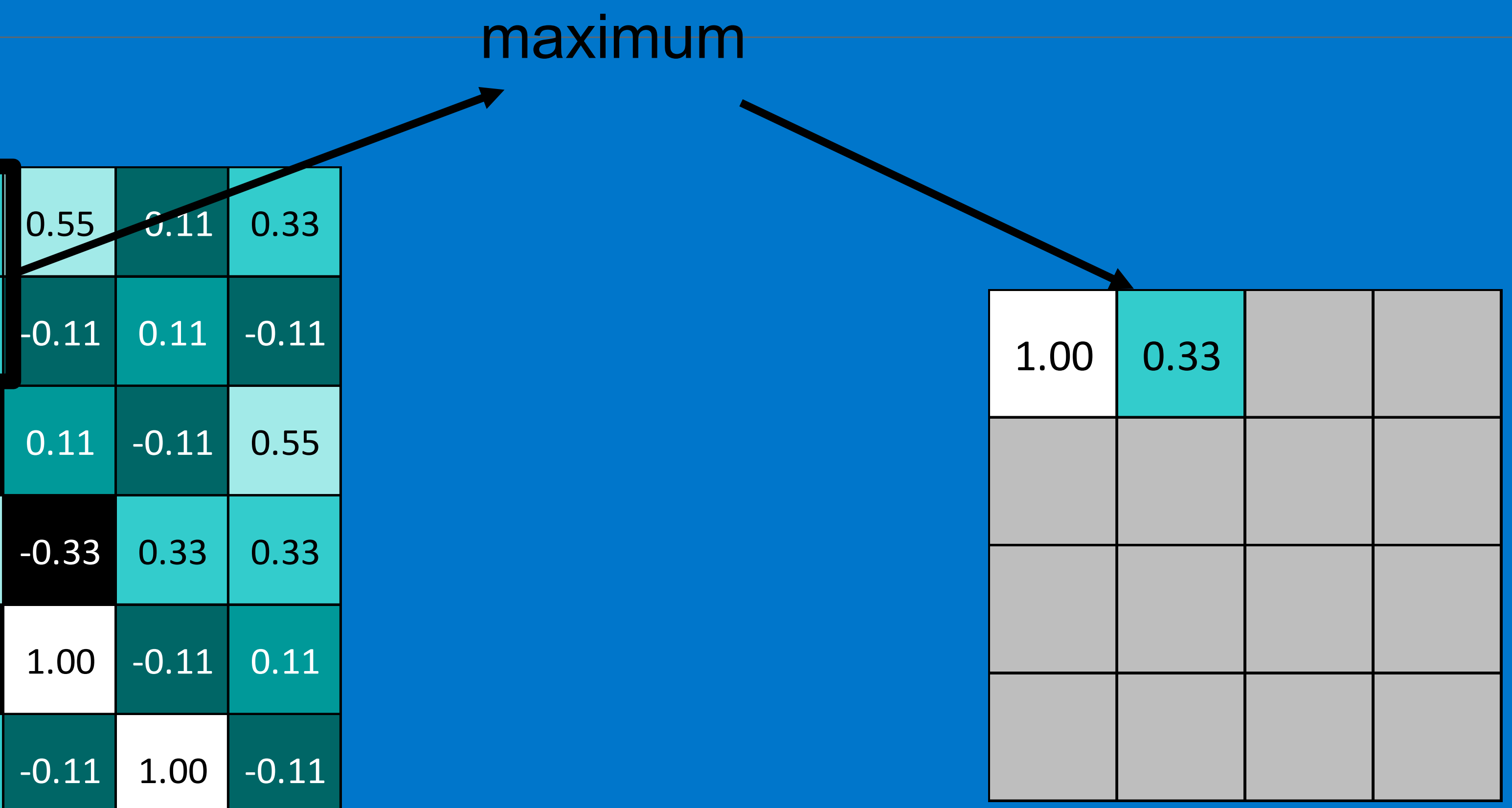
Pooling

0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77



Pooling

0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77



Pooling

0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

maximum

1.00	0.33	0.55	

Pooling

maximum

0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

1.00	0.33	0.55	0.33

Pooling

0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

maximum

1.00	0.33	0.55	0.33
0.33			

Pooling

0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

max pooling

1.00	0.33	0.55	0.33
0.33	1.00	0.33	0.55
0.55	0.33	1.00	0.11
0.33	0.55	0.11	0.77

0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

1.00	0.33	0.55	0.33
0.33	1.00	0.33	0.55
0.55	0.33	1.00	0.11
0.33	0.55	0.11	0.77

0.33	-0.55	0.11	-0.11	0.11	-0.55	0.33
-0.55	0.55	-0.55	0.33	-0.55	0.55	-0.55
0.11	-0.55	0.55	-0.77	0.55	-0.55	0.11
-0.11	0.33	-0.77	1.00	-0.77	0.33	-0.11
0.11	-0.55	0.55	-0.77	0.55	-0.55	0.11
-0.55	0.55	-0.55	0.33	-0.55	0.55	-0.55
0.33	-0.55	0.11	-0.11	0.11	-0.55	0.33

0.55	0.33	0.55	0.33
0.33	1.00	0.55	0.11
0.55	0.55	0.55	0.11
0.33	0.11	0.11	0.33

0.33	-0.11	0.55	0.33	0.11	-0.11	0.77
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.77	-0.11	0.11	0.33	0.55	-0.11	0.33

0.33	0.55	1.00	0.77
0.55	0.55	1.00	0.33
1.00	1.00	0.11	0.55
0.77	0.33	0.55	0.33

Pooling layer

A stack of images becomes a stack of smaller images.

0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

0.33	-0.55	0.11	-0.11	0.11	-0.55	0.33
-0.55	0.55	-0.55	0.33	-0.55	0.55	-0.55
0.11	-0.55	0.55	-0.77	0.55	-0.55	0.11
-0.11	0.33	-0.77	1.00	-0.77	0.33	-0.11
0.11	-0.55	0.55	-0.77	0.55	-0.55	0.11
-0.55	0.55	-0.55	0.33	-0.55	0.55	-0.55
0.33	-0.55	0.11	-0.11	0.11	-0.55	0.33

0.33	-0.11	0.55	0.33	0.11	-0.11	0.77
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.77	-0.11	0.11	0.33	0.55	-0.11	0.33

1.00	0.33	0.55	0.33
0.33	1.00	0.33	0.55
0.55	0.33	1.00	0.11
0.33	0.55	0.11	0.77

0.55	0.33	0.55	0.33
0.33	1.00	0.55	0.11
0.55	0.55	0.55	0.11
0.33	0.11	0.11	0.33

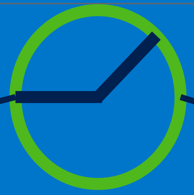
0.33	0.55	1.00	0.77
0.55	0.55	1.00	0.33
1.00	1.00	0.11	0.55
0.77	0.33	0.55	0.33

Normalization

Keep the math from breaking by tweaking each of the values just a bit.

Change everything negative to zero.

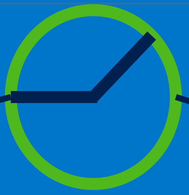
Rectified Linear Units (ReLUs)



0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

0.77						

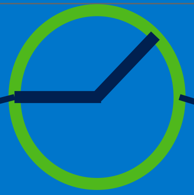
Rectified Linear Units (ReLUs)



0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

0.77	0					

Rectified Linear Units (ReLUs)

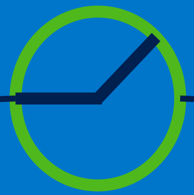


0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

0.77	0	0.11	0.33	0.55	0	0.33

Rectified Linear Units (ReLUs)

0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77



0.77	0	0.11	0.33	0.55	0	0.33
0	1.00	0	0.33	0	0.11	0
0.11	0	1.00	0	0.11	0	0.55
0.33	0.33	0	0.55	0	0.33	0.33
0.55	0	0.11	0	1.00	0	0.11
0	0.11	0	0.33	0	1.00	0
0.33	0	0.55	0.33	0.11	0	0.77

ReLU layer

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

0.77	-0.11	0.11	0.33	0.55	-0.11	0.33
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.33	-0.11	0.55	0.33	0.11	-0.11	0.77

0.33	-0.55	0.11	-0.11	0.11	-0.55	0.33
-0.55	0.55	-0.55	0.33	-0.55	0.55	-0.55
0.11	-0.55	0.55	-0.77	0.55	-0.55	0.11
-0.11	0.33	-0.77	1.00	-0.77	0.33	-0.11
0.11	-0.55	0.55	-0.77	0.55	-0.55	0.11
-0.55	0.55	-0.55	0.33	-0.55	0.55	-0.55
0.33	-0.55	0.11	-0.11	0.11	-0.55	0.33

0.33	-0.11	0.55	0.33	0.11	-0.11	0.77
-0.11	0.11	-0.11	0.33	-0.11	1.00	-0.11
0.55	-0.11	0.11	-0.33	1.00	-0.11	0.11
0.33	0.33	-0.33	0.55	-0.33	0.33	0.33
0.11	-0.11	1.00	-0.33	0.11	-0.11	0.55
-0.11	1.00	-0.11	0.33	-0.11	0.11	-0.11
0.77	-0.11	0.11	0.33	0.55	-0.11	0.33

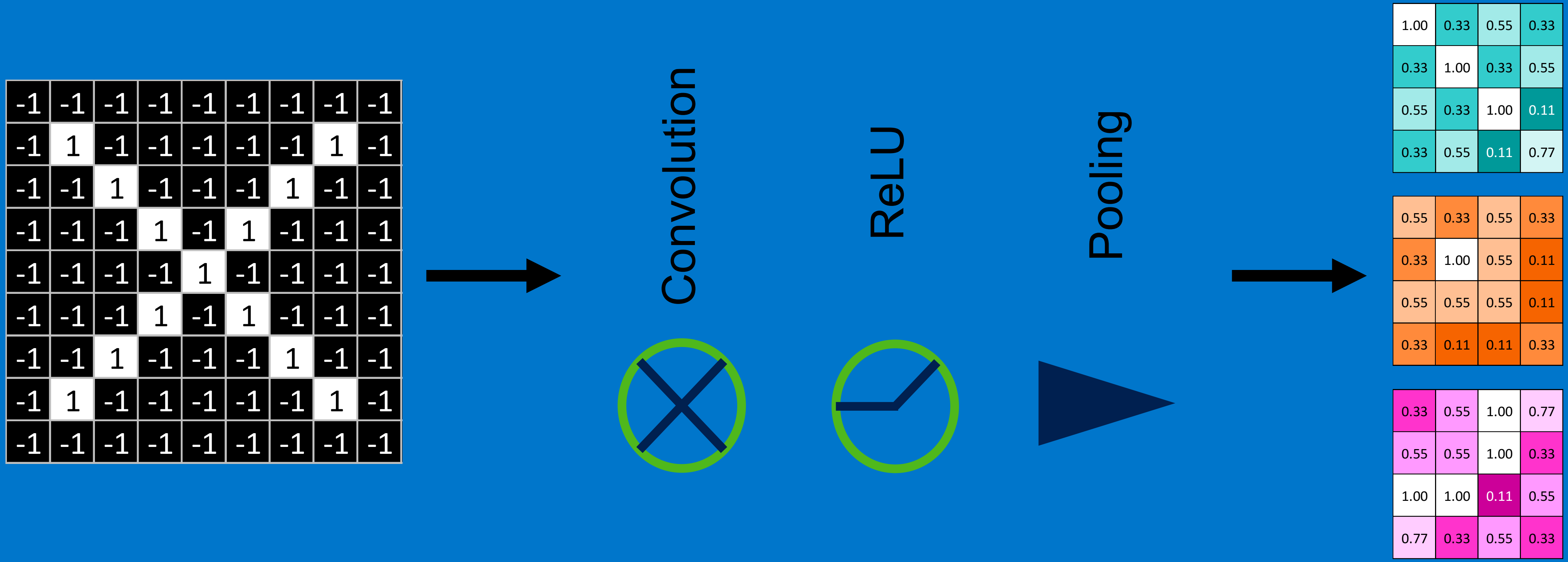
0.77	0	0.11	0.33	0.55	0	0.33
0	1.00	0	0.33	0	0.11	0
0.11	0	1.00	0	0.11	0	0.55
0.33	0.33	0	0.55	0	0.33	0.33
0.55	0	0.11	0	1.00	0	0.11
0	0.11	0	0.33	0	1.00	0
0.33	0	0.55	0.33	0.11	0	0.77

0.33	0	0.11	0	0.11	0	0.33
0	0.55	0	0.33	0	0.55	0
0.11	0	0.55	0	0.55	0	0.11
0	0.33	0	1.00	0	0.33	0
0.11	0	0.55	0	0.55	0	0.11
0	0.55	0	0.33	0	0.55	0
0.33	0	0.11	0	0.11	0	0.33

0.33	0	0.55	0.33	0.11	0	0.77
0	0.11	0	0.33	0	1.00	0
0.55	0	0.11	0	1.00	0	0.11
0.33	0.33	0	0.55	0	0.33	0.33
0.11	0	1.00	0	0.11	0	0.55
0	1.00	0	0.33	0	0.11	0
0.77	0	0.11	0.33	0.55	0	0.33

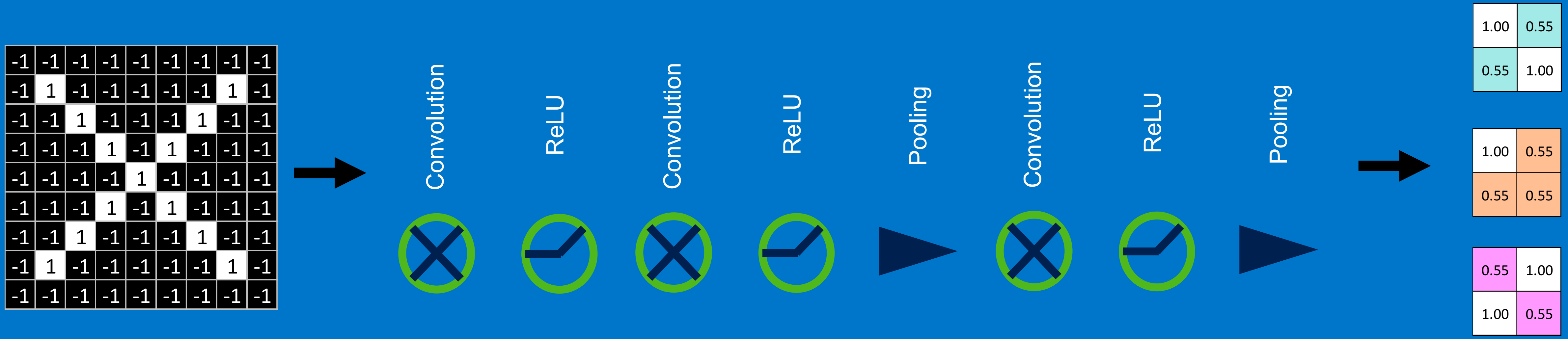
Layers get stacked

The output of one becomes the input of the next.



