深度学习平台与应用

第五讲：卷积神经网络

范琦

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2024年10月9日

大　　纲

- 卷积神经网络-引言
- 卷积神经网络

课程回顾

南京大学 NANJING UNIVERSITY

- 图像分类

假设有一个标签集合
{人，狗，猫，汽车，…}

模型的分类预测 → 猫

课程回顾：线性分类器

输入图像

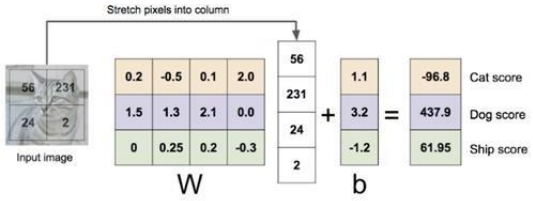
$$f(x,W) = Wx + b$$

$$f(x,W) \longrightarrow$$

571.3	猫
1.25	狗
-132.2	船

Algebraic Viewpoint

$$f(x,W) = Wx$$

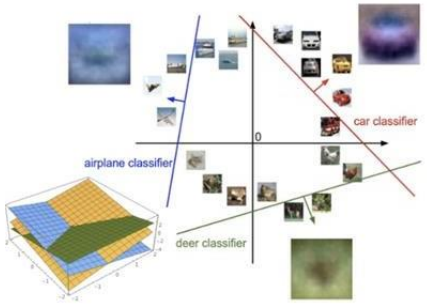


Visual Viewpoint

One template per class

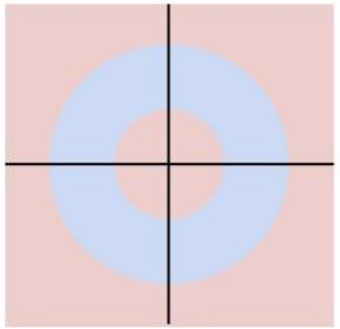
Geometric Viewpoint

Hyperplanes cutting up space



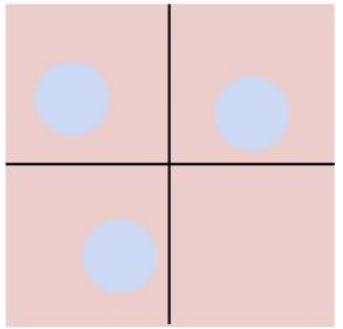
Class 1:
1 <= L2 norm <= 2

Class 2:
Everything else



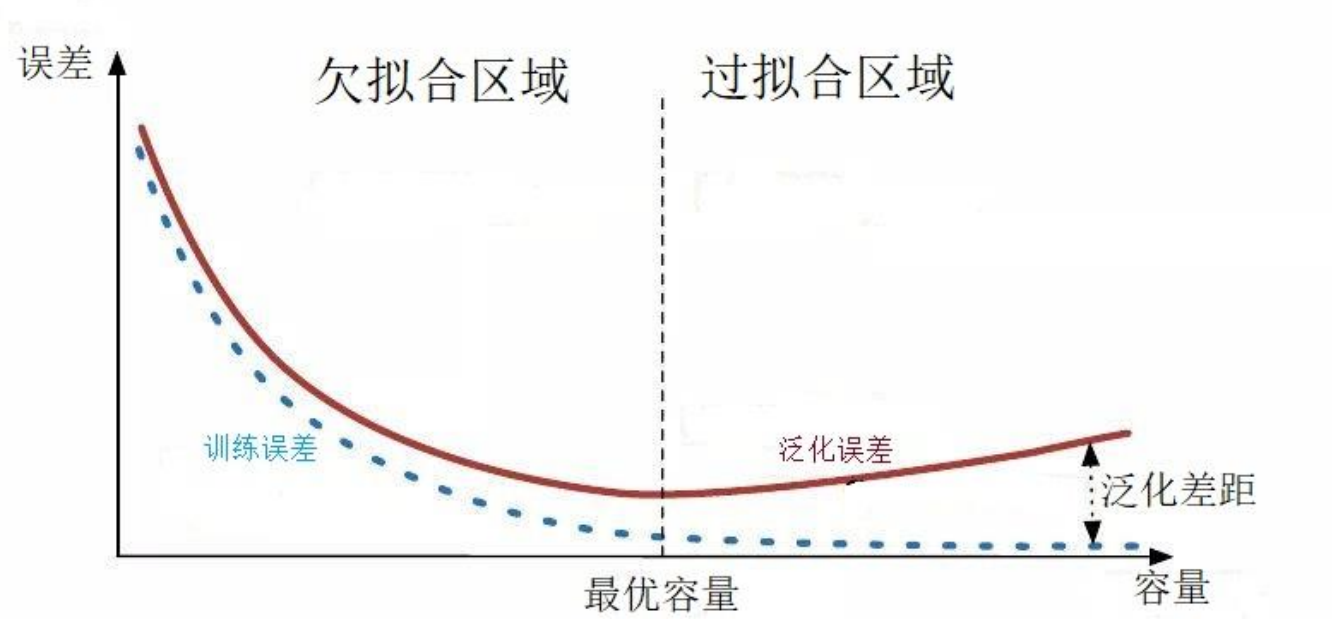
Class 1:
Three modes

Class 2:
Everything else



课程回顾：损失函数与优化

- 我们有训练数据：$\{(x_i, y_i)\}_{i=1}^{N}$
- 我们有线性分类预测：$s = f(x; W) = Wx$
- 我们有损失函数：$L = \frac{1}{N}\sum_{i=1}^{N} L_i + R(W)$
- 优化模型来降低模型在数据上的损失：SGD, SGD+Momentum, RMSProp, Adam



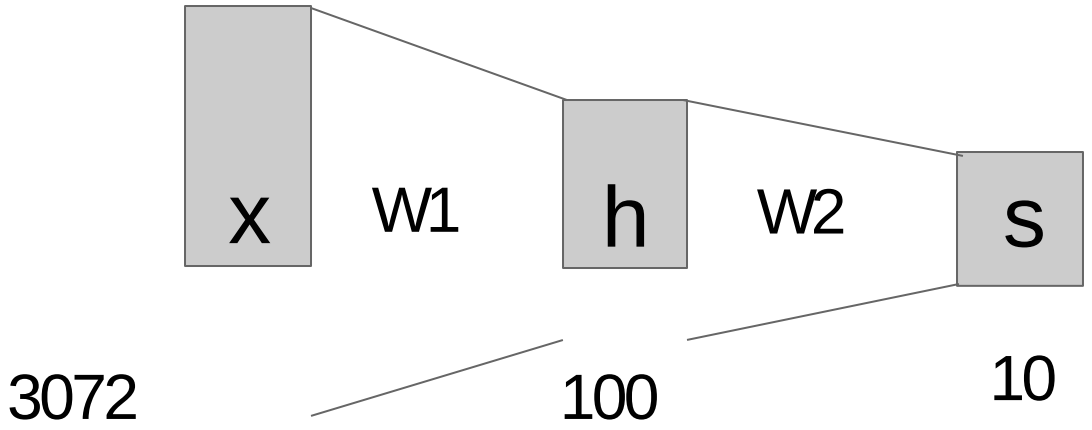
课程回顾：神经网络

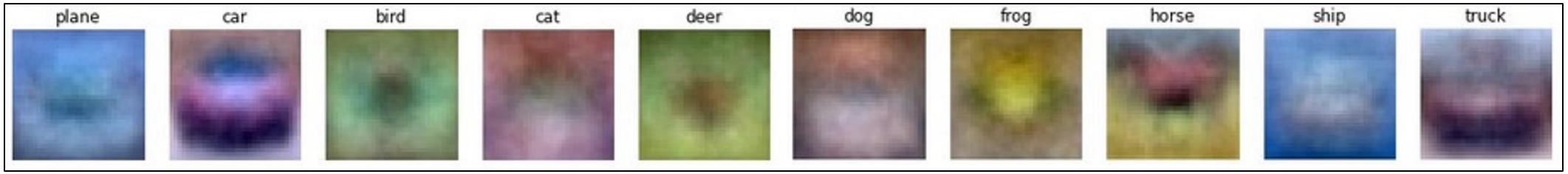
- 线性分类器

$$f = Wx$$

- 2 层神经网络

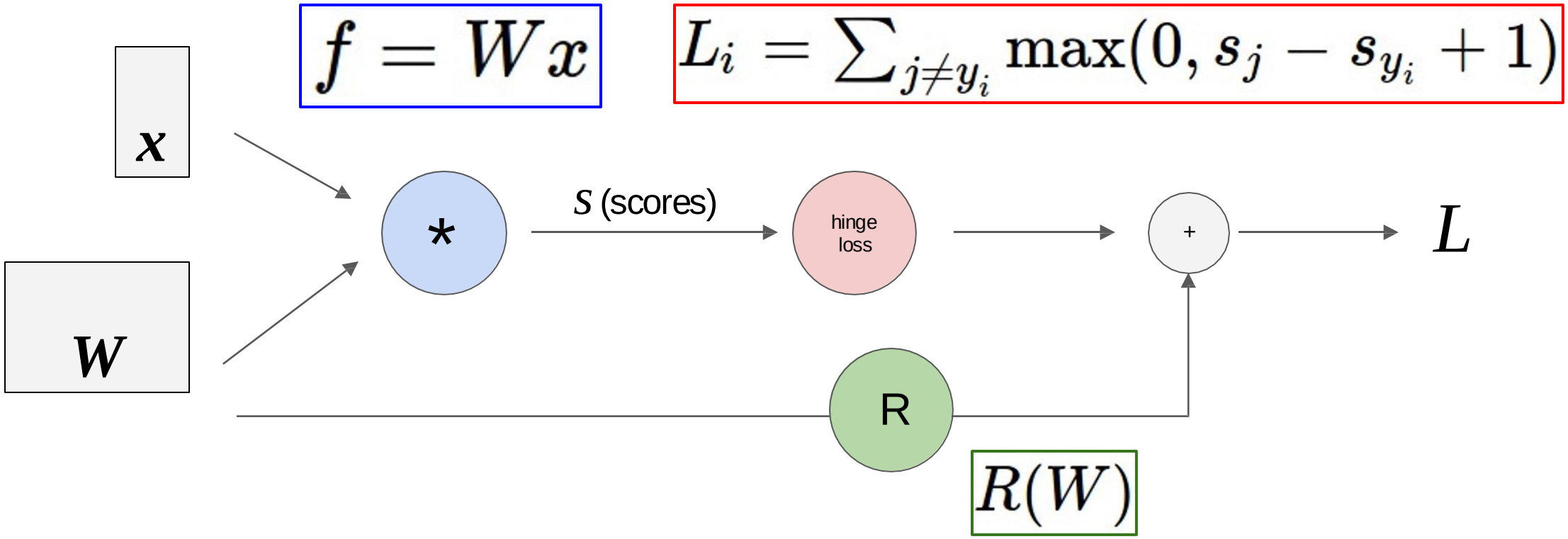
$$f = W_2 \max(0, W_1 x)$$





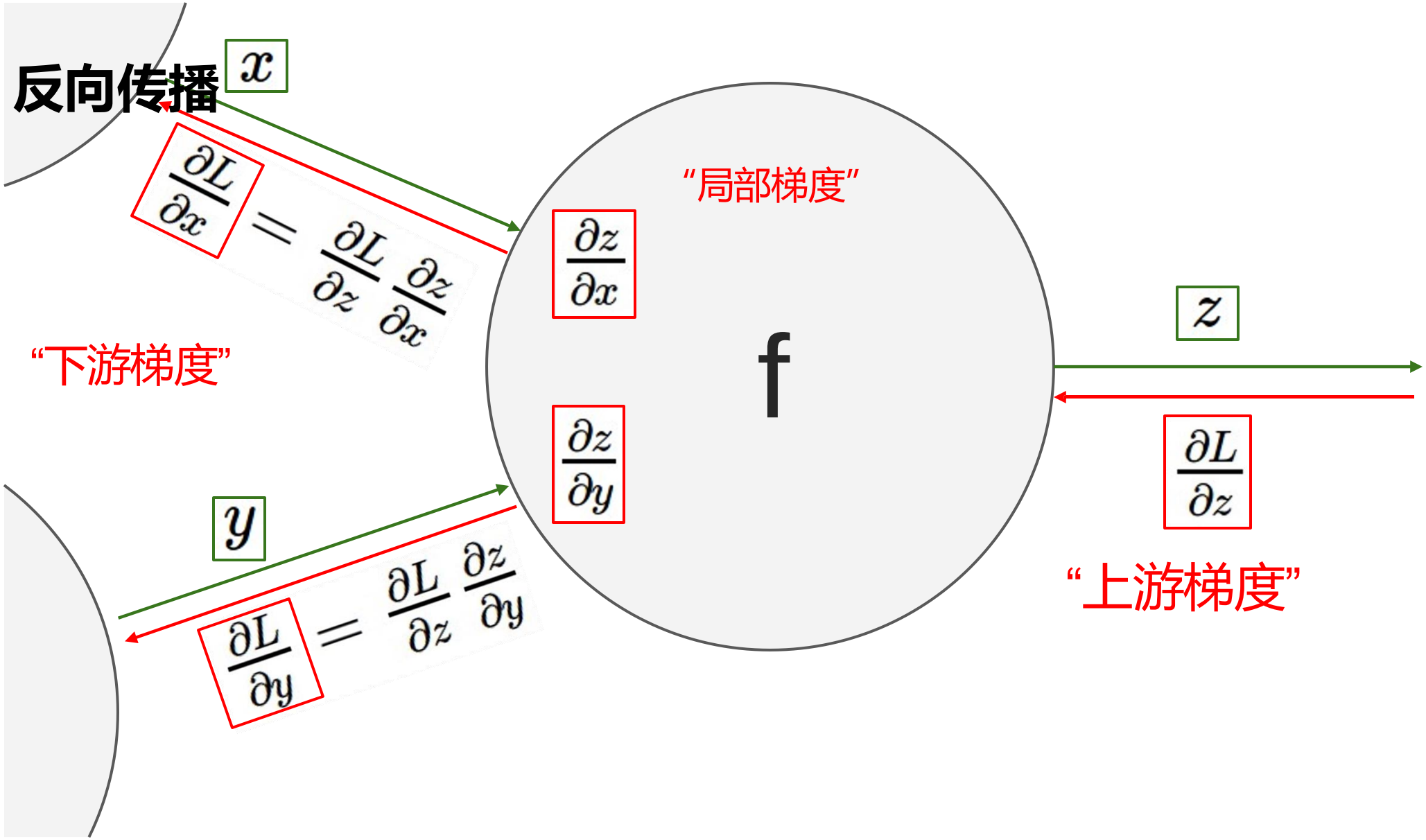
课程回顾：神经网络

- 计算图+反向传播



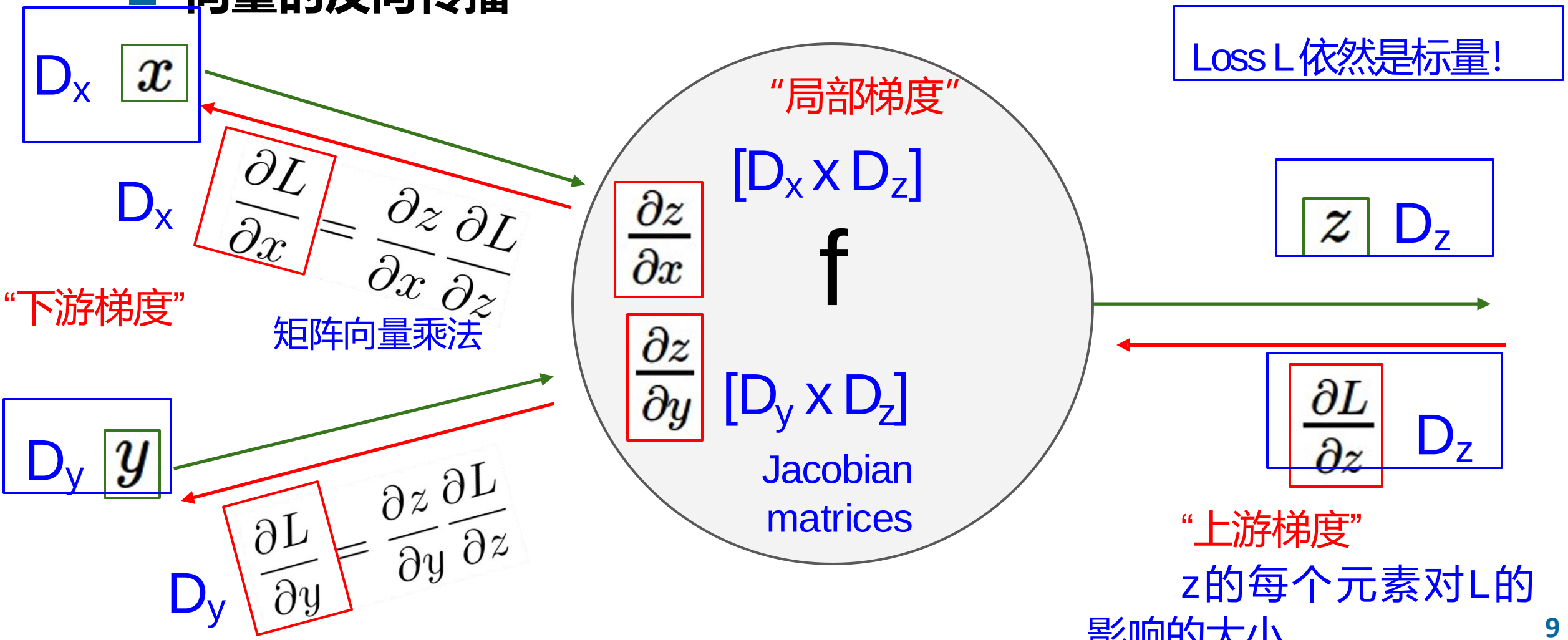
课程回顾：神经网络

- 反向传播



课程回顾：神经网络

向量的反向传播

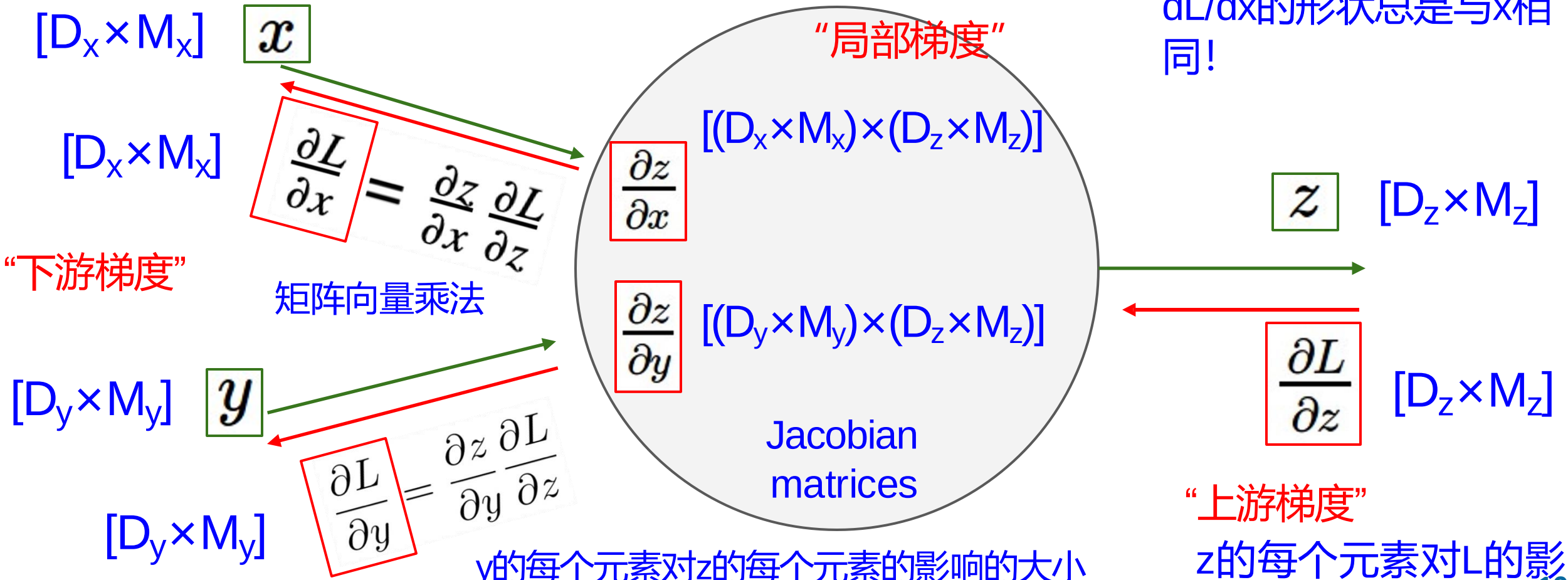


课程回顾：神经网络

- **矩阵的反向传播**

Loss L 依然是标量！

dL/dx的形状总是与x相同！



图像分类

- 图像分类是**最核心的计算机视觉任务**

假设有一个标签集合
{人，狗，猫，汽车，…}

模型的分类预测

Class Scores

图像分类

- **基于图像像素**的图像分类

假设有一个标签集合
{飞机，狗，猫，汽车，…}

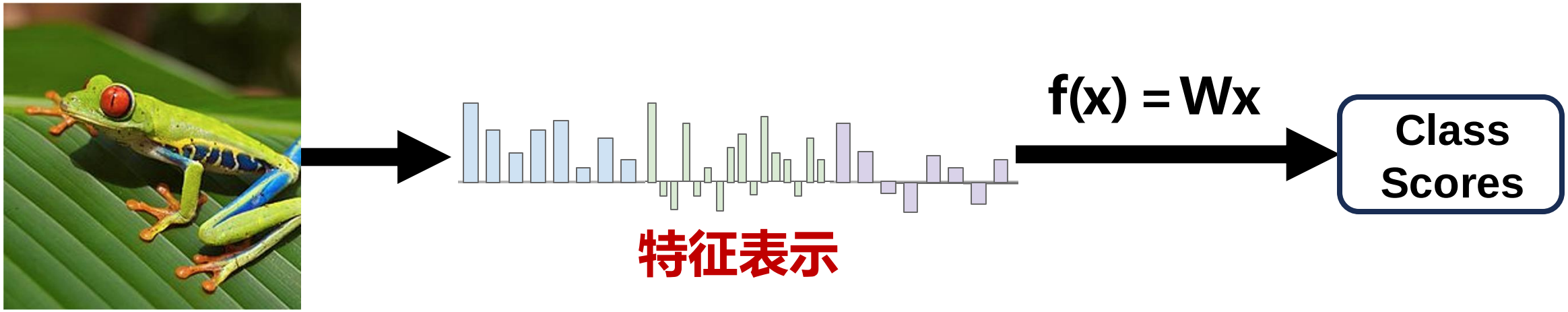
$f(x) = Wx$

Class Scores

图像分类

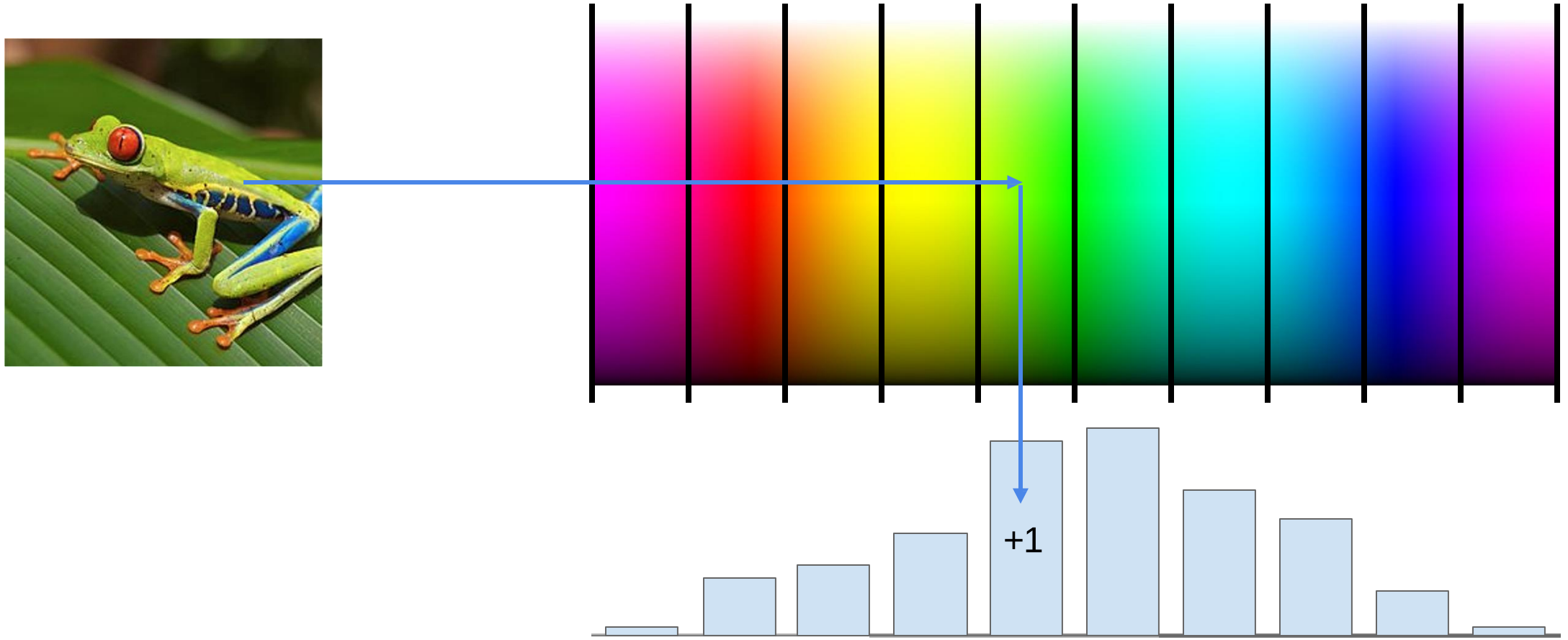
- **基于图像特征**的图像分类

假设有一个标签集合
{飞机，狗，猫，汽车，…}



图像分类

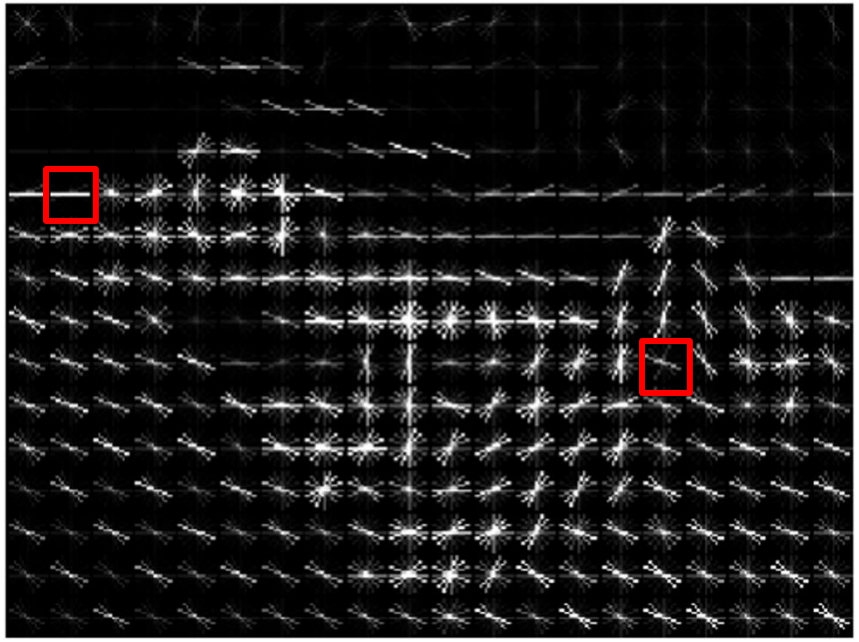
- 特征提取：颜色直方图（Color Histogram）



图像分类

- 方向梯度直方图（Histogram of Oriented Gradients, HoG）

HoG：将图像以8x8为基础区域进行划分。在每个基础区域内，将边缘方向量化为9个数字



例子：320x240的图像被划分为40x30的区域；每个区域中有9个数字，因此特征向量有30*40*9=10800个数字

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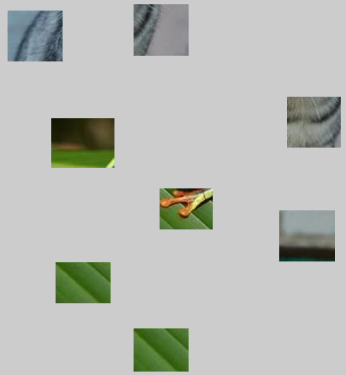
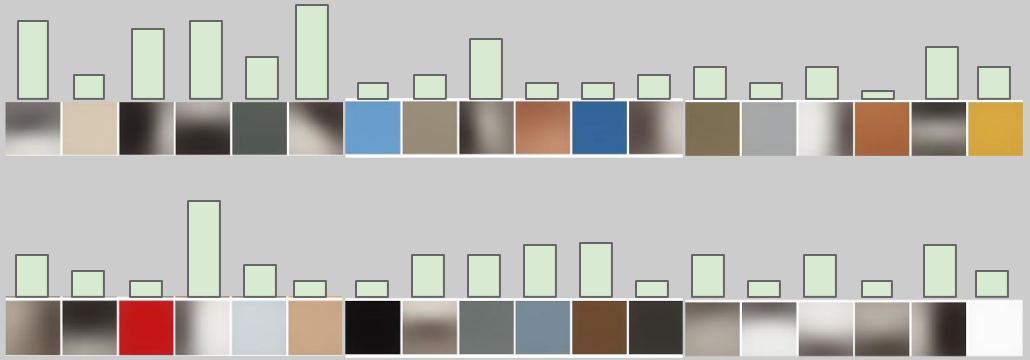
词袋（Bag of Words）

Step 1: 构建 codebook

提取随机图像块



聚类图像块，形成“visual words”的codebook



图像分类

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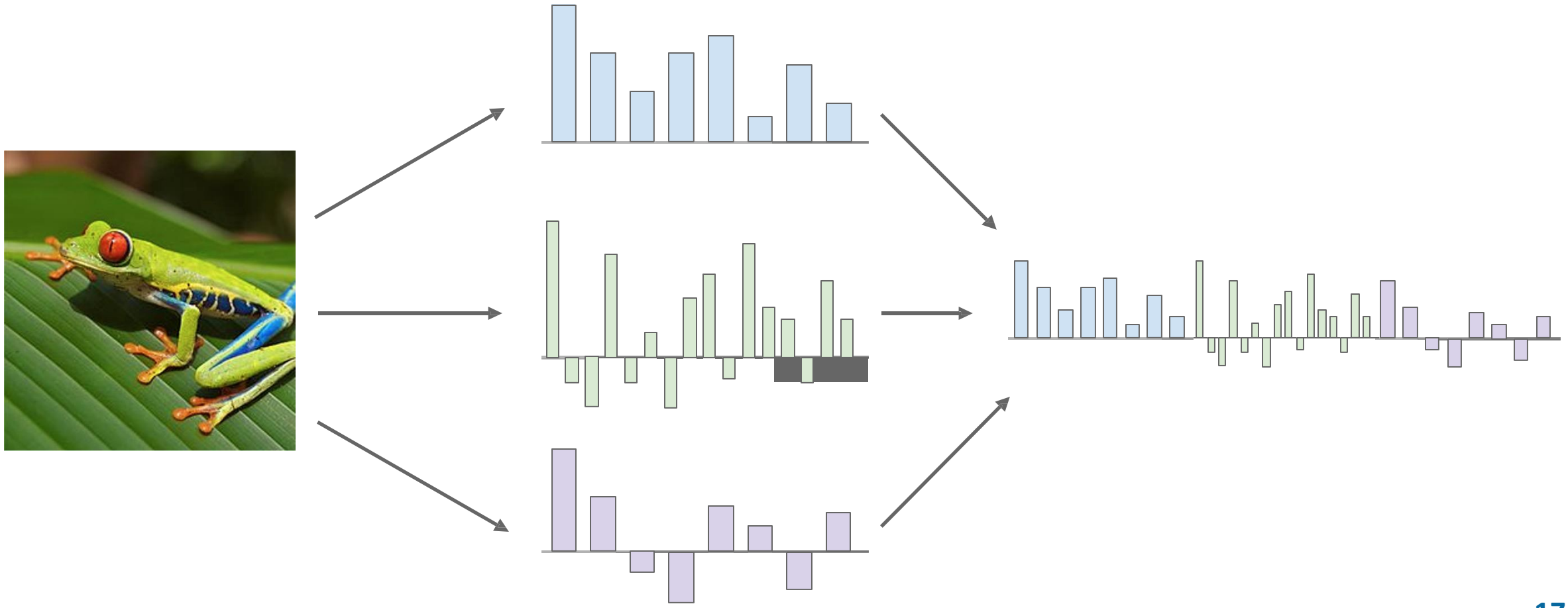
- 图像特征



图像分类

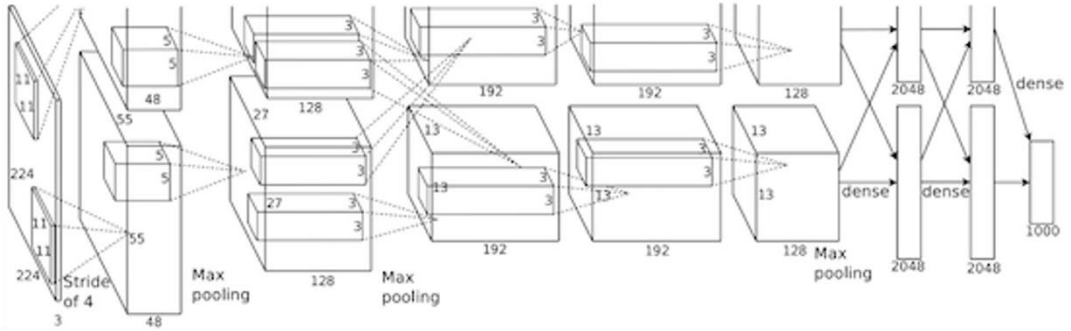
手工图像特征与卷积神经网络

Feature Extraction

f

分类得分

training



Krizhevsky, Sutskever, and Hinton, “Imagenet classification with deep convolutional neural networks”, NIPS 2012. Figure copyright Krizhevsky, Sutskever, and Hinton, 2012. Reproduced with permission.