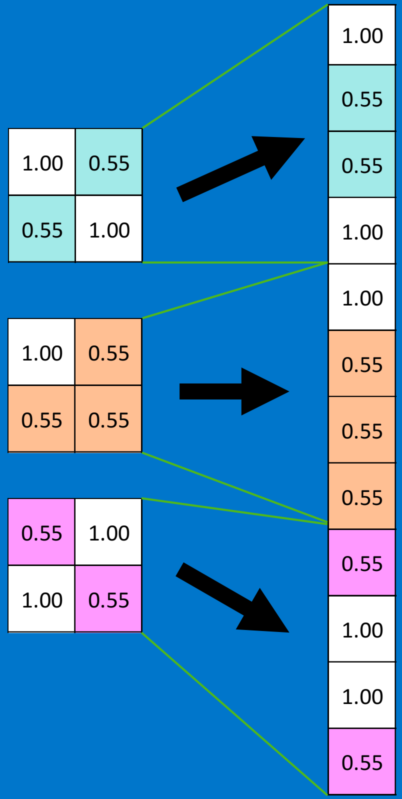
Deep stacking

Layers can be repeated several (or many) times.



Fully connected layer

Every value gets a vote

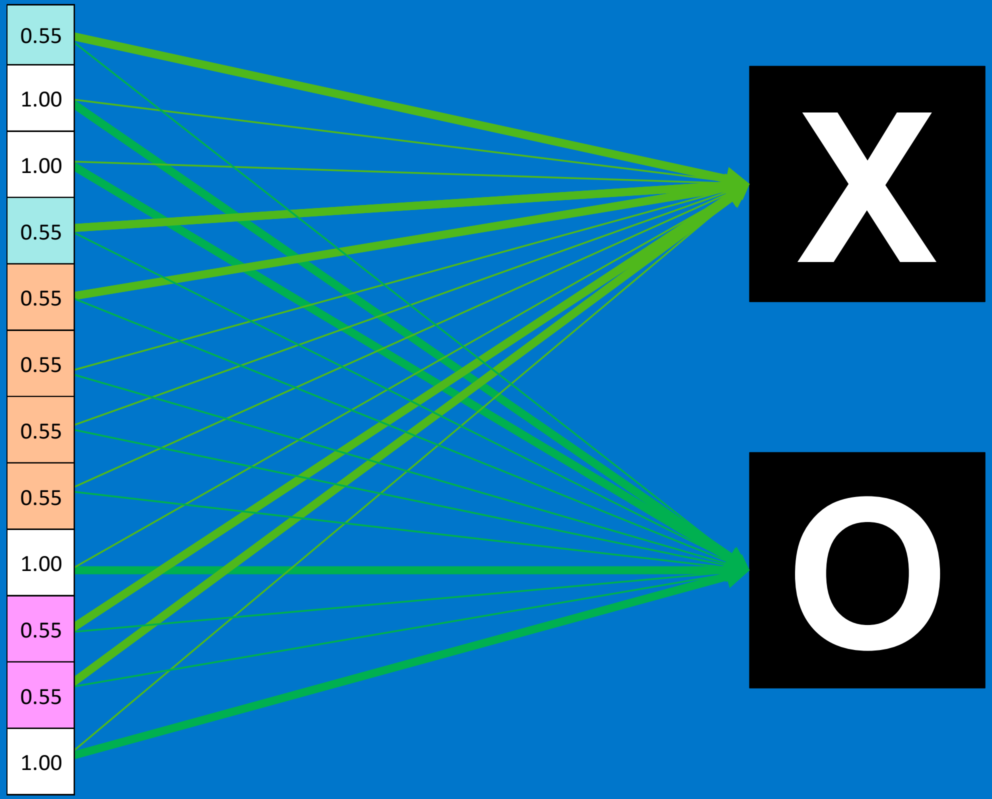


Fully connected layer

Vote depends on how strongly a value predicts X or O

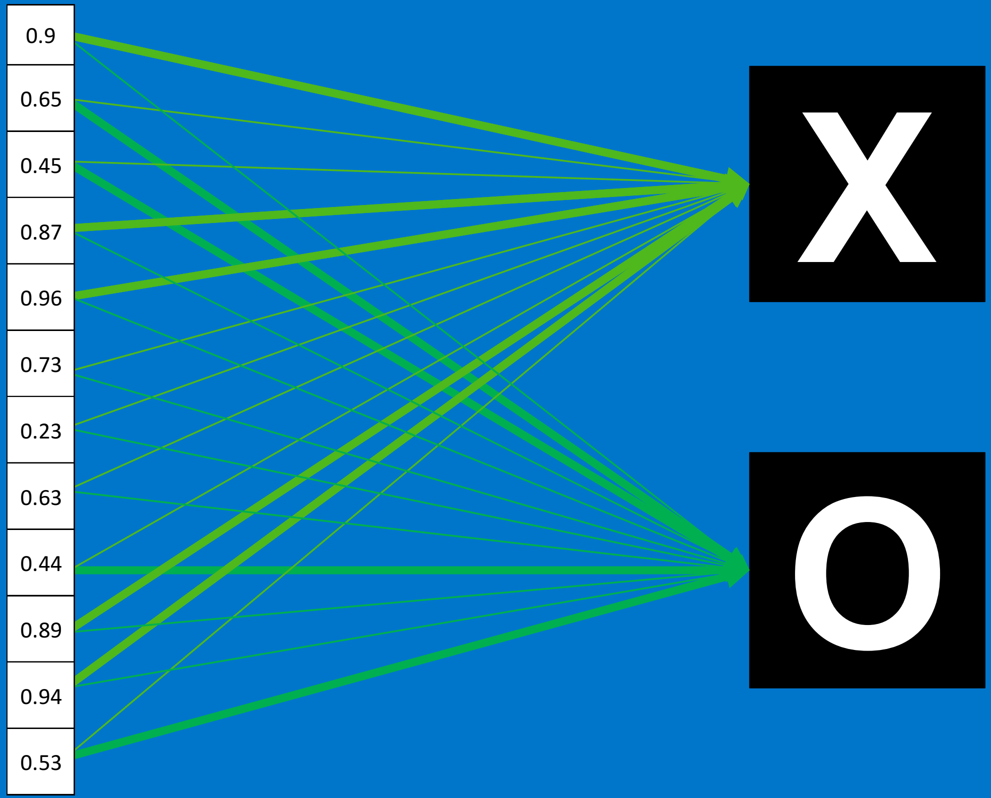
Fully connected layer

Vote depends on how strongly a value predicts X or O



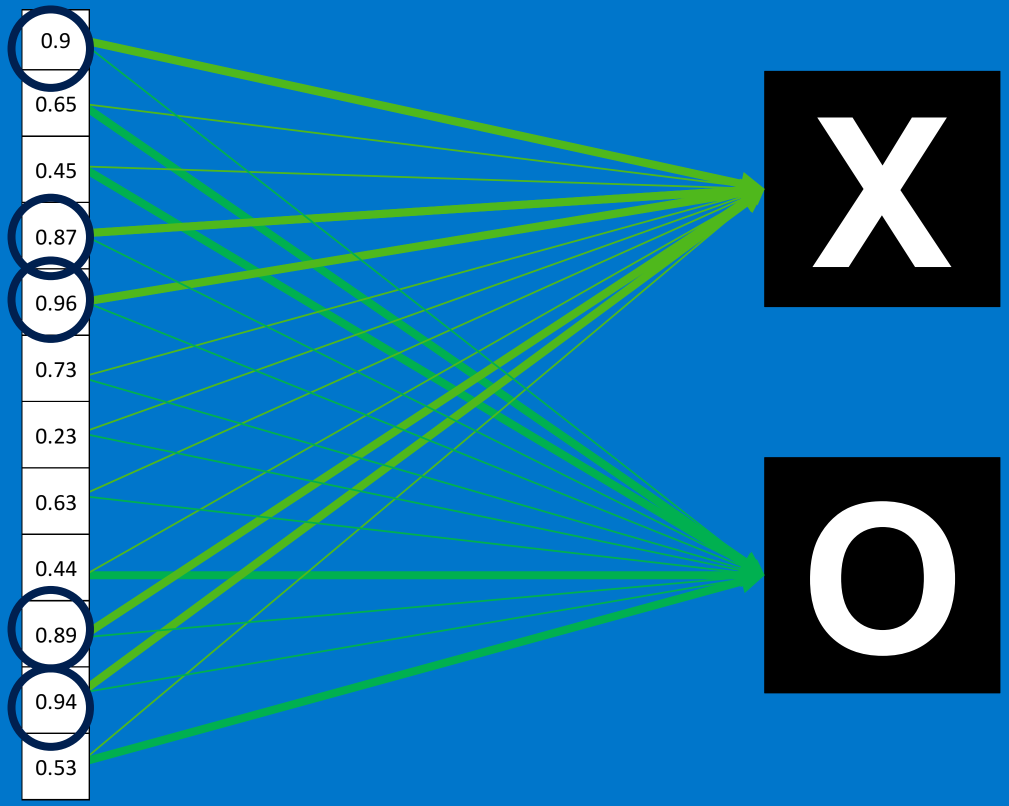
Fully connected layer

Future values vote on X or O



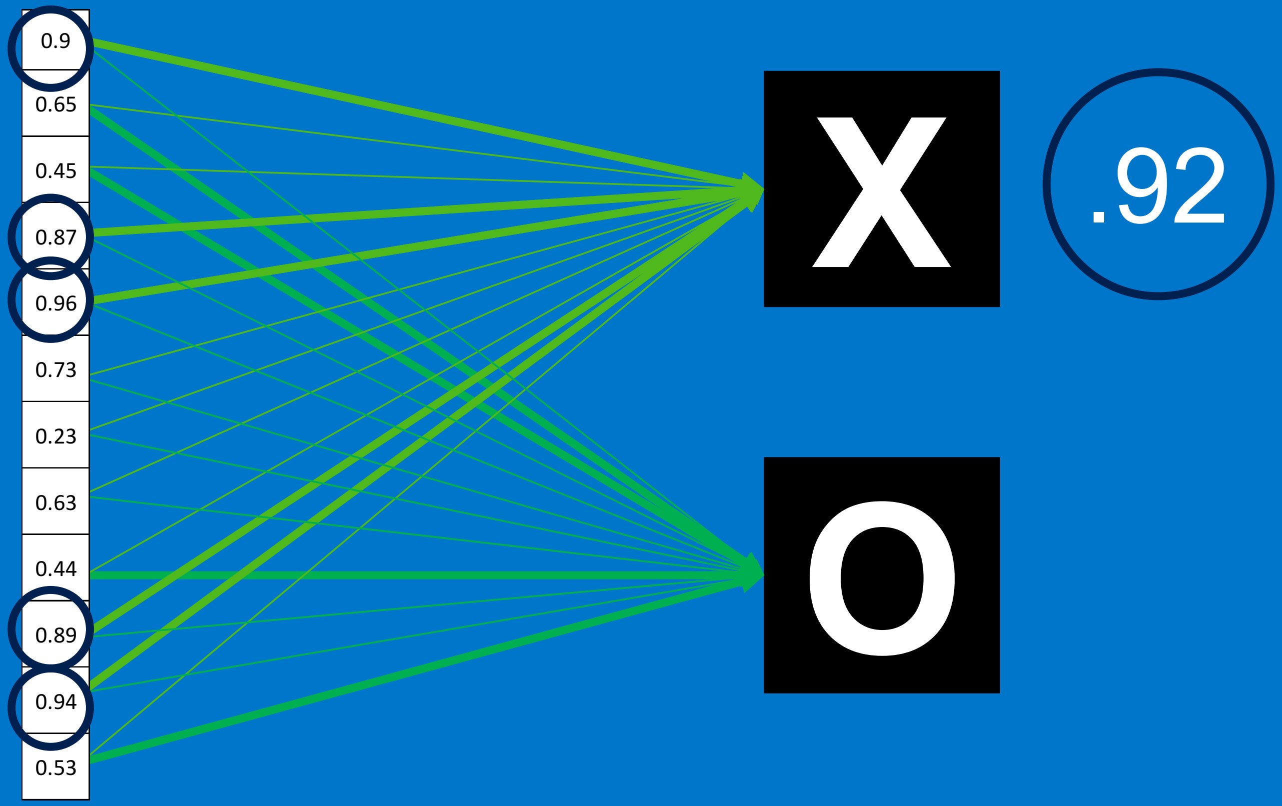
Fully connected layer

Future values vote on X or O



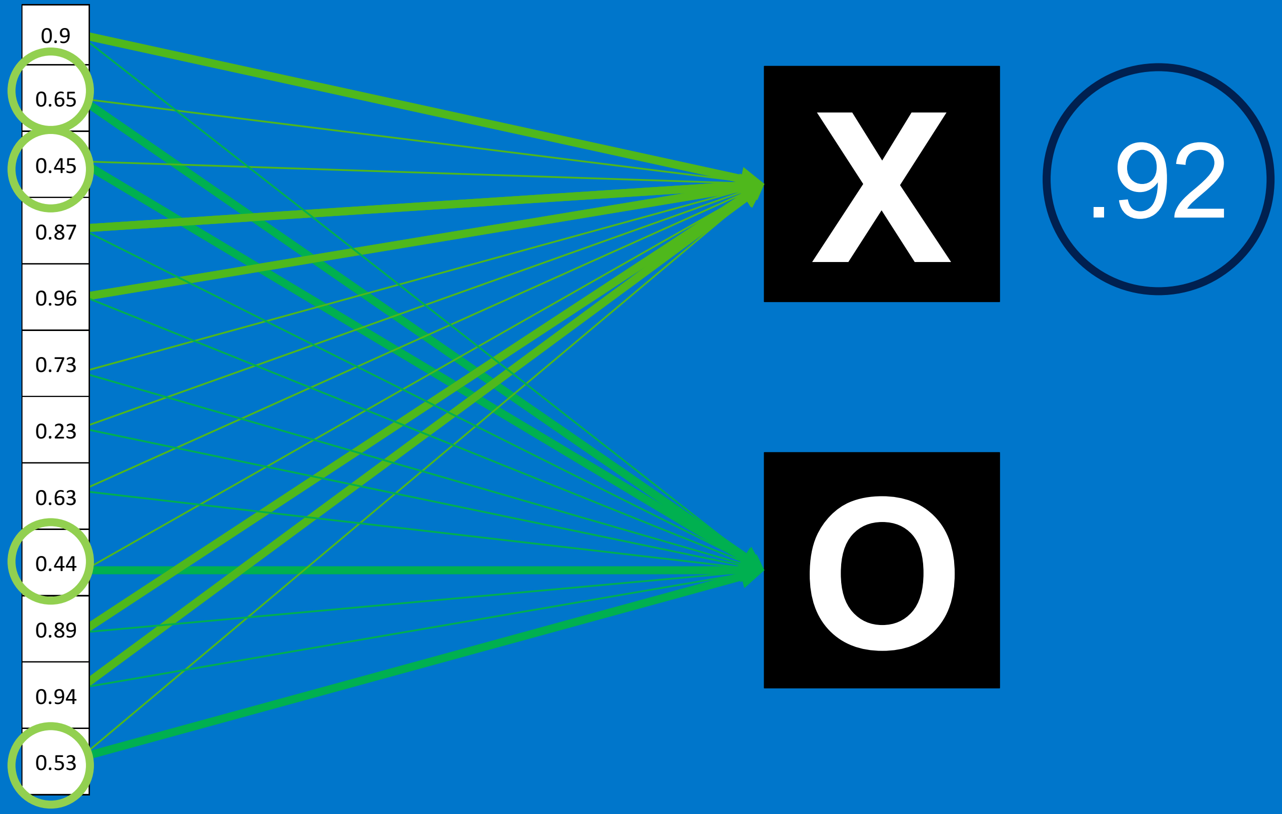
Fully connected layer

Future values vote on X or O



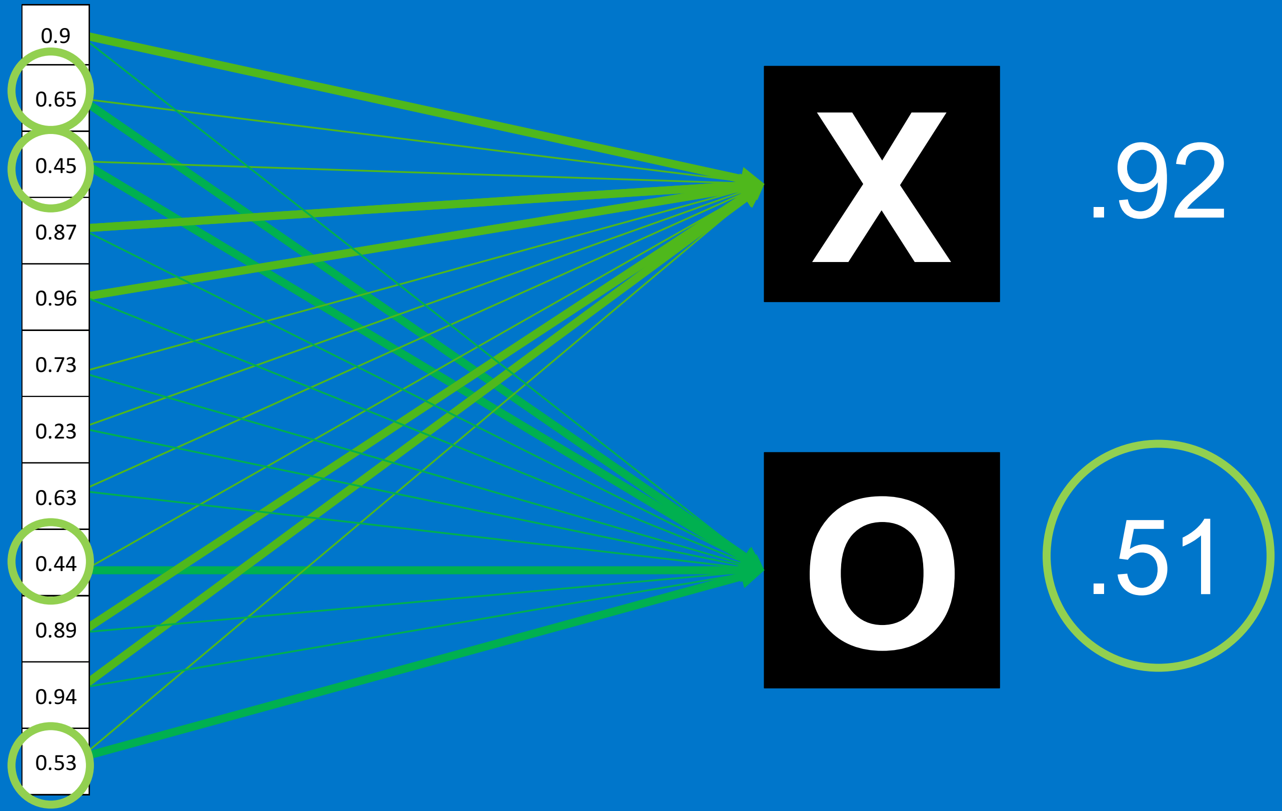
Fully connected layer

Future values vote on X or O



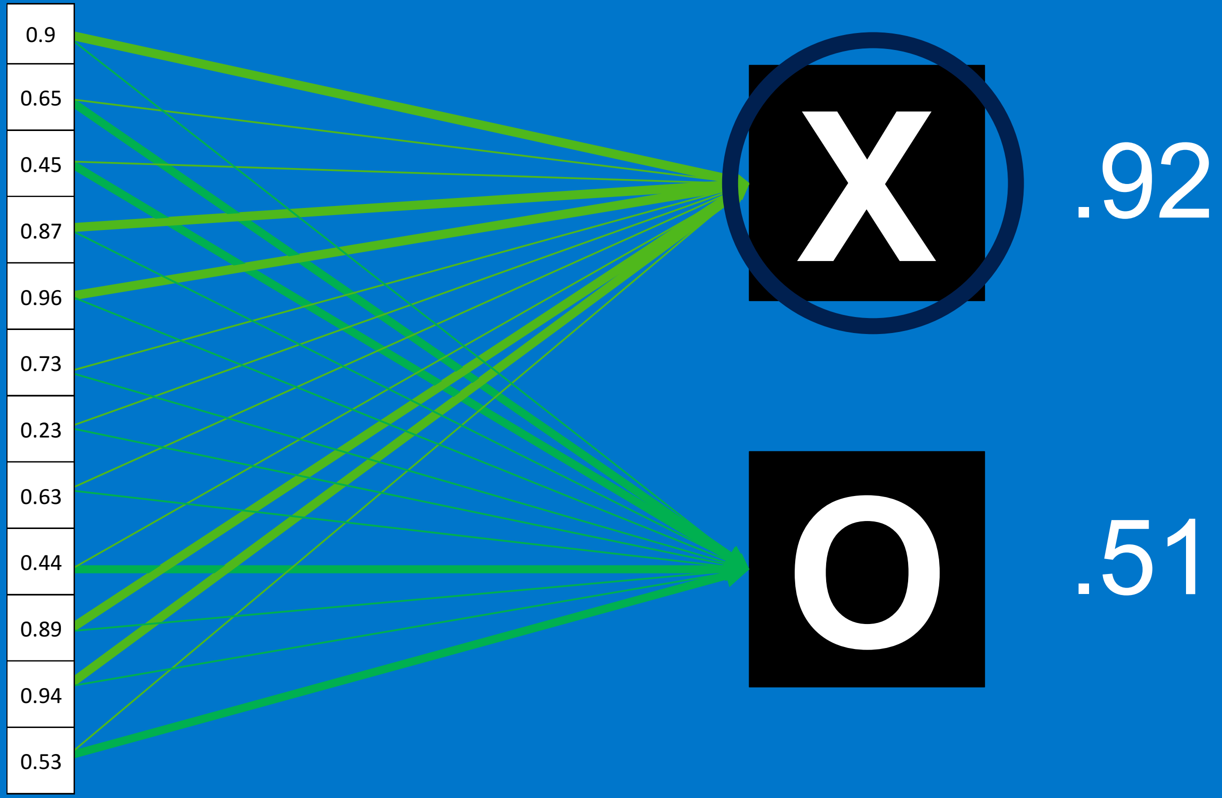
Fully connected layer

Future values vote on X or O



Fully connected layer

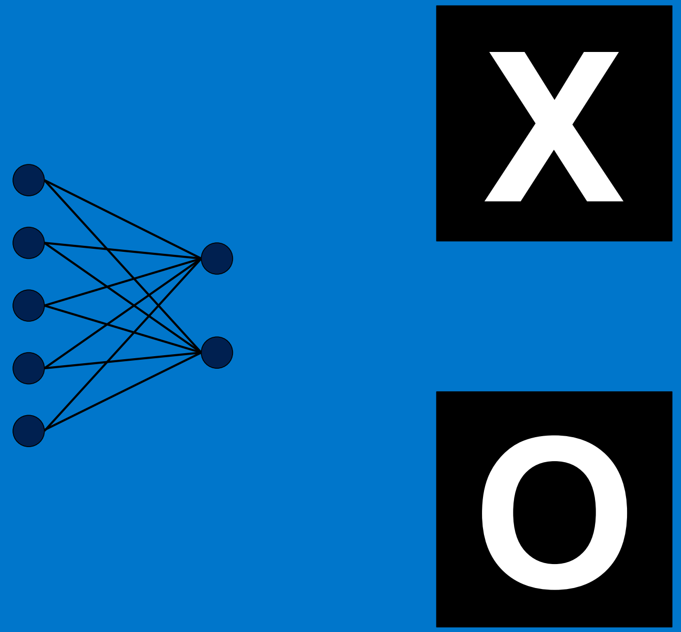
Future values vote on X or O



Fully connected layer

A list of feature values becomes a list of votes.

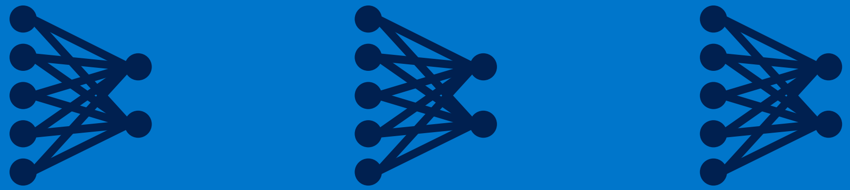
0.9
0.65
0.45
0.87
0.96
0.73
0.23
0.63
0.44
0.89
0.94
0.53



Fully connected layer

These can also be stacked.

0.9
0.65
0.45
0.87
0.96
0.73
0.23
0.63
0.44
0.89
0.94
0.53

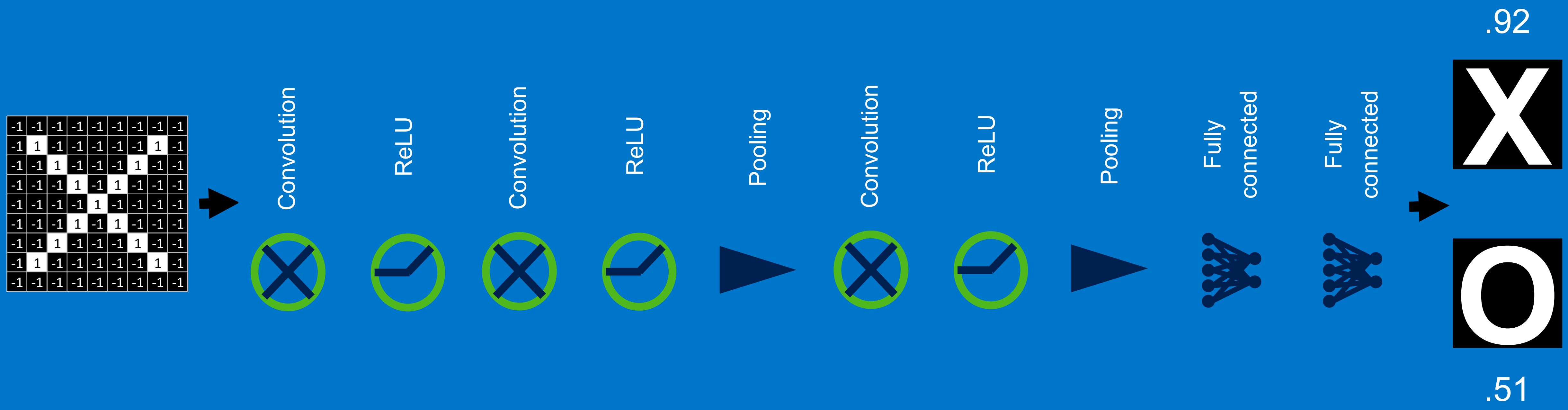


X

O

Putting it all together

A set of pixels becomes a set of votes.



Learning

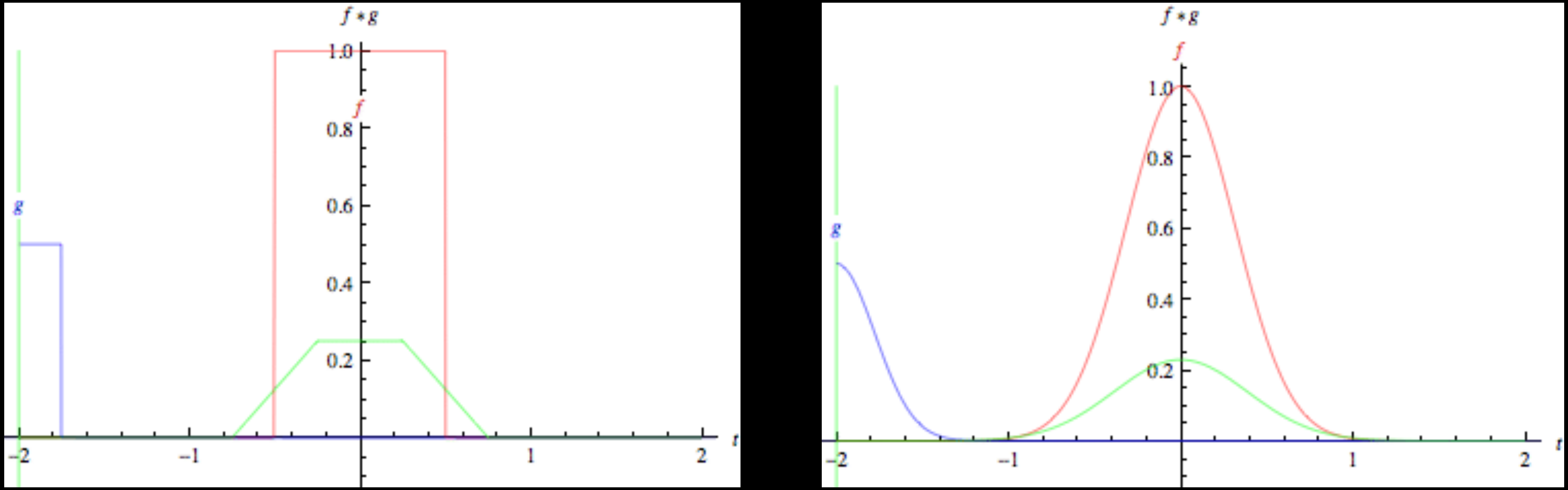
Q: Where do all the magic numbers come from?