分类得分

training

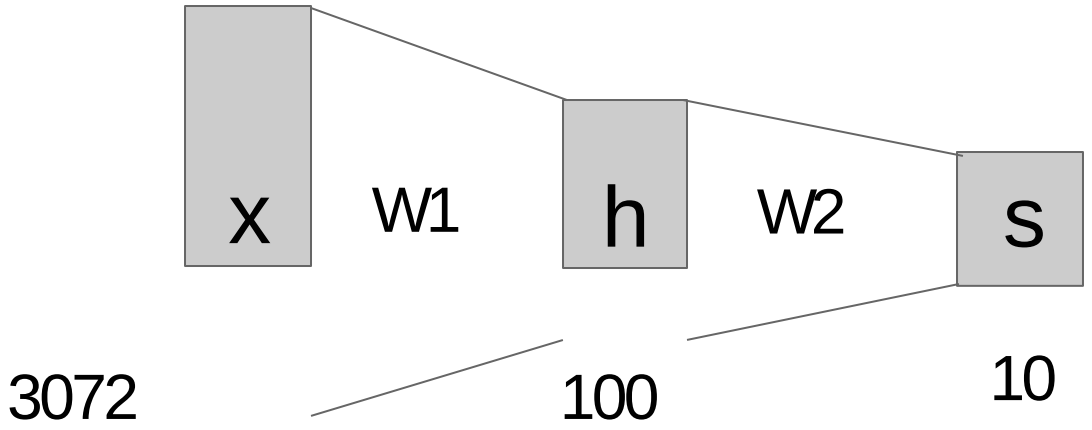
神经网络

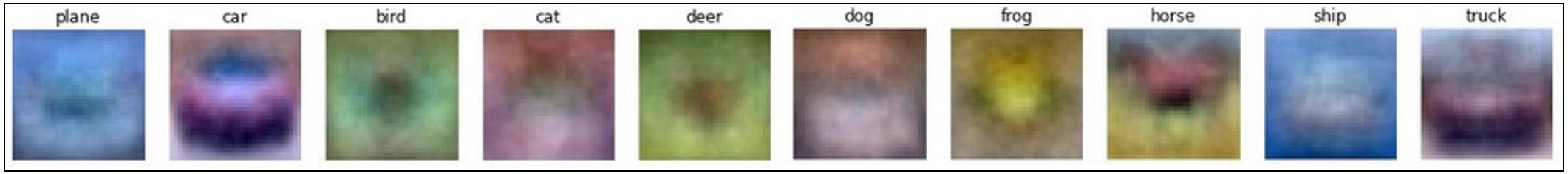
- 线性分类器

$$f = Wx$$

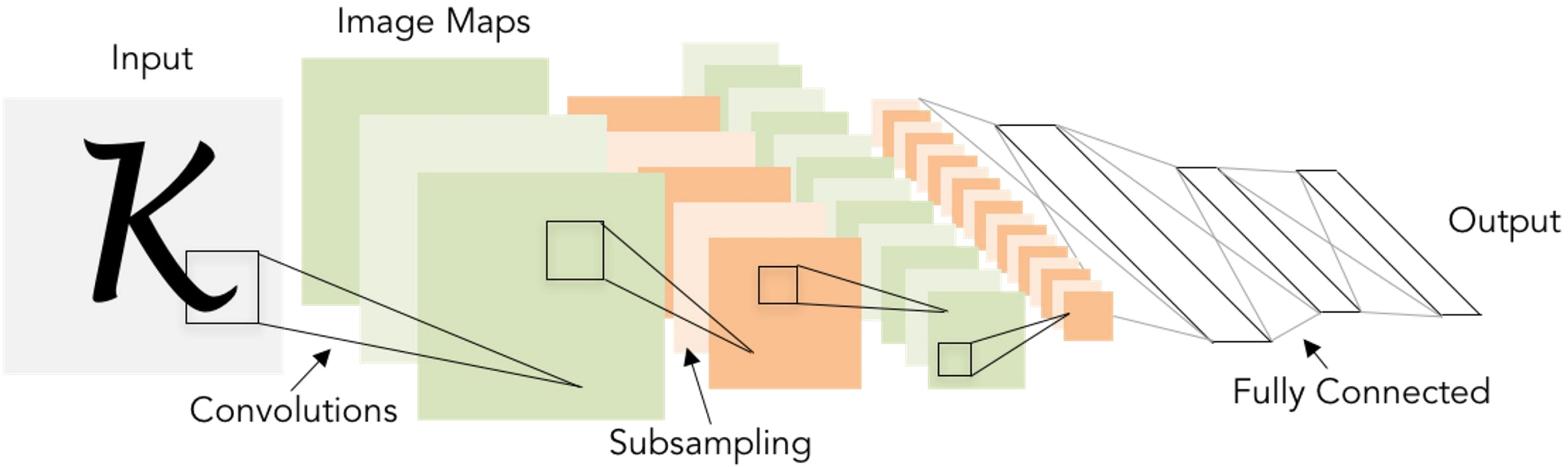
- 2 层神经网络

$$f = W_2 \max(0, W_1 x)$$





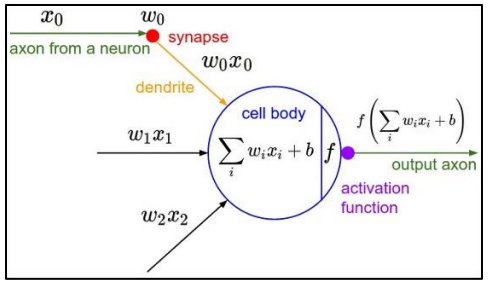
卷积神经网络


Input
Image Maps
Output
Convolutions
Subsampling
Fully Connected

卷积神经网络

- 神经网络的发展历史
- 第一个感知机：Mark I 感知机
- 识别字母：

$$f(x) = \begin{cases} 1 & \text{if } w \cdot x + b > 0 \\ 0 & \text{otherwise} \end{cases}$$



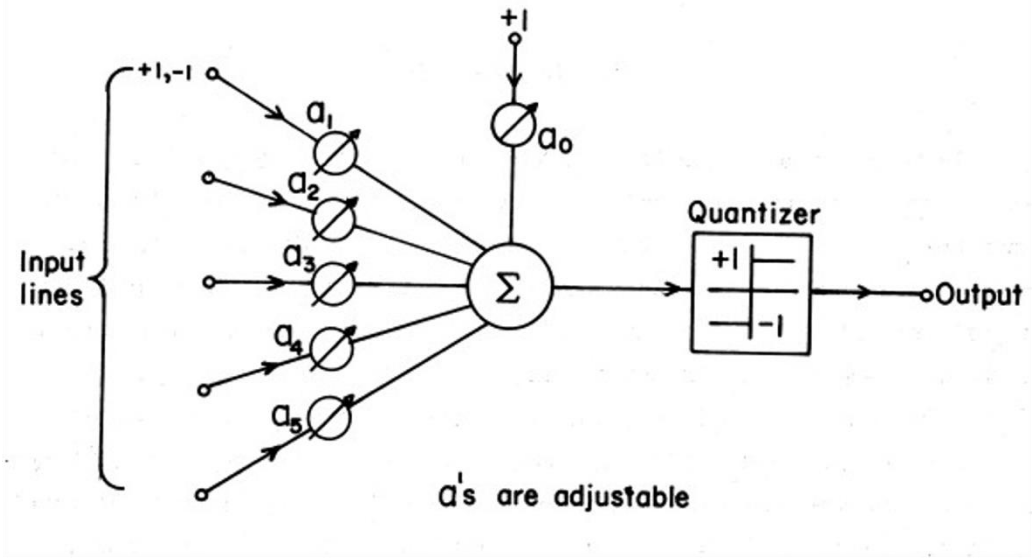
- 网络权重更新规则：

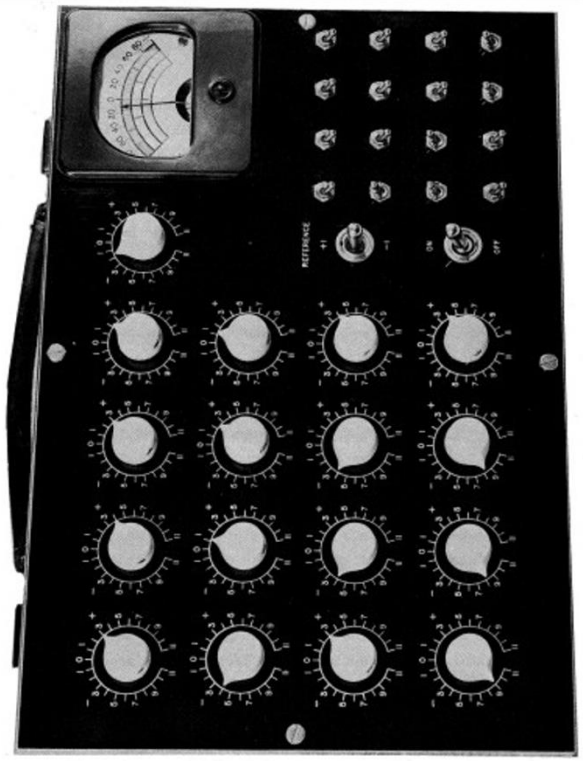
$$w_i(t+1) = w_i(t) + \alpha(d_j - y_j(t))x_{j,i},$$

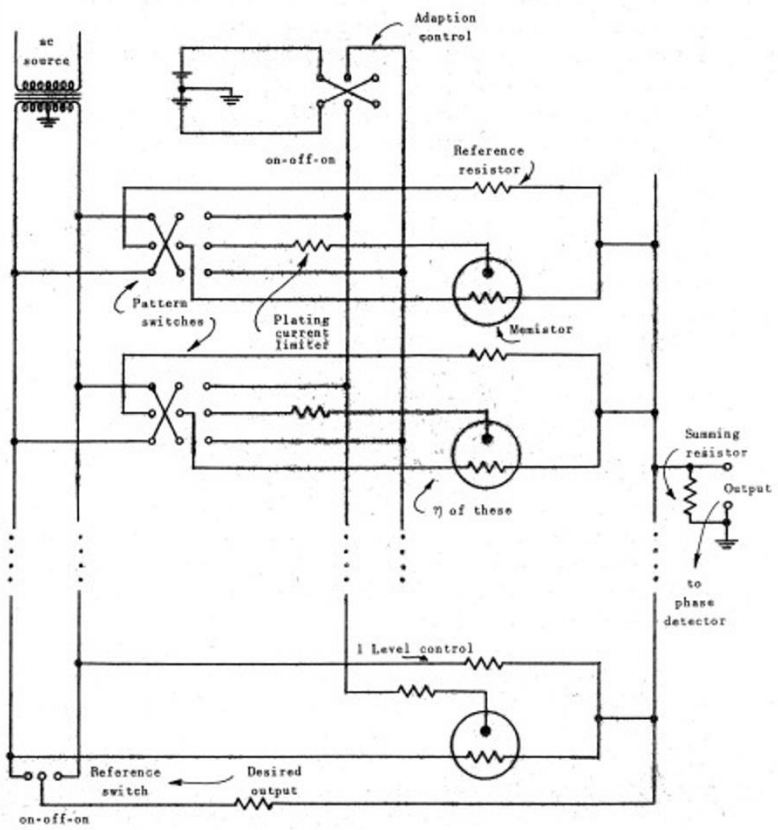
- Frank Rosenblatt, ~1957: Perceptron

卷积神经网络

- 神经网络的发展历史



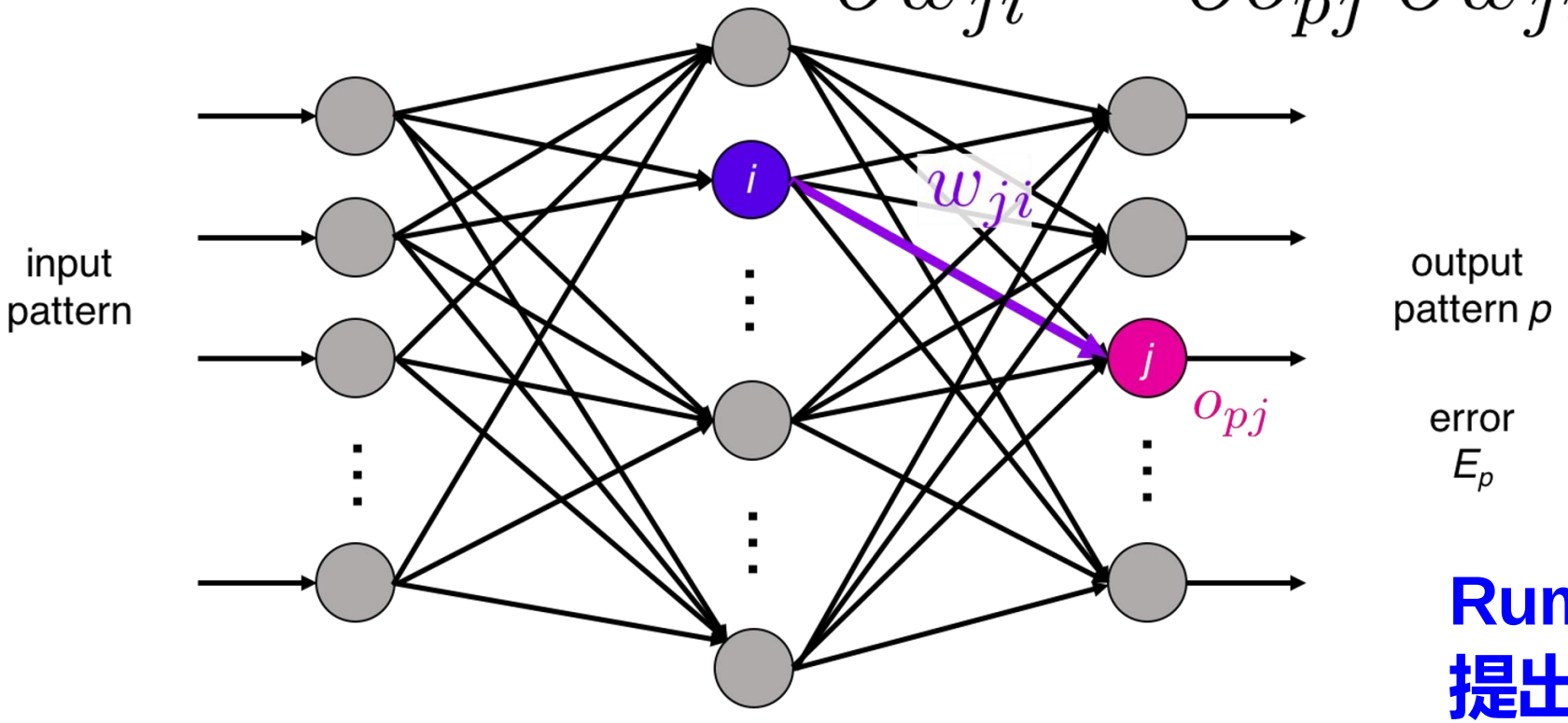




Widrow and Hoff, ~1960 : Adaline/Madaline

- 神经网络的发展历史

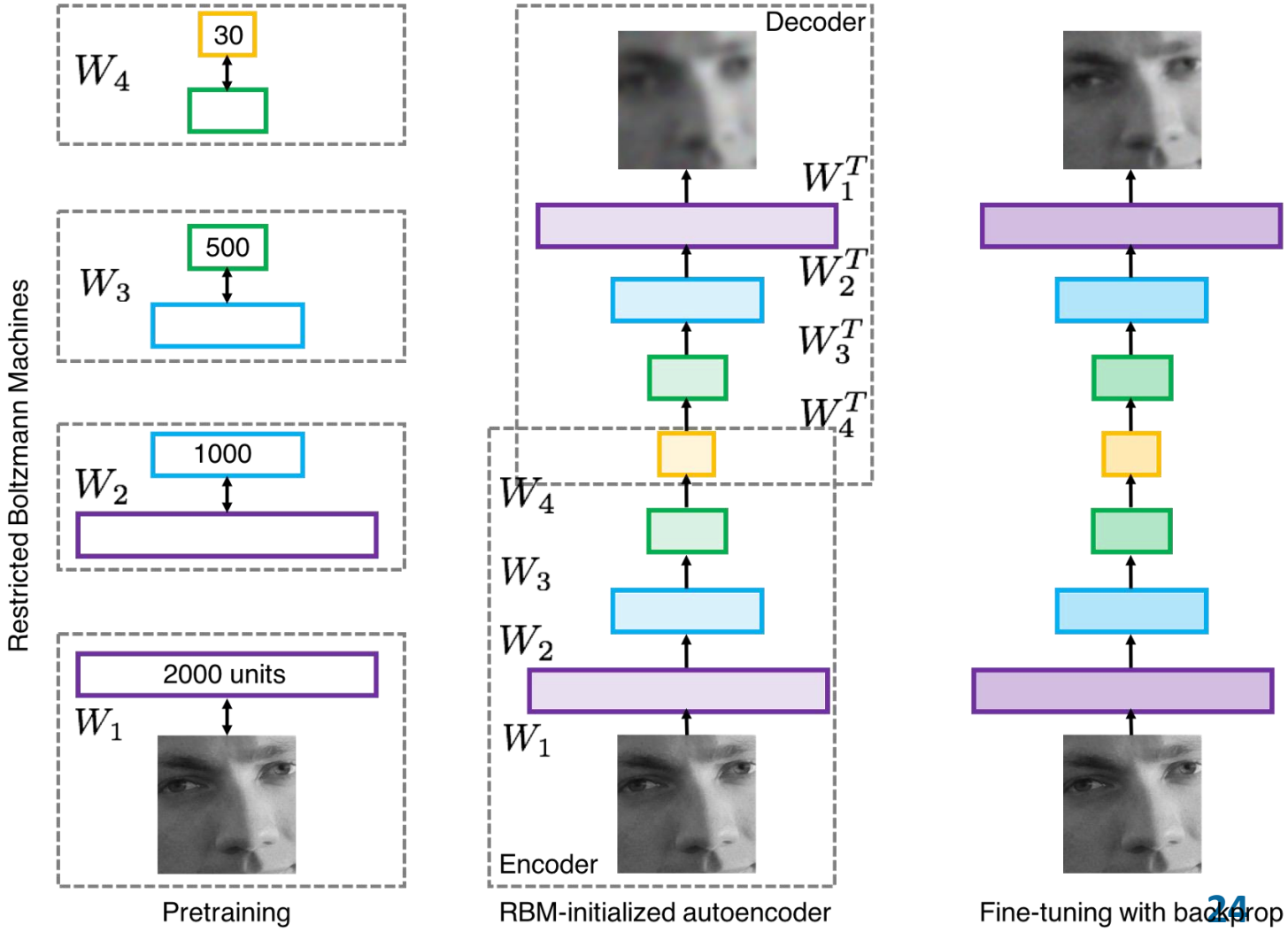
$$\frac{\partial E_p}{\partial w_{ji}} = \frac{\partial E_p}{\partial o_{pj}} \frac{\partial o_{pj}}{\partial w_{ji}}$$



Rumelhart et al., 1986: 提出反向传播

卷积神经网络

- 神经网络的发展历史
- [Hinton and Salakhutdinov 2006]
- 受限玻尔兹曼机
- 重振深度学习研究



卷积神经网络

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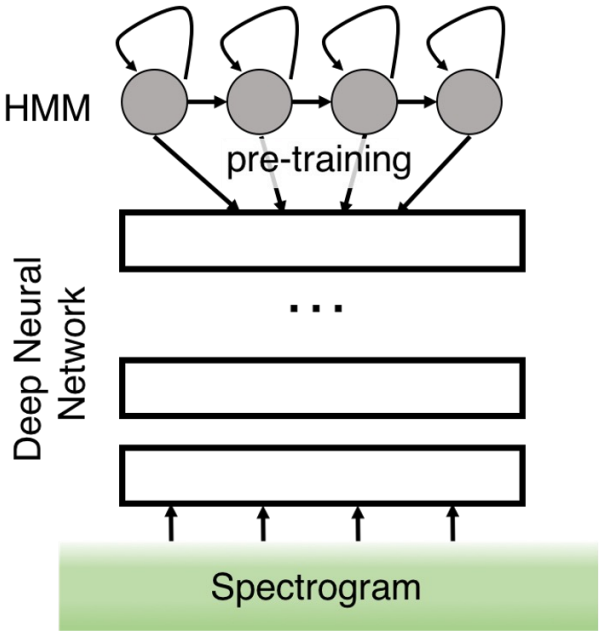
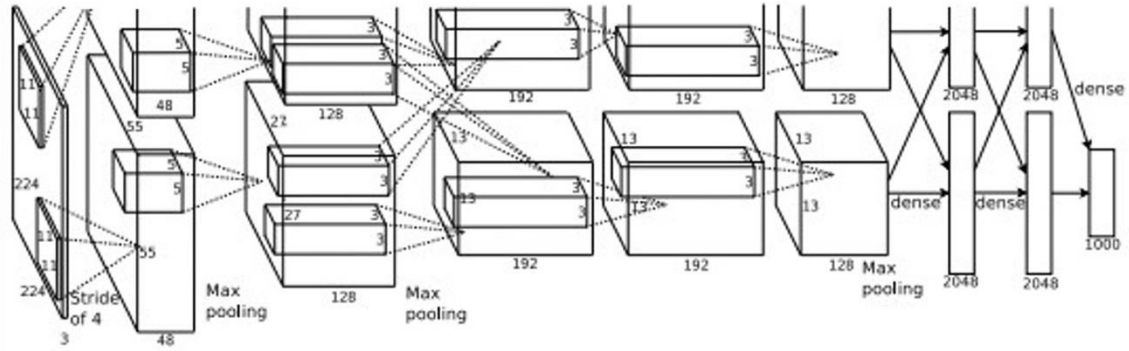
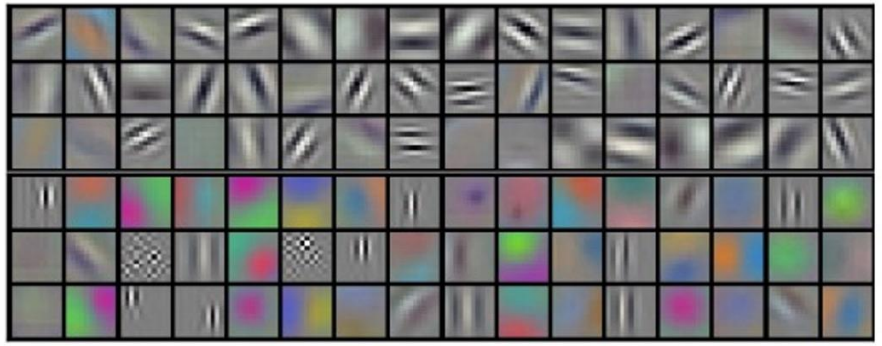
神经网络的发展历史

Acoustic Modeling using Deep Belief Networks
Abdel-rahman Mohamed, George Dahl, Geoffrey Hinton, 2010
Context-Dependent Pre-trained Deep Neural Networks
for Large Vocabulary Speech Recognition
George Dahl, Dong Yu, Li Deng, Alex Acero, 2012



Imagenet classification with deep convolutional
neural networks
Alex Krizhevsky, Ilya Sutskever, Geoffrey E Hinton, 2012





卷积神经网络

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卷积神经网络的发展历史

Hubel & Wiesel,

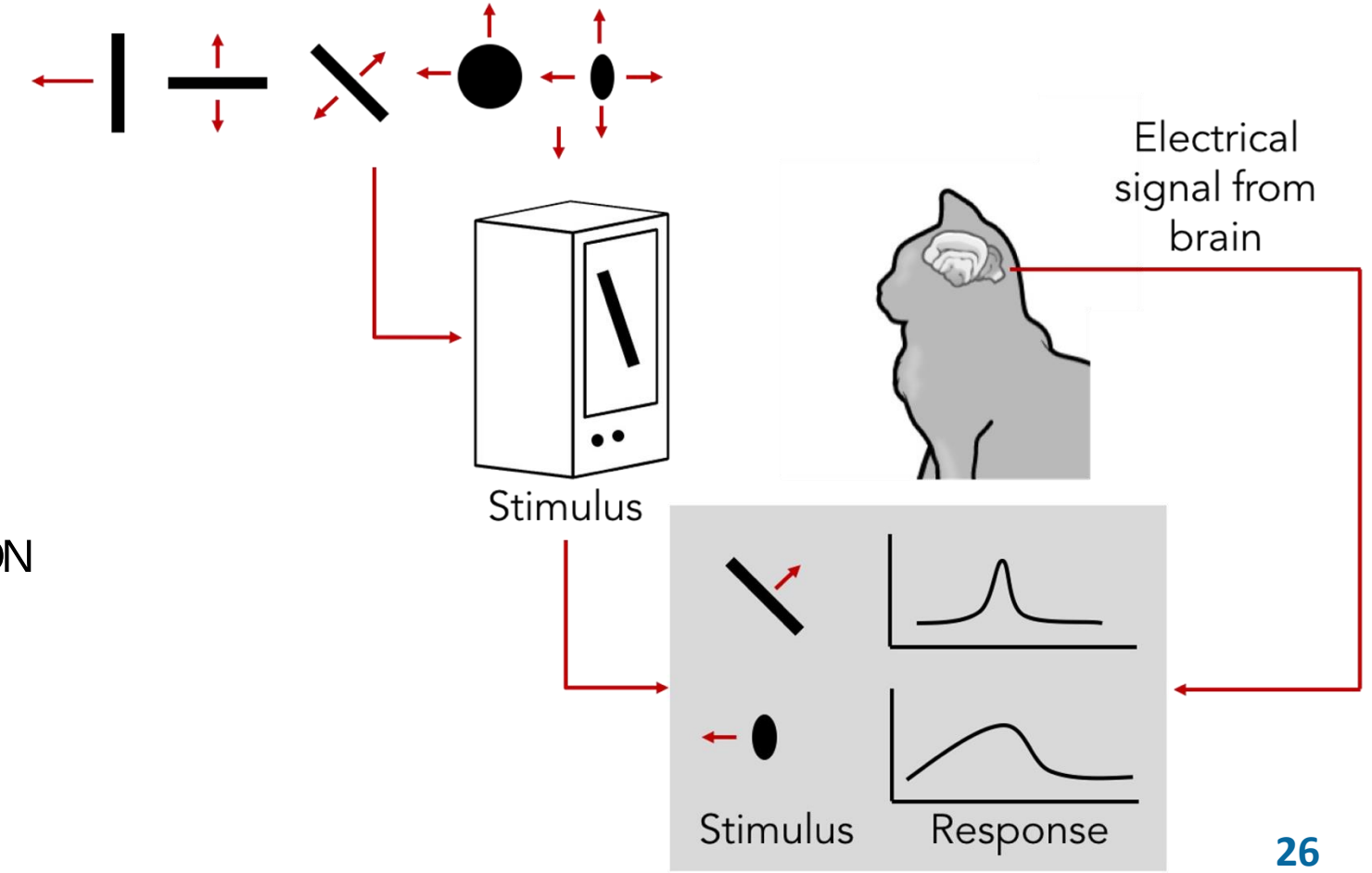
1959

RECEPTIVE FIELDS OF SINGLE NEURONES IN THE CAT'S STRIATE CORTEX

1962

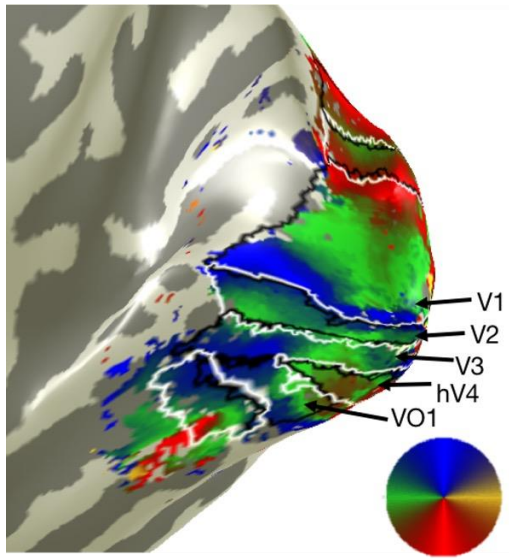
RECEPTIVE FIELDS, BINOCULAR INTERACTION AND FUNCTIONAL ARCHITECTURE IN THE CAT'S VISUAL CORTEX

1968...

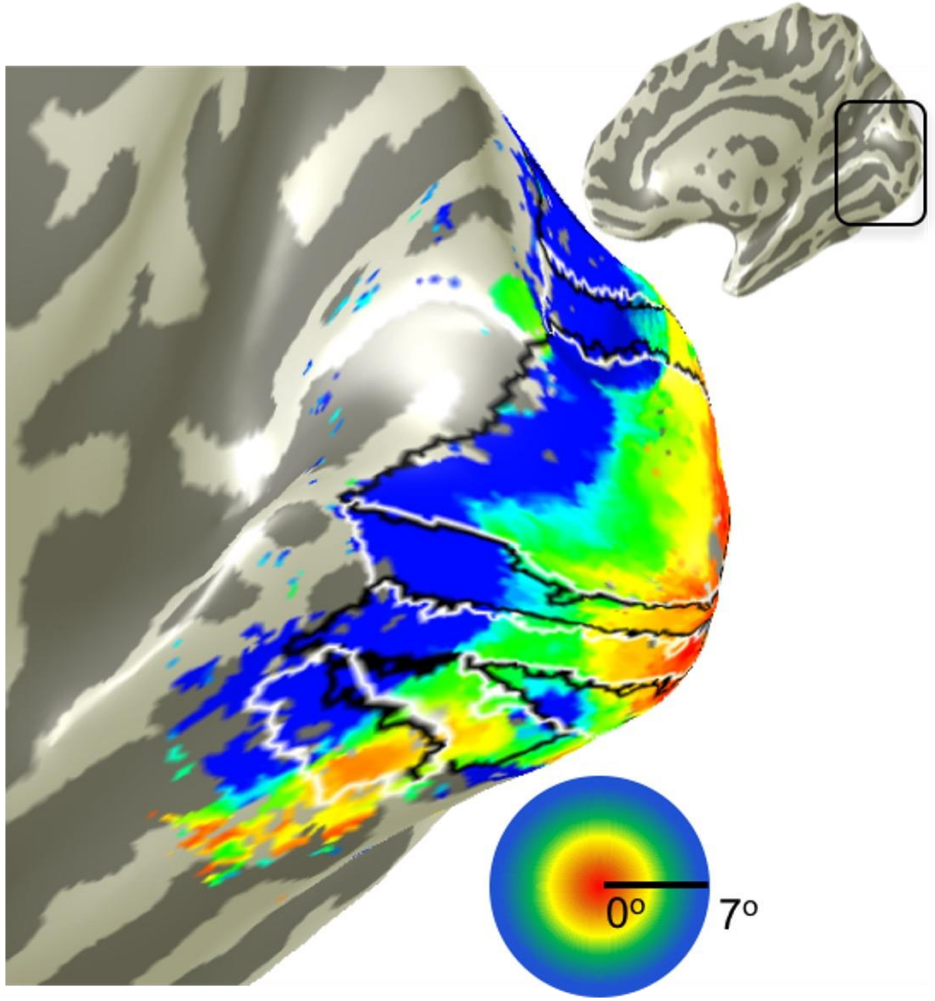


卷积神经网络

- 卷积神经网络的发展历史
- 皮层地形图：大脑皮层中的相邻细胞被视野中的相邻区域激活

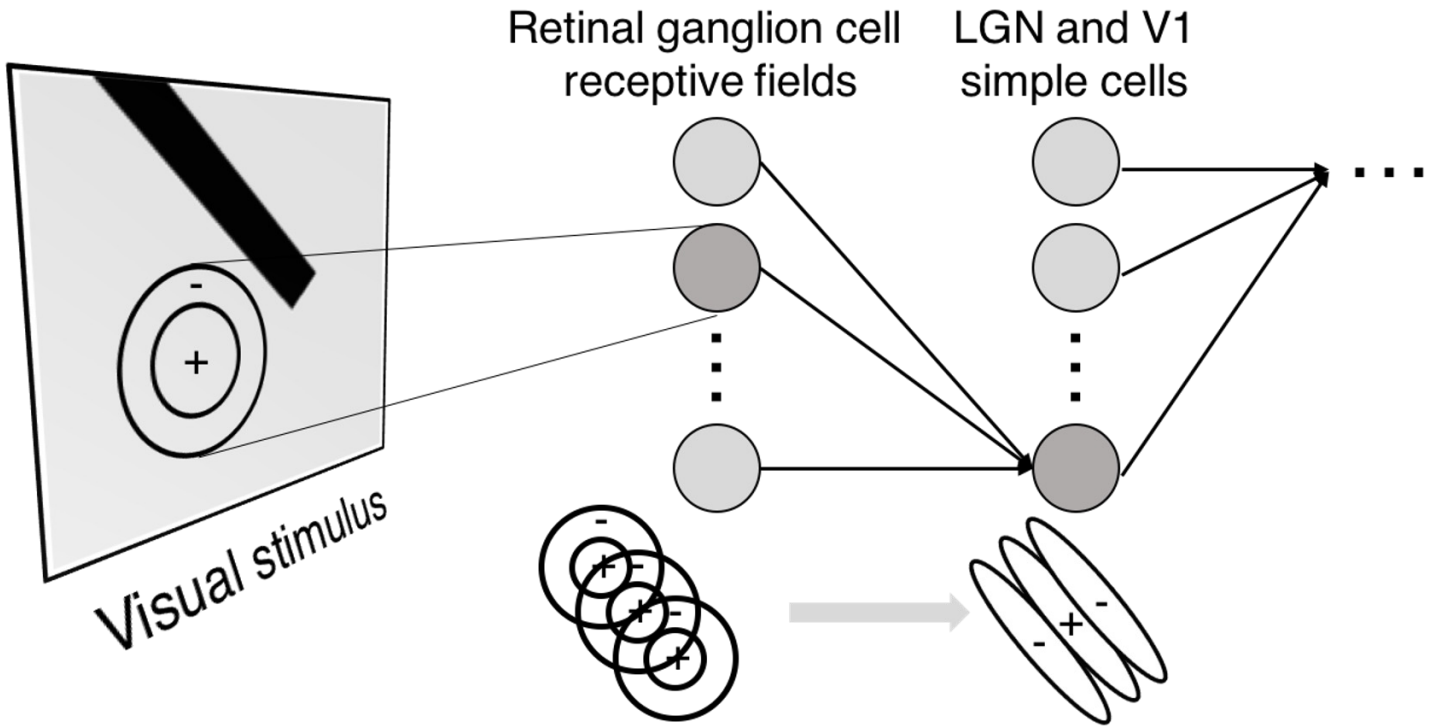


人类大脑



卷积神经网络

- 卷积神经网络的发展历史
- 视觉分级感知



Simple cells:
Response to light orientation

Complex cells:
Response to light orientation and movement

Hypercomplex cells:
response to movement with an end point

No response

Response (end point)

卷积神经网络

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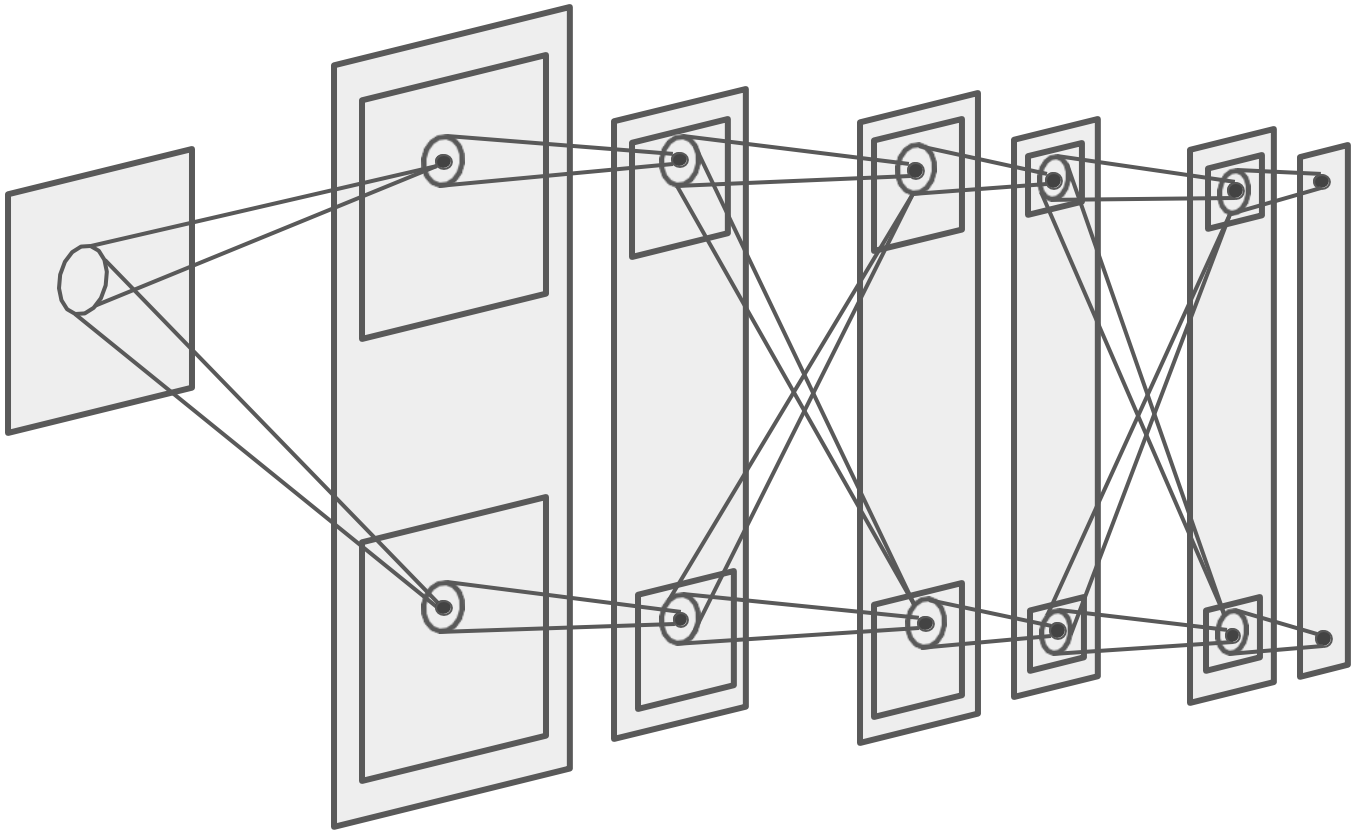
- **卷积神经网络的发展历史**

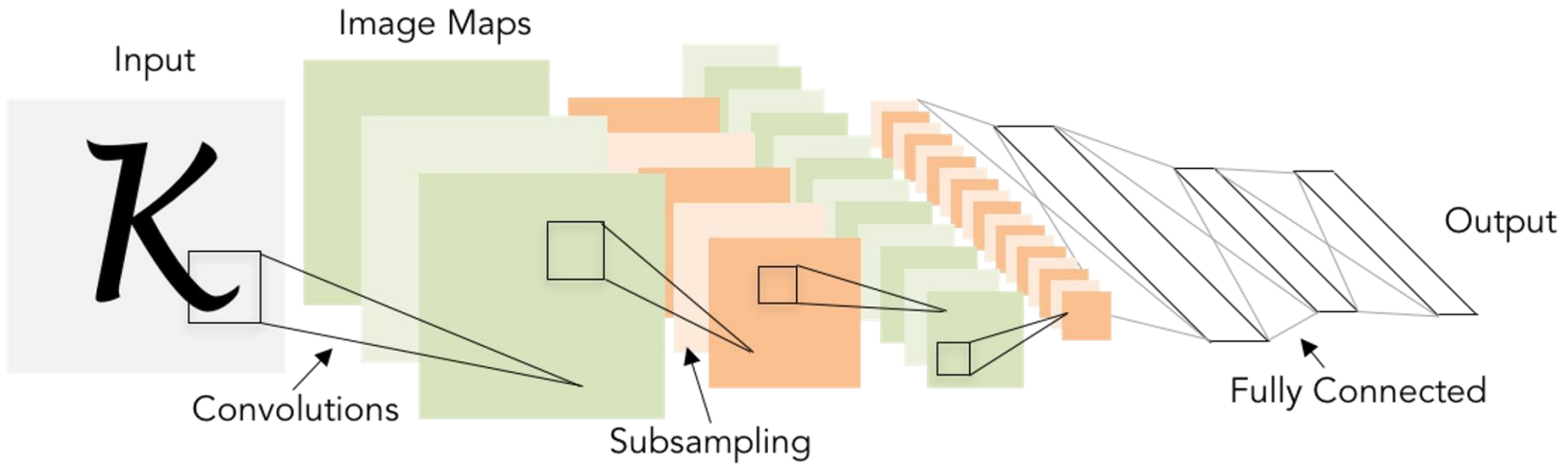
Neocognitron
[Fukushima 1980]



三明治结构 (SCSCSC…)
simple cells: modifiable parameters
complex cells: perform pooling

卷积神经网络

- 卷积神经网络的发展历史
- 将基于梯度优化的卷积网络应用到文档识别
- [LeCun, Bottou, Bengio, Haffner 1998]



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卷积神经网络的发展历史

ImageNet Classification with Deep Convolutional Neural Networks [Krizhevsky, Sutskever, Hinton, 2012]

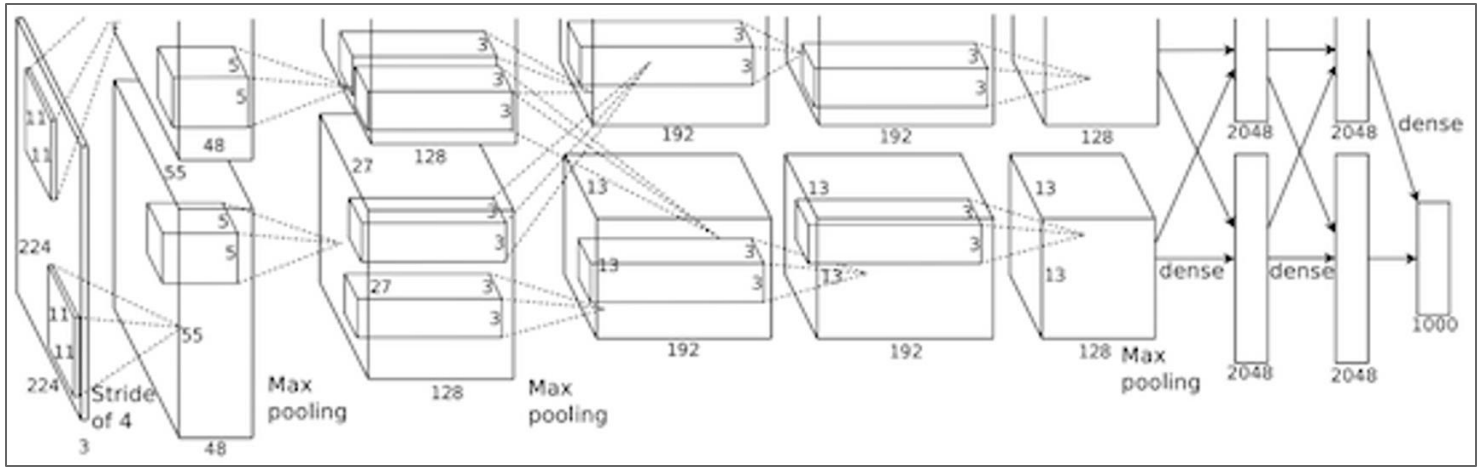

Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.

"AlexNet"

卷积神经网络

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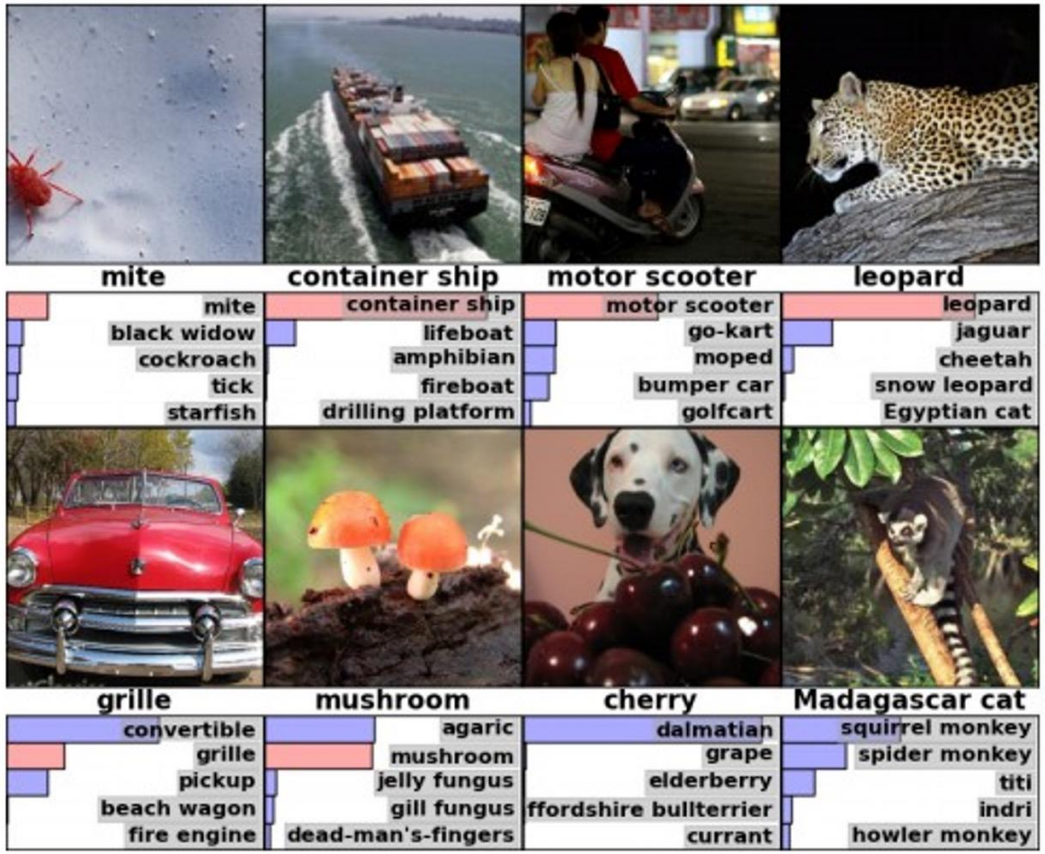
卷积神经网络的广泛应用

Classification



Retrieval

卷积神经网络

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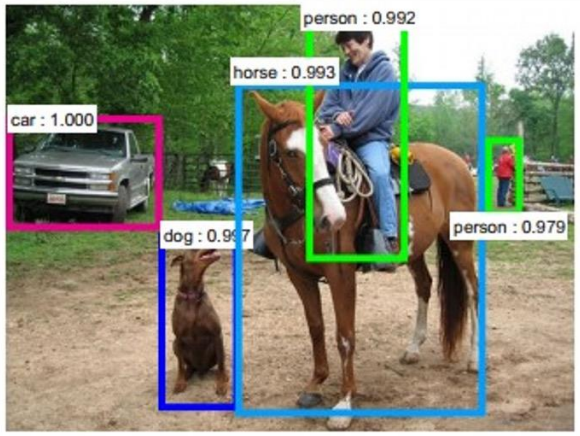
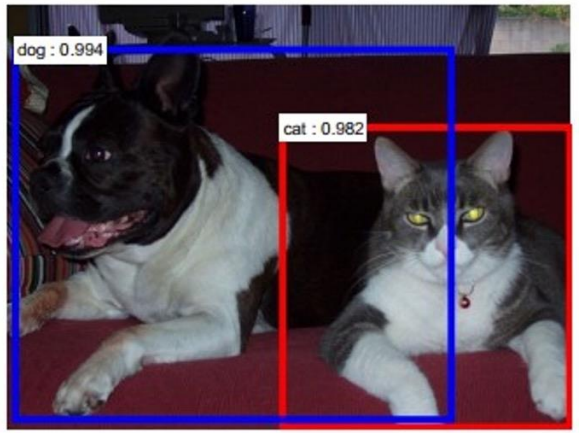
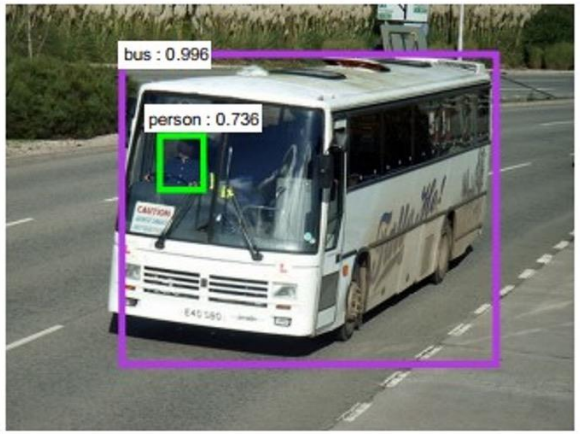
卷积神经网络的广泛应用

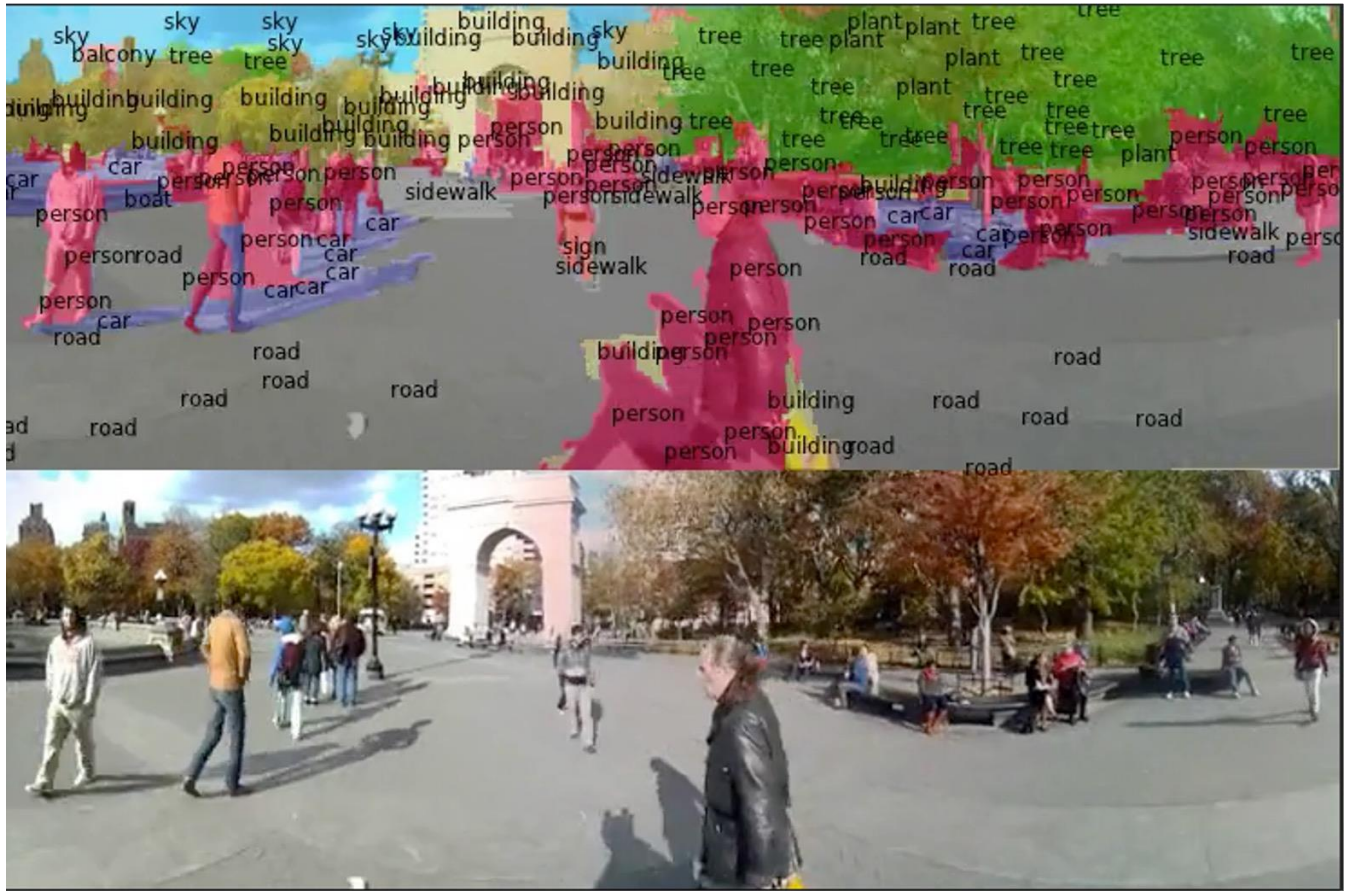
Detection







Segmentation



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卷积神经网络的广泛应用

自动驾驶汽车

NVIDIA Tesla 系列显卡

卷积神经网络

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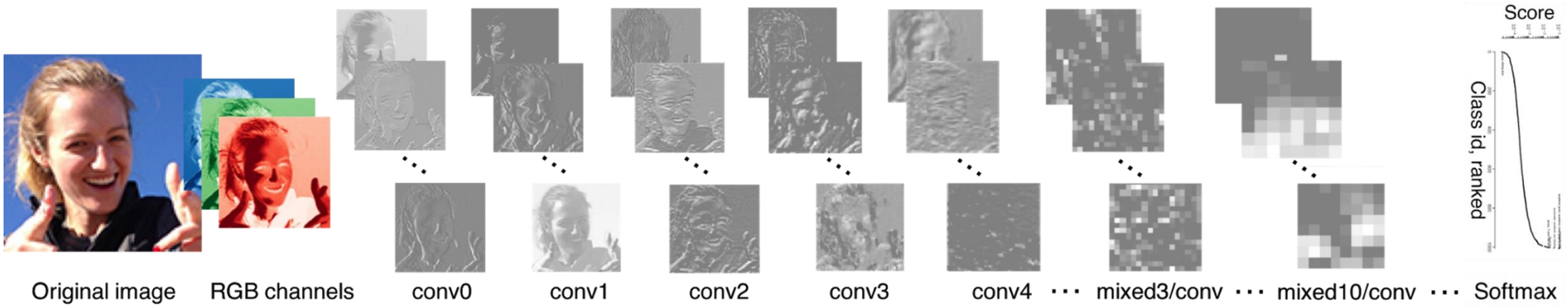
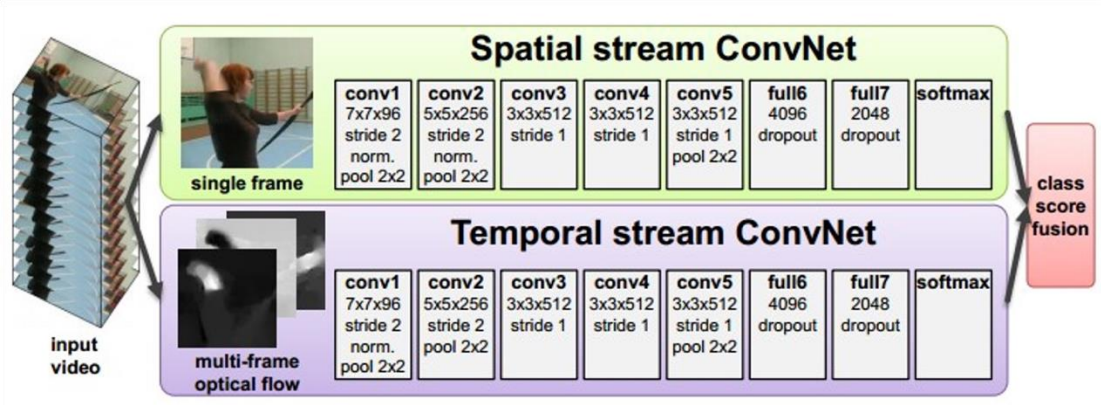
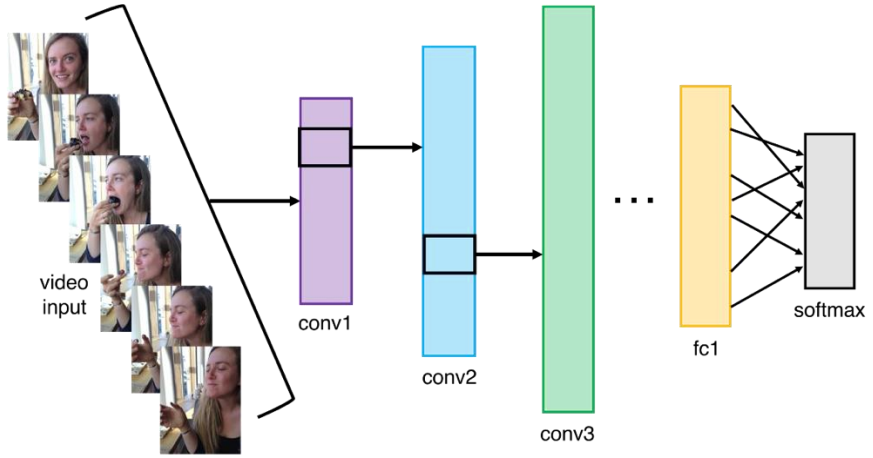
卷积神经网络的广泛应用



[Taigman et al. 2014]



[Simonyan et al. 2014]



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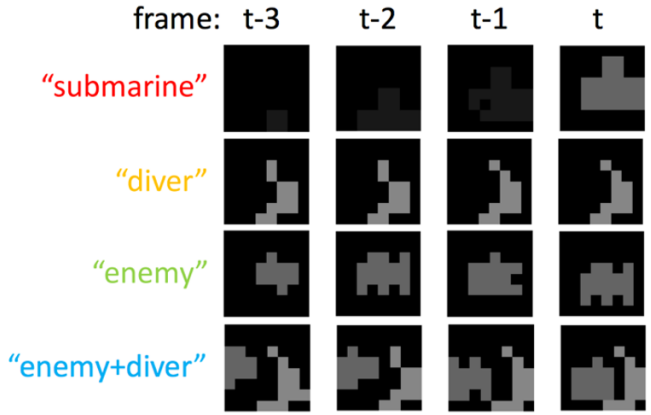
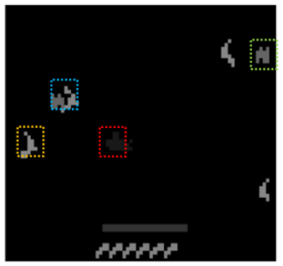
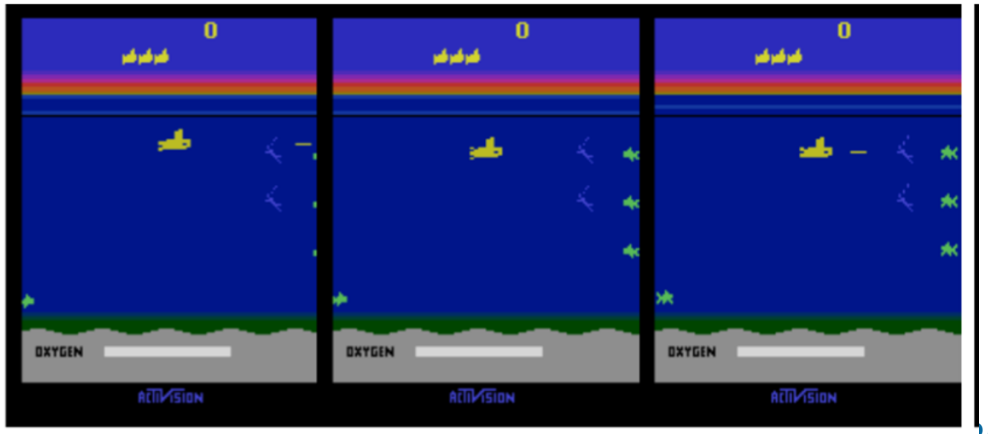
[Toshev, Szegedy 2014]







[Guo et al. 2014]

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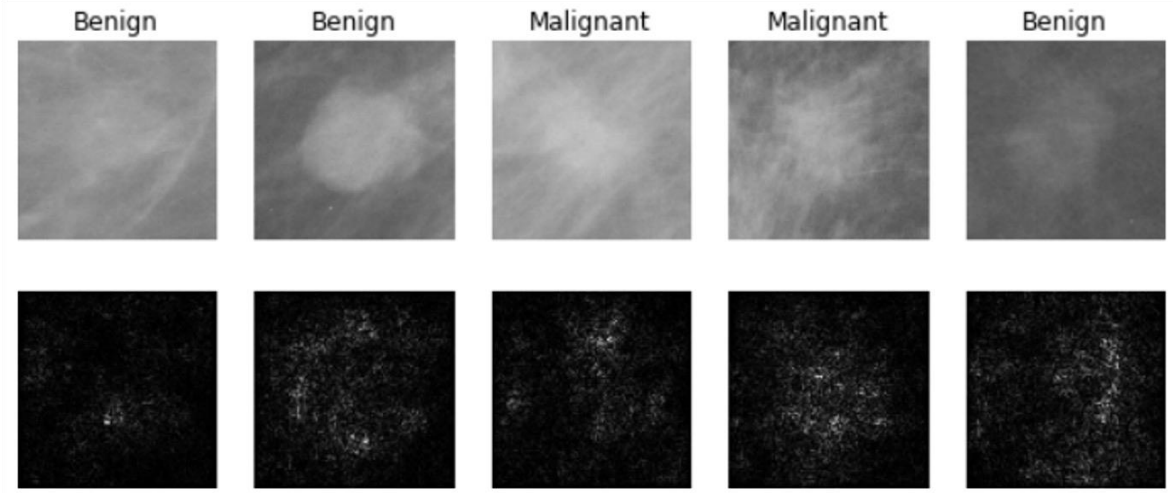
卷积神经网络的广泛应用



[Levy et al. 2016]

[Dieleman et al. 2014]

[Sermanet et al. 2011]
[Ciresan et al.]

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- 卷积神经网络的广泛应用

Kaggle Challenge

Mnih and Hinton, 2010

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卷积神经网络的广泛应用

No errors

A white teddy bear sitting in the grass

A man riding a wave on top of a surfboard

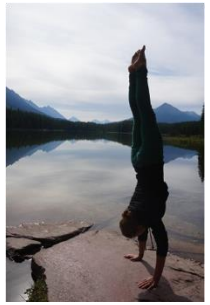
Minor errors

A man in a baseball uniform throwing a ball

A cat sitting on a suitcase on the floor

Somewhat related

A woman is holding a cat in her hand



A woman standing on a beach holding a surfboard

图像描述

[Vinyals et al., 2015]
[Karpathy and Fei-Fei, 2015]

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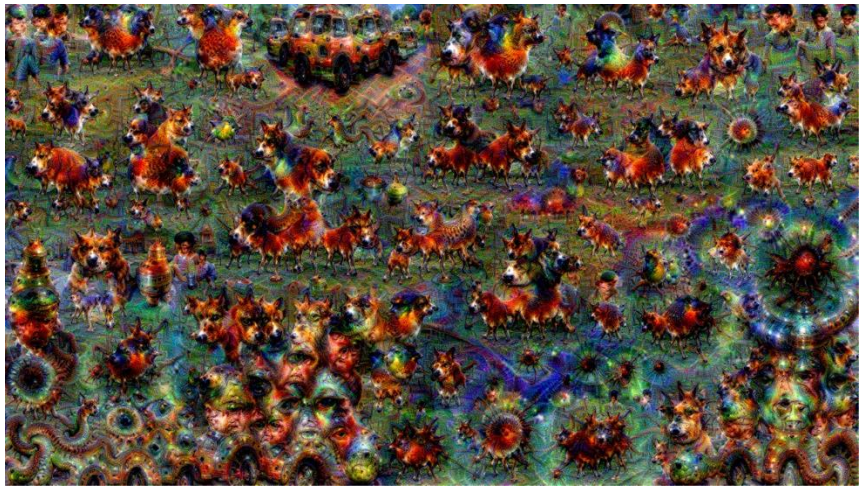
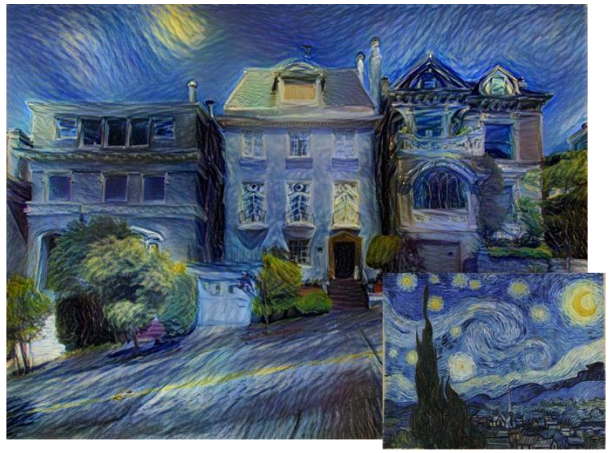
卷积神经网络的广泛应用



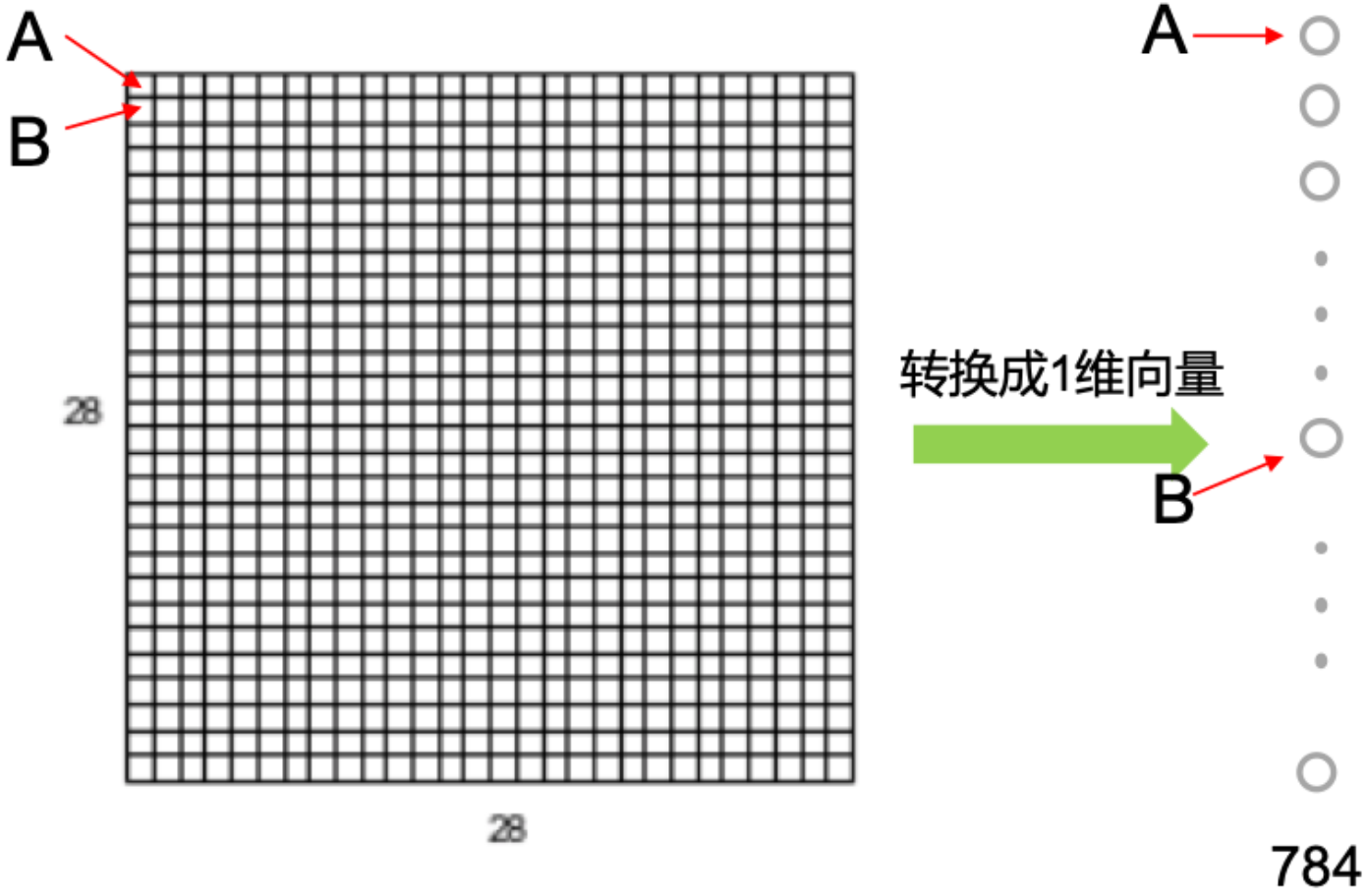


大　　纲

- 卷积神经网络-引言
- 卷积神经网络

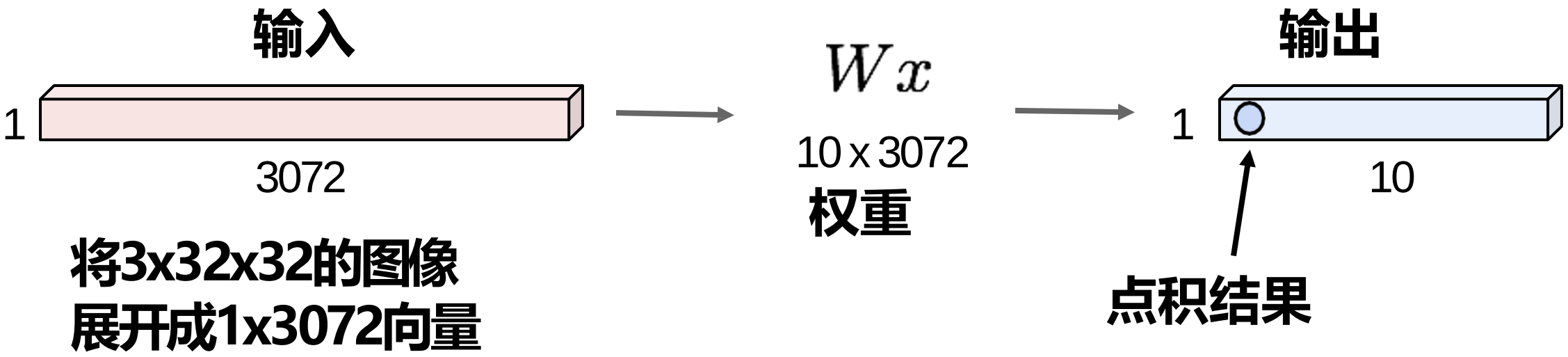
卷积神经网络

- 全连接层（参数量，优化，空间信息）



卷积神经网络

- 全连接层（参数量，优化，空间信息）



卷积神经网络

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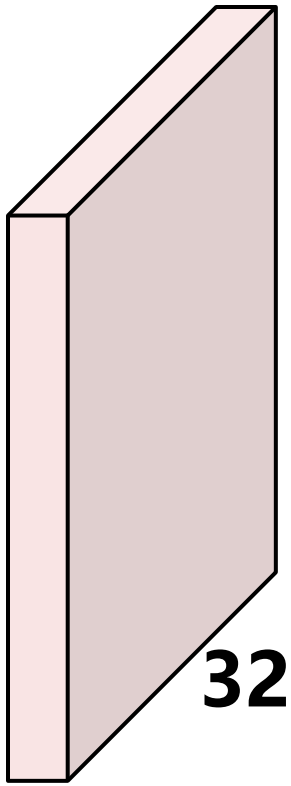
- 卷积层

3x32x32图像：保持图像的空间结构



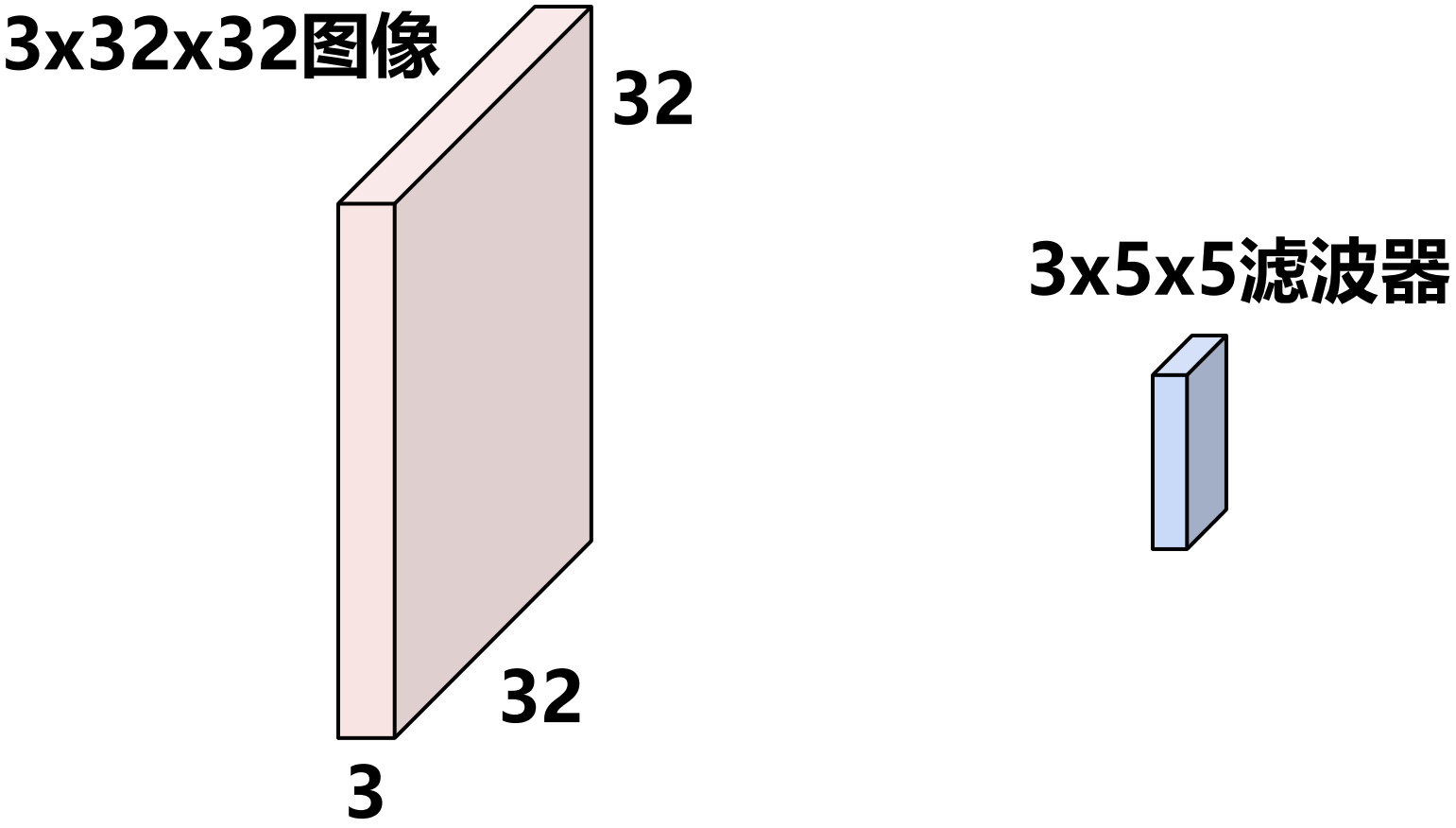
32（高度，height）

32（宽度，width）

3（深度，depth）

卷积神经网络

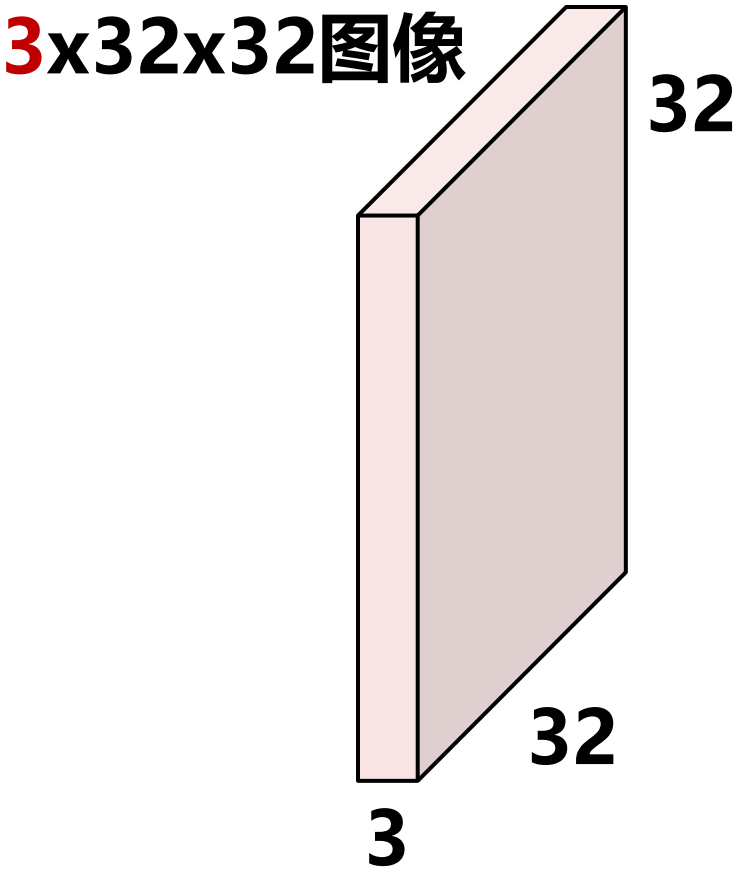
- 卷积层

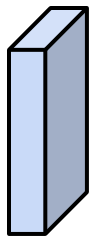


卷积神经网络

- 卷积层

滤波器的深度始终与输入的深度相同

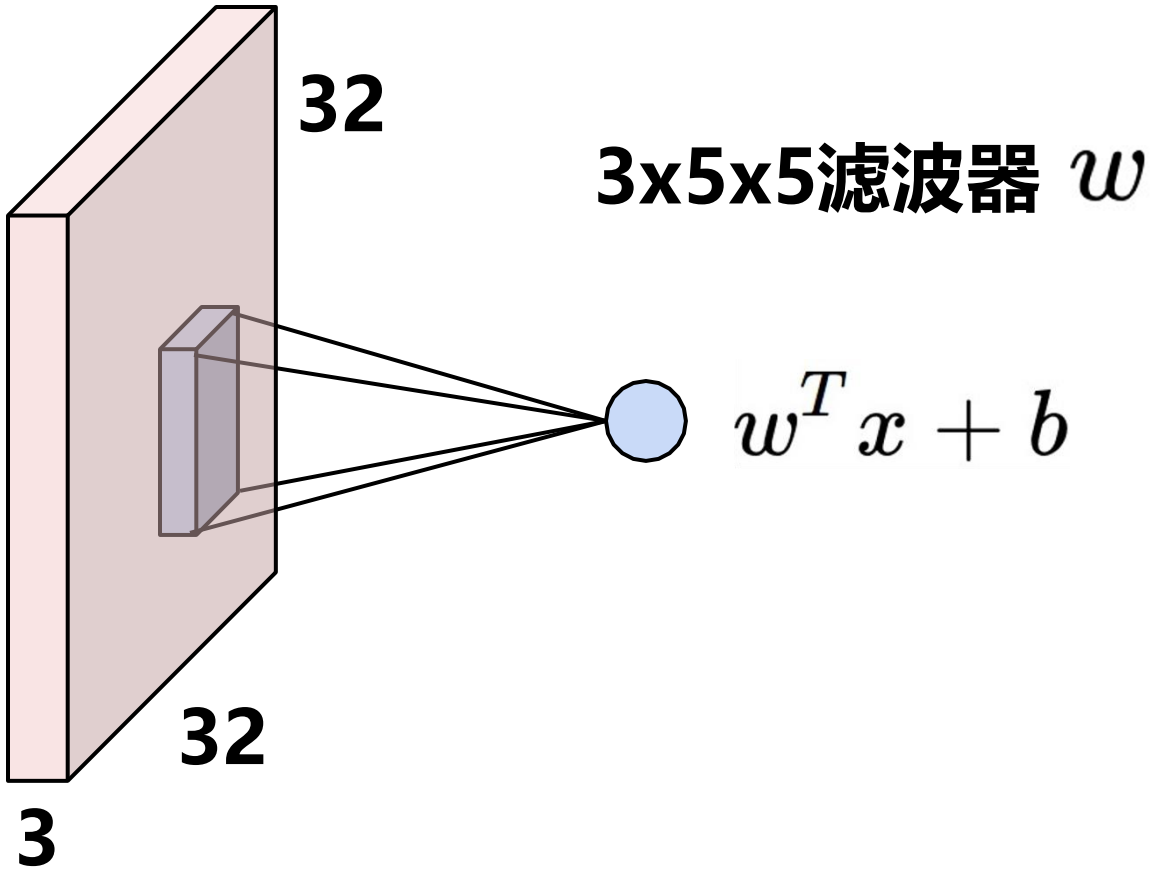




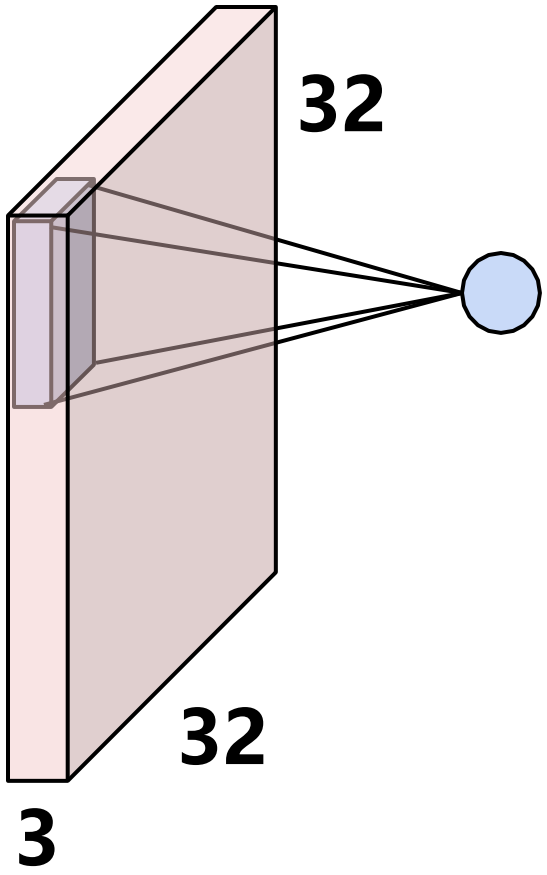
将滤波器与图像卷积，
即“在图像上空间滑动，计算点积”

卷积神经网络

卷积层



卷积层



卷积神经网络

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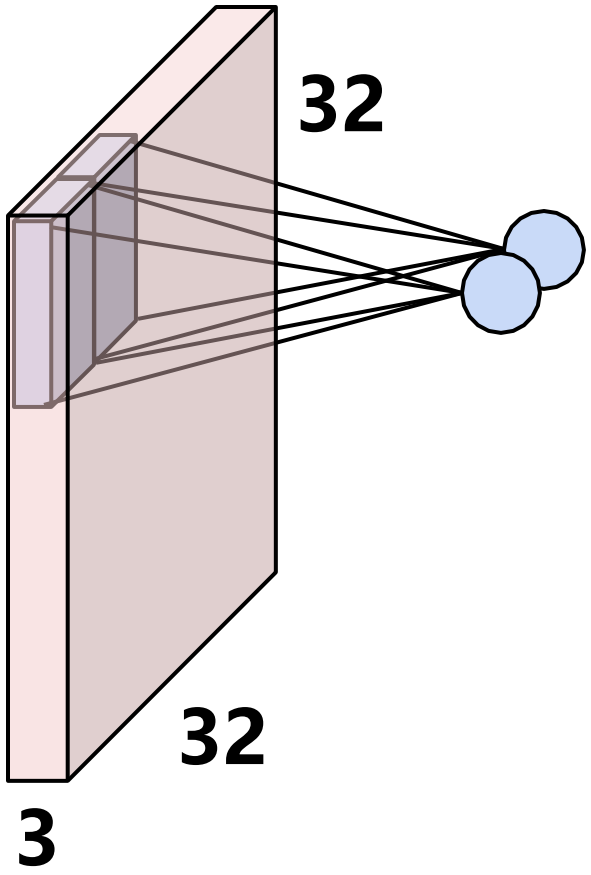
卷积层