- **Features in convolutional layers**
- **Voting weights in fully connected layers**

A: Backpropagation ！ ！ ！

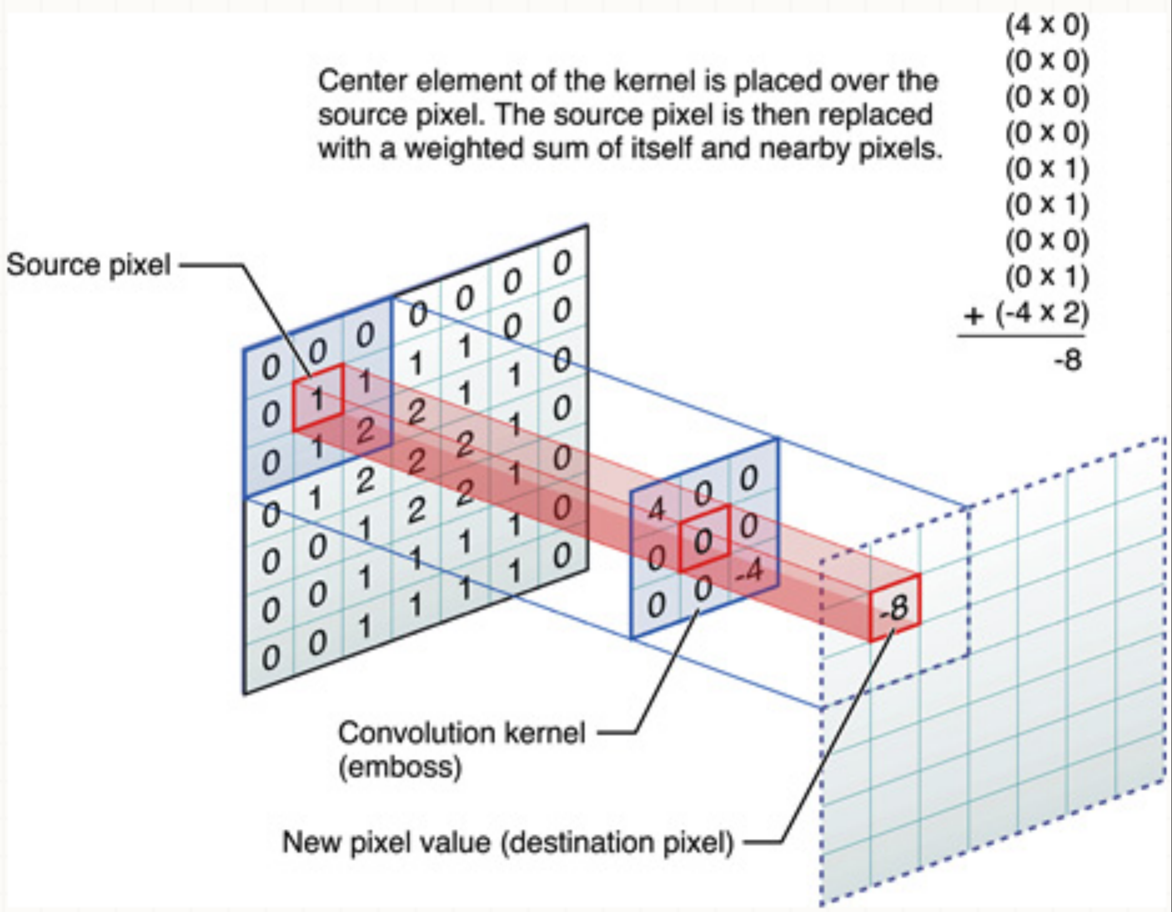
Convolution

$$f \otimes g = \int_{-\infty}^{\infty} f(\tau) g(t-\tau) d\tau$$

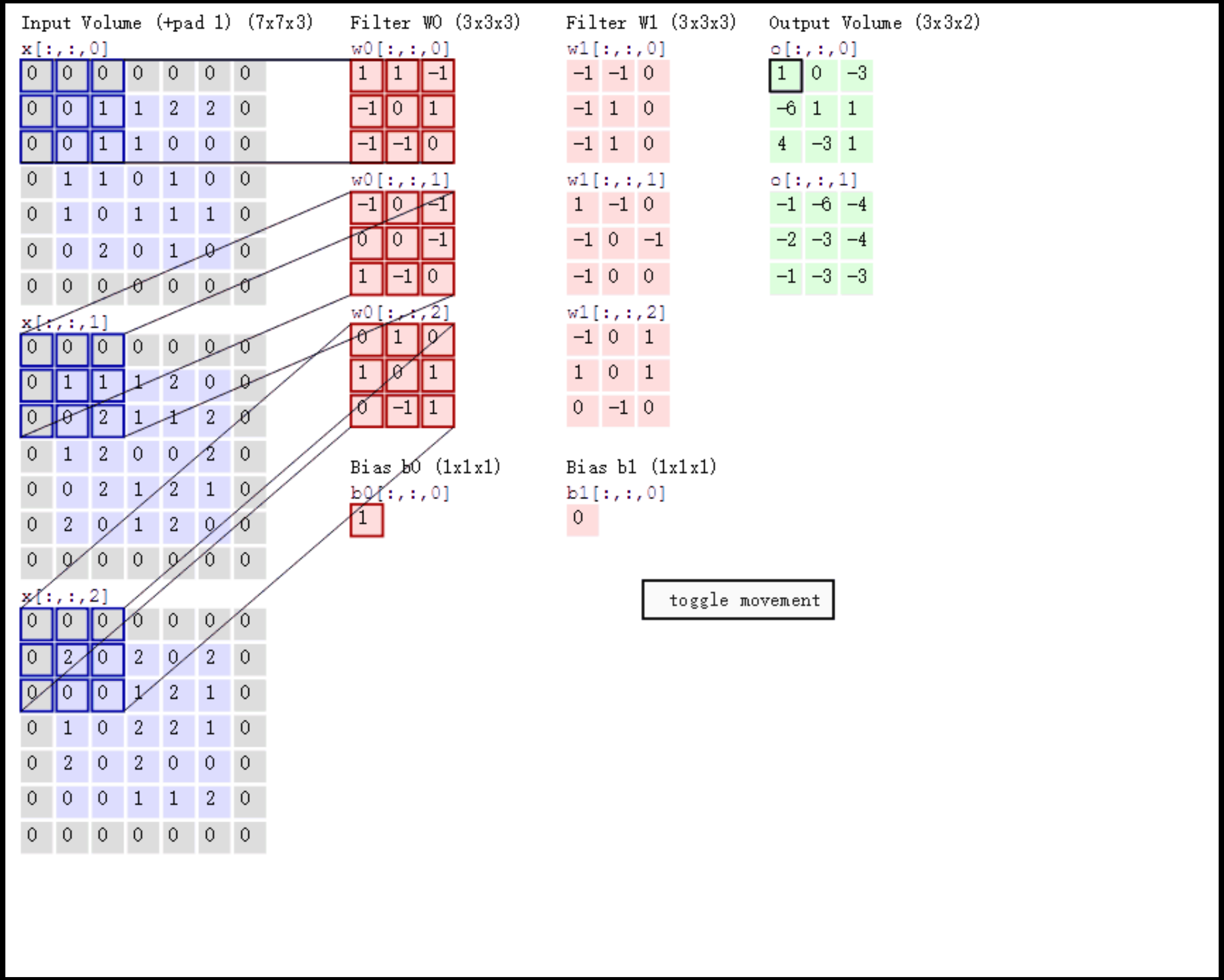


Mathworld. "The green curve shows the convolution of the blue and red curves as a function of t, the position indicated by the vertical green line. The gray region indicates the product g(tau)f(t-tau) as a function of t, so its area as a function of t is precisely the convolution."

CNN 是在空间上权值共享的网络

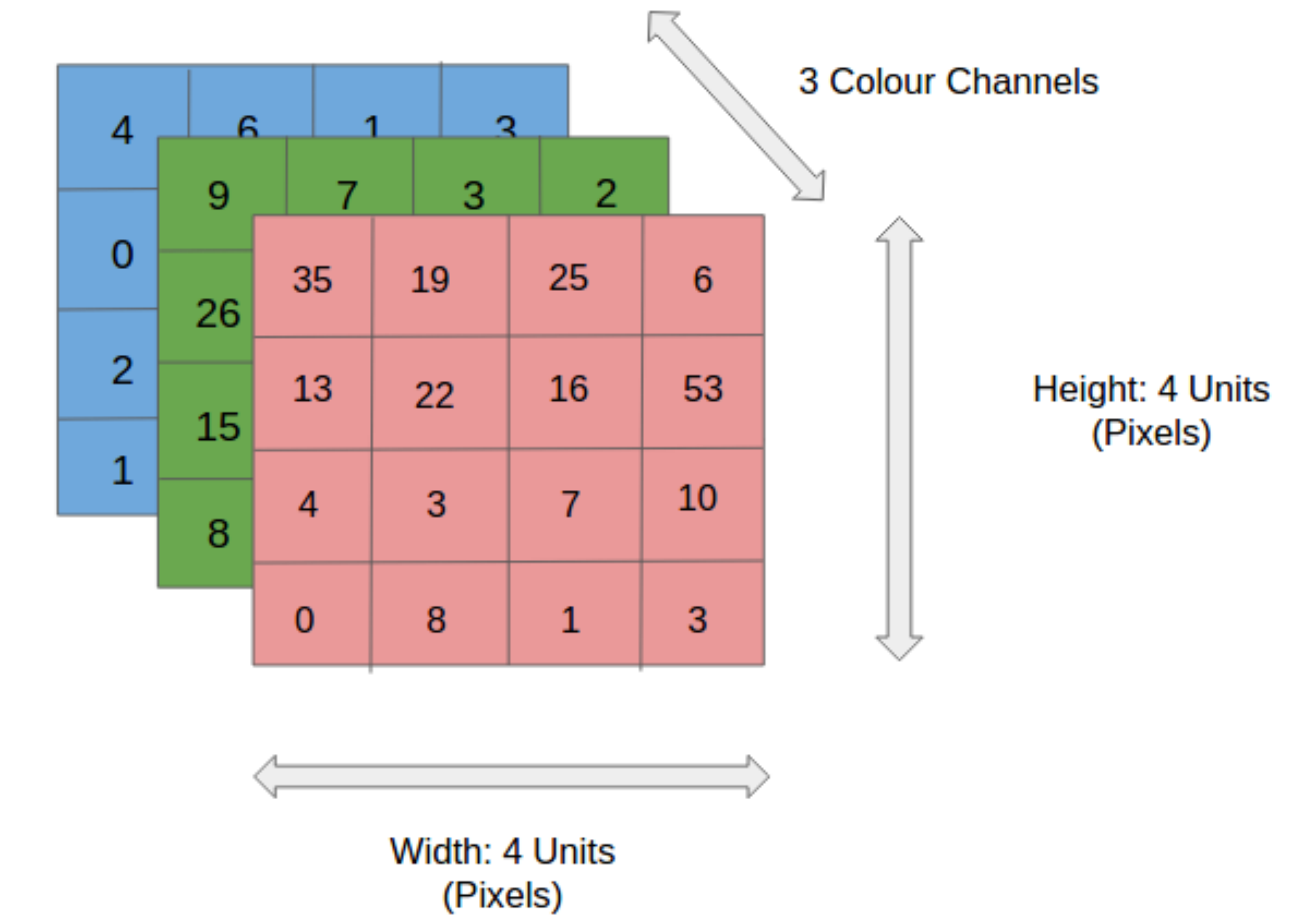


Convolution Filter 滤波器



Andrej Karpathy

Color Channels

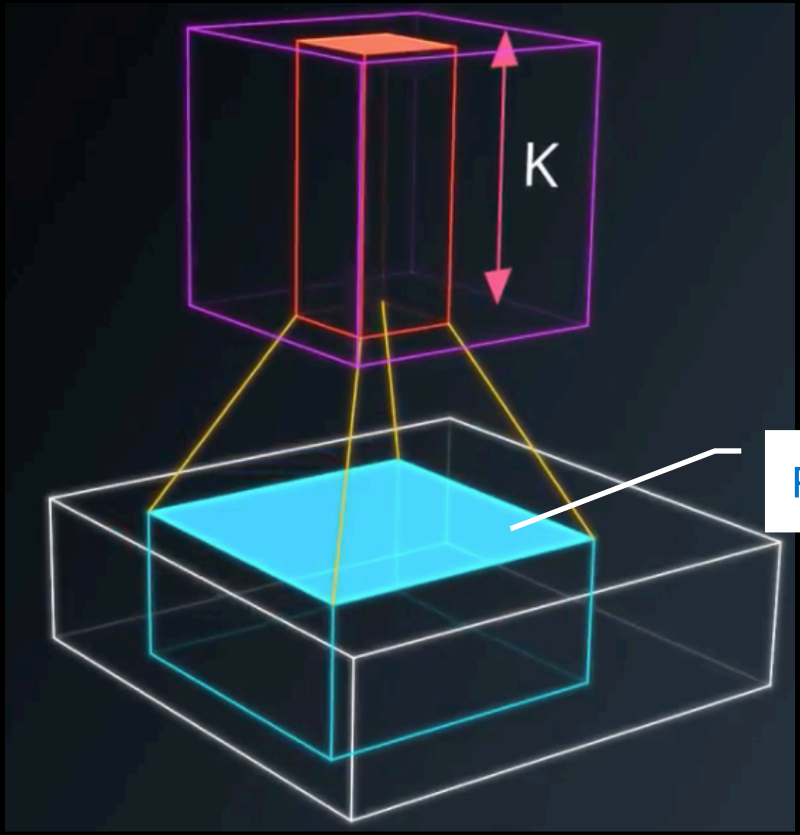


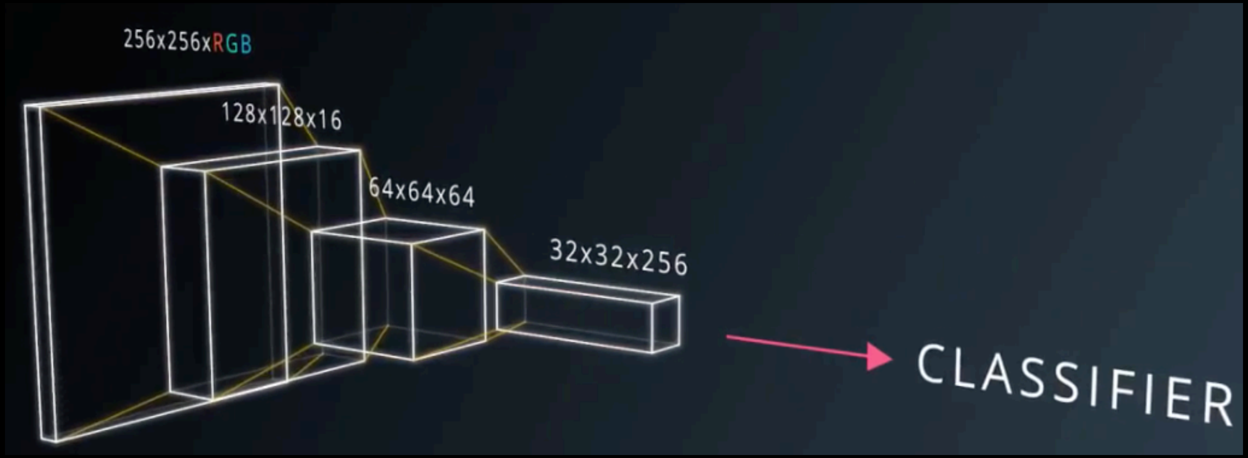
http://xrds.acm.org/blog/wp-content/uploads/2016/06/Figure1.png