卷积神经网络

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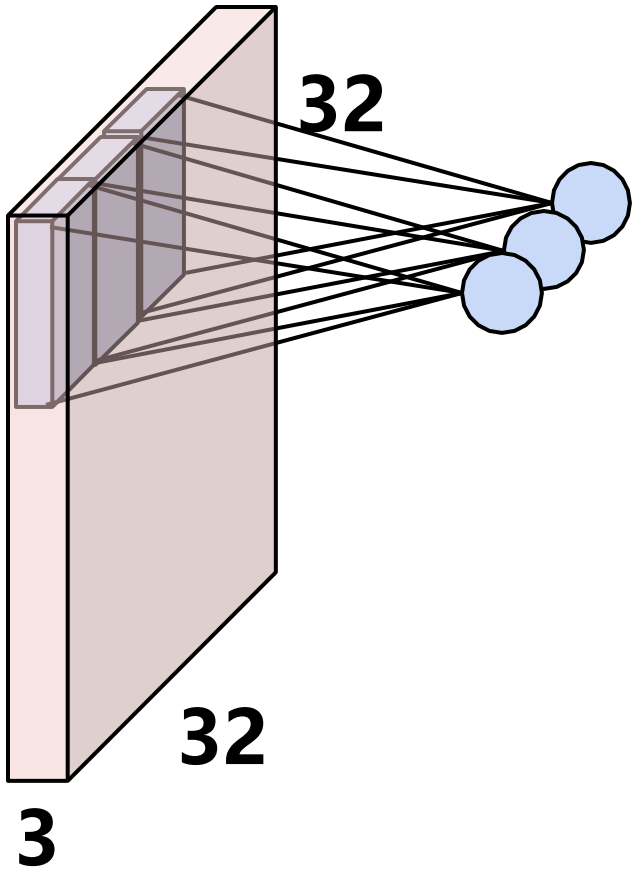
卷积层



卷积神经网络

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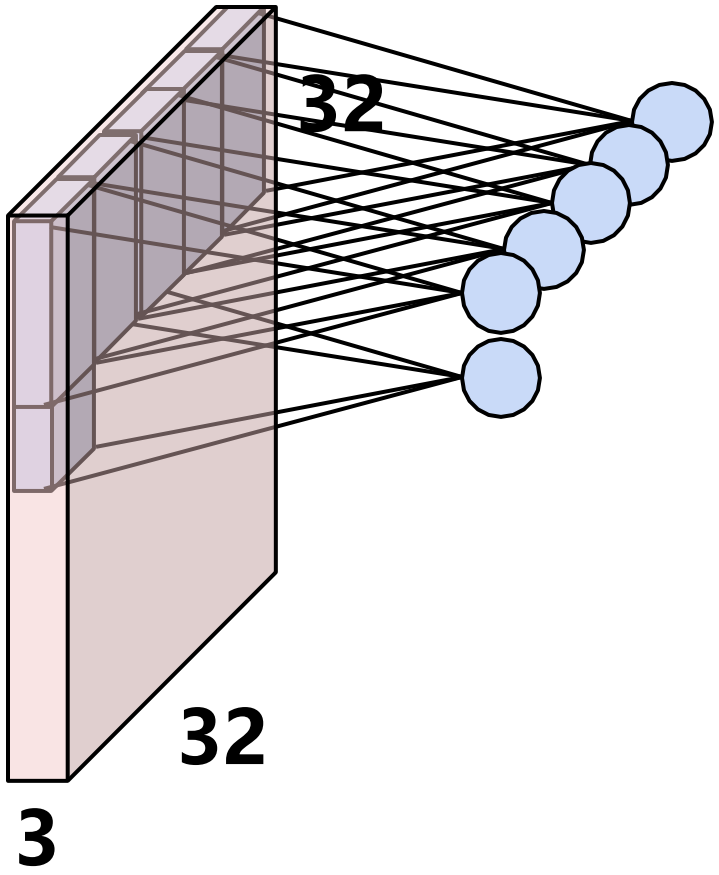
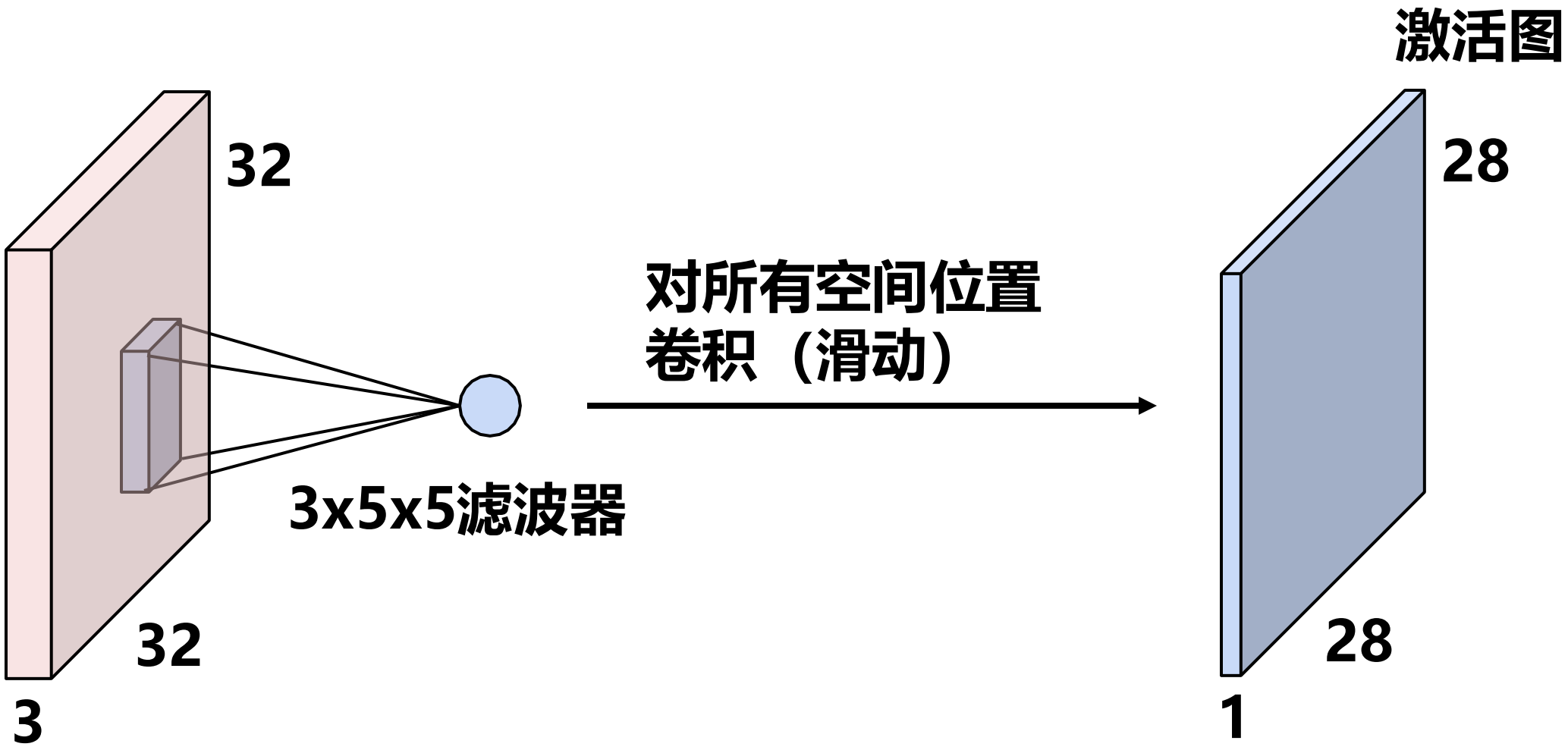
卷积层



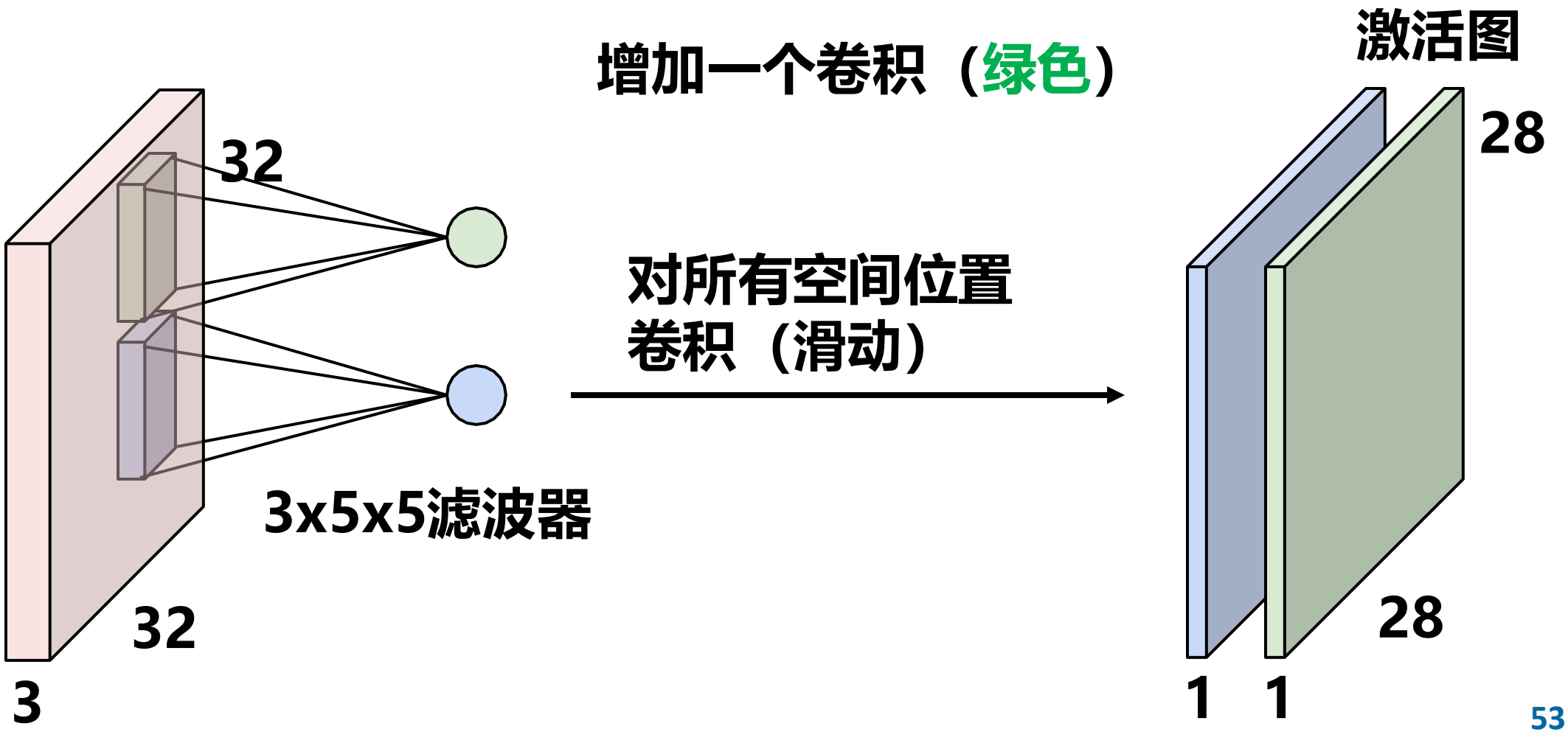
卷积神经网络

- 卷积层



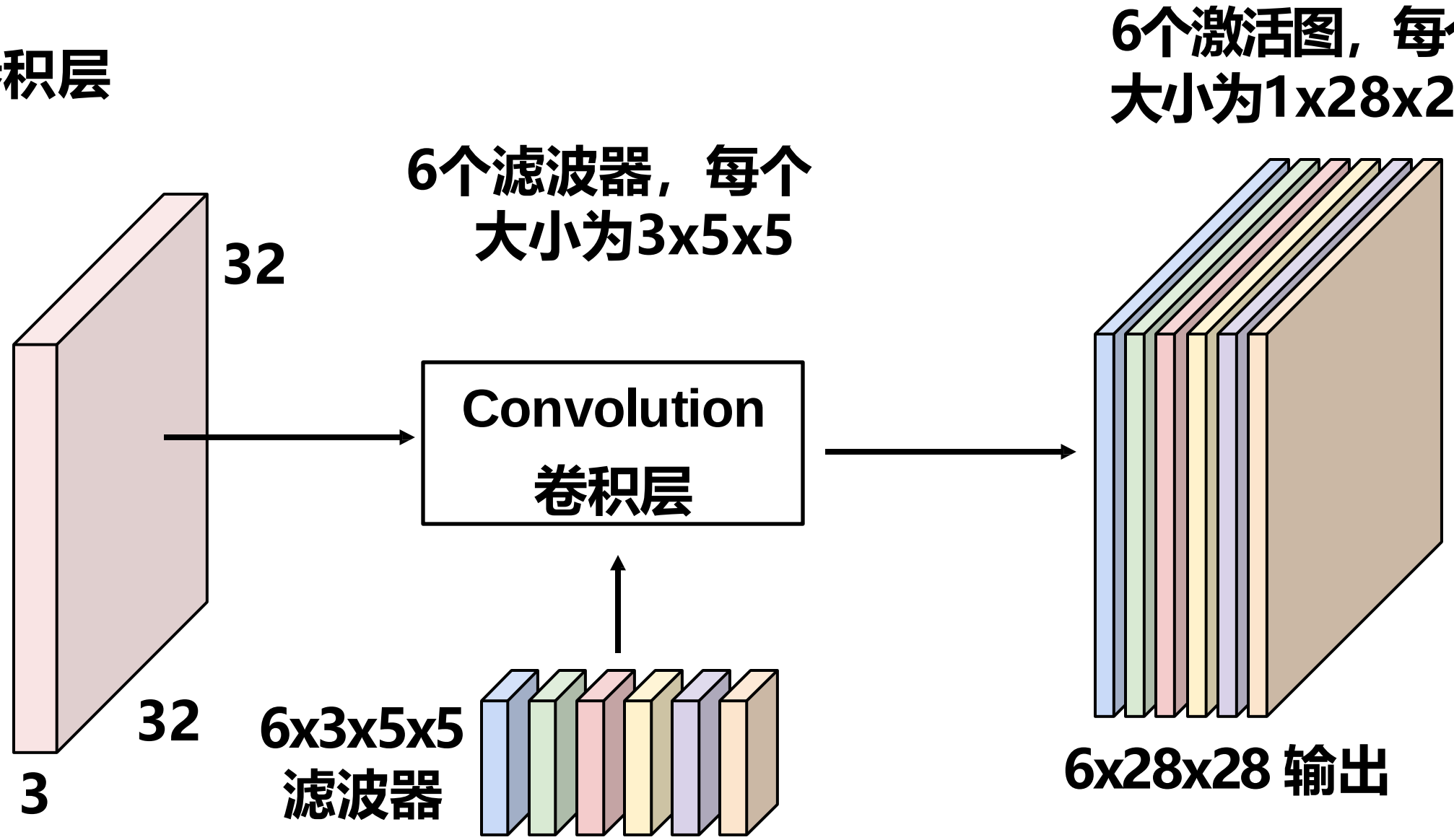
卷积神经网络

- 卷积层



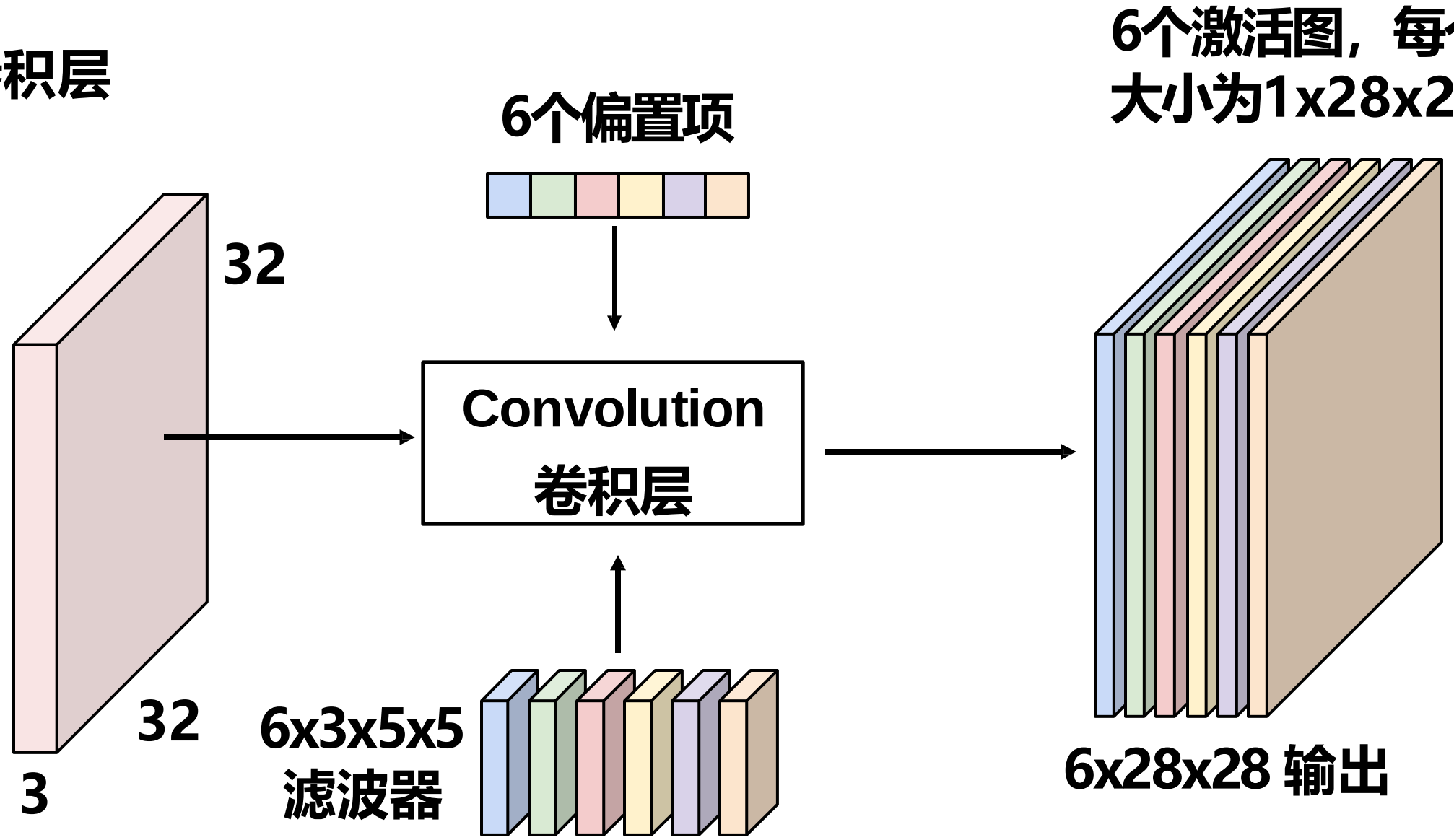
卷积神经网络

- 卷积层


6个激活图，每个
大小为1x28x28
6个滤波器，每个
大小为3x5x5
32
32
3
Convolution
卷积层
6x3x5x5
滤波器
6x28x28 输出

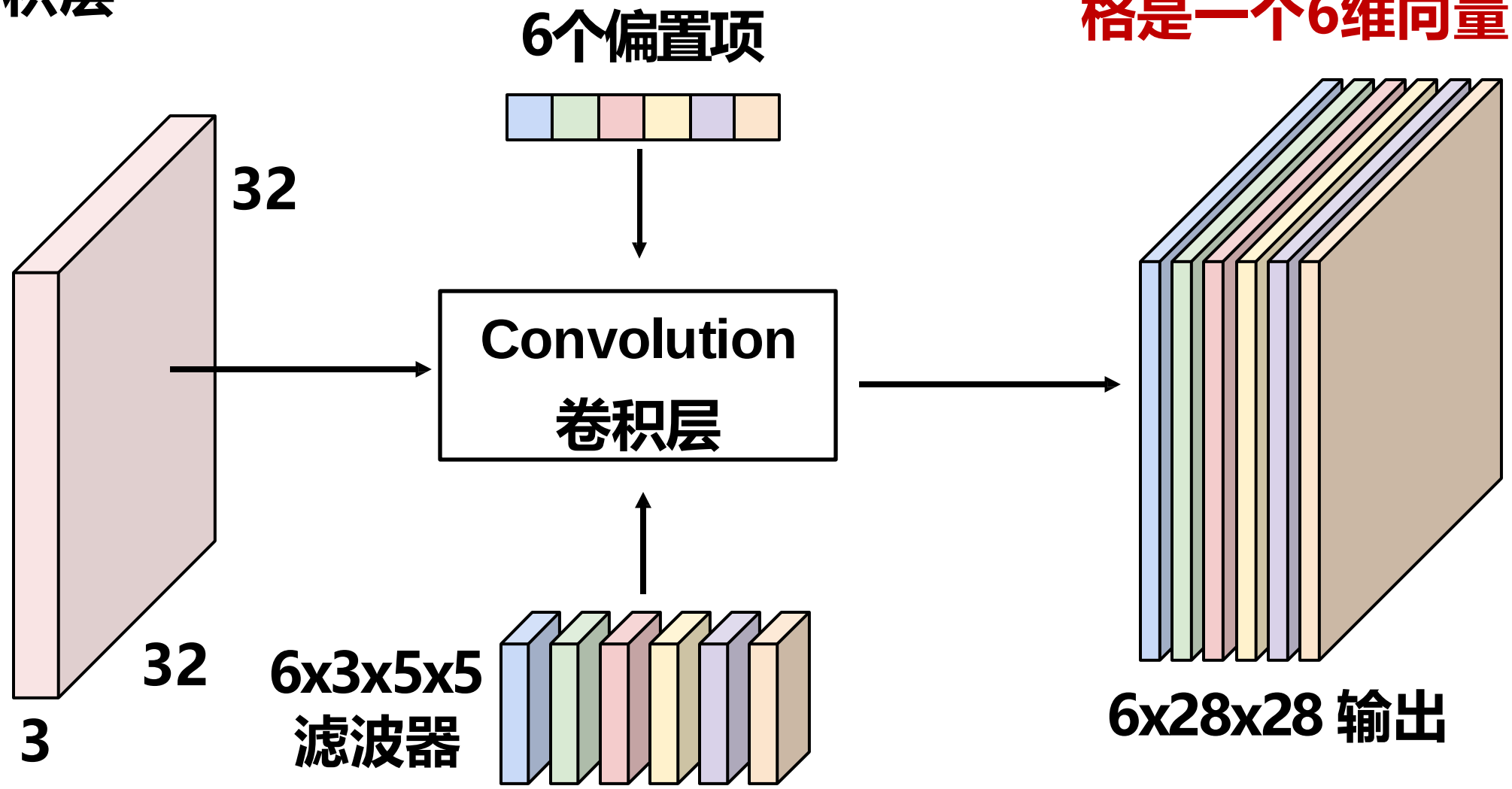
卷积神经网络

- 卷积层


6个偏置项
6个激活图，每个大小为1x28x28
32
32
3
Convolution
卷积层
6x3x5x5
滤波器
6x28x28 输出

卷积神经网络

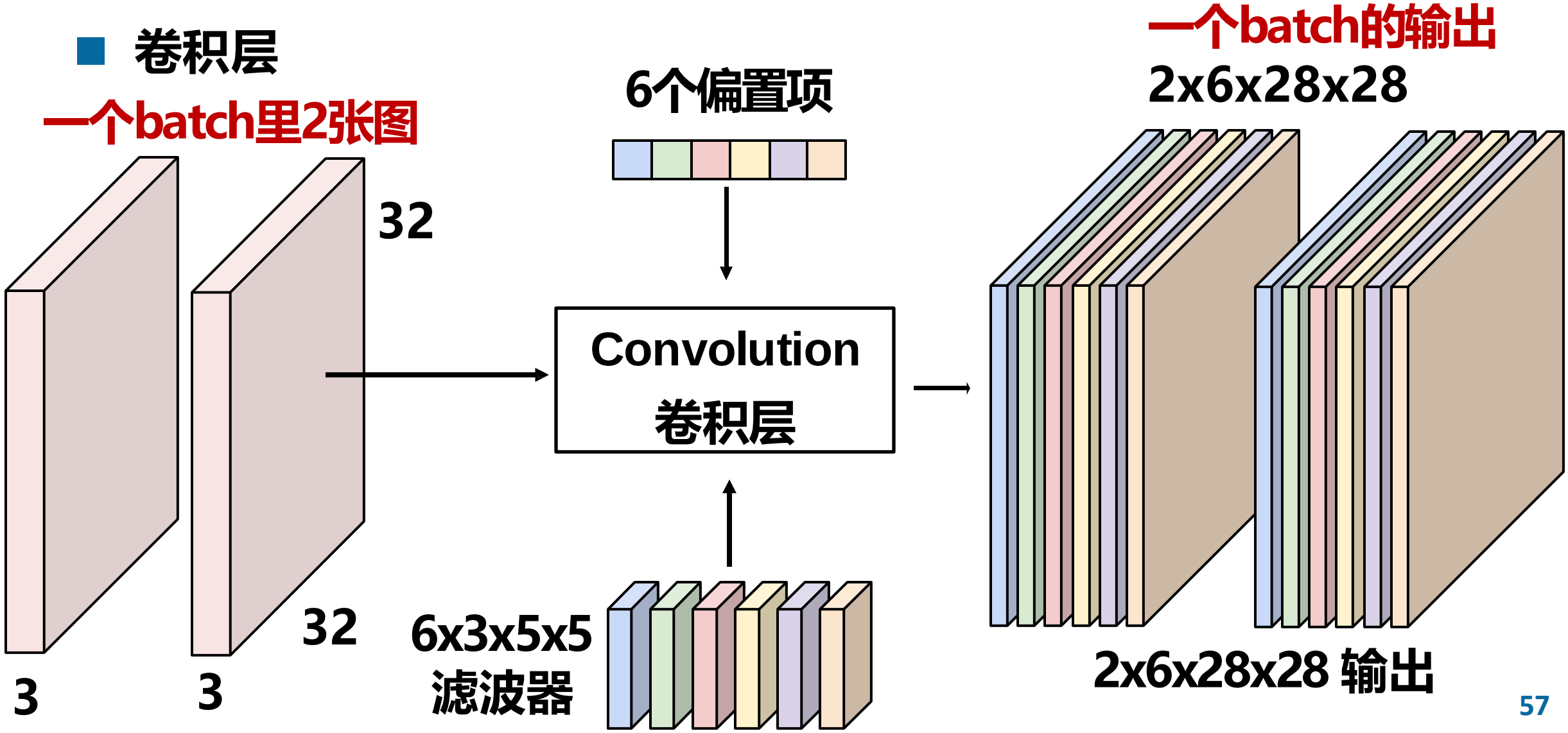
- 卷积层



28x28网格，每个网格是一个6维向量

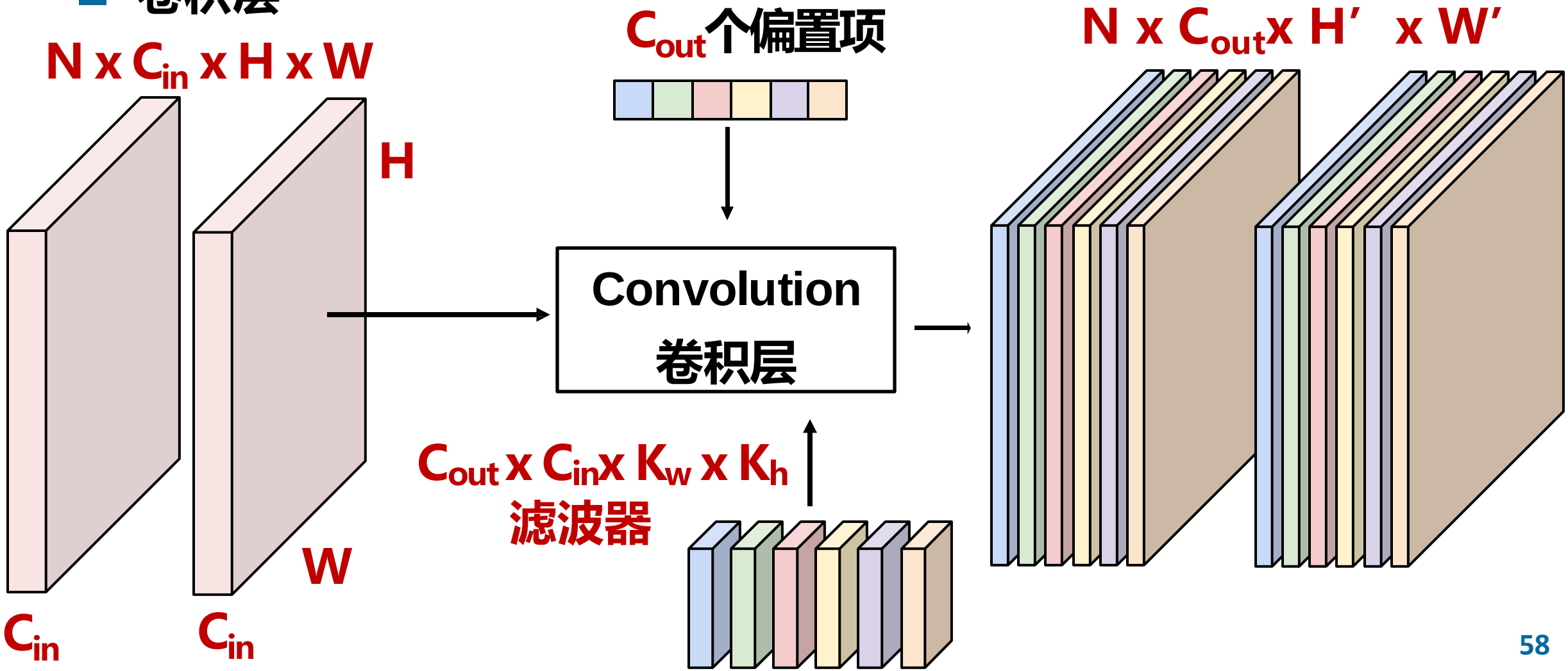
卷积神经网络

- 卷积层


一个batch里2张图
32
32
3
3
6个偏置项
Convolution
卷积层
6x3x5x5
滤波器
一个batch的输出
2x6x28x28
2x6x28x28 输出

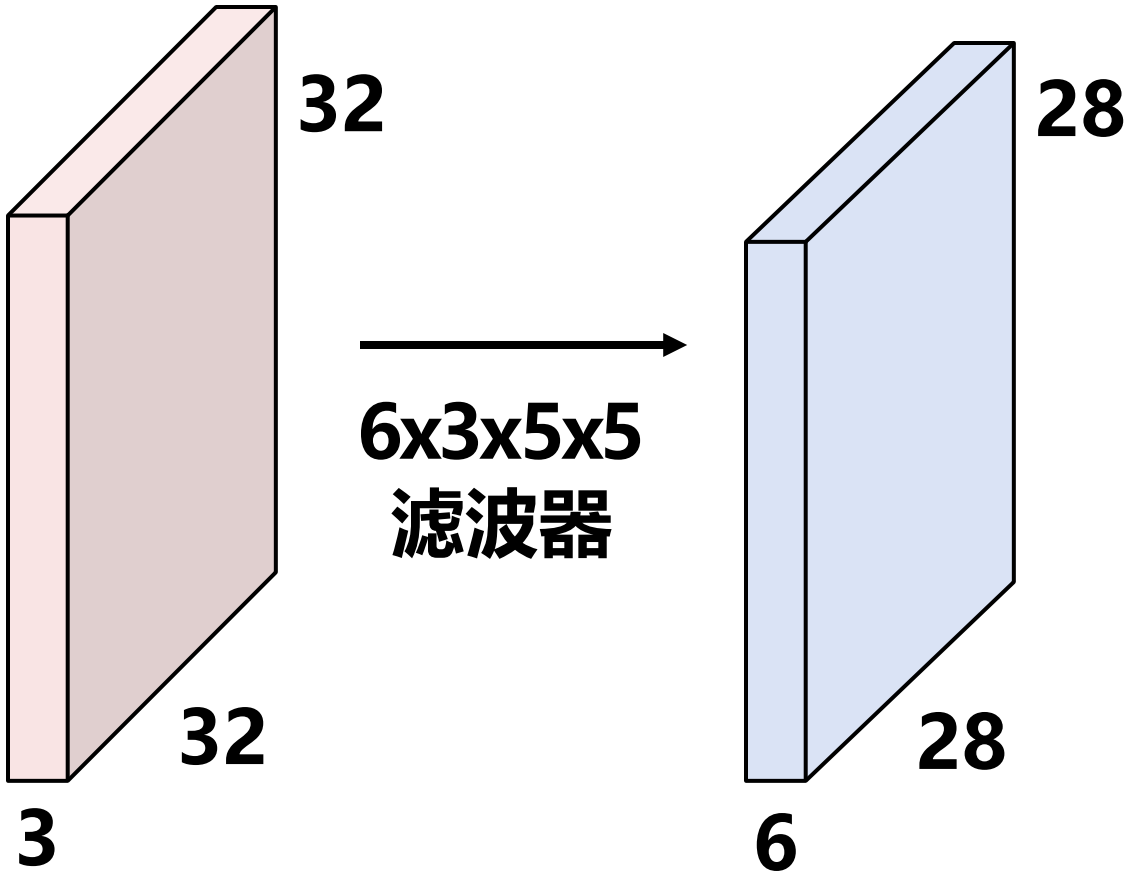
卷积神经网络

- 卷积层


N x C_{in} x H x W
H
W
C_{in}
C_{in}
C_{out}个偏置项
Convolution
卷积层
C_{out} x C_{in}x K_w x K_h
滤波器
N x C_{out}x H′ x W′

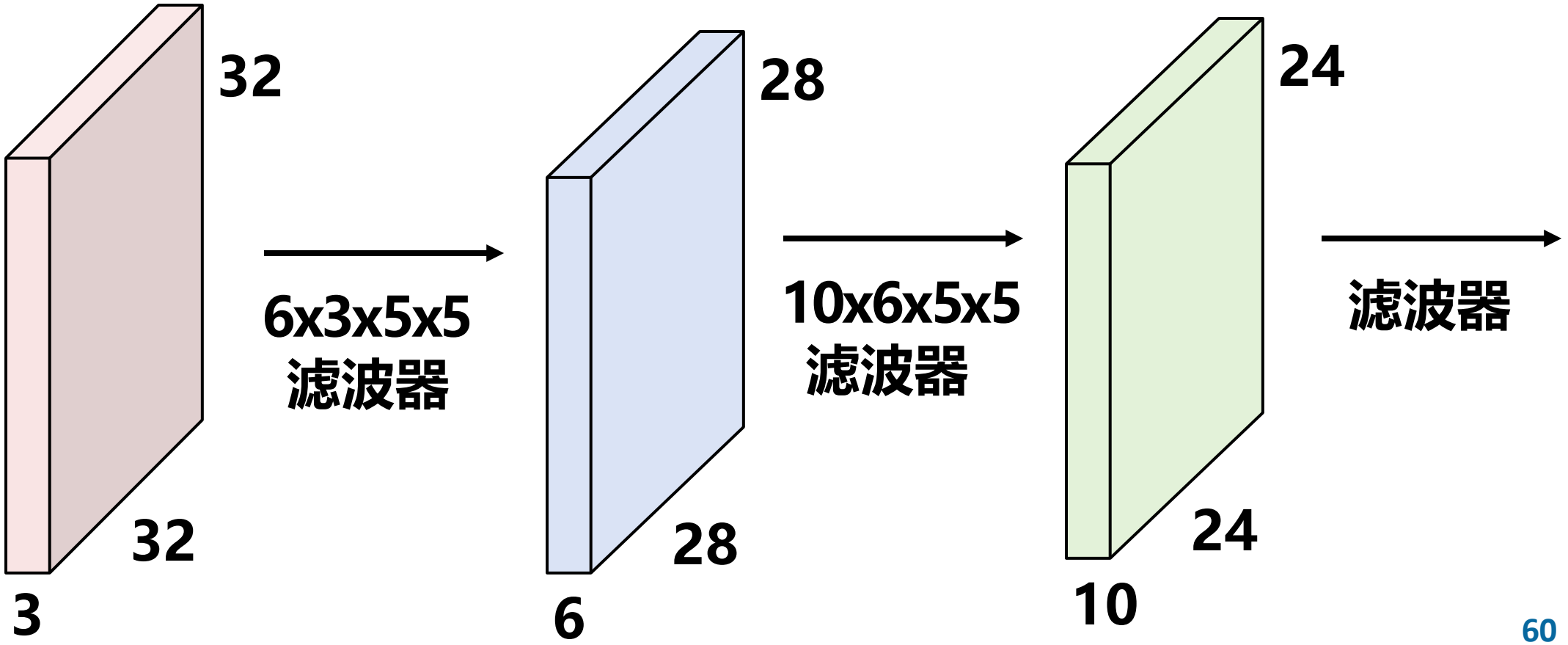
卷积神经网络

- 卷积神经网络由一系列卷积层组成



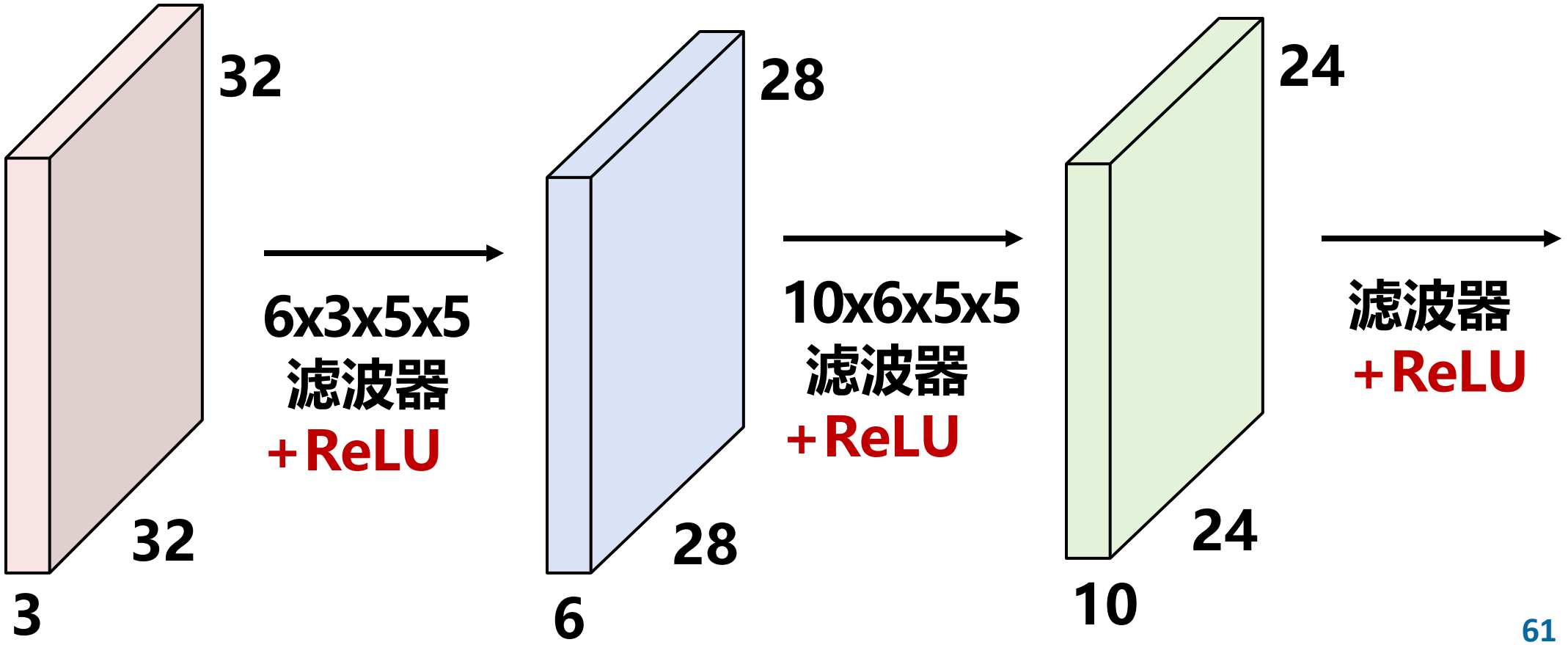
卷积神经网络

- 卷积神经网络由一系列卷积层组成



卷积神经网络

- 卷积神经网络由一系列卷积层组成



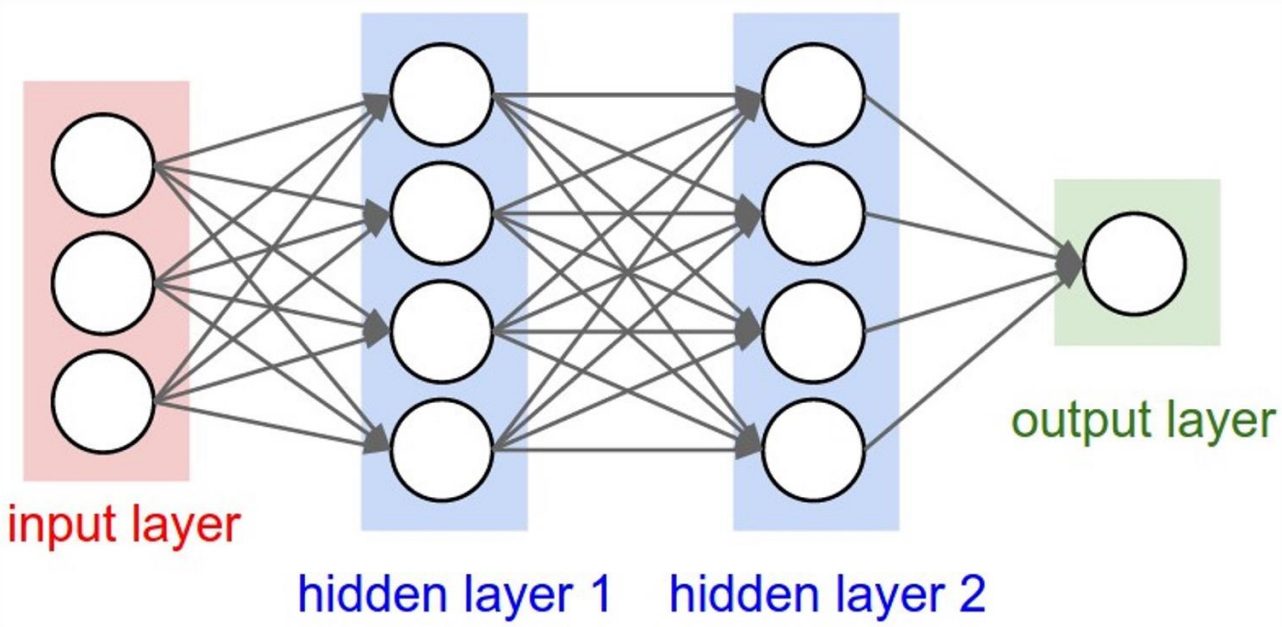
- 线性分类器学到了什么?