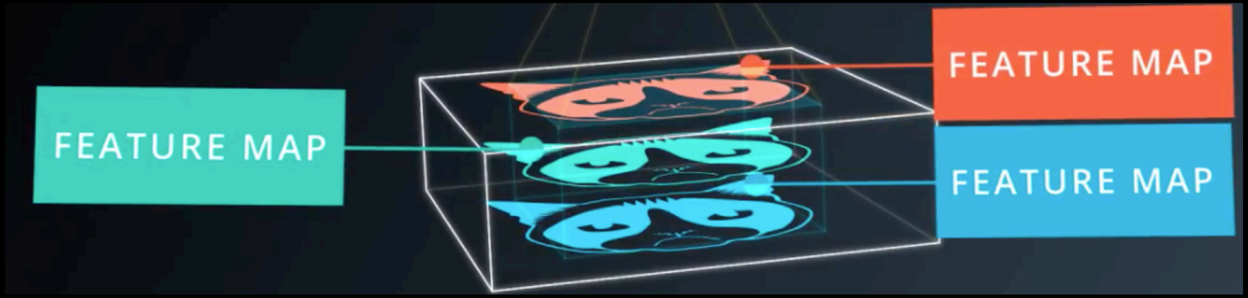
RGB输入图像

Udacity

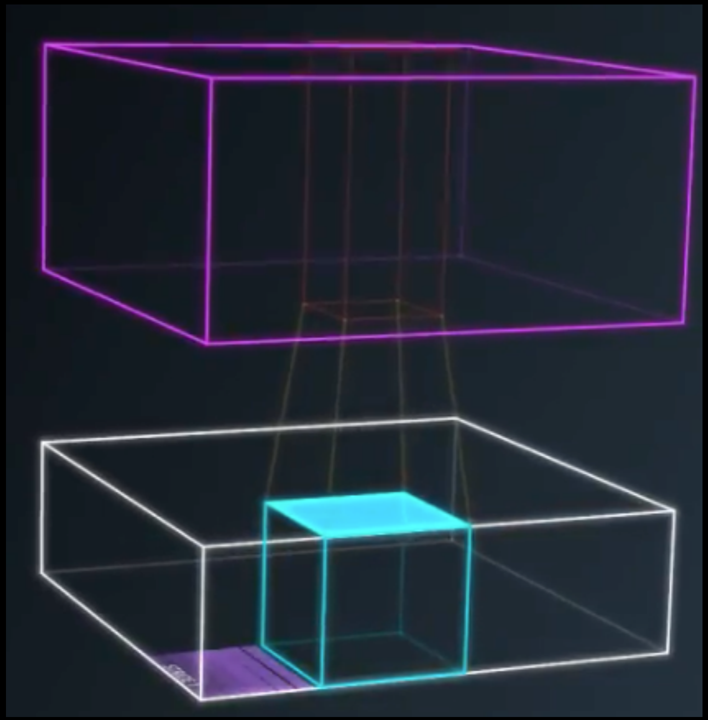
CNN架构与术语


K
Patch / Kernel

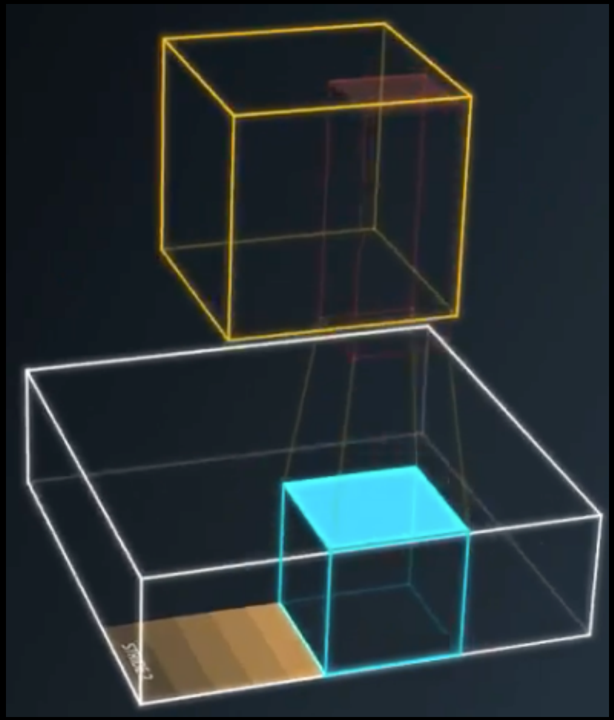

256x256xRGB
128x128x16
64x64x64
32x32x256
CLASSIFIER


FEATURE MAP
FEATURE MAP
FEATURE MAP

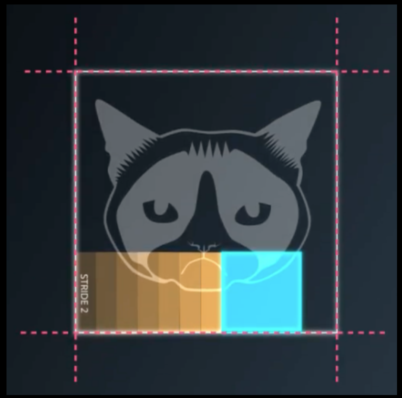
Stride & Padding



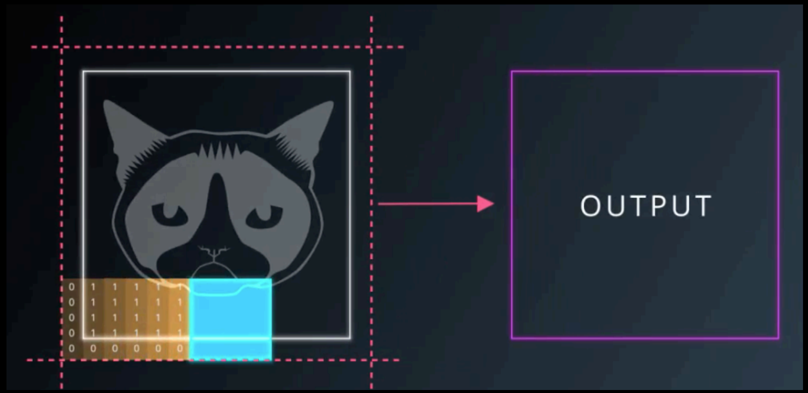
Stride = 1



Stride = 2



Valid Padding



Same Padding

CNN参数计算

Same Padding

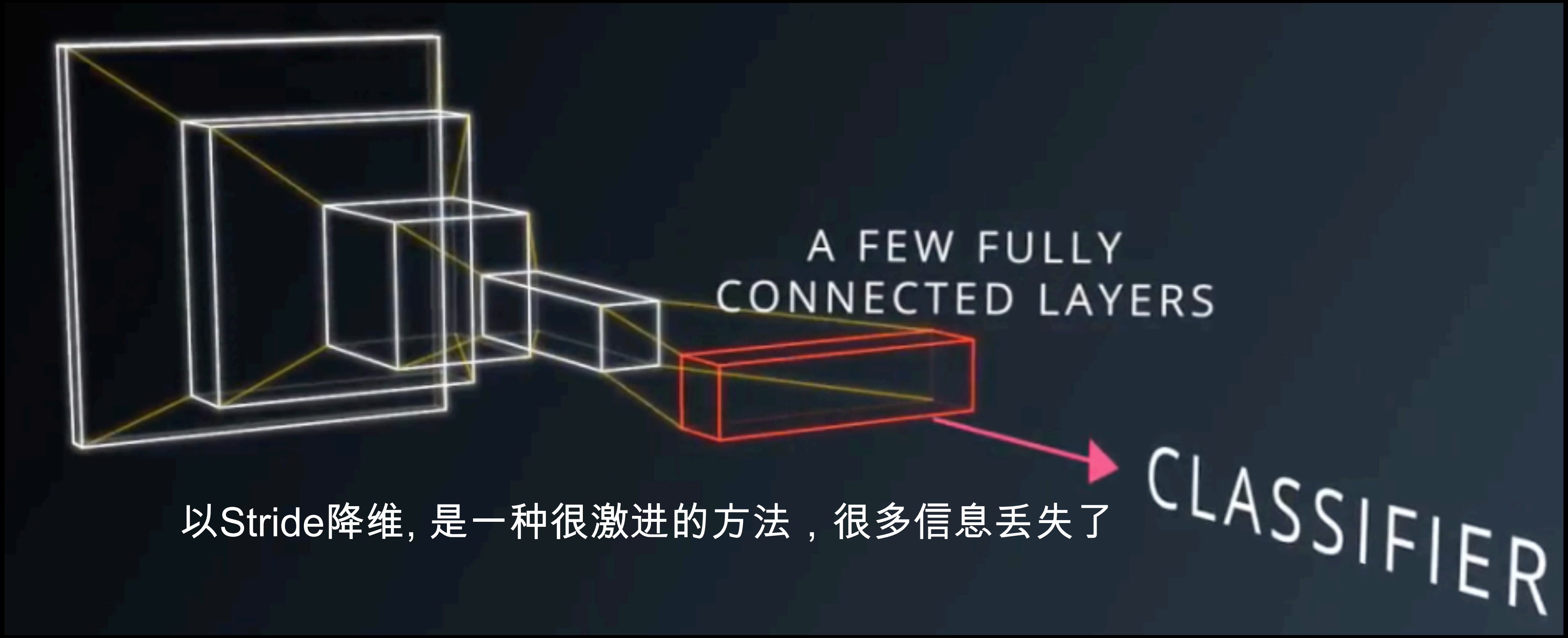
CNN参数计算

输入层：Width / Height：W / H
卷积层： 滤波器 F×F
Stride：S
Padding: P
Filter depth: K

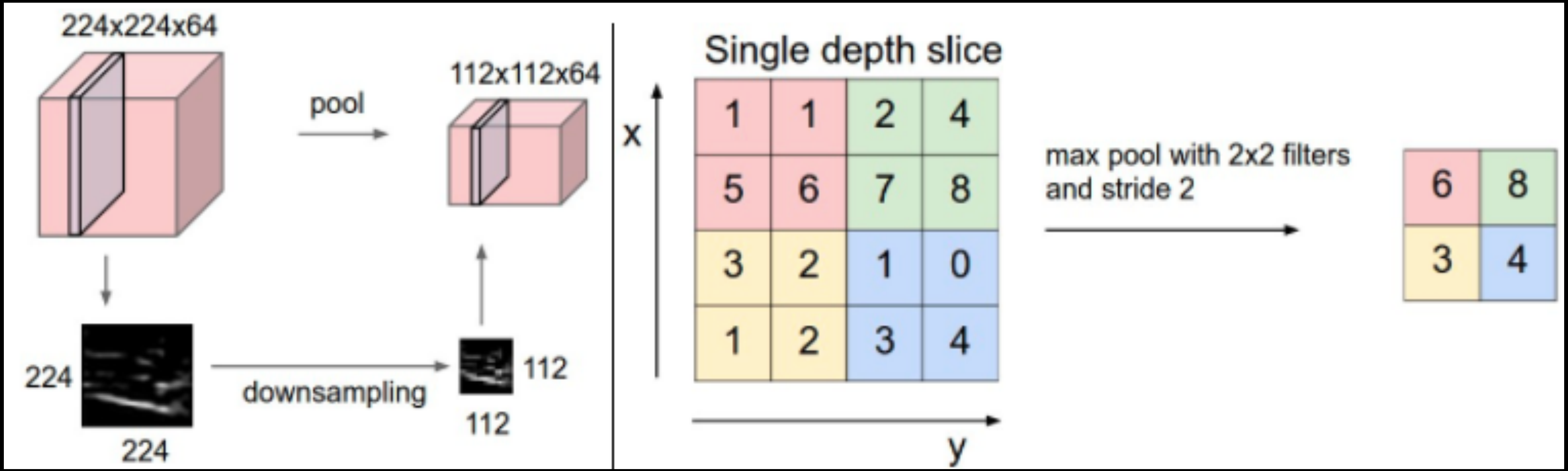
输出层:
Width: $W\_out = (W-F+2P)/S+1$
Height: $H\_out = (H-F+2P)/S + 1$
Depth: $D\_out = K$
Output volume: $V\_out = W\_out * H\_out * D\_out$

Same Padding

无池化层的CNN


A FEW FULLY
CONNECTED LAYERS
CLASSIFIER
以Stride降维，是一种很激进的方法，很多信息丢失了

Max Pooling & Down Sampling



1	1	2	4
5	6	7	8
3	2	1	0
1	2	3	4

6	8
3	4

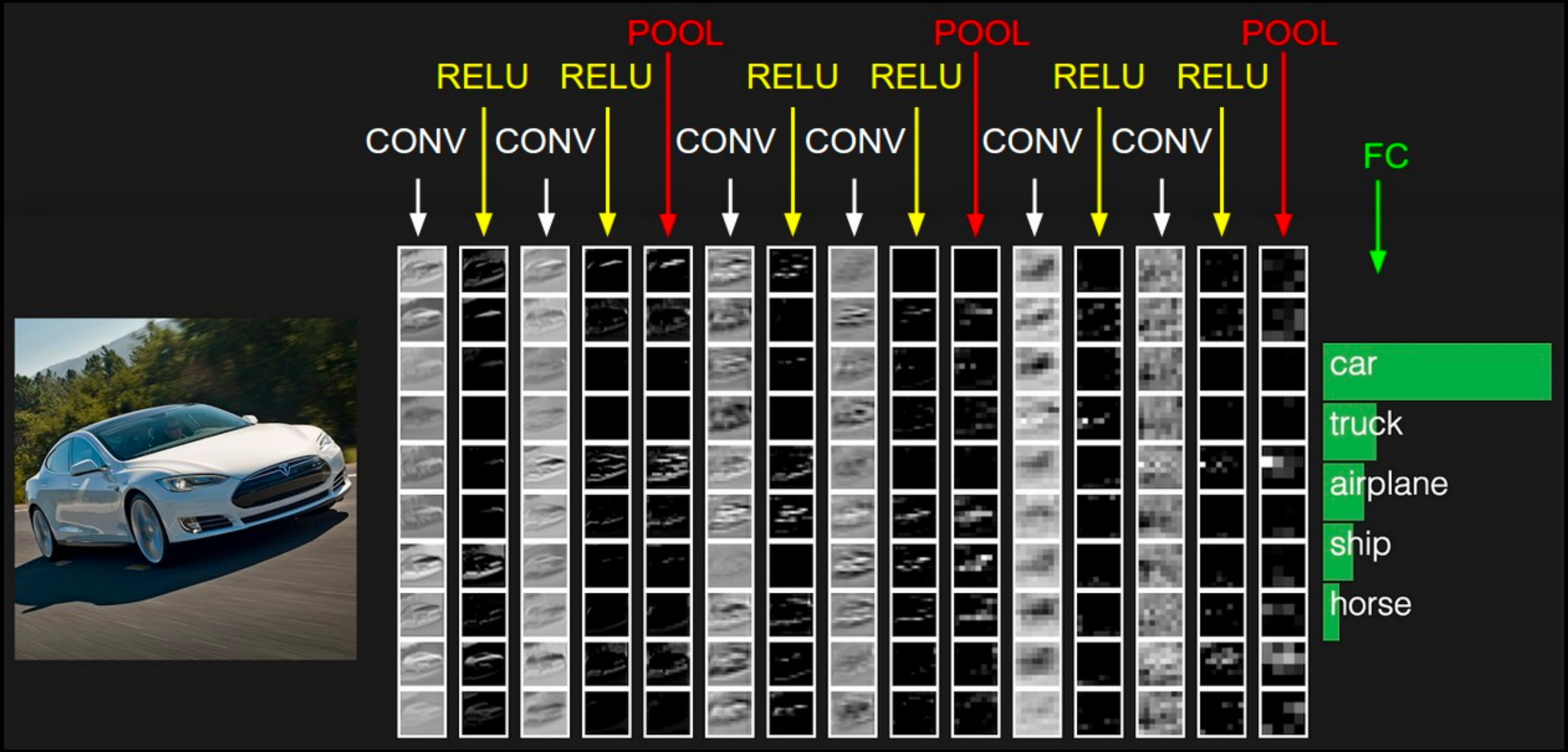
Pooling layer downsamples the volume spatially, independently in each depth slice of the input volume. **Left:** In this example, the input volume of size [224x224x64] is pooled with filter size 2, stride 2 into output volume of size [112x112x64]. Notice that the volume depth is preserved. **Right:** The most common downsampling operation is max, giving rise to **max pooling**, here shown with a stride of 2. That is, each max is taken over 4 numbers (little 2x2 square).

Andrej Karpathy

- 减少输出的大小
- 防止过拟合（参数减少了）

$$W \times H \times D \rightarrow \left(\frac{W-F}{S}+1\right) \times \left(\frac{H-F}{S}+1\right) \times D$$

Overview of CNN

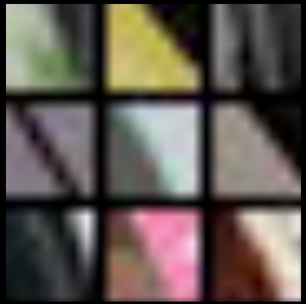


Andrej Karpathy

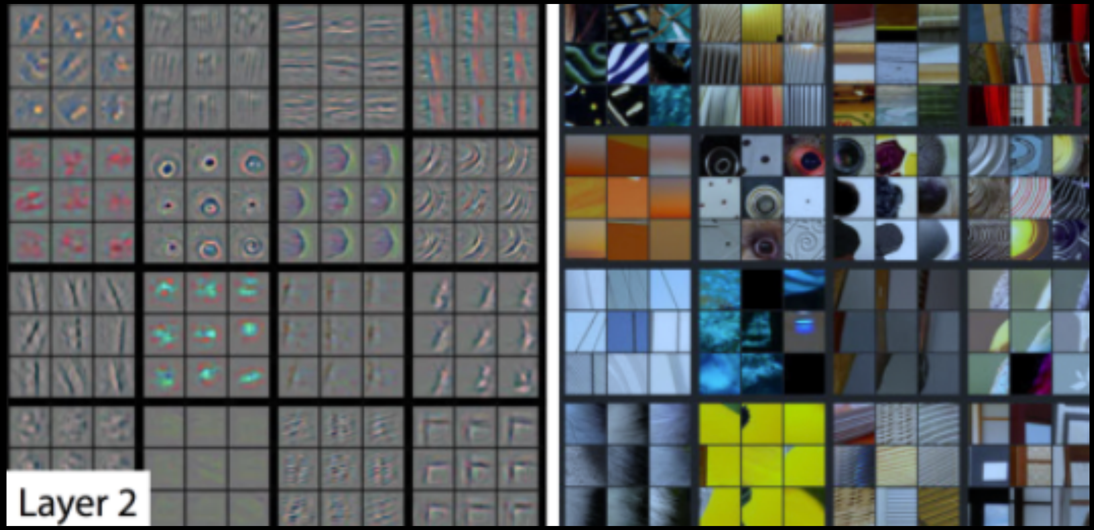
The activations of an example ConvNet architecture. The initial volume stores the raw image pixels (left) and the last volume stores the class scores (right). Each volume of activations along the processing path is shown as a column. Since it's difficult to visualize 3D volumes, we lay out each volume's slices in rows. The last layer volume holds the scores for each class, but here we only visualize the sorted top 5 scores, and print the labels of each one.

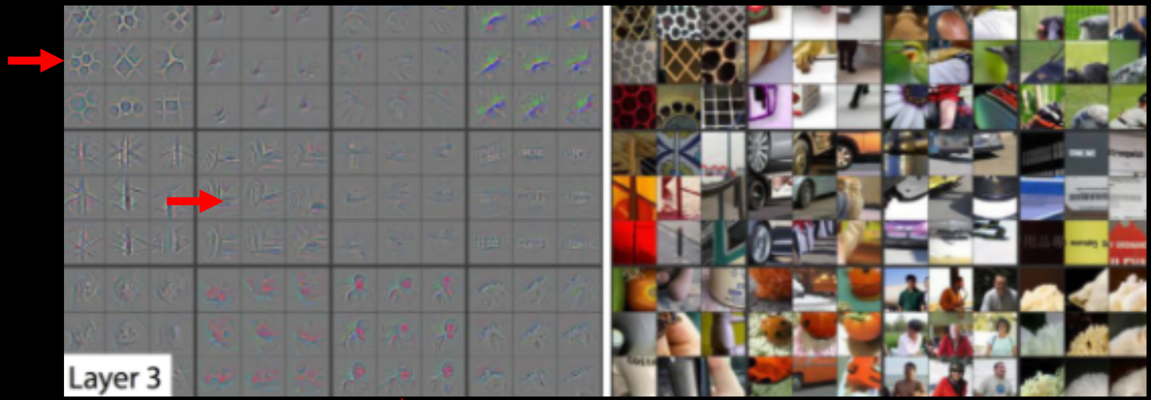
Visualizing ConvNet (ImageNet)

Layer 1

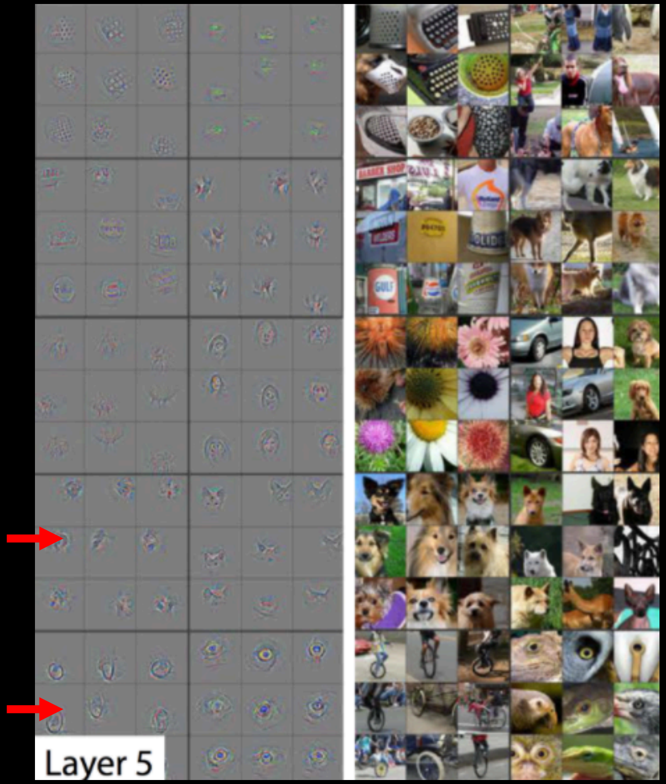


Example Patches activated the -45 degree line detector



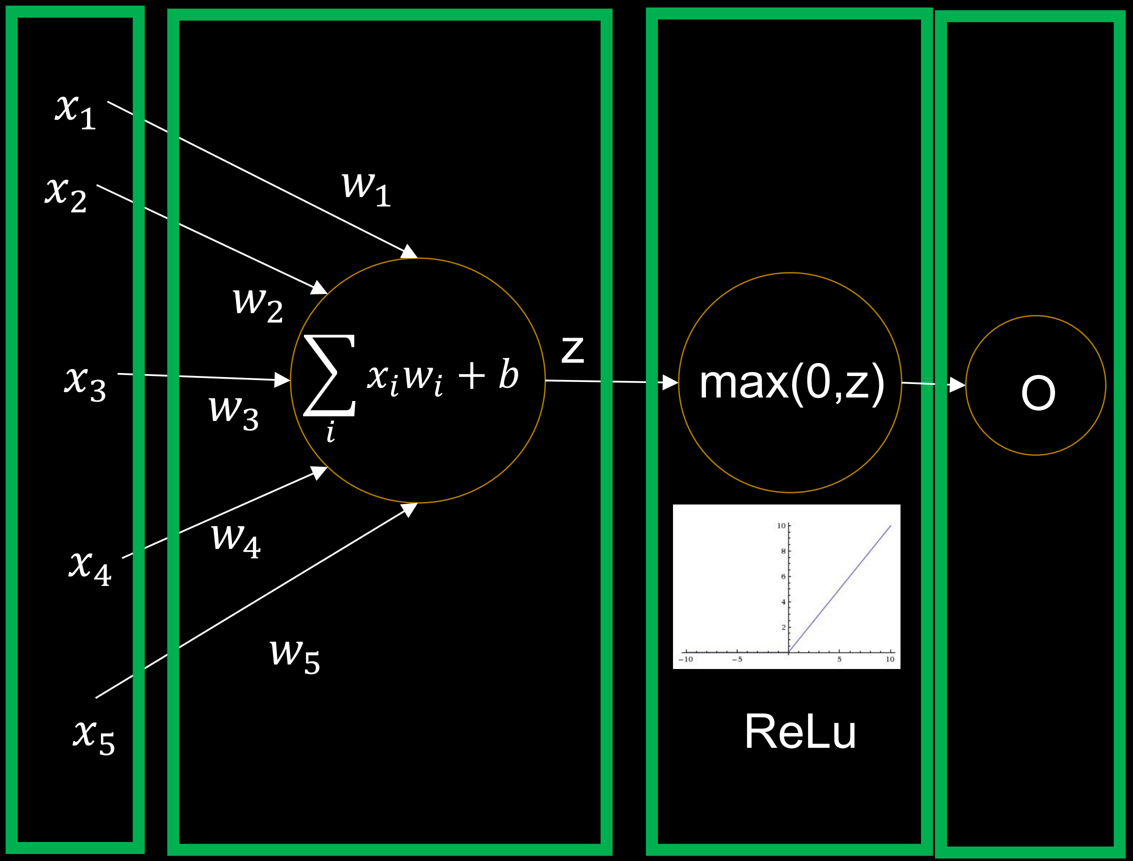


Human Faces



Bicycles

FC Layer 全联接层



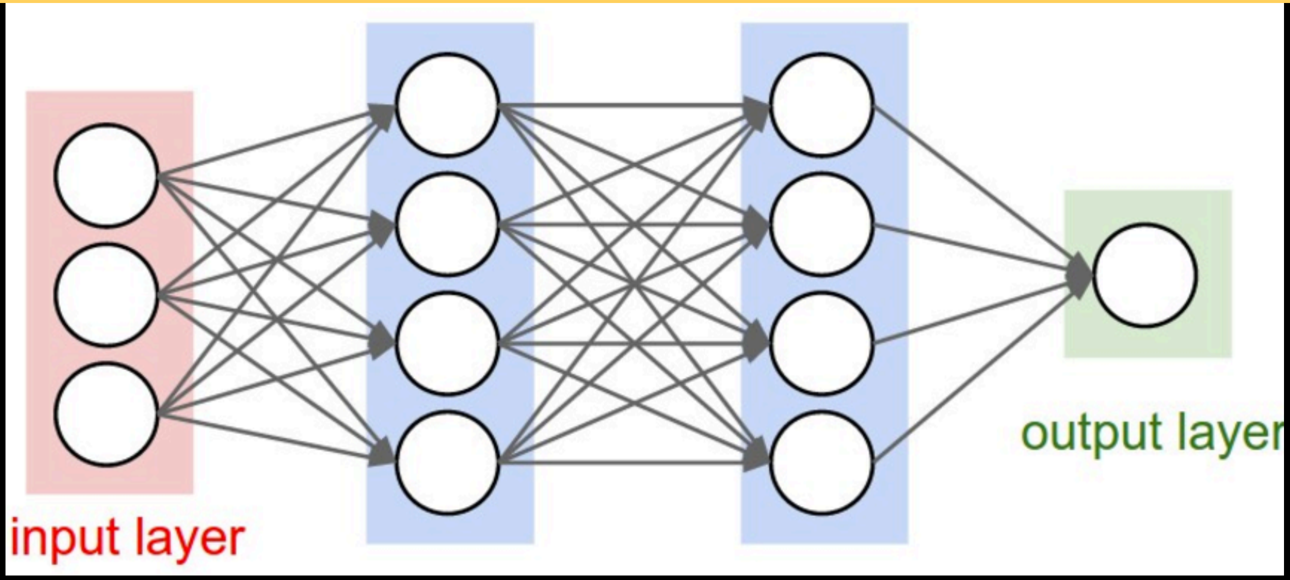
Input Layer

Network Layer

Activation Layer

Output Layer

Parameters = Size of Prev. Layer X Size of Current Layer



Network + Activation Layer 1

Network + Activation Layer 2

Output layer parameters = 4 X 1 = 4

Layer 1 parameters = 3 X 4 = 12

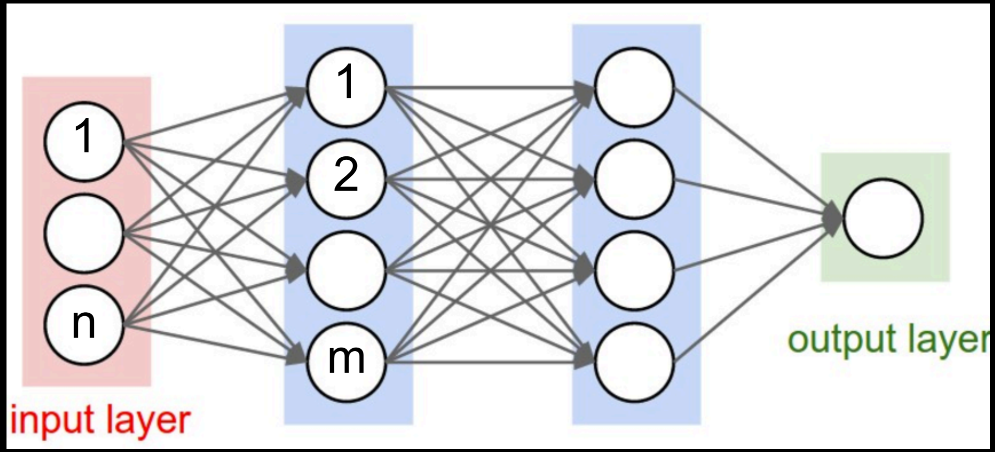
Layer 2 parameters = 4 X 4 = 16

FC Layer 全联接层

$$\begin{matrix}[x_{11}, x_{12}, \dots, x_{1n}] \\ [x_{21}, x_{22}, \dots, x_{2n}]\end{matrix} \times \begin{bmatrix} w_{11} & \cdots & w_{1m} \\ \vdots & \ddots & \vdots \\ w_{n1} & \cdots & w_{nm} \end{bmatrix} = \begin{matrix}[o_{11}, o_{12}, \dots, o_{1m}] \\ [o_{21}, o_{22}, \dots, o_{2m}]\end{matrix}$$