$$f(x,W) = Wx + b$$

每个类别的模板

卷积神经网络

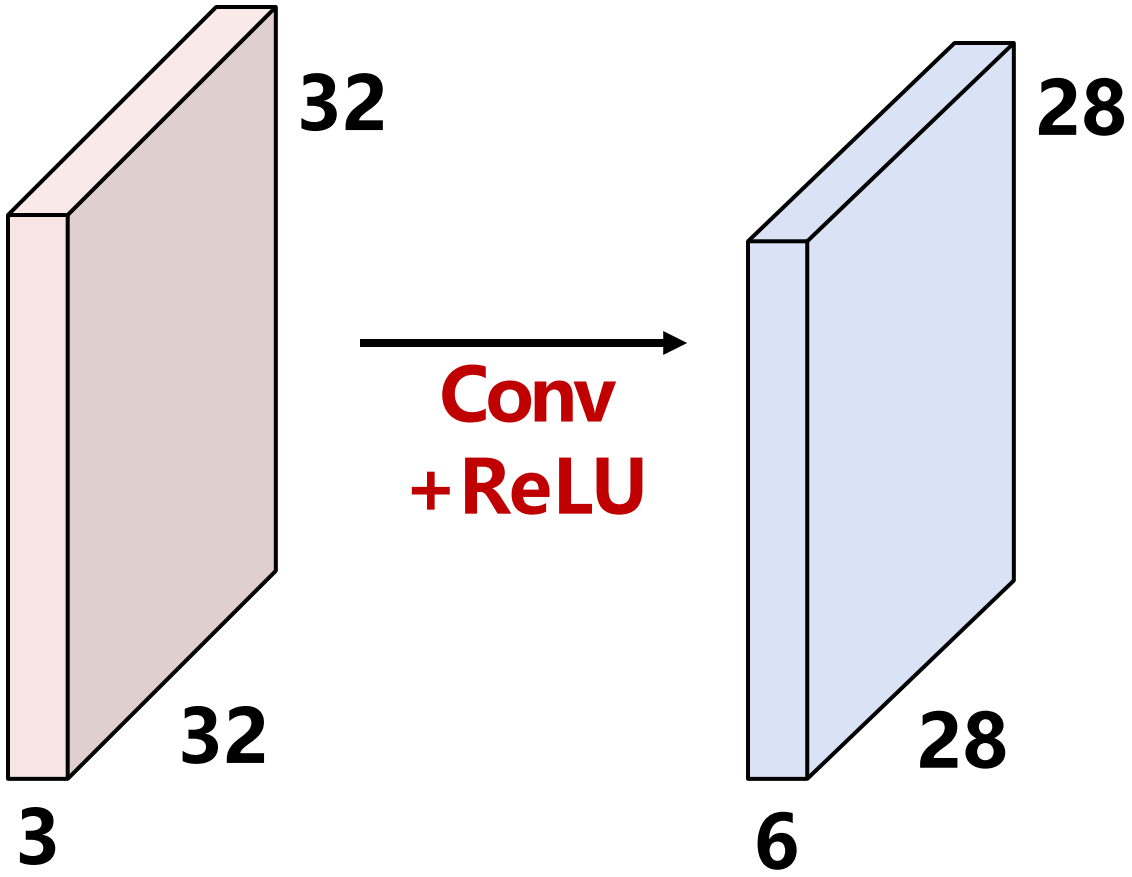
- 全连接神经网络学到了什么？



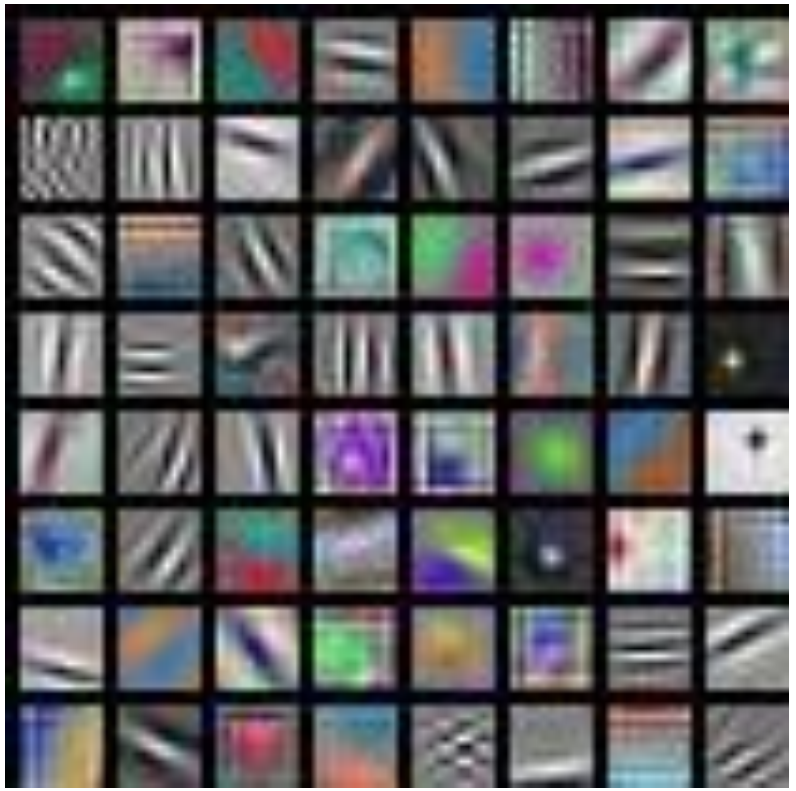
整张图像的的模板库

卷积神经网络

- 滤波器学到了什么?



第一层卷积滤波器：局部图像模板
（通常学习边缘、颜色等纹理）



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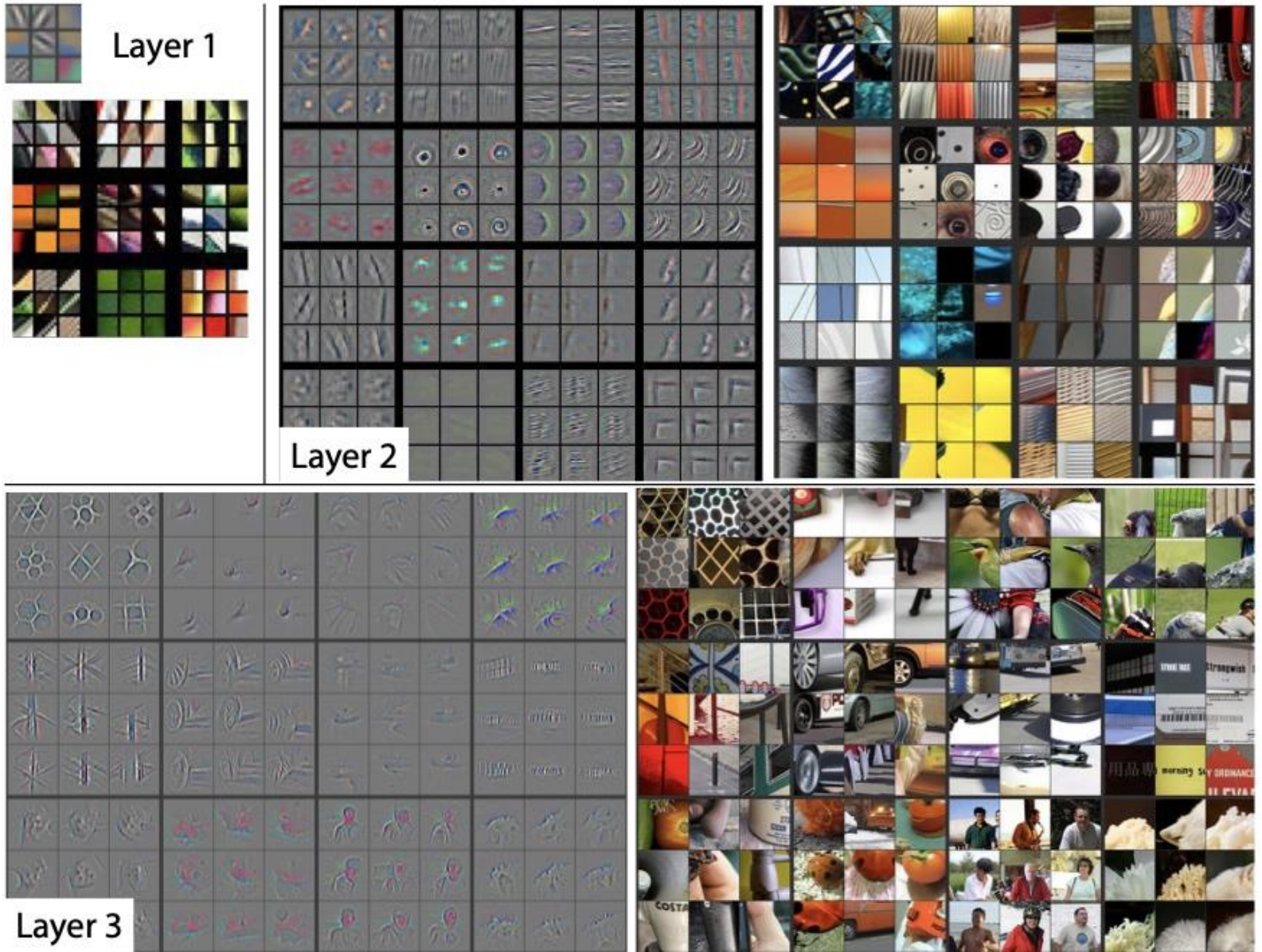
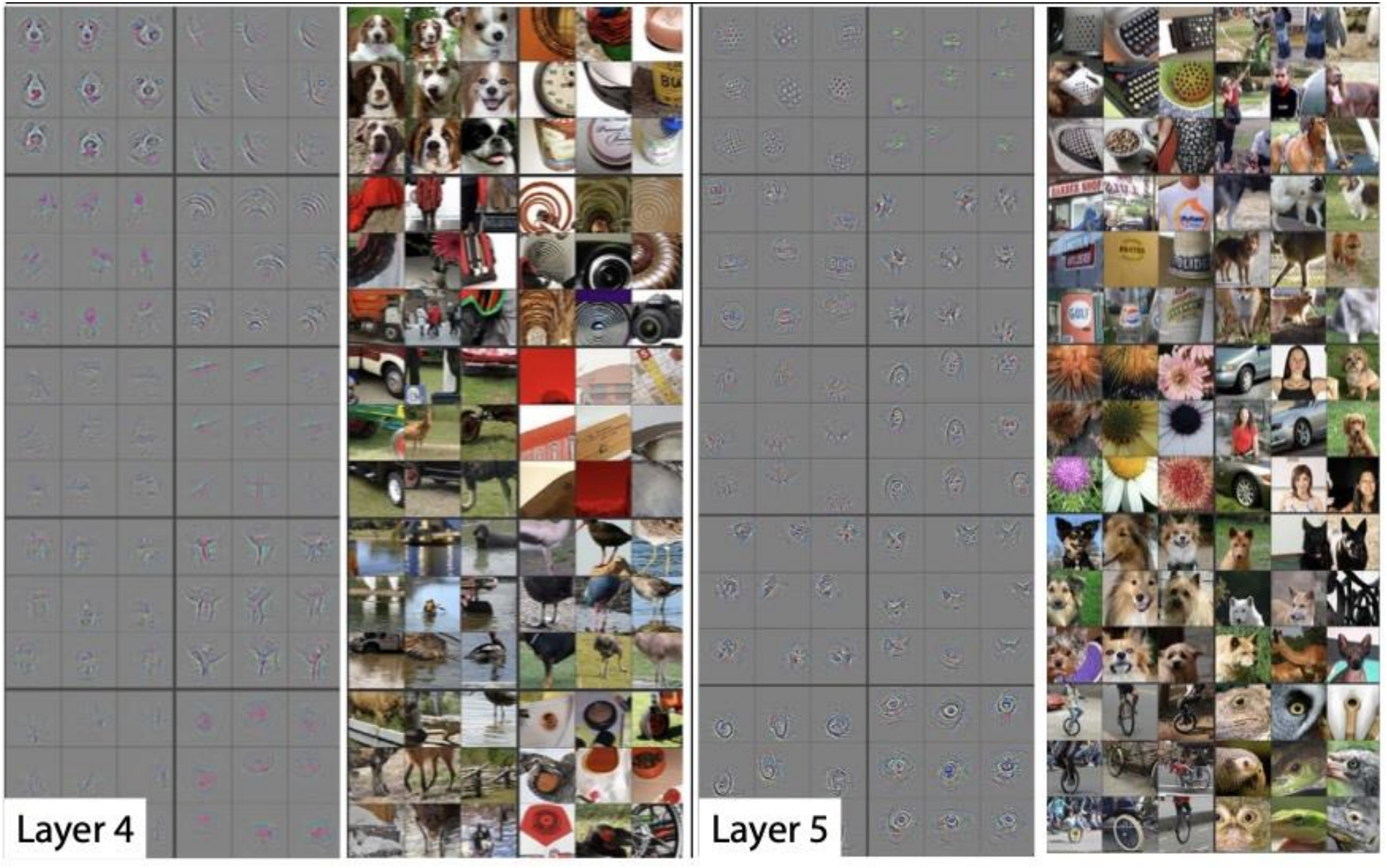
- 滤波器

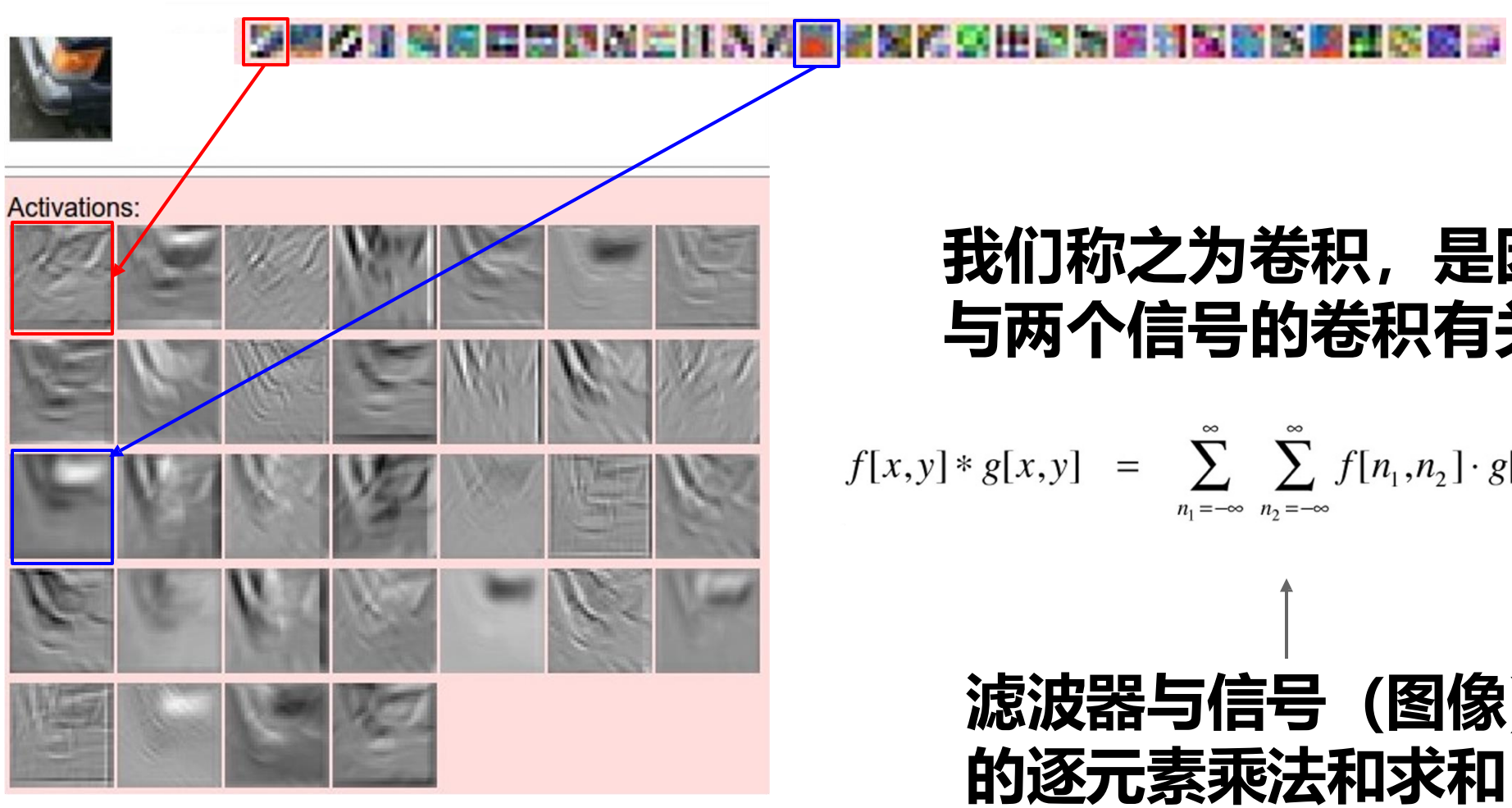


卷积神经网络



卷积神经网络

- 卷积神经网络　　一个滤波器-->一个激活图



我们称之为卷积，是因为它与两个信号的卷积有关：

$$f[x,y] * g[x,y] = \sum_{n_1=-\infty}^{\infty} \sum_{n_2=-\infty}^{\infty} f[n_1,n_2] \cdot g[x-n_1, y-n_2]$$

滤波器与信号（图像）的逐元素乘法和求和

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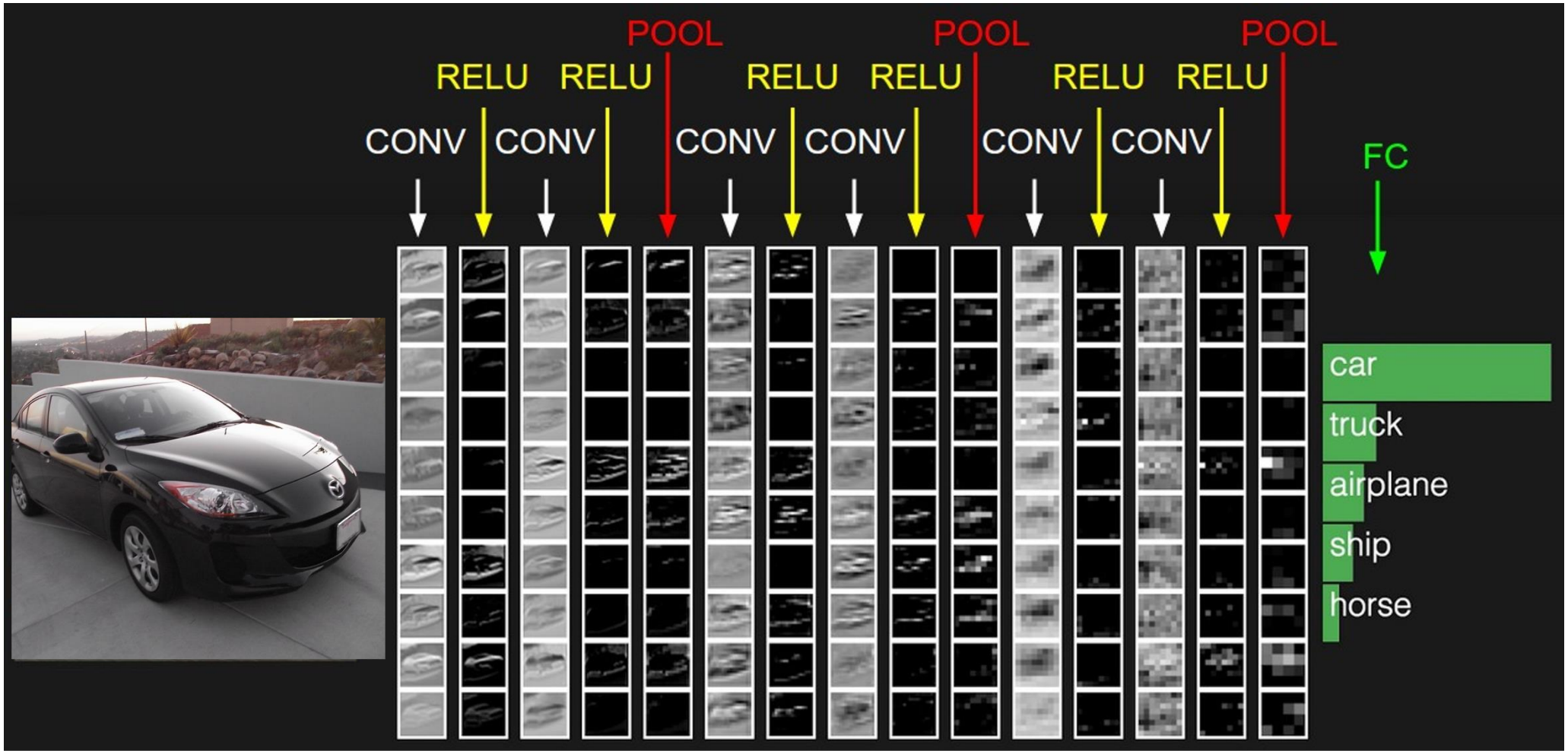
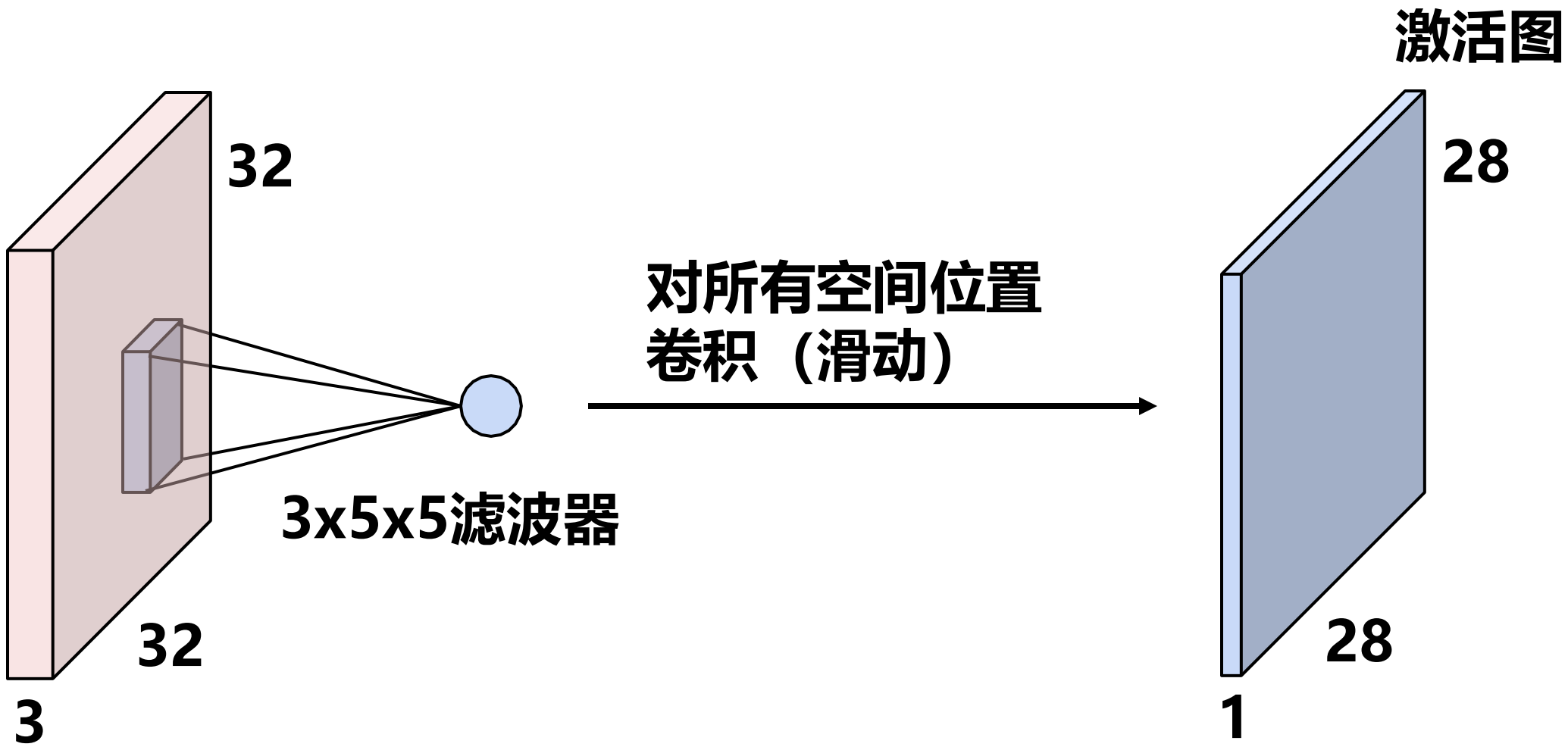
卷积神经网络



卷积神经网络

- 卷积输出的空间尺寸



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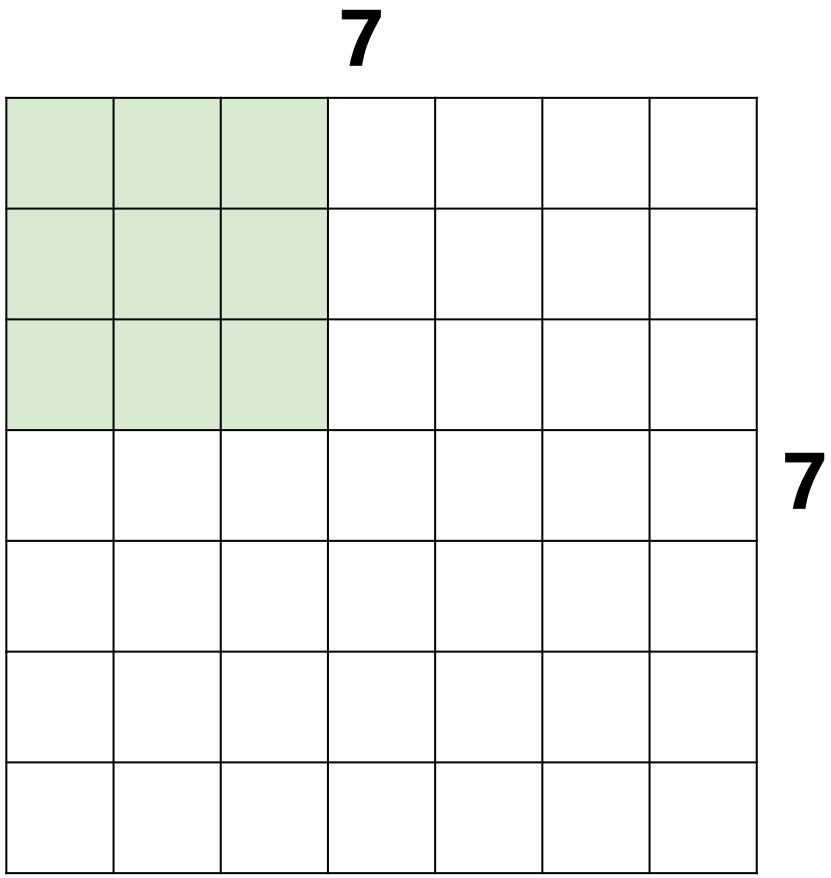
- 卷积输出的空间尺寸



7x7输入
3x3滤波器

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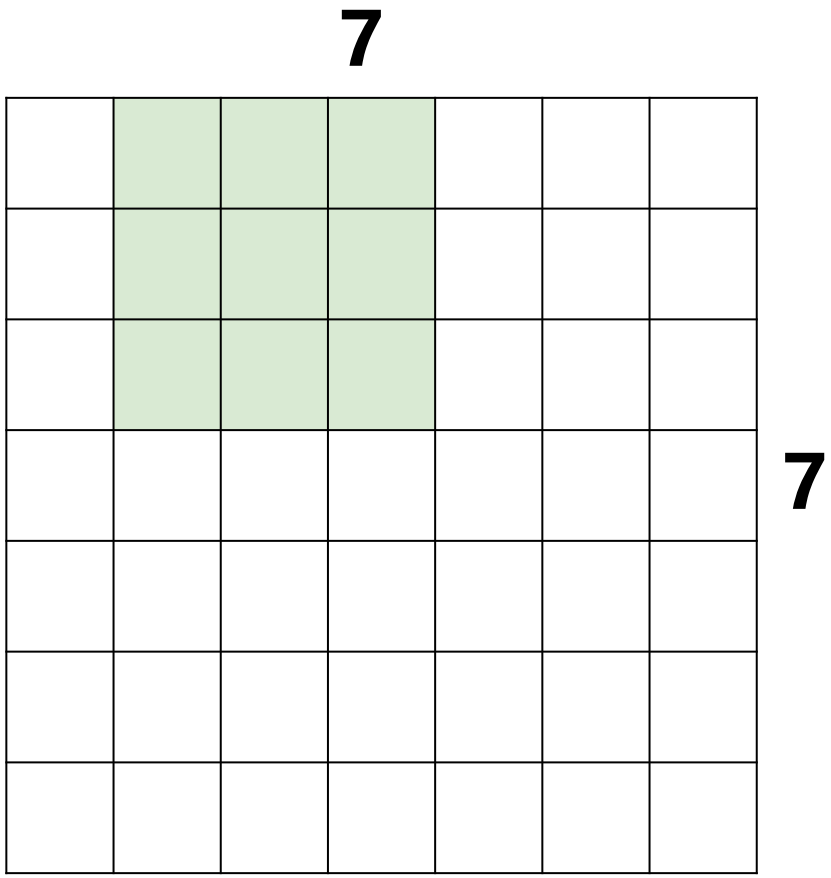
- 卷积输出的空间尺寸



7x7输入
3x3滤波器

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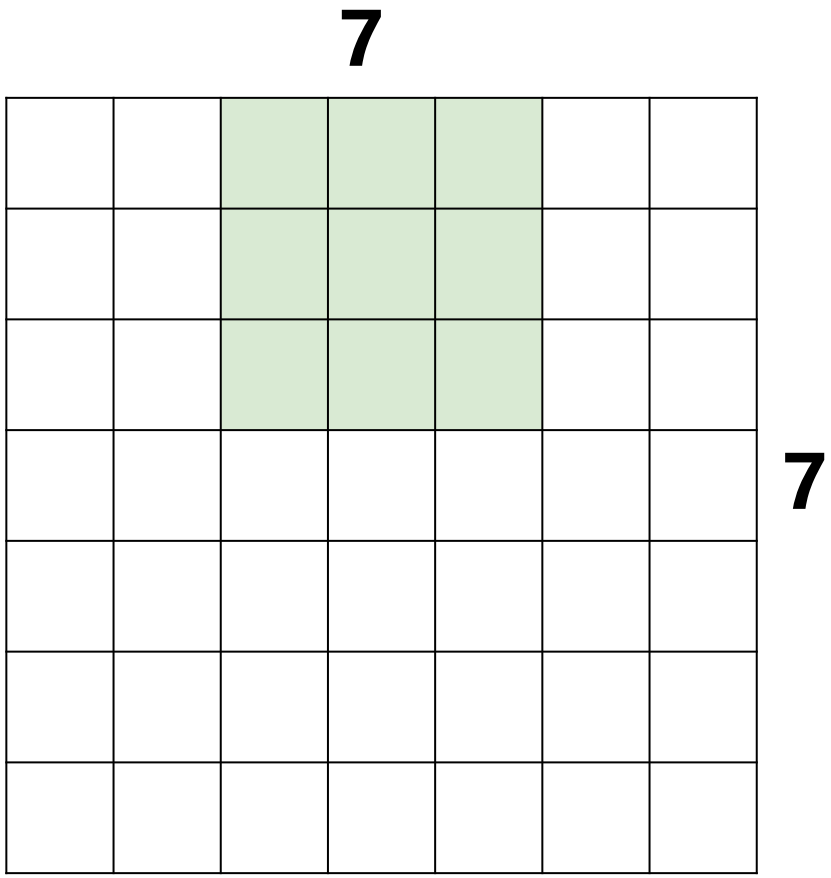
- 卷积输出的空间尺寸



7x7输入
3x3滤波器

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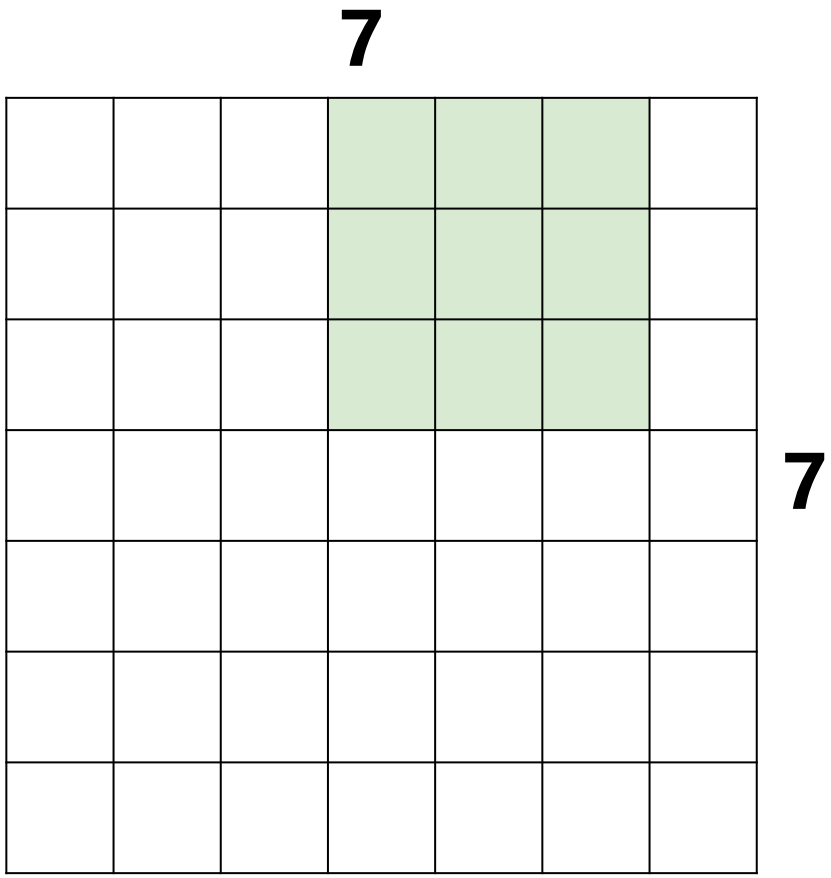
- 卷积输出的空间尺寸



7x7输入
3x3滤波器

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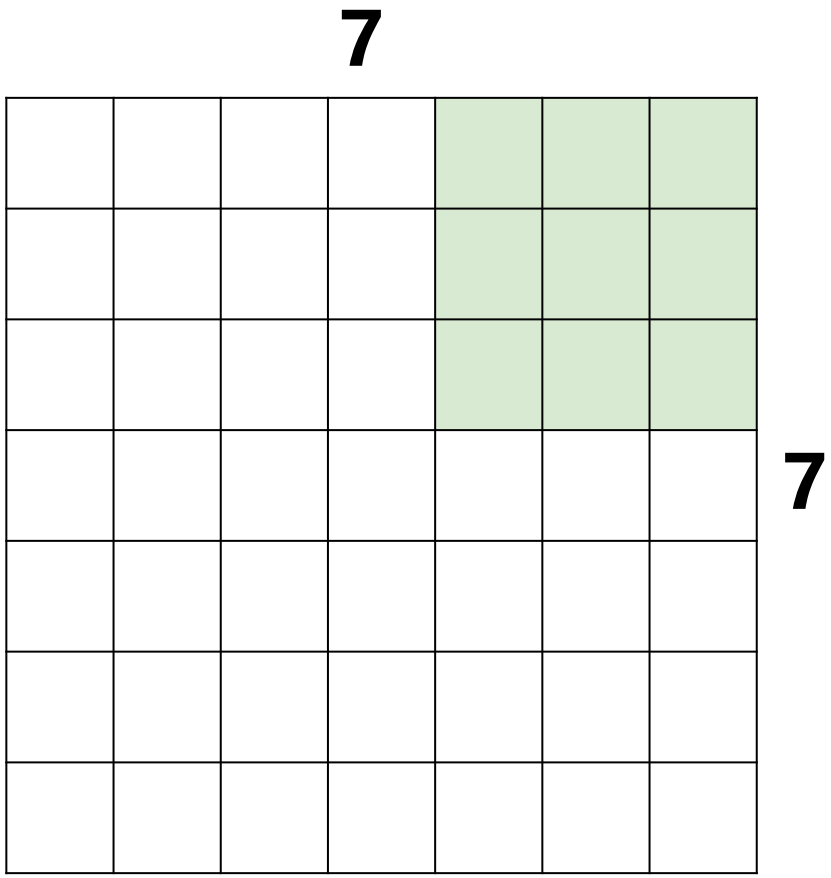
卷积输出的空间尺寸



7x7输入
3x3滤波器

5x5输出

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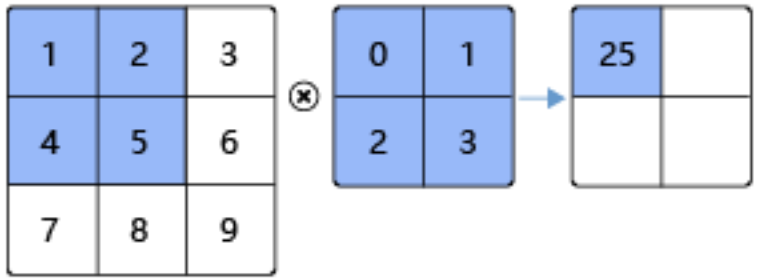
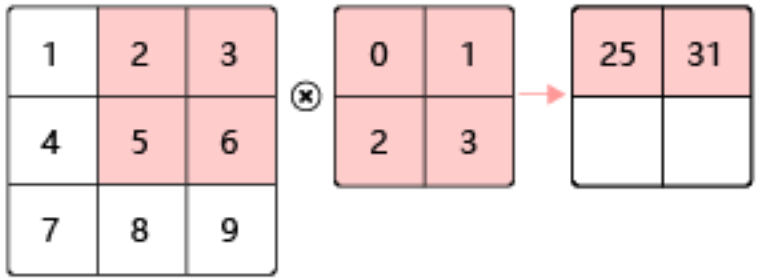
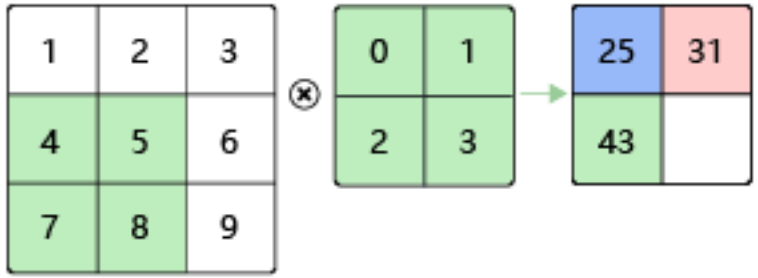
卷积层



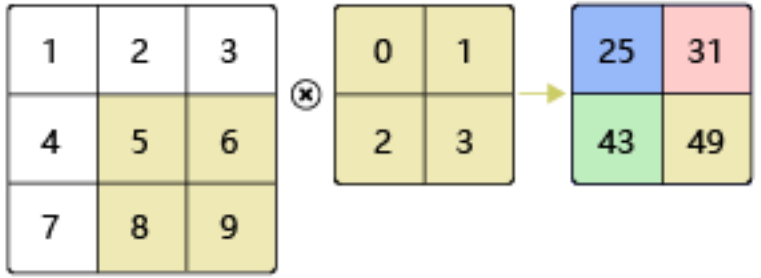
(a) 0x1+1x2+2x4+3x5=25



(b) 0x2+1x3+2x5+3x6=31



(c) 0x4+1x5+2x7+3x8=43



(d) 0x5+1x6+2x8+3x9=49

卷积神经网络

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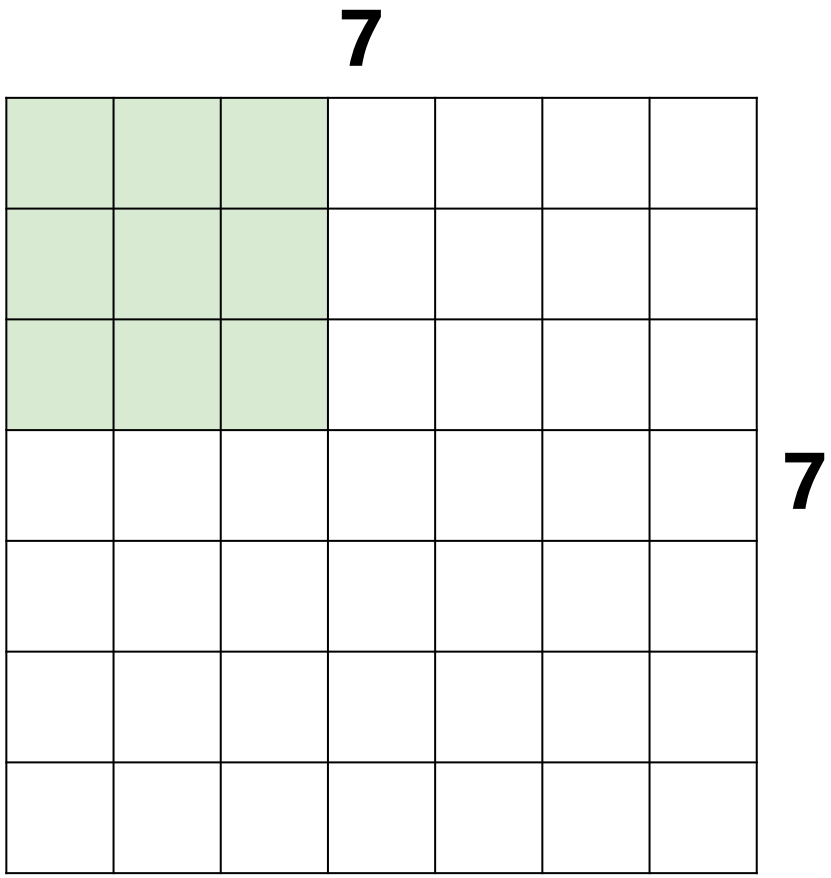
- 卷积输出的空间尺寸



7x7输入
3x3滤波器
2步长

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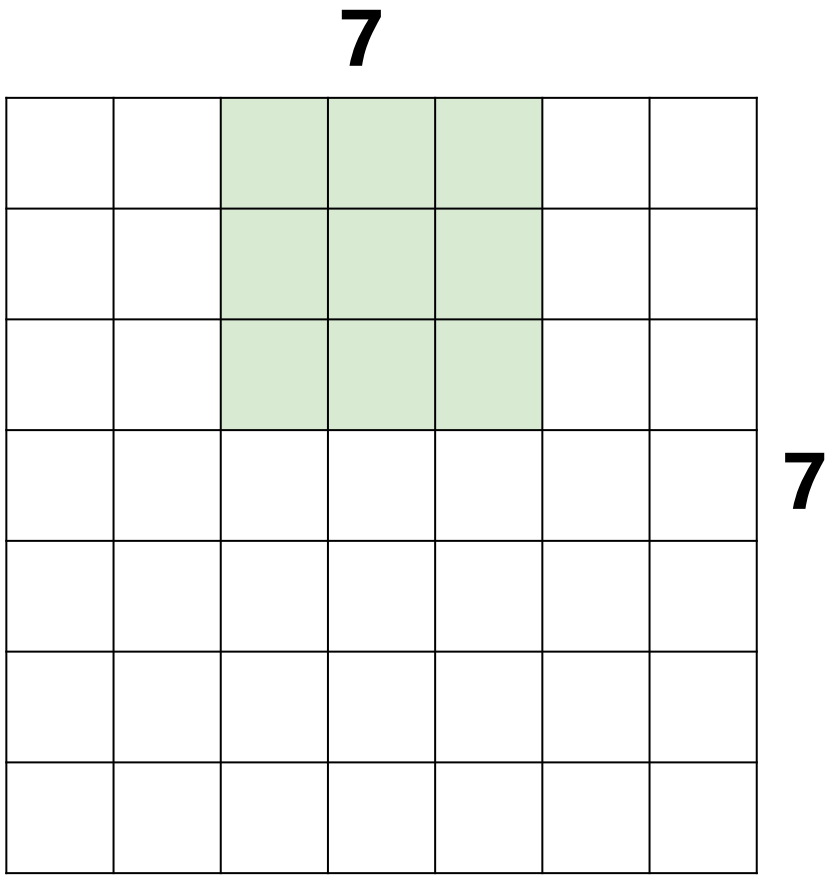
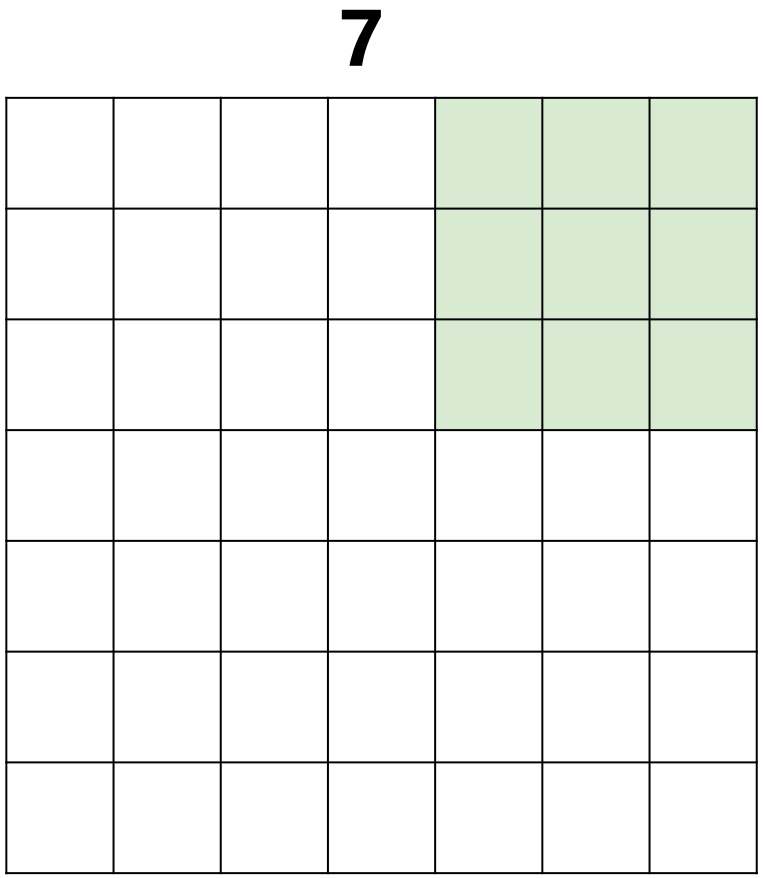
卷积输出的空间尺寸



7x7输入
3x3滤波器
2步长

卷积神经网络

- 卷积输出的空间尺寸

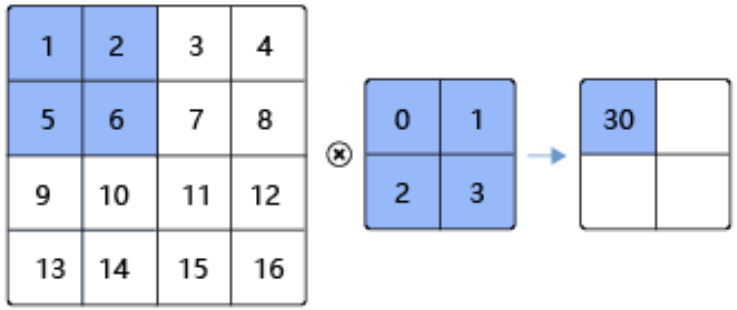


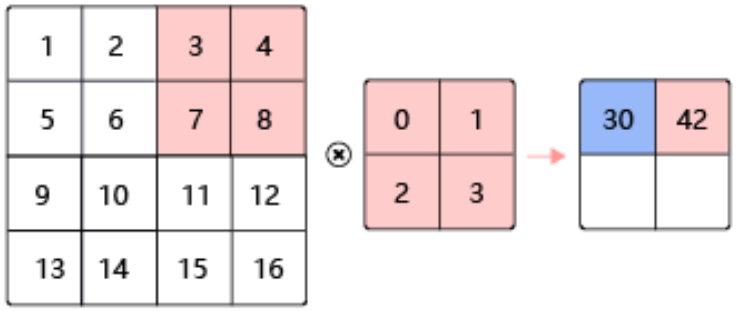
7x7输入
3x3滤波器
2步长

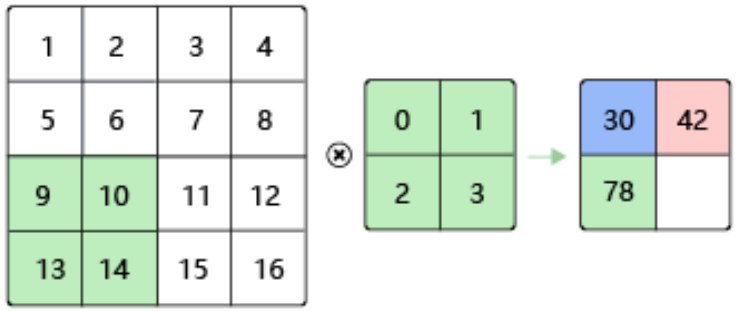
3x3输出

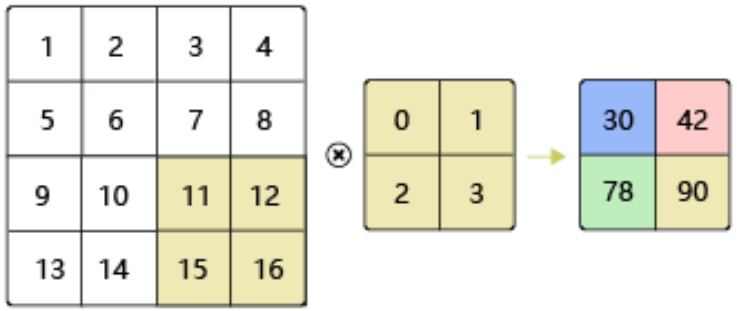
卷积神经网络

卷积层

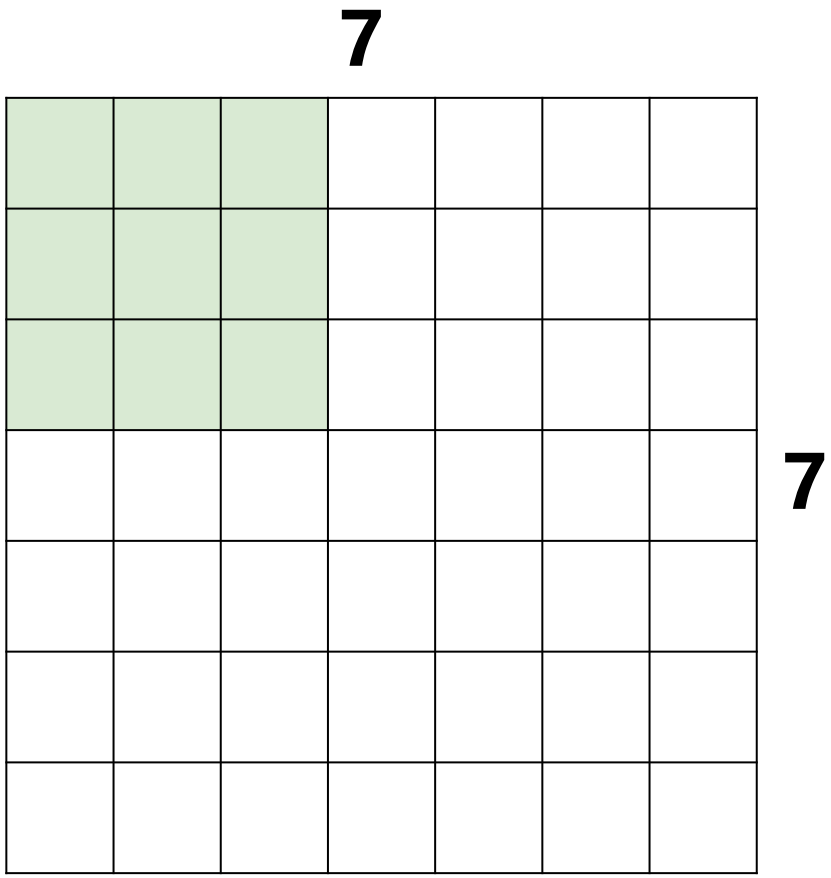

1 2 3 4
5 6 7 8
9 10 11 12
13 14 15 16
0 1
2 3
30


1 2 3 4
5 6 7 8
9 10 11 12
13 14 15 16
0 1
2 3
30 42


1 2 3 4
5 6 7 8
9 10 11 12
13 14 15 16
0 1
2 3
30 42
78


1 2 3 4
5 6 7 8
9 10 11 12
13 14 15 16
0 1
2 3
30 42
78 90

- 卷积输出的空间尺寸



7x7输入
3x3滤波器
3步长?

不可以!
尺寸不匹配

卷积神经网络

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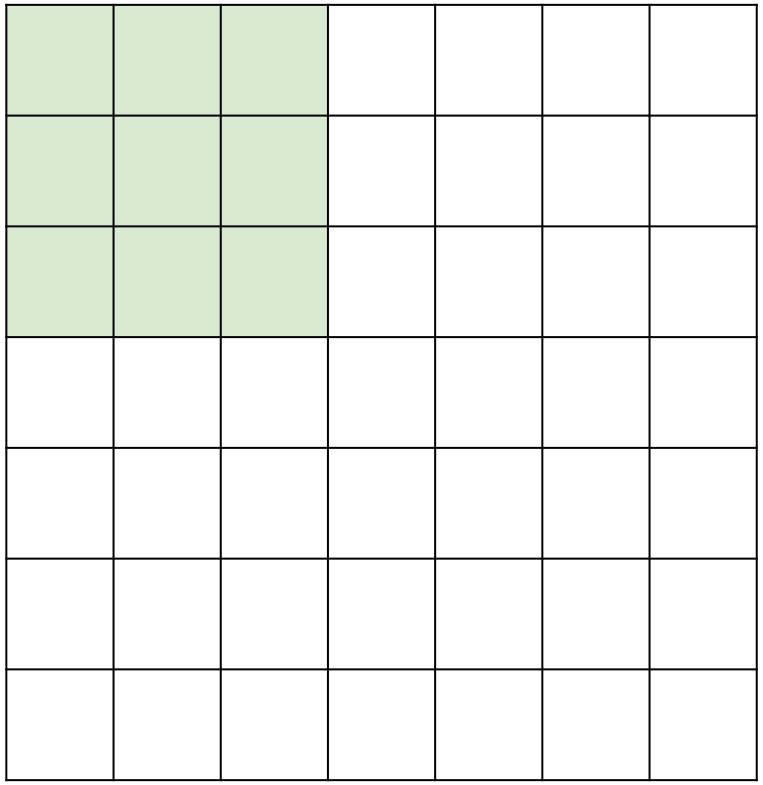
卷积输出的空间尺寸



NxN 输入
FxF 滤波器
S 步长
输出大小：(N-F)/S+1

例如：N = 7, F = 3:
步长 1 => (7 - 3)/1 + 1 = 5
步长 2 => (7 - 3)/2 + 1 = 3
步长 3 => (7 - 3)/3 + 1 = 2.33

卷积神经网络

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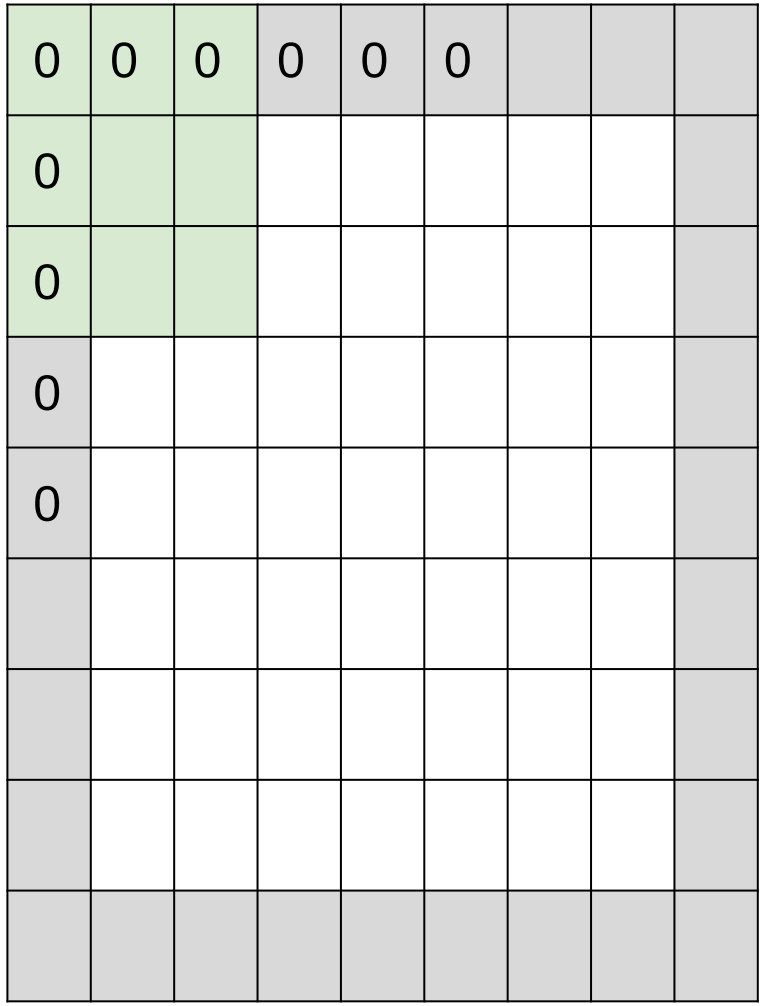
卷积输出的空间尺寸



7x7 输入 NxN
3x3 滤波器 FxF
1 步长 S
1 Padding P
输出尺寸?

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卷积输出的空间尺寸

0	0	0	0	0	0
0	13	14	15	16	0
0	9	10	11	12	0
0	5	6	7	8	0
0	1	2	3	4	0
0	0	0	0	0	0

(a)padding=1

0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0
0	0	13	14	15	16	0	0
0	0	9	10	11	12	0	0
0	0	5	6	7	8	0	0
0	0	1	2	3	4	0	0
0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0

(b)padding=2

卷积神经网络

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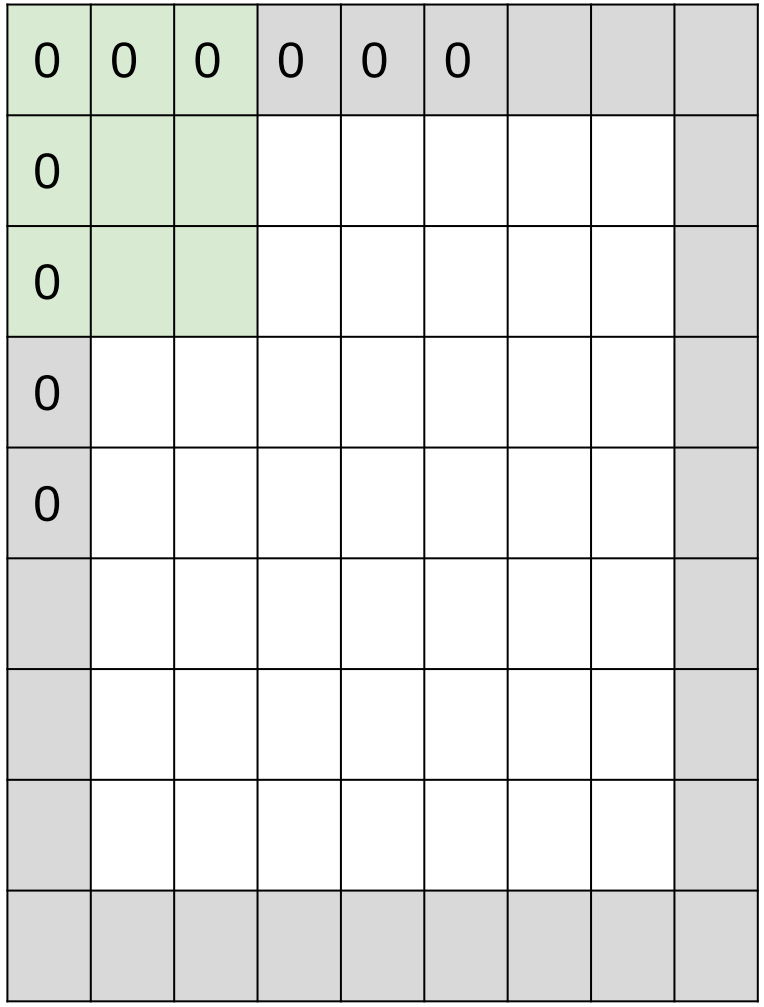
卷积输出的空间尺寸



7x7 输入 NxN
3x3 滤波器 FxF
1 步长 S
1 Padding P
7x7 输出

输出：(N+2P-F)/S+1

卷积神经网络

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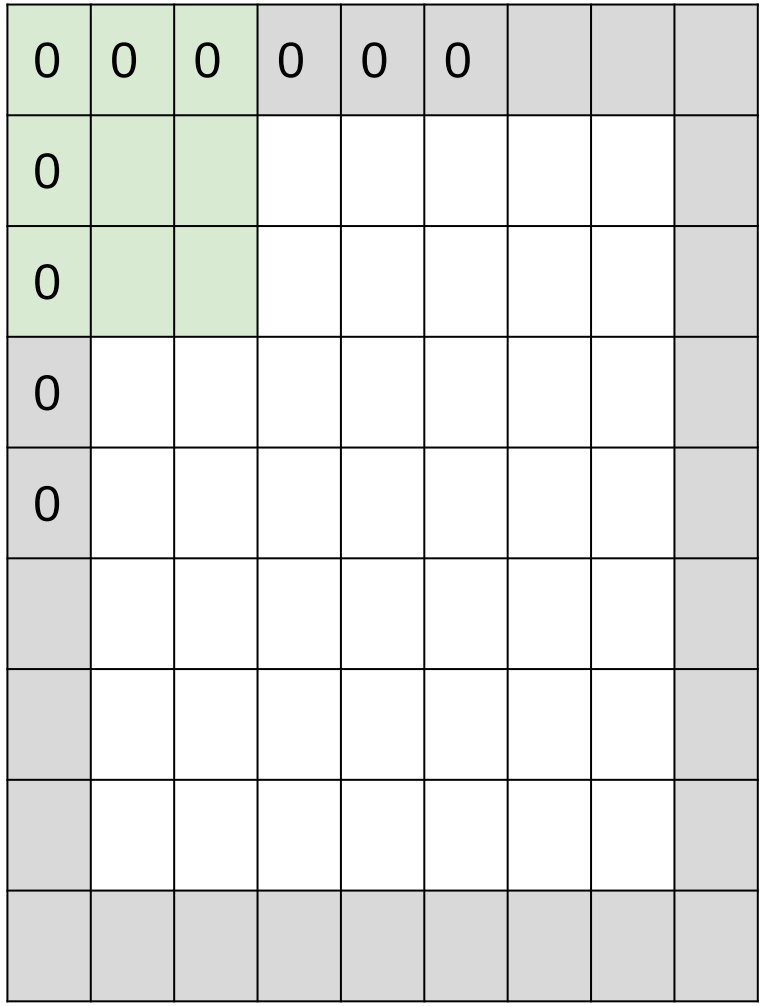
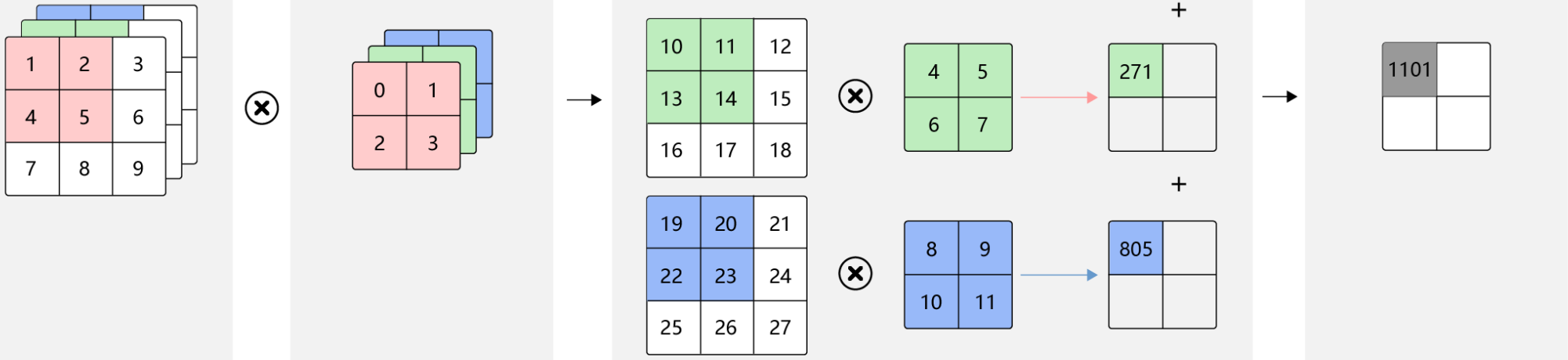
卷积输出的空间尺寸



为了保持输出的空间尺寸大小：
CONV层步幅为1
滤波器大小为FxF
零填充为（F-1）/2

F = 3 => zero pad with 1
F = 5 => zero pad with 2
F = 7 => zero pad with 3

多输入通道卷积



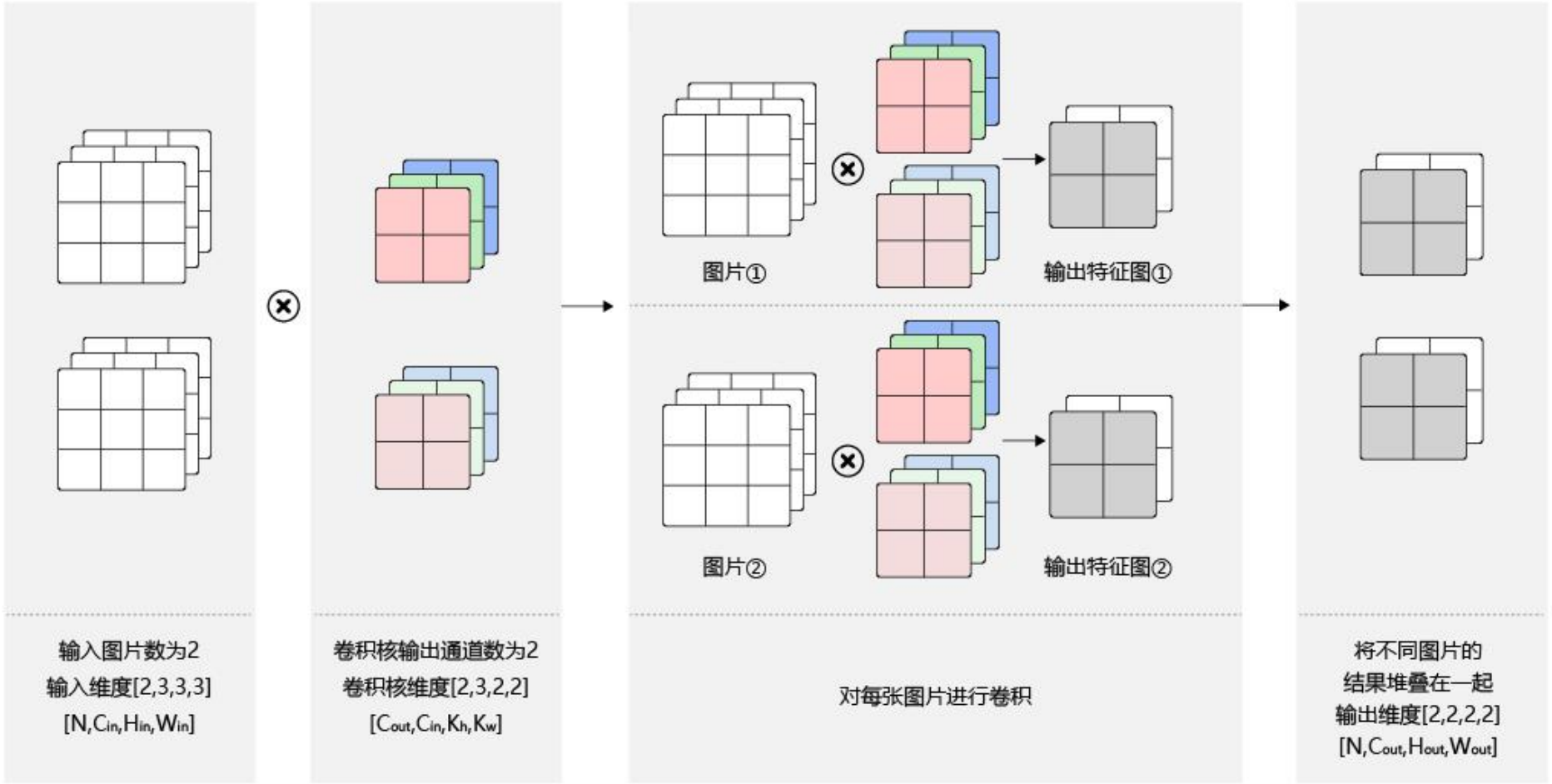
输入通道数为3
输入维度[3,3,3]
$[C_{in},H_{in},W_{in}]$

卷积核输入通道数为3
卷积核维度[3,2,2]
$[C_{in},K_h,K_w]$

对每个输入通道分别计算，
并将每个通道的输出结果求和

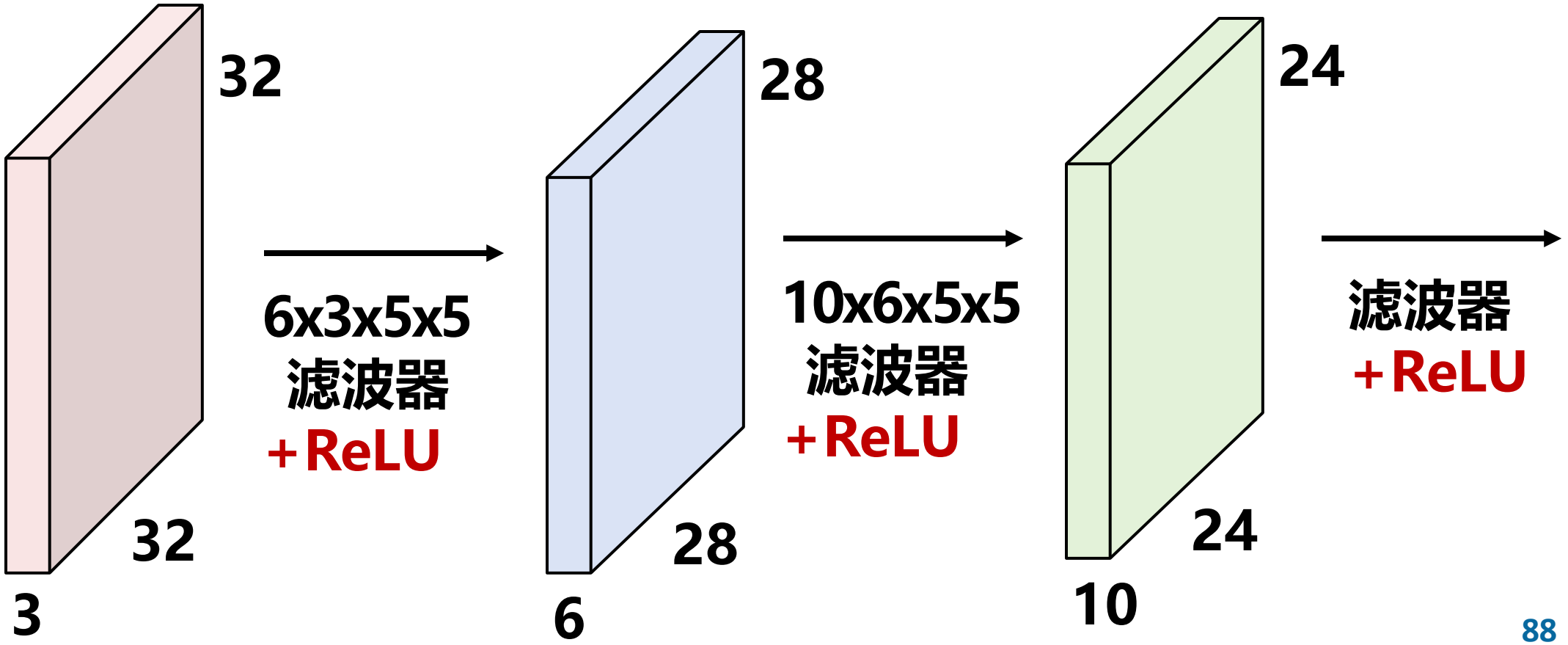
最终输出结果
输出维度[2,2]
$[H_{out},W_{out}]$

多输出通道卷积


图片①
输出特征图①
图片②
输出特征图②
输入图片数为2
输入维度[2,3,3,3]
[N,Cin,Hin,Win]
卷积核输出通道数为2
卷积核维度[2,3,2,2]
[Cout,Cin,Kh,Kw]
对每张图片进行卷积
将不同图片的
结果堆叠在一起
输出维度[2,2,2,2]
[N,Cout,Hout,Wout]

卷积神经网络

- 激活图尺寸：32x32→28x28→24x24



卷积神经网络

- 卷积输出的空间尺寸
- 假设：
  - 输入：3x32x32
  - 滤波器：10x5x5
  - 步长：1
  - Padding：2
- 输出多少?