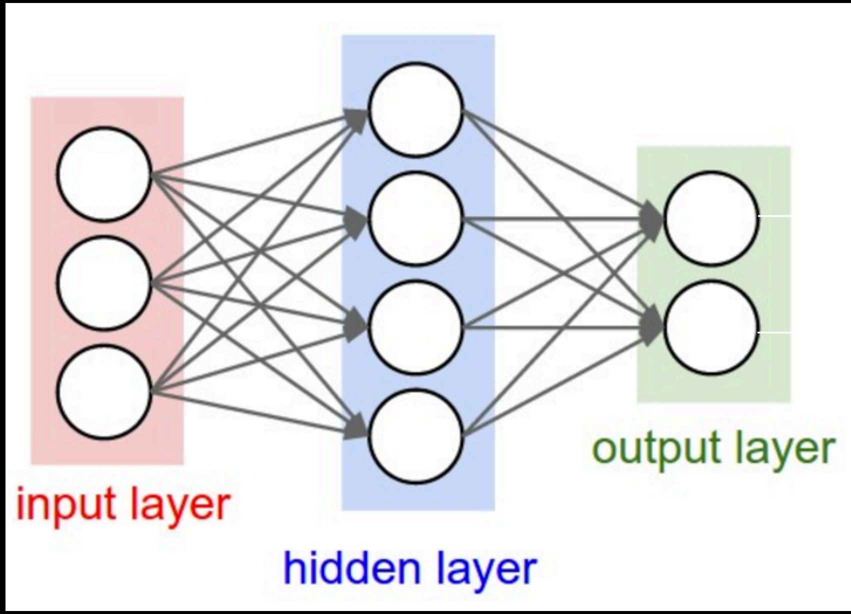
H_1 $\qquad$ H_m

H



Cost Function (Cross Entropy)

Forward Pass



Backward Pass

Actual Label

Pred Label

Total Classes

Actual label

Predicted label

$$L_i = -\sum_{j=c}^{C} \hat{y}_j \log(y_j)$$

For i[th] example

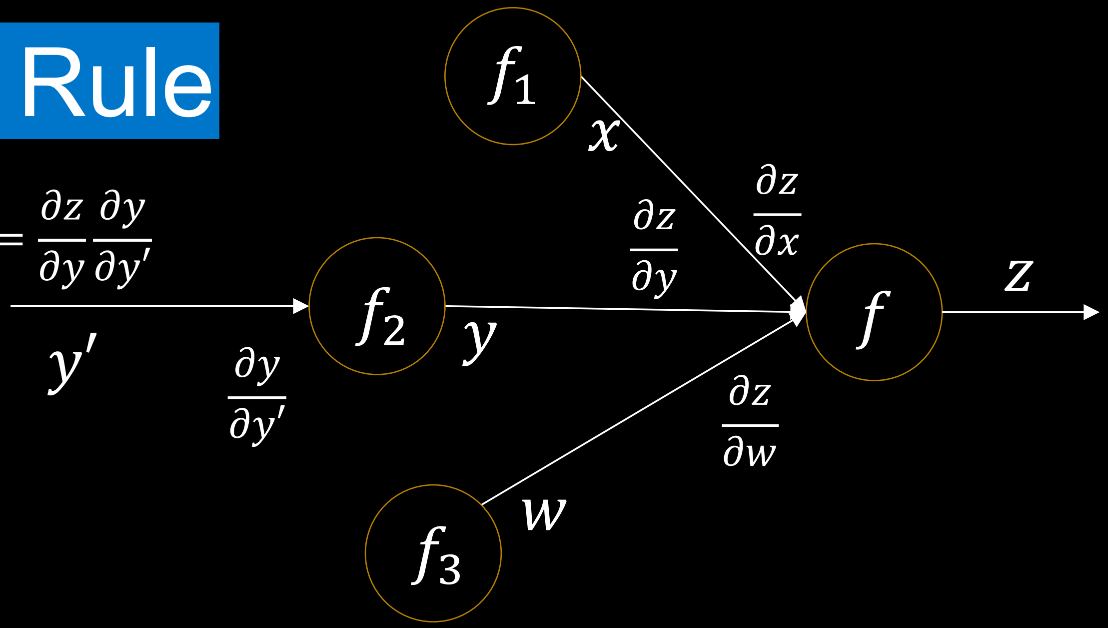
$$where\ y_j = \sigma(z)_j = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}}$$

To minimize loss, we need to find the direction of change which decreases L_i with respect to $y_i = \frac{\partial L_i}{\partial y_j}$

BP Revisit

Chain Rule

$$\frac{\partial z}{\partial y'} = \frac{\partial z}{\partial y}\frac{\partial y}{\partial y'}$$



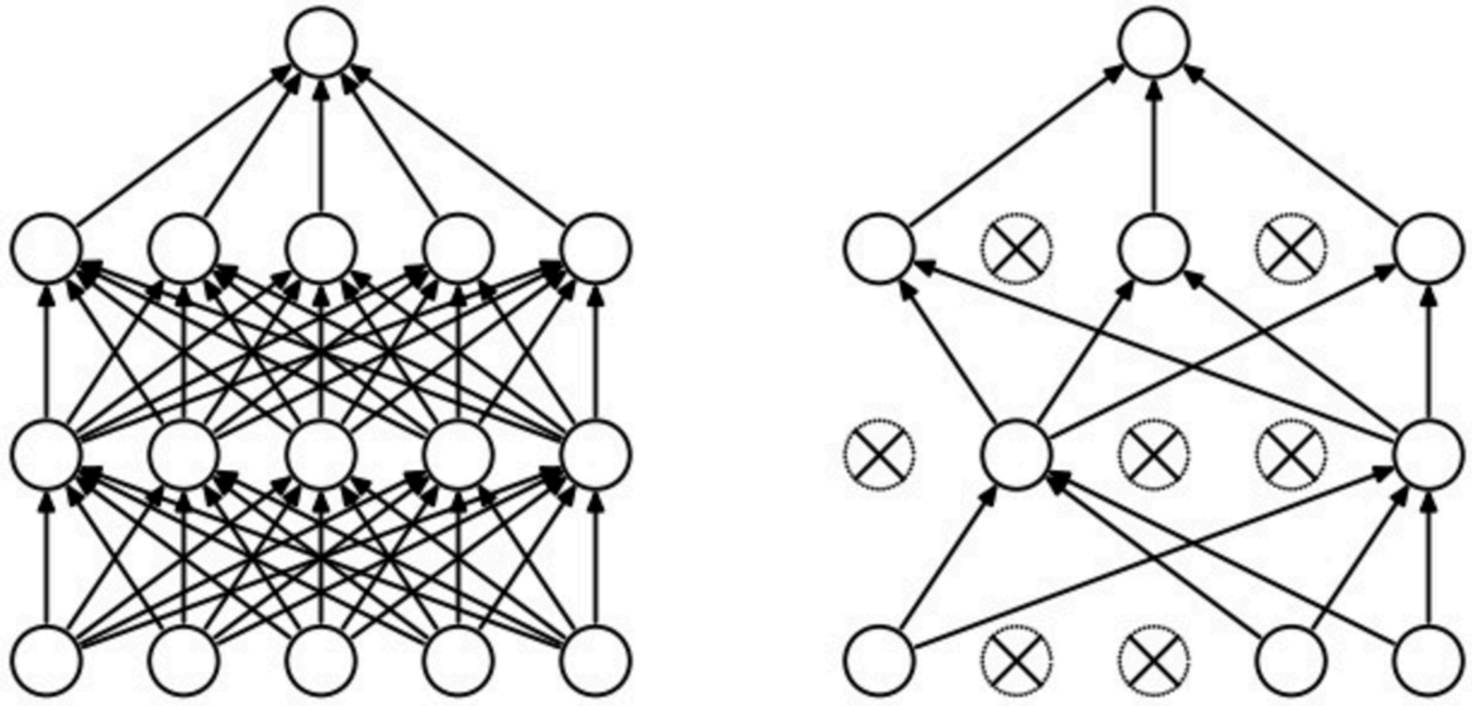
Learning Rate

$$x \leftarrow x - \lambda\frac{\partial z}{\partial x},$$
$$y \leftarrow y - \lambda\frac{\partial z}{\partial y},$$
$$w \leftarrow w - \lambda\frac{\partial z}{\partial w},$$
$$y' \leftarrow y' - \lambda\frac{\partial z}{\partial y'}$$

$$forward: z = f(x,y,w)$$

$$\text{backward: } \nabla f(x,y,w) = \left[\frac{\partial z}{\partial x},\frac{\partial z}{\partial y},\frac{\partial z}{\partial w}\right], \nabla f_2(y') = \left[\frac{\partial y}{\partial y'}\right]$$

Dropout Regularization

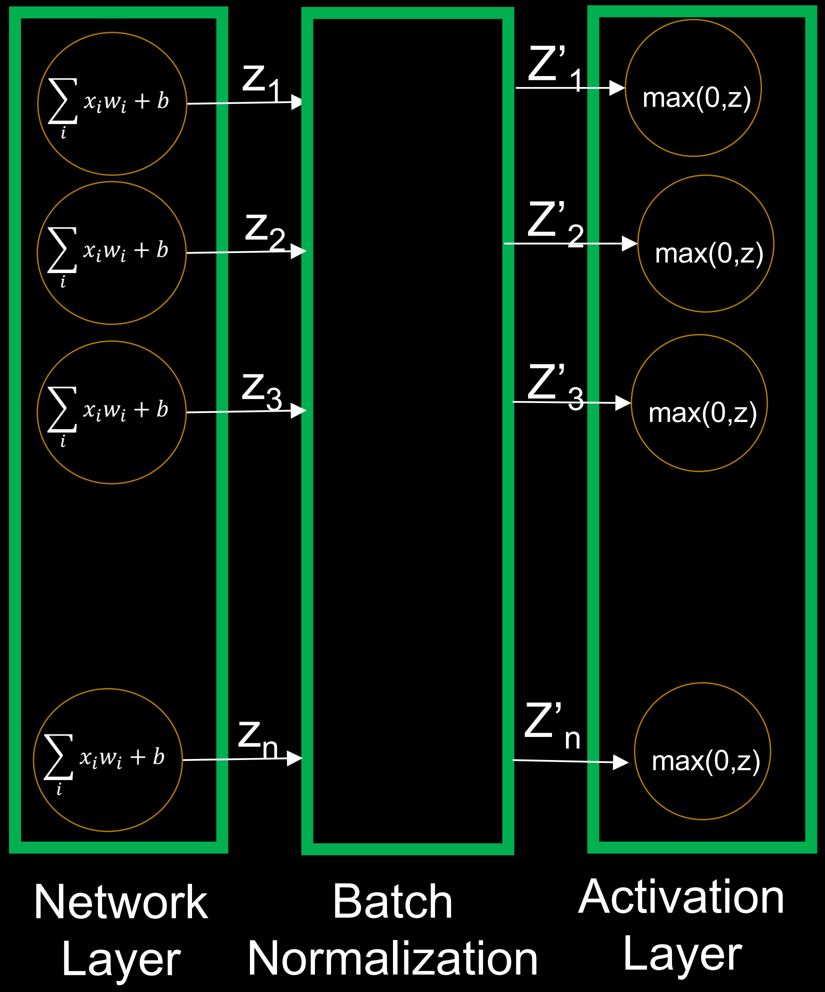


(a) Standard Neural Net (b) After applying dropout.

Nitish Srivastava
Geoffrey Hinton
Alex Krizhevsky
Ilya Sutskever
Ruslan Salakhutdinov

Source：http://www.cs.toronto.edu/~rsalakhu/papers/srivastava14a.pdf

Batch Normalization



No Parameters

$$BN_{initial}(z_i) = \frac{z_i - \mu_B}{\sqrt{(\sigma_B^2 + \epsilon)}}$$

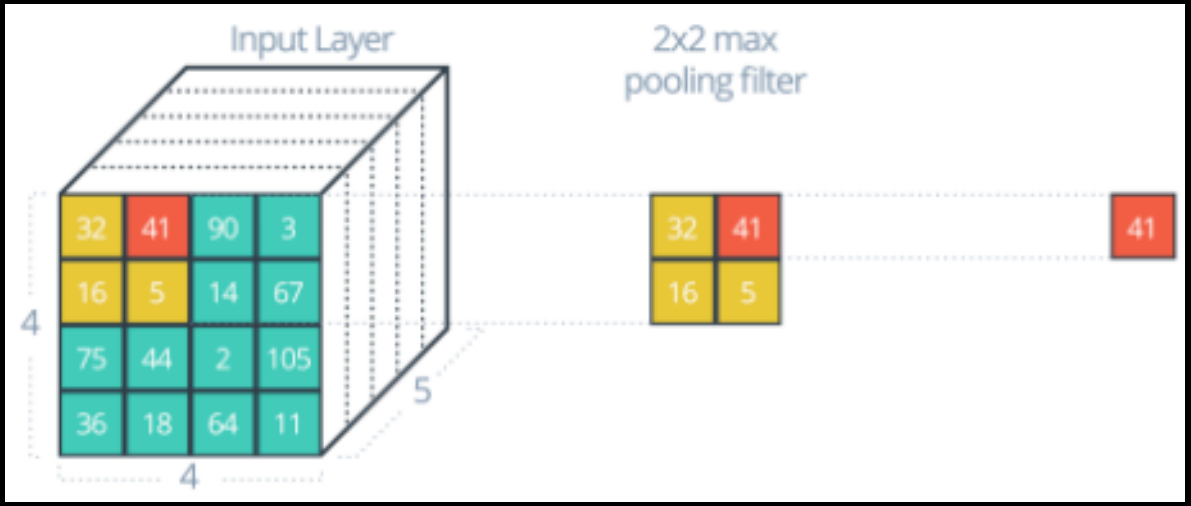
$$BN\ (z_i) = \gamma\left(\frac{z_i - \mu_B}{\sqrt{\sigma_B^2 + \epsilon}}\right) + \beta$$

Convolution Layer with TensorFlow

```
# Output depth
k_output = 64
# Image Properties
image_width = 10
image_height = 10
color_channels = 3
# Convolution filter
filter_size_width = 5
filter_size_height = 5
# Input/Image
input = tf.placeholder( tf.float32, shape=[None, image_height, image_width, color_channels])
# Weight and bias
weight = tf.Variable(tf.truncated_normal( [filter_size_height, filter_size_width, color_channels, k_output]))
bias = tf.Variable(tf.zeros(k_output))
# Apply Convolution
conv_layer = tf.nn.conv2d(input, weight, strides=[1, 2, 2, 1], padding='SAME')
# Add bias
conv_layer = tf.nn.bias_add(conv_layer, bias)
# Apply activation function
conv_layer = tf.nn.relu(conv_layer)
```

[Batch, Input_height, Input_width, Input_channels]