卷积神经网络

- 卷积输出的空间尺寸
- 假设：
  - 输入：3x32x32
  - 滤波器：10x5x5
  - 步长：1
  - Padding：2
- 输出：32x32x10，即 (32+2*2-5)/1+1 = 32

卷积神经网络

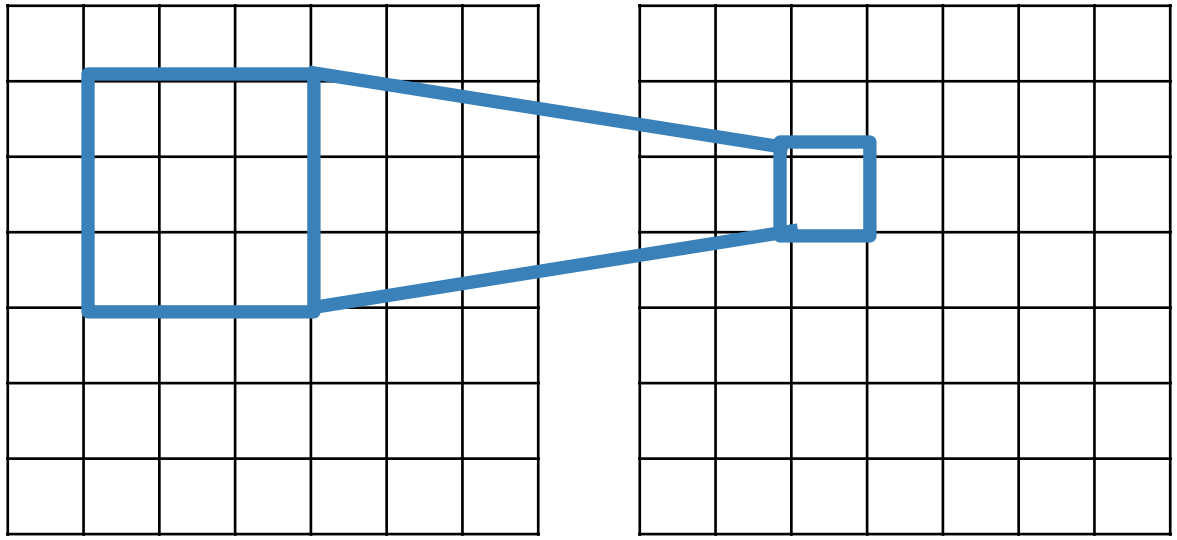
- 卷积输出的空间尺寸
- 假设：
  - 输入：3x32x32
  - 滤波器：10x5x5
  - 步长：1
  - Padding：2
- 参数量?

卷积神经网络

- 卷积输出的空间尺寸
- 假设：
  - 输入：3x32x32
  - 滤波器：10x5x5
  - 步长：1
  - Padding：2
- 参数量：(5x5x3+1)x10

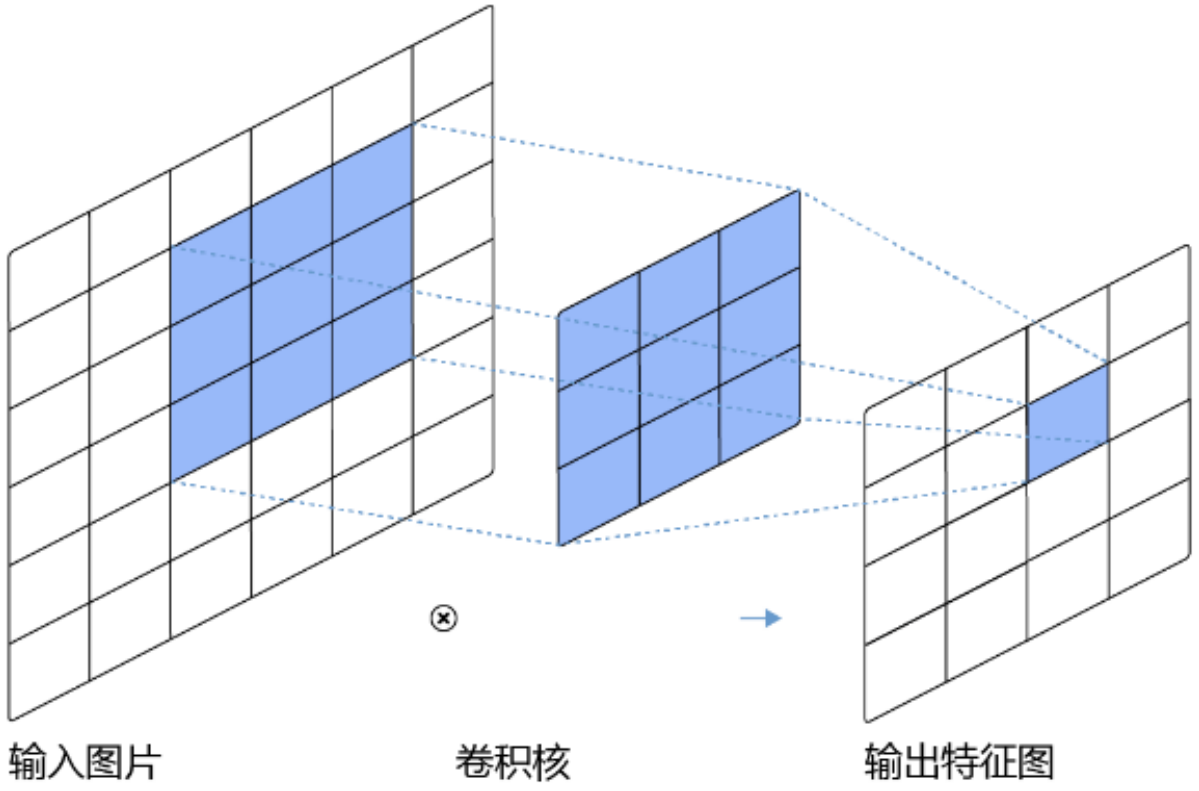
卷积神经网络

- 卷积层的感受野
- 对于核大小为K的卷积，输出中的每个元素都取决于输入中的K x K感受野



卷积层的感受野

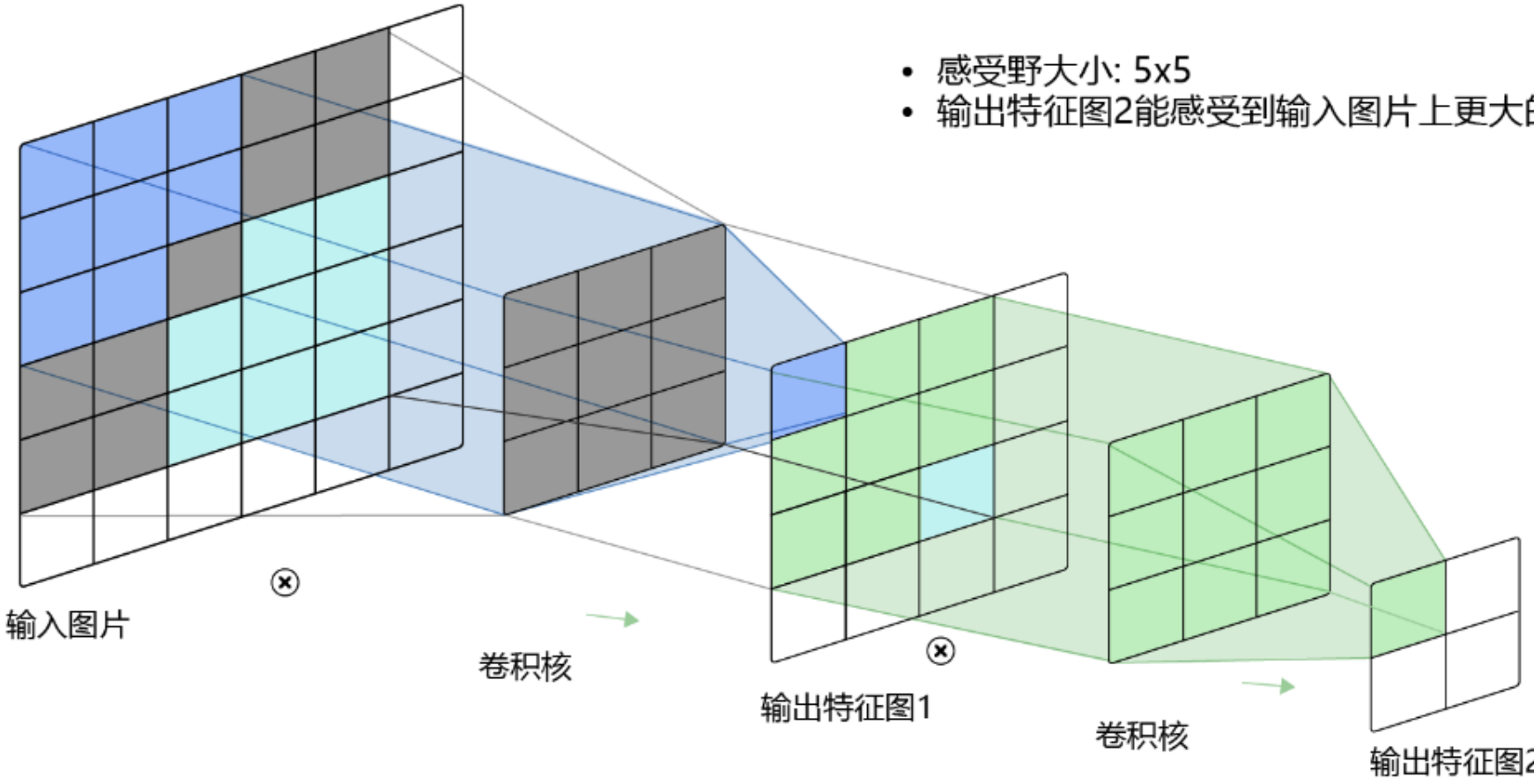
单层卷积



- 感受野大小: 3x3
- 输出特征图上的像素点所能感受到的输入数据的范围

卷积层的感受野

两层卷积



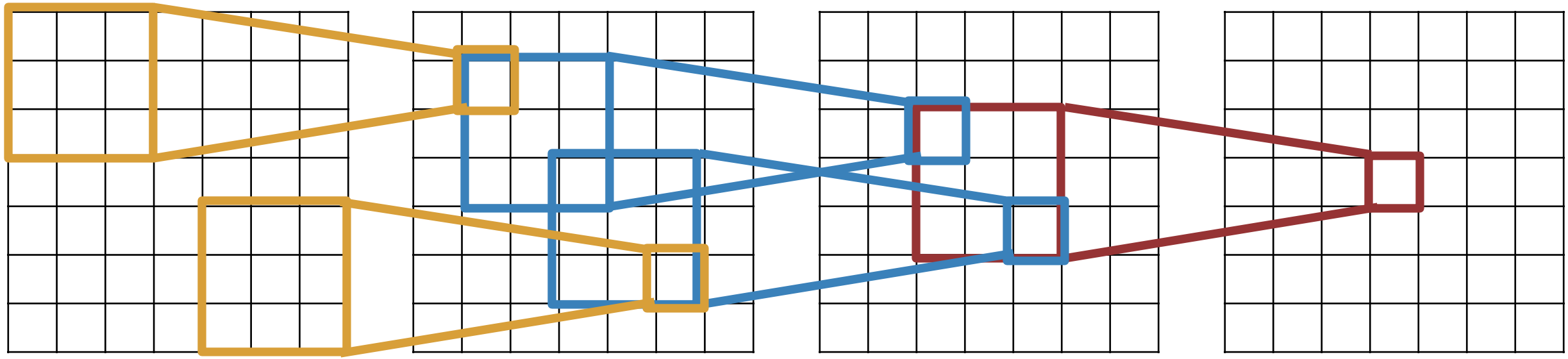
- 感受野大小: 5x5
- 输出特征图2能感受到输入图片上更大的范围

卷积神经网络

- 卷积层的感受野
- 每次连续的卷积都会使感受野大小增加K-1。

  对于L层，感受野大小为1+L*（K-1）

注意区分：
在前一层上的感受野
在输入图像上的感受野



卷积神经网络

- 卷积层的感受野
- 问题：对于大图像，我们需要使用许多卷积层，才能“看到”整个图像
- 解决方案：下采样
  - 大步长
  - 池化层

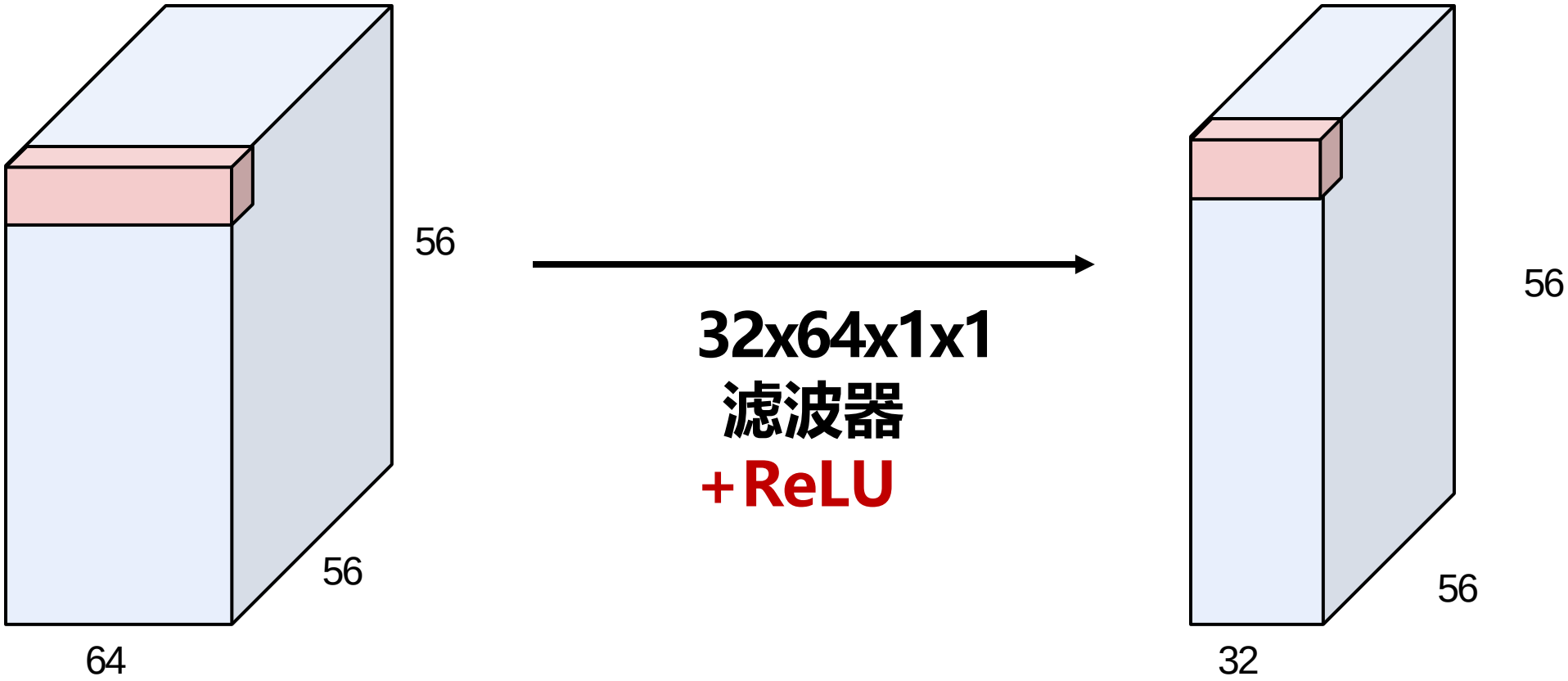
卷积神经网络

- 卷积层总结
- 输入： $W_1 \times H_1 \times C$
- 卷积超参：
  - 滤波器数量 K
  - 滤波器大小 F
  - 步长 S
  - Padding P
- 输出：$W_2 \times H_2 \times C$
  - $W_2 = (W_1 - F + 2P)/S + 1$
  - $H_2 = (H_1 - F + 2P)/S + 1$
- 参数量：
  - F^2CK+K，其中K是bias数量

卷积神经网络

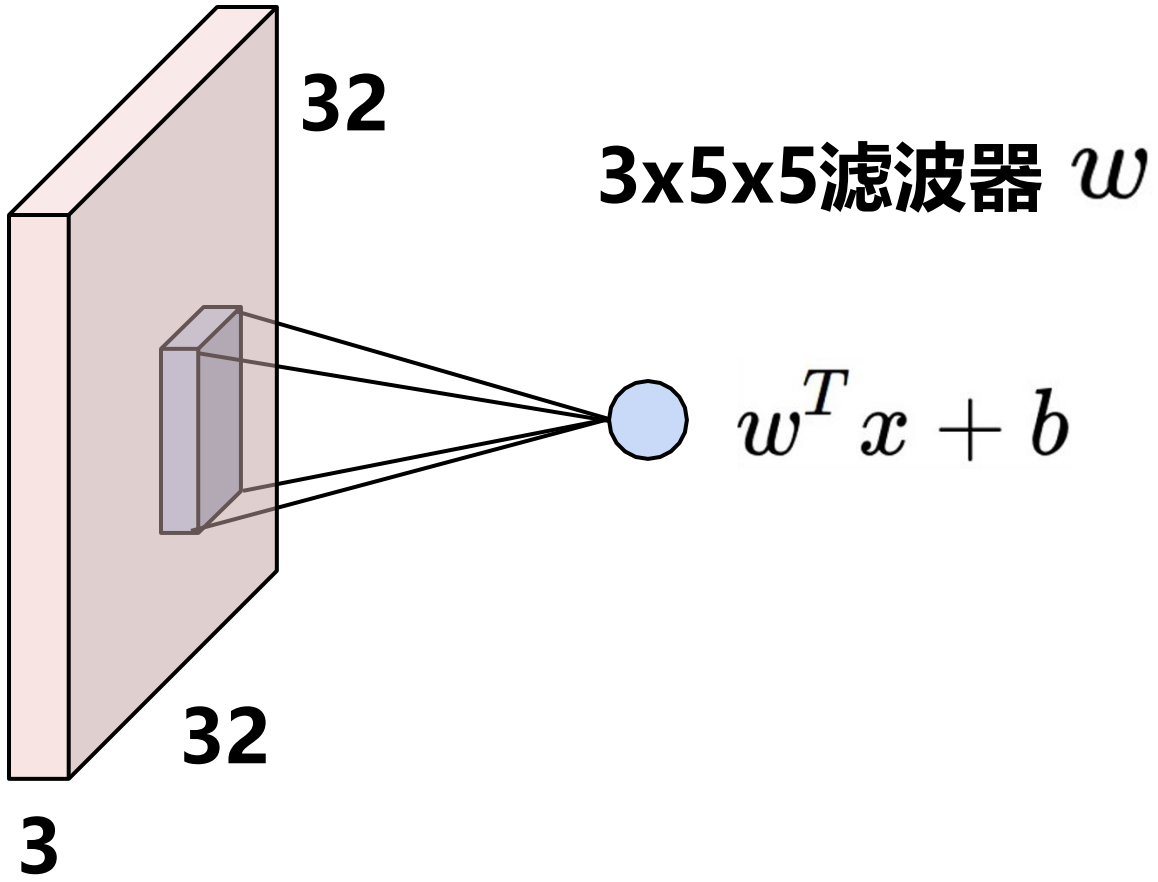
- 卷积层总结
- 输入： W_1 x H_1 x C
- 卷积超参：
  - 滤波器数量 K
  - 滤波器大小 F
  - 步长 S
  - Padding P
- K = (2的指数, e.g. 32, 64, 128, 512)
- F = 3, S = 1, P = 1
- F = 5, S = 1, P = 2
- F = 5, S = 2, P = ？ (匹配尺寸)
- F = 1, S = 1, P = 0

- 1x1卷积层



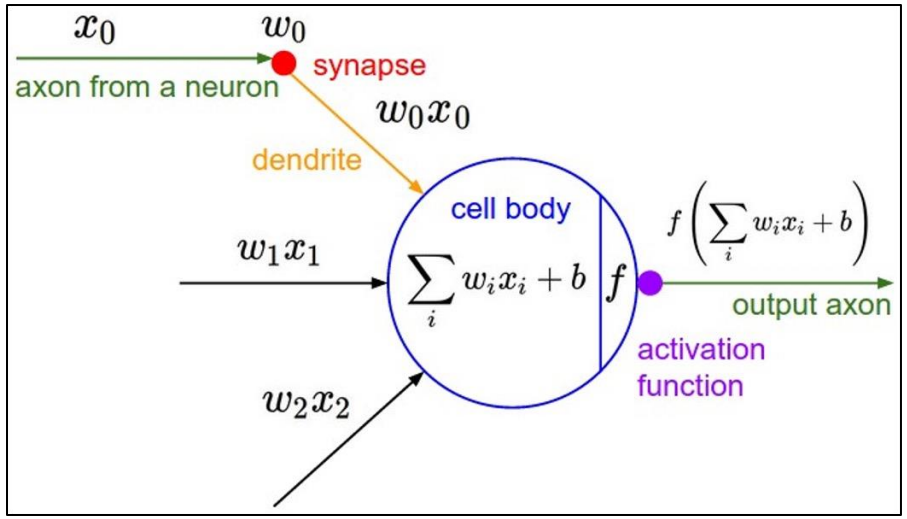
卷积神经网络

- 从大脑/神经元角度理解卷积层

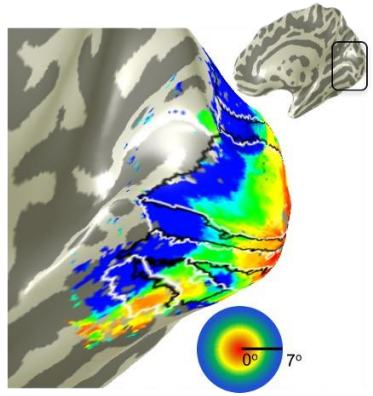


3x5x5滤波器 w

$w^T x + b$

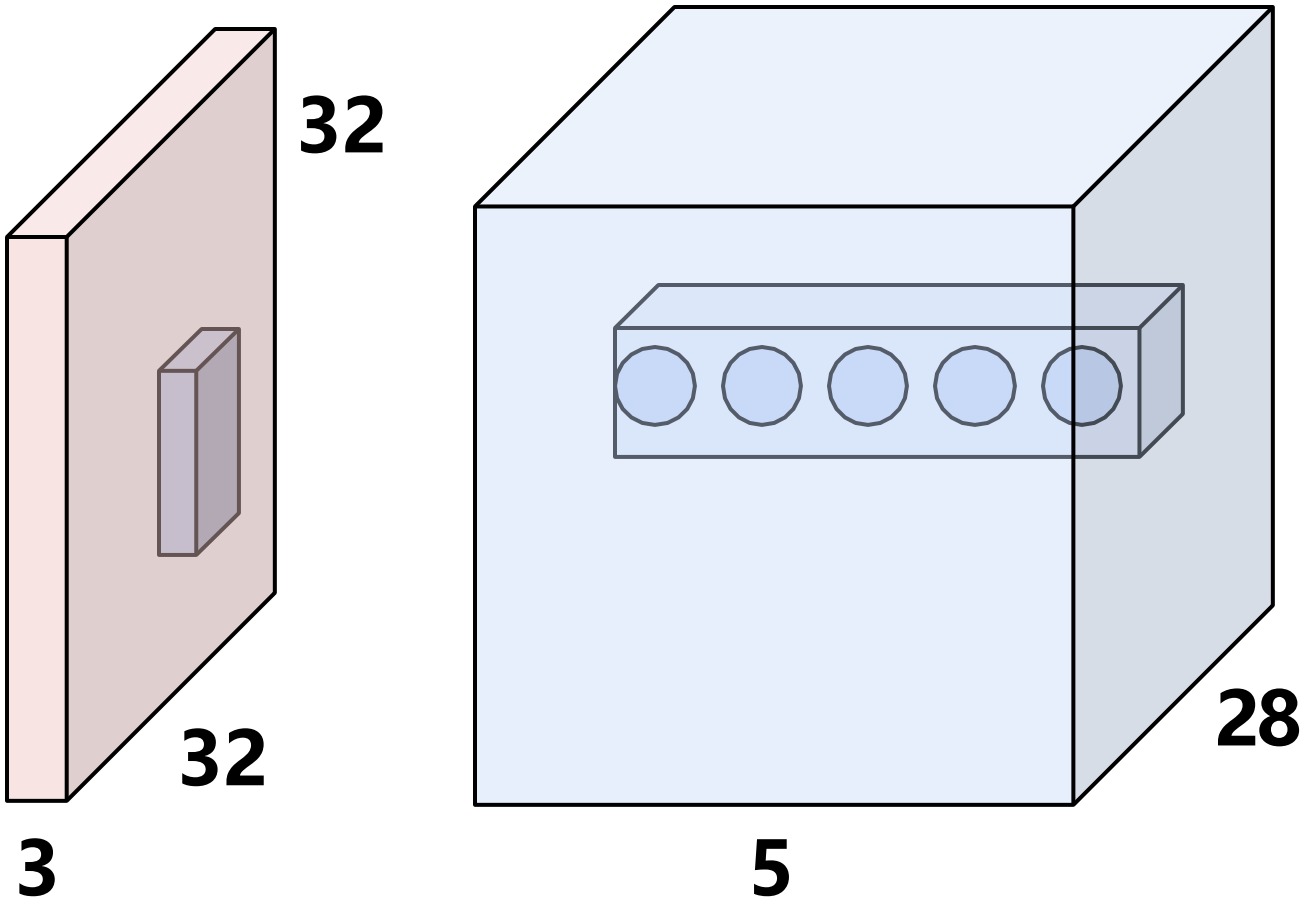


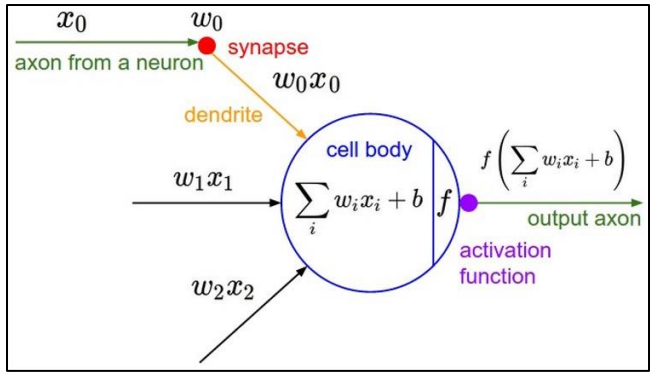
具有局部连接的神经元



卷积神经网络

- 从大脑/神经元角度理解卷积层

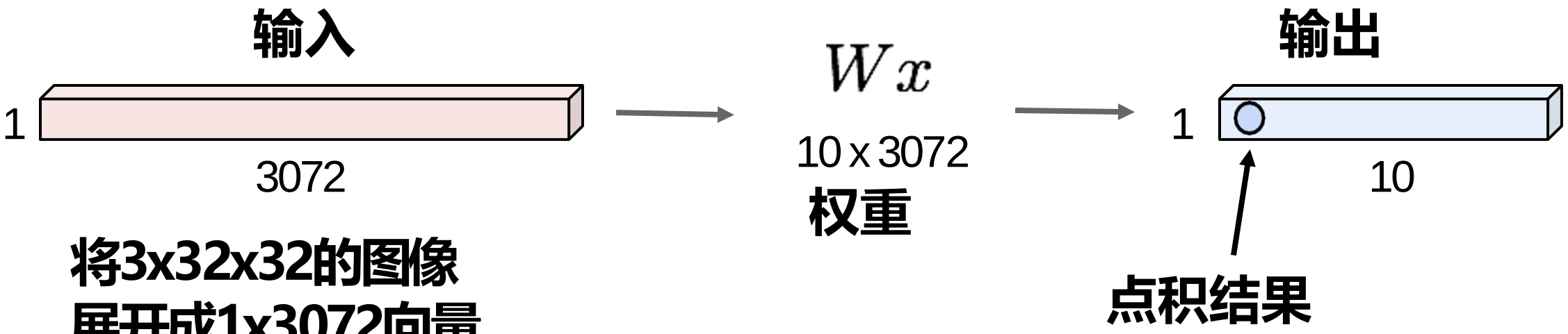




5个不同的神经元都在观察输入体积中的同一区域

卷积神经网络

- 从大脑/神经元角度理解全连接层



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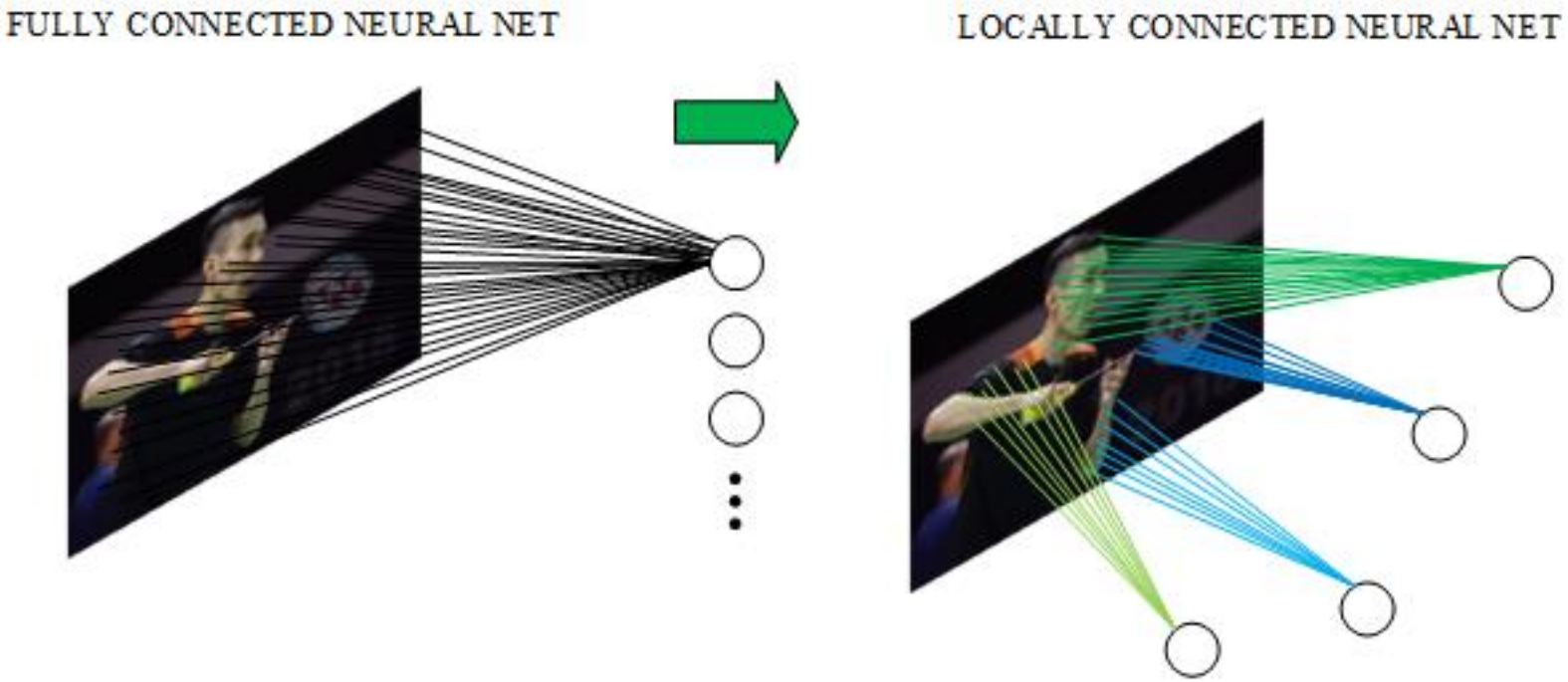
卷积层 v.s. 全连接层



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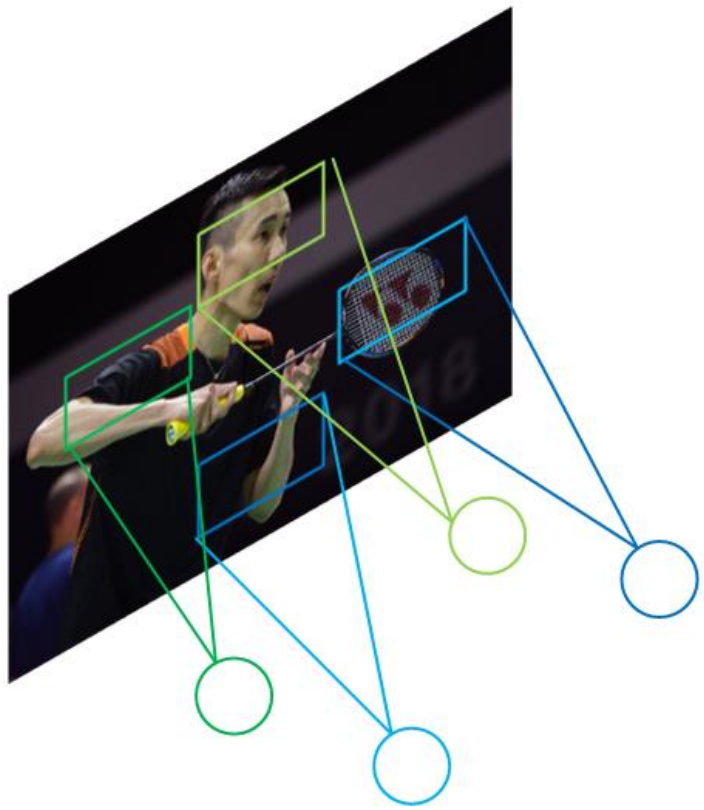
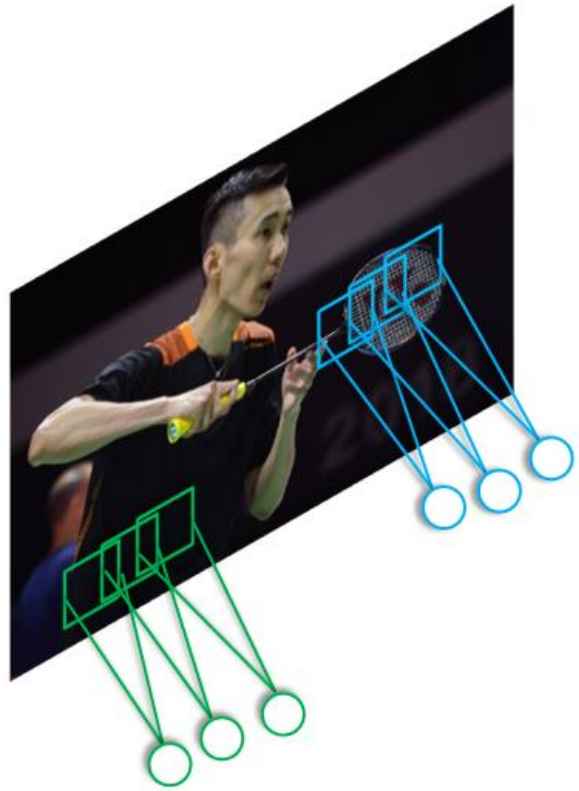
卷积层 v.s. 局部全连接层

LOCALLY CONNECTED NEURAL NET



CONVOLUTIONAL NET



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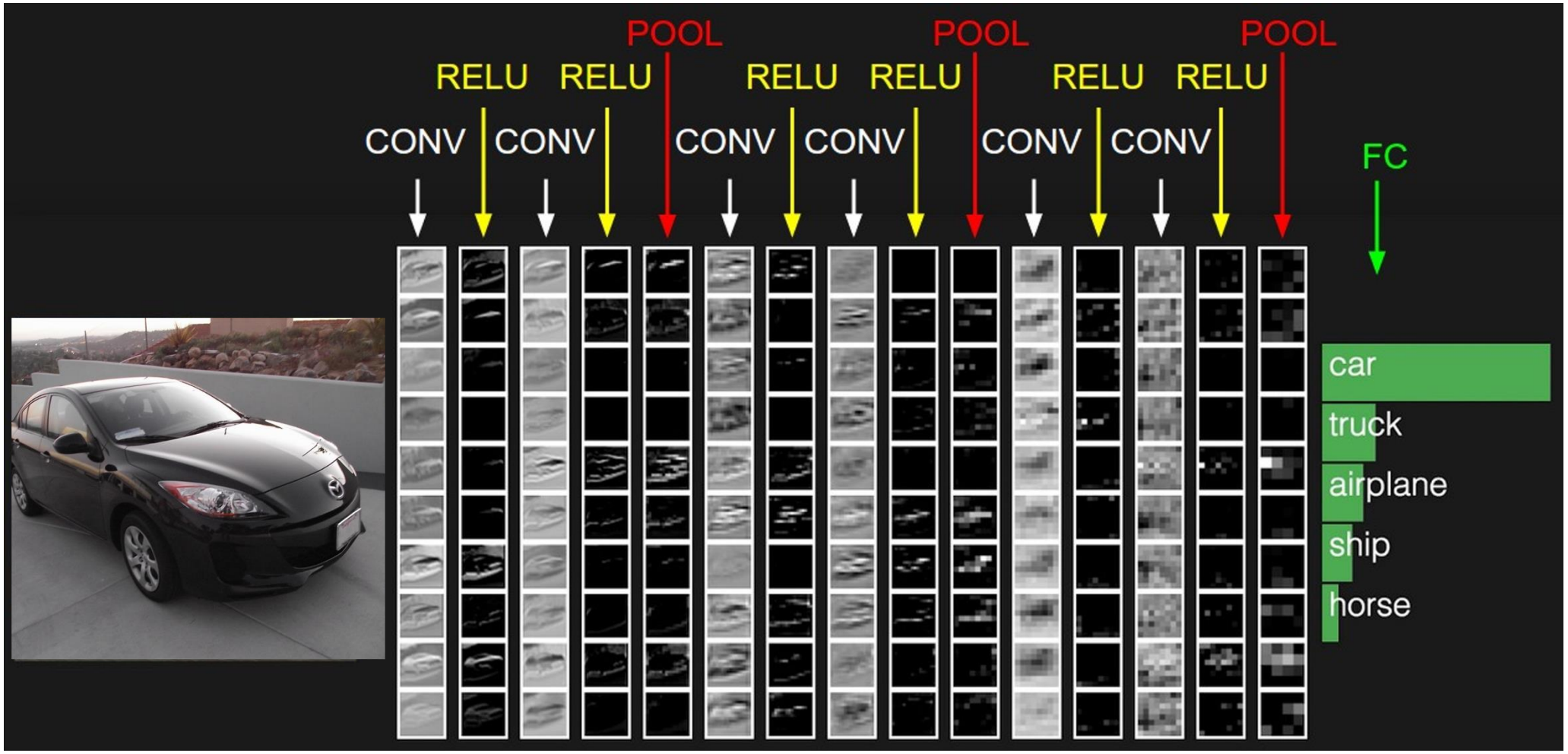
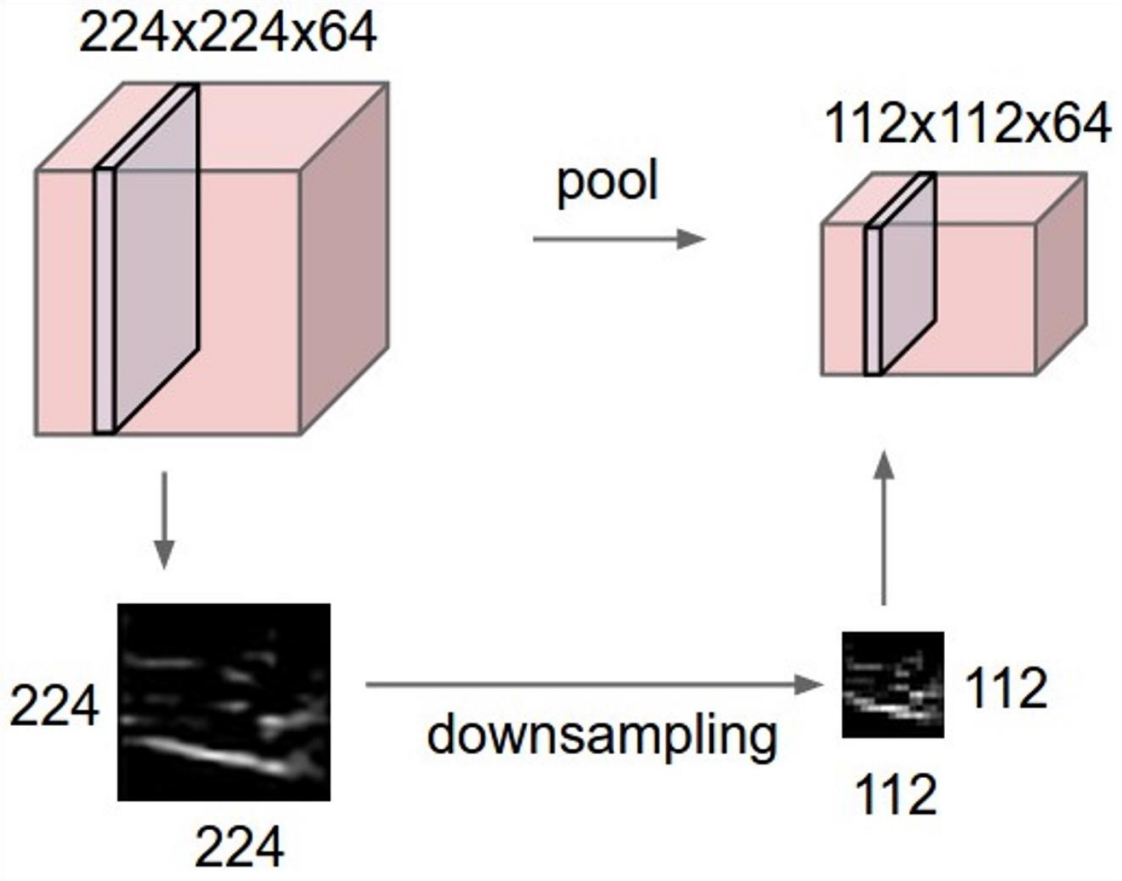
- 池化层