Max Pooling



Note：池化层输出Depth与输入层是相同的，同时，池化操作会在输入层的每一切片上进行。

近年来，池化层有些不再是标配的趋势，因为

1）数据集大而复杂，欠拟合比过拟合更让人担心

2）Dropout 是要好的多的Regularizer

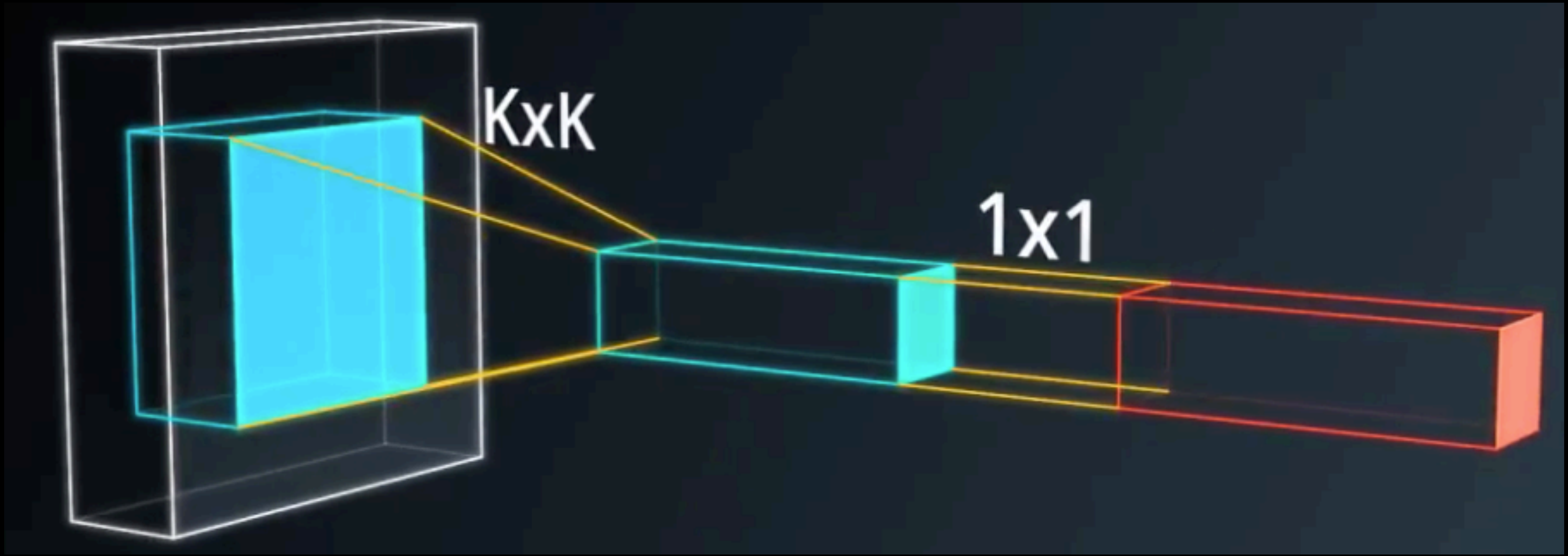
3）Pooling导致信息损失

Max Pooling

```
conv_layer = tf.nn.conv2d(input, weight, strides=[1, 2, 2, 1], padding='SAME')
conv_layer = tf.nn.bias_add(conv_layer, bias)
conv_layer = tf.nn.relu(conv_layer)
```

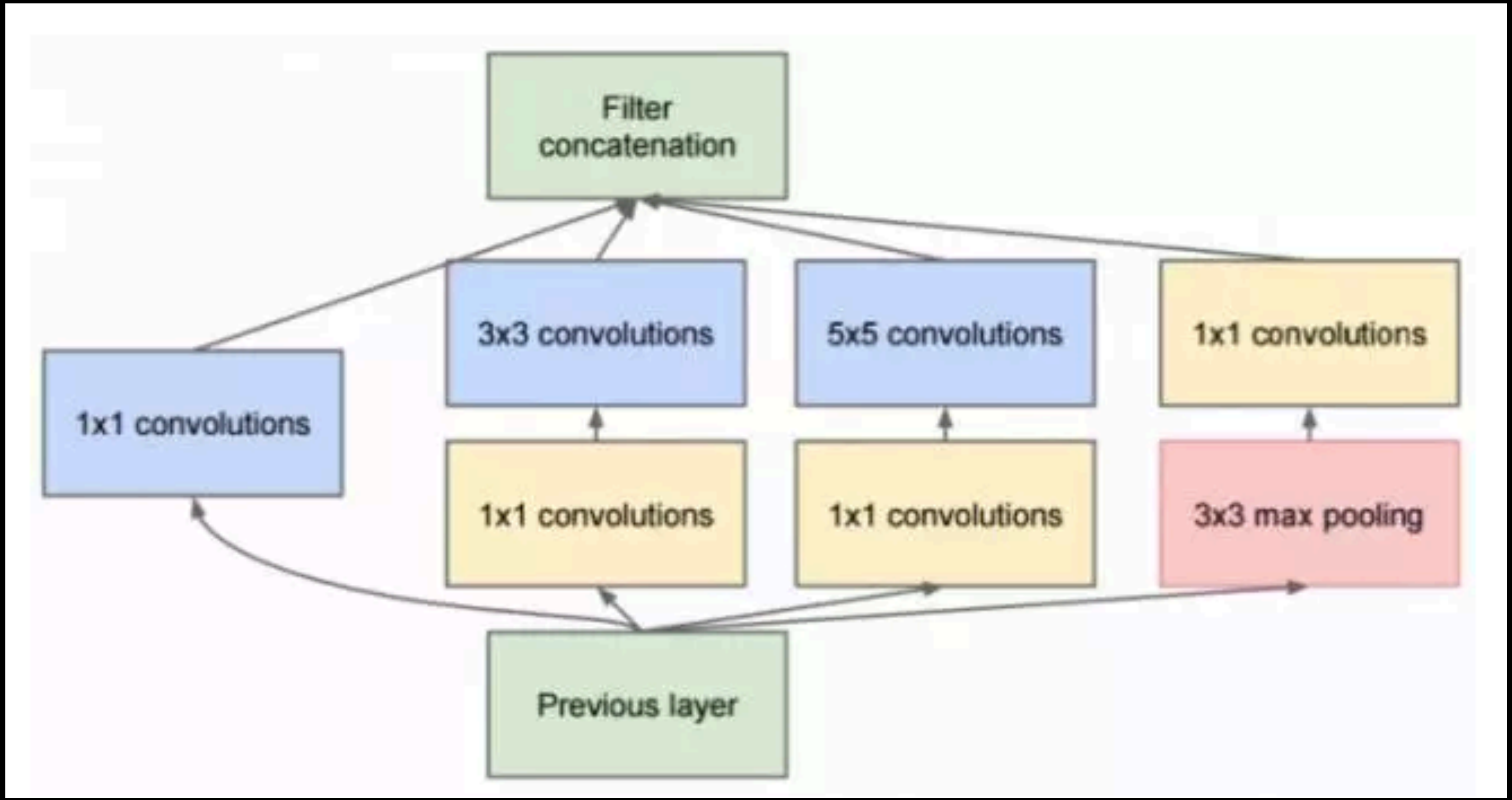
```
conv_layer = tf.nn.max_pool(
    conv_layer,
    ksize=[1, 2, 2, 1],        ← 滤波器参数
    strides=[1, 2, 2, 1],
    padding='SAME')
```

1 X 1卷积

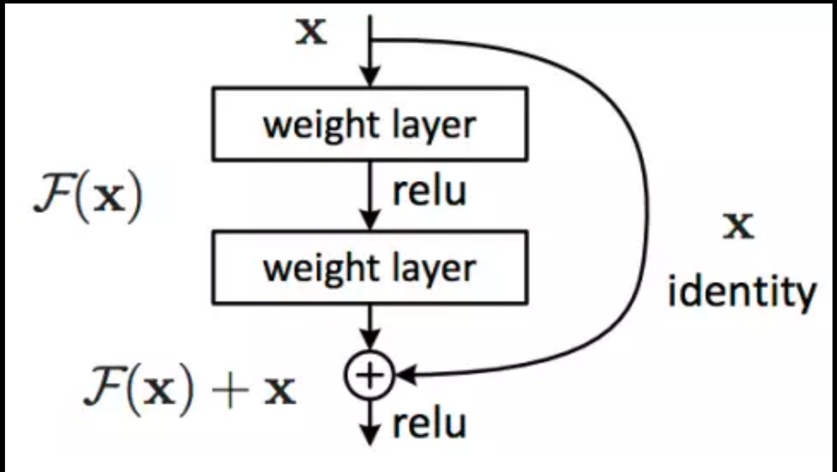


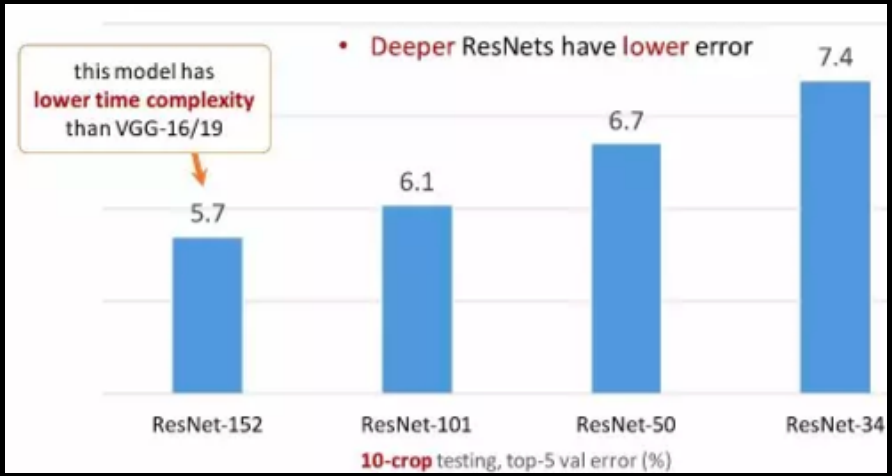
经典卷积层本质上是个小型的基于Patch的分类器，但仅是个线性分类器，如果在其中插入一个1X1的卷积层，我们就有了一个小型的神经网络，是一个使网络更深，参数更多但是成本很低的方法。

Inception Module



残差学习单元





- $y_l = h(x_l) + F(x_l, w_l), y_{l+1} = f(y_l)$
- 与LSTM的提出者瑞士教授Schmidhuber提出的Highway Network结构相似
- Highway NetWork允许保留一定比例的原始输入x，这样前面一层的信息，有一定比例（类似LSTM的Gate）可不经过矩阵乘法和非线性变换，直接传输到下一层，仿佛一条信息高速公路，因此得名
- Inception V4将Inception Module和ResNet相结合

Hyper-parameter Optimization (Selection)

Hyper-parameters

- Number of layers
- Different parameters for each layer (number of hidden units, filter size for convolutional layer, ...)
- Type of activation functions
- Parameter initialization method
- Learning rate
- Loss function

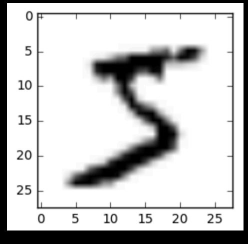
Optimization Approaches

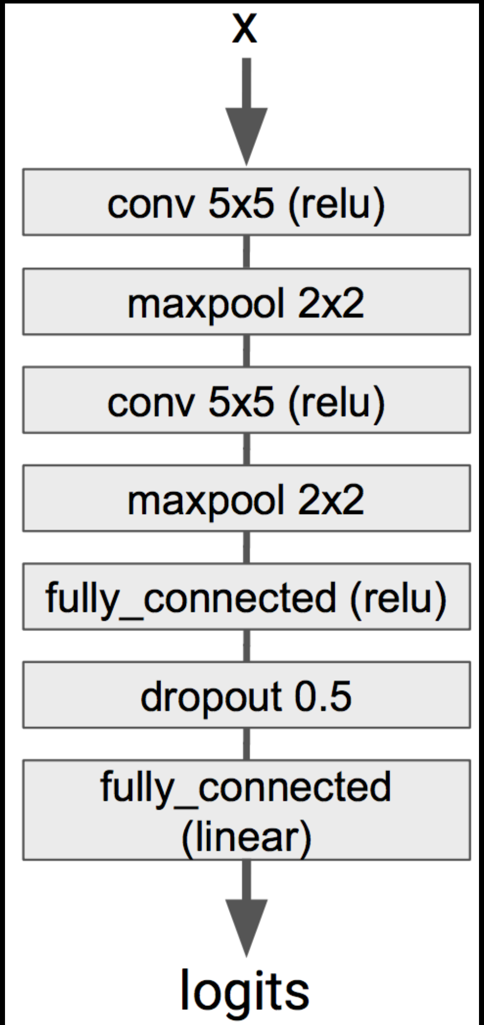
- **Grid Search**
- **Random Search**
- **Hand Tuning**
- **Bayesian Optimization**
- **Gaussian Process with Acquisition Function, Find number of hidden units**
- **Tree Structured Parzen Estimators (TPE)**

TF DNN Code

```
conv1 = tf.nn.conv2d(x, conv1_wts[5,5,1,32],strides=[1],padding='SAME')
relu1 = tf.nn.relu(conv1+bias1_wts[32])
pool1 = tf.nn.max_pool(relu1,ksize=[2,2],strides=[2,2],padding='SAME')
conv2 = tf.nn.conv2d(x, conv2_wts[5,5,32,64],strides=[1],padding='SAME')
relu2 = tf.nn.relu(conv1+bias2_wts[64])
pool2 = tf.nn.max_pool(relu2,ksize=[2,2],strides=[2,2],padding='SAME')
fc1 = tf.matmul(tf.reshape(pool2), fc1_weights) + fc1_biases
relu3 = tf.nn.relu(fc1)
drop = tf.nn.dropout(relu3,0.5,SEED)
logits = tf.matmul(drop, fc2_weights) + fc2_biases
train_predictions = tf.nn.softmax(logits)
loss = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits( logits, train_labels))
optimizer = tf.train.MomentumOptimizer(learning_rate,0.9)
train = optimizer.minimize(loss, global_step=batch)
```

Build graph





Tips and Tricks

- Try something simple first: Input->[Conv->ReLU]*2->Pool->ReLU->Conv->ReLU->Pool->Fully Connected
- Divide your data into a training set, validation set and test set.
- Try to make sure that the validation set and test set are from the same distribution.
- Use mini-batch size between 50-100 to train your network on the training data set.
- If training error is high you have the following options to take:

    (1) **Choose a bigger network**

    (2) Train for a longer time

    (3) Change to a new model architecture (less recommended)
- If validation error is high try out the following:

    (1) **Get more data**

    (2) Try better regularization

    (3) Change to a new model architecture (less recommended)

Tips and Tricks

- Data Augmentation:

  As NN require a lot of data, try different small transformations on the data to create more data points

- Pre-process the input data to zero mean and unit standard deviation
- Try this formula for initialization of the network (has been shown to work best)
- >>> w = np.random.randn(n) * sqrt(2.0/n)
- Smaller filter sizes and strides work better (less number of parameters, thorough scanning)
- Ilya Sutskever recommended dividing the gradients by mini batch size
- Start with LR = 0.01 and when it starts stagnating on the validation set do LR/2 or LR/5
- Regularization using dropout = 0.5 is good
- Batch Normalization has been shown to increase training speed by 14 times
- To win benchmarking competitions try to use an ensemble of models
  - using different initialization
  - using different data sets to pre-train the networks
  - use the top-k networks learnt from cross-validation
- Alternative Option: Take a pre-exisiting network and train on your own data. But make sure the previous and your data are similar data sets.

Hand-on

- http://selfdrivingcars.mit.edu/deeptrafficjs/
- TensorFlow MNIST / CFAR-10 教程
- http://www.tensorfly.cn/tfdoc/tutorials/deep_cnn.html
- 参考资料：
- Andrej Karpathy's CS231n Stanford Course on CNN

Thank you!

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