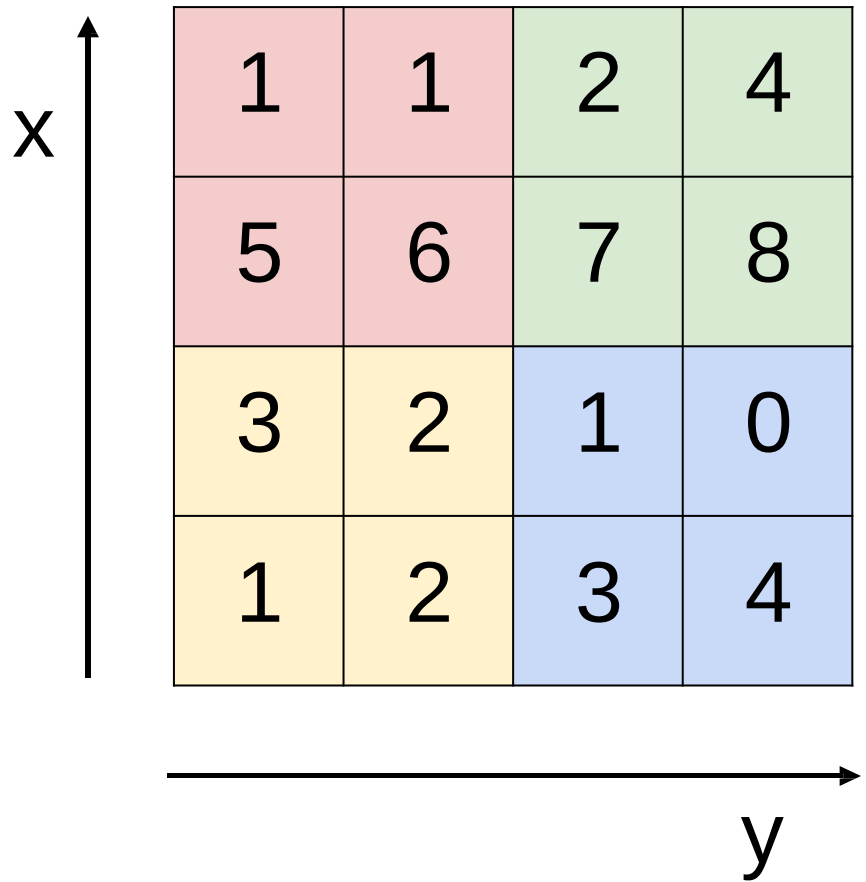


卷积神经网络

- 池化层
- 使特征更小，更易于处理
- 独立操作每个激活图



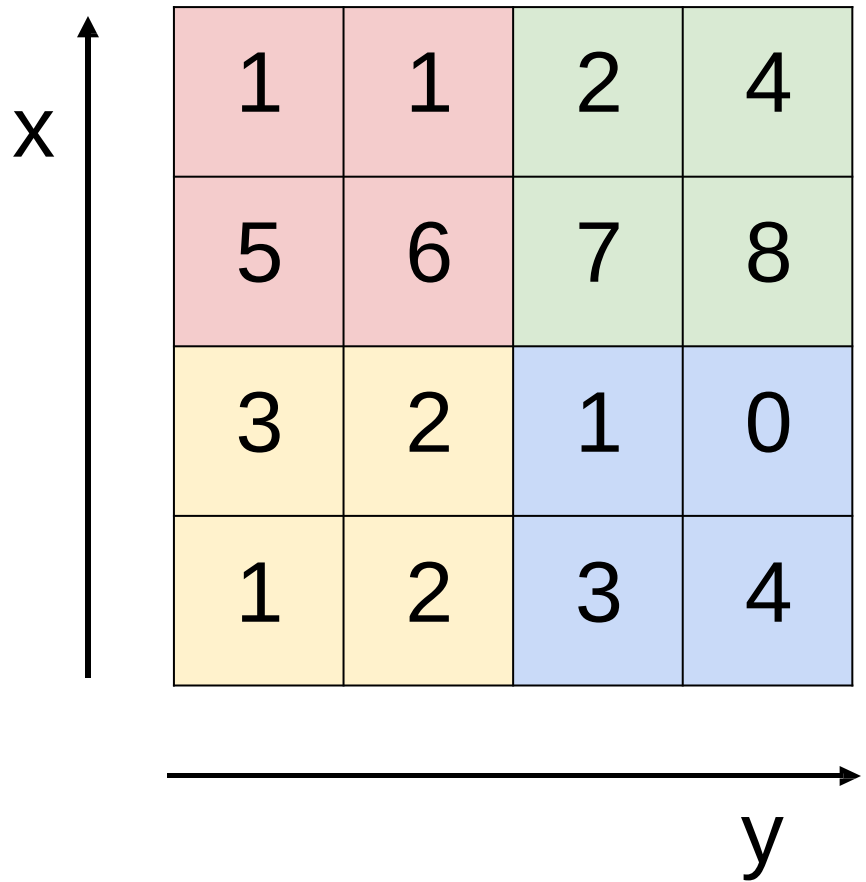
- 最大池化（Max Pooling）



Max Pooling
2x2 大小和 2 步长

6	8
3	4

- 最大池化（Max Pooling）



Max Pooling
2x2 大小和 2 步长

6	8
3	4

没有可学习参数
引入空间不变性

卷积神经网络

- 池化层总结
- 输入： $W_1 \times H_1 \times C$
- 卷积超参：
  - 滤波器大小 F
  - 步长 S
- 输出： $W_2 \times H_2 \times C$
  - $W_2 = (W_1 - F)/S + 1$
  - $H_2 = (H_1 - F)/S + 1$
- 参数量：
  - 0

卷积神经网络

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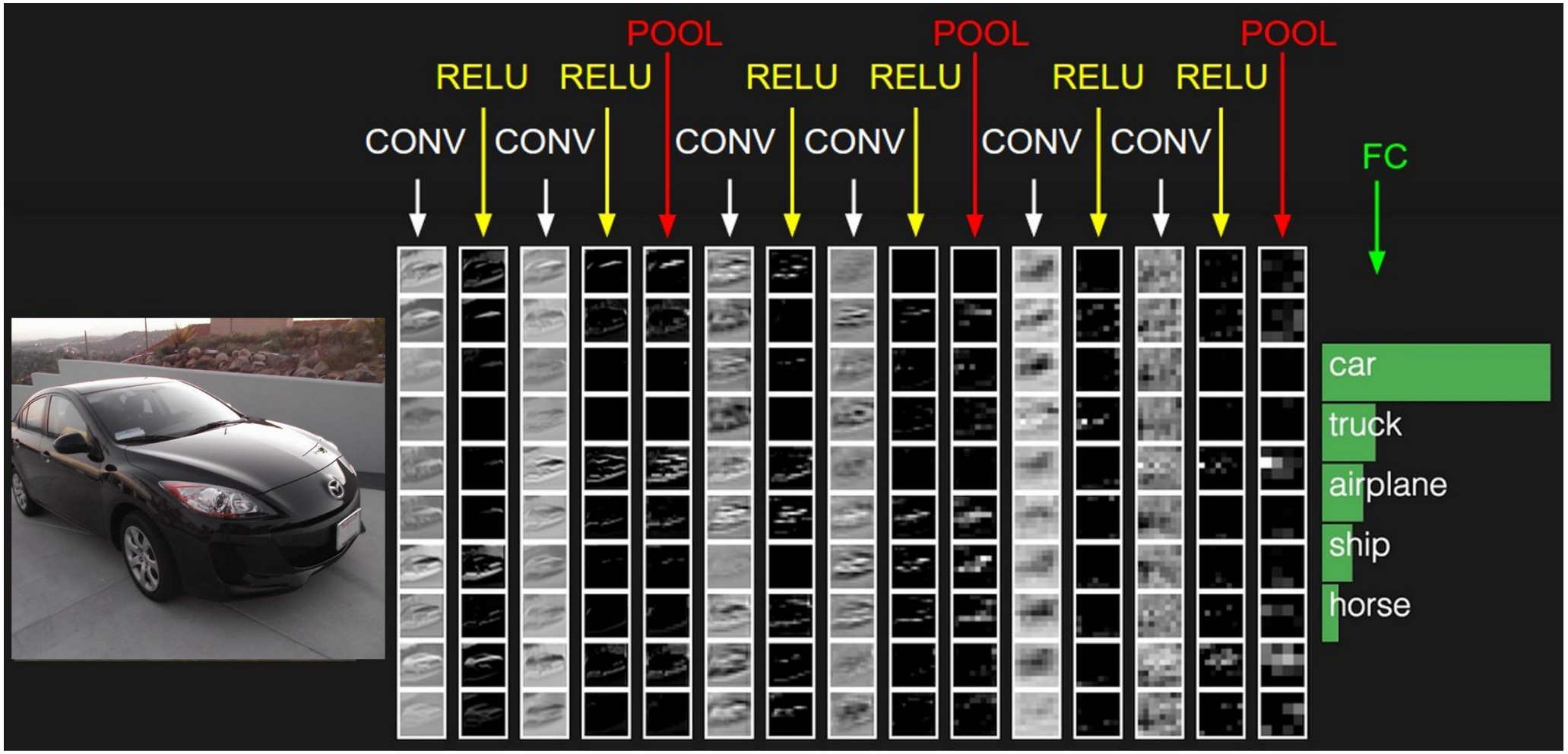
全连接层



卷积神经网络

- 卷积层+池化层+全连层+激活函数
- 趋向于更小的滤波器和更深的层
- 趋向于舍弃池化层和全连接层
- 以往常见的卷积网络架构：
  - [(Conv-ReLU)*N-Pooling]*M-(FC-ReLU)*K-Softmax
  - N一般为~5，M较大，K一般在0~2
- 新型卷积网络（ResNet，GoogLeNet）提出了新的架构

卷积神经网络

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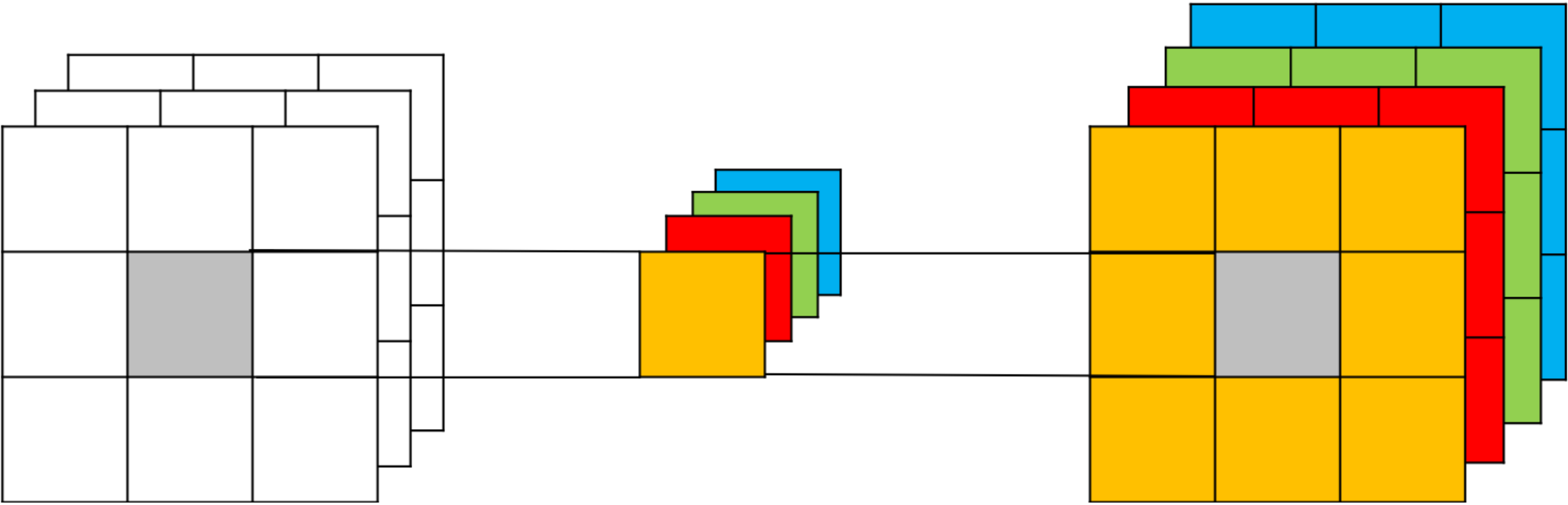
- 1x1卷积



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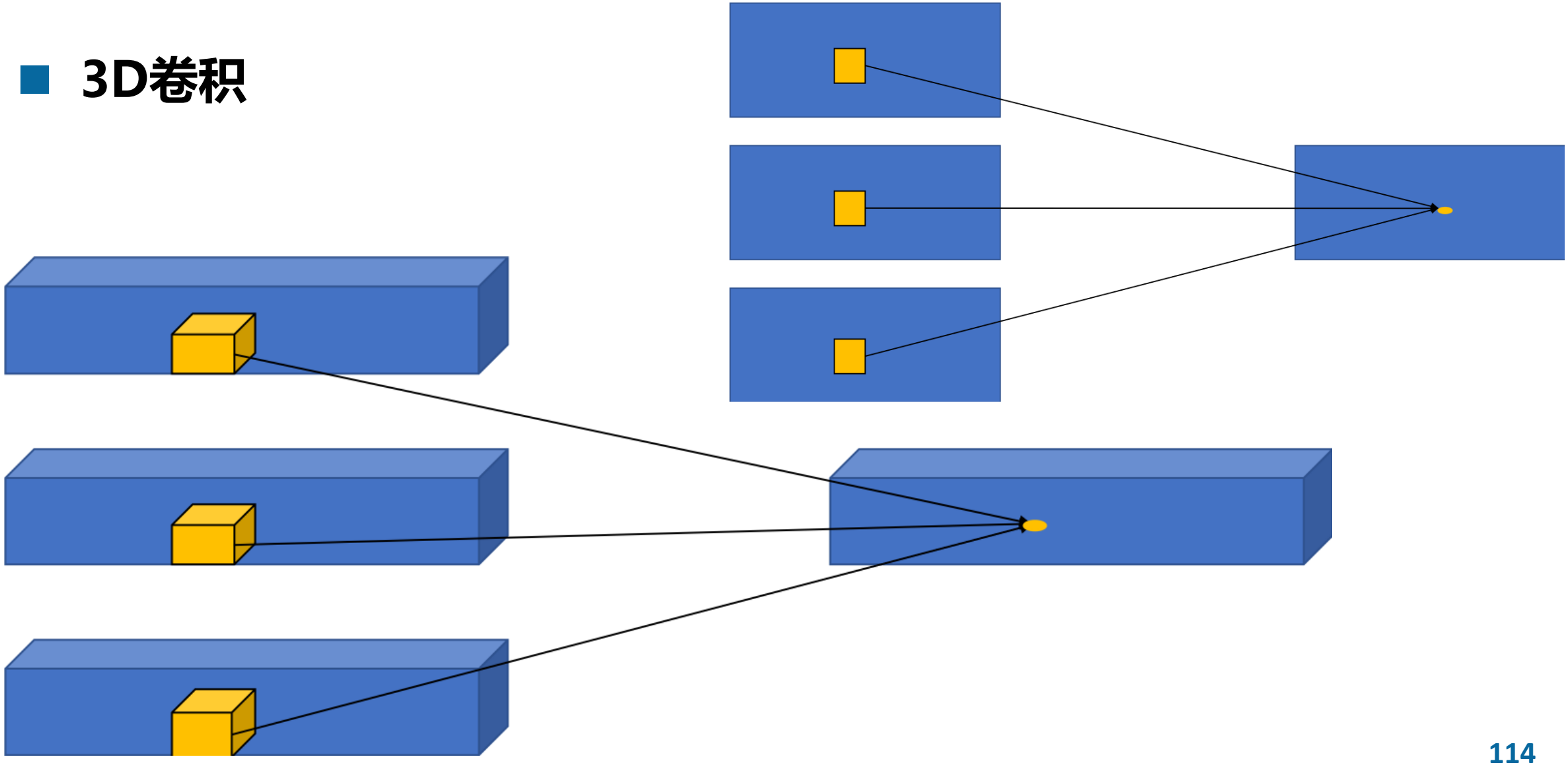
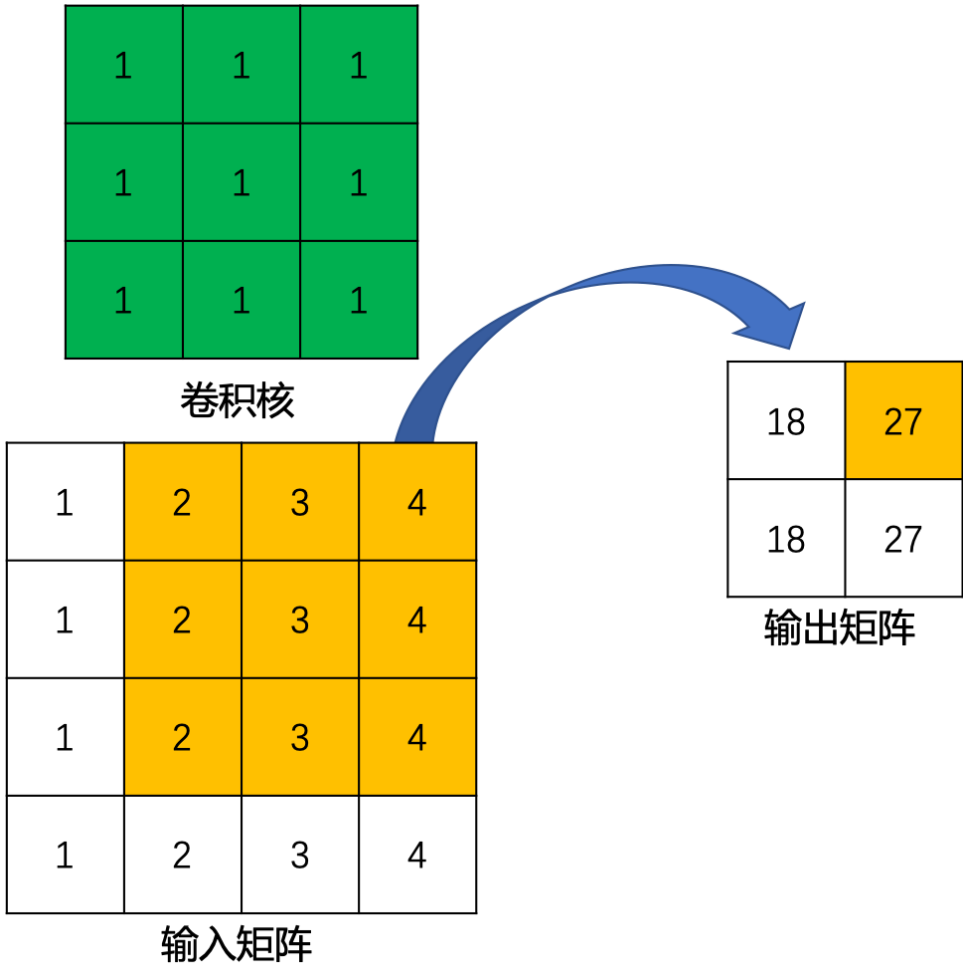
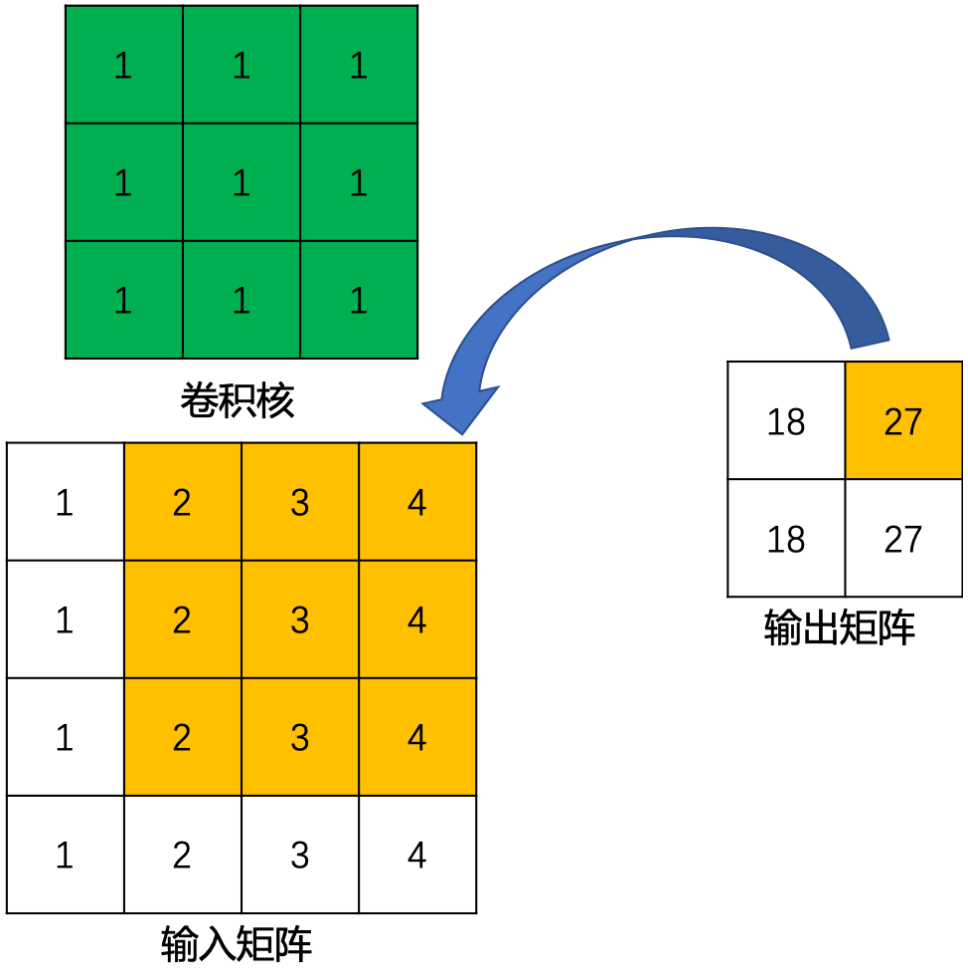
- 3D卷积



转置卷积


1 1 1
1 1 1
1 1 1
卷积核
18 27
18 27
输出矩阵
1 2 3 4
1 2 3 4
1 2 3 4
1 2 3 4
输入矩阵


1 1 1
1 1 1
1 1 1
卷积核
18 27
18 27
输出矩阵
1 2 3 4
1 2 3 4
1 2 3 4
1 2 3 4
输入矩阵

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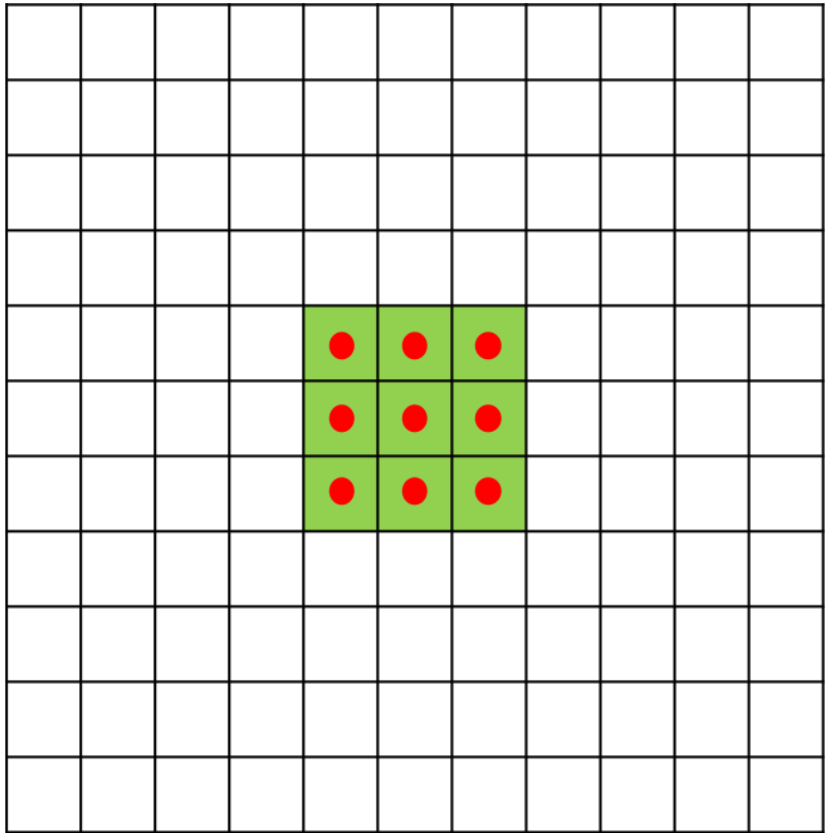
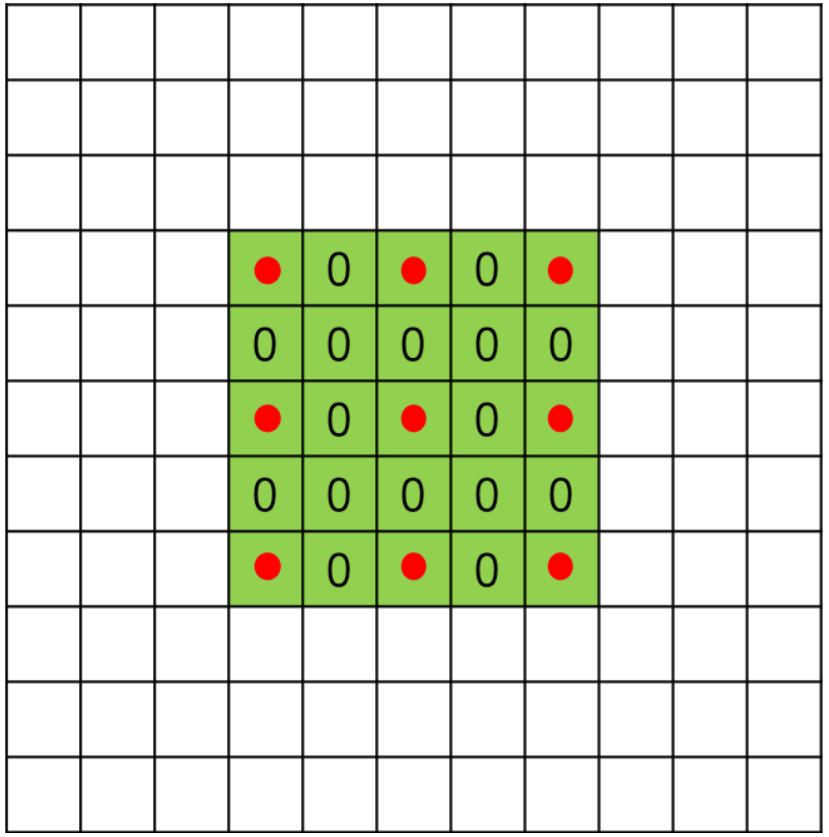
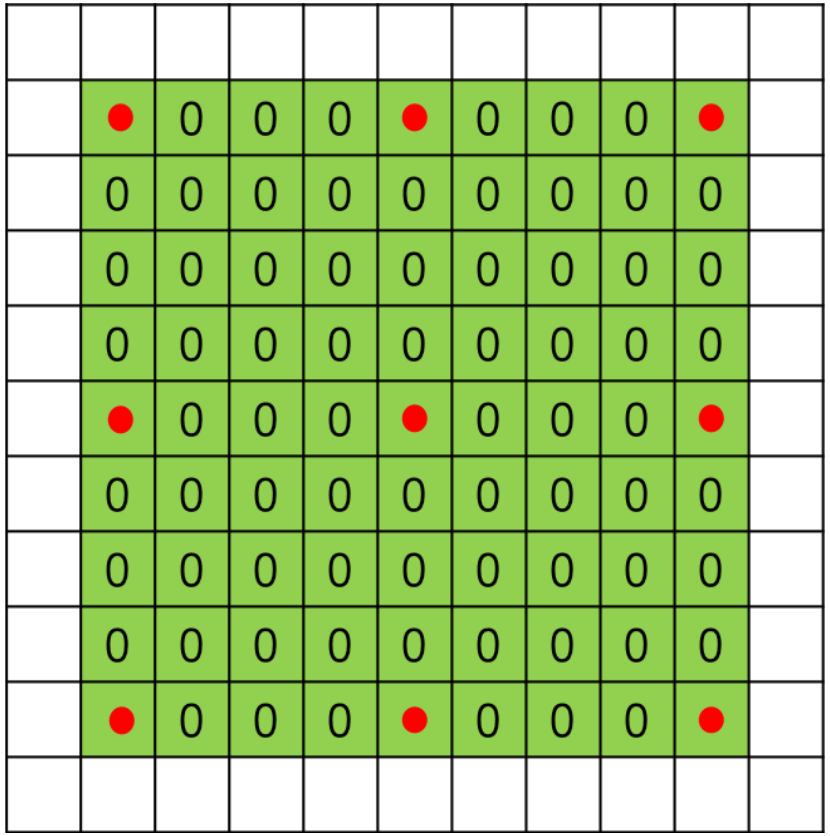
空洞卷积

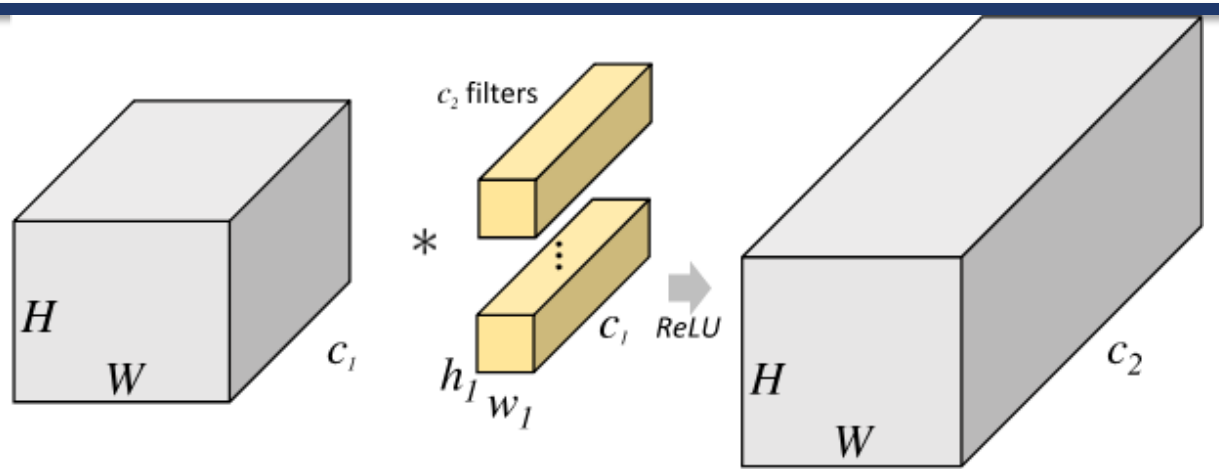


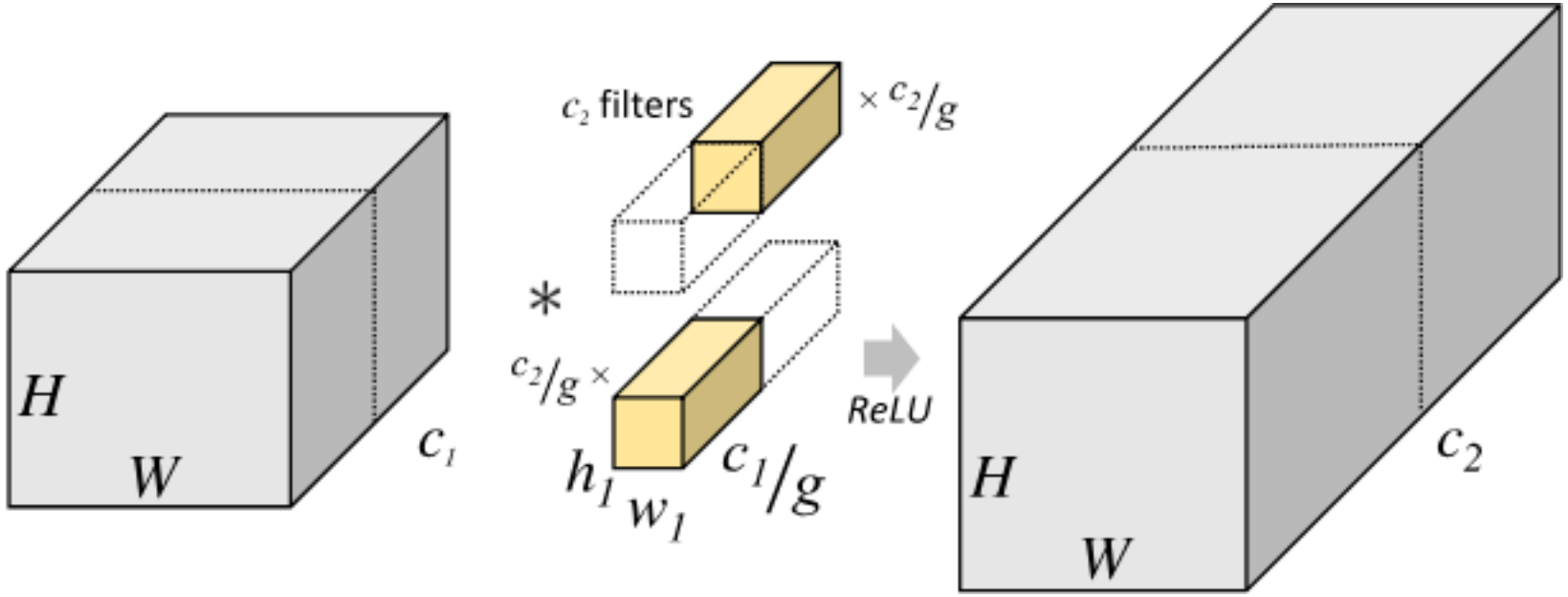




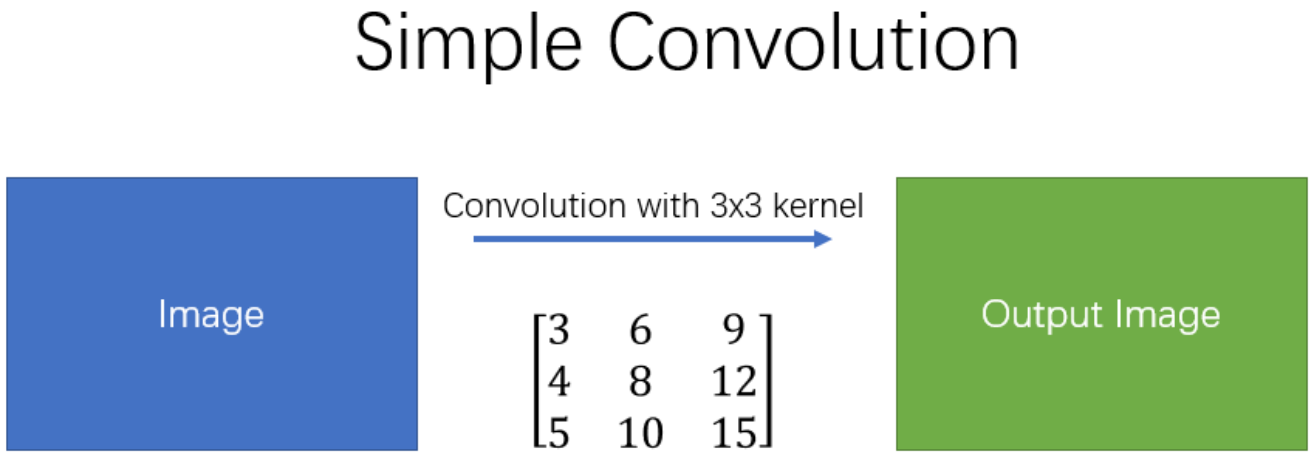
卷积神经网络

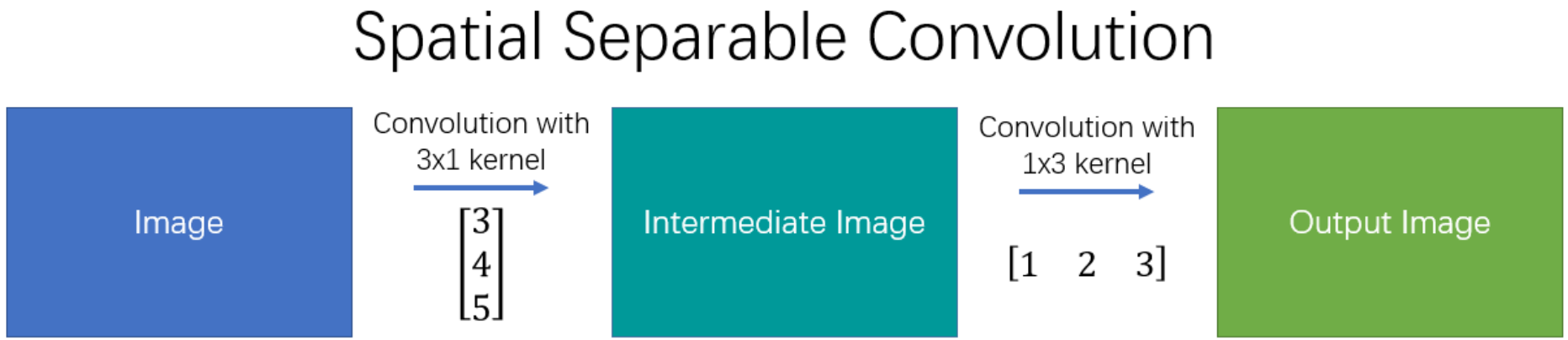
- 分组卷积


H
W
c_1
c_2 filters
h_1
w_1
c_1
ReLU
H
W
c_2


H
W
c_1
c_2 filters
$\times c_2/g$
$c_2/g \times$
h_1
w_1
c_1/g
ReLU
H
W
c_2

可分离卷积


Simple Convolution
Image
Convolution with 3x3 kernel
3 6 9
4 8 12
5 10 15
Output Image


Spatial Separable Convolution
Image
Convolution with 3x1 kernel
3
4
5
Intermediate Image
Convolution with 1x3 kernel
1 2 3
Output Image

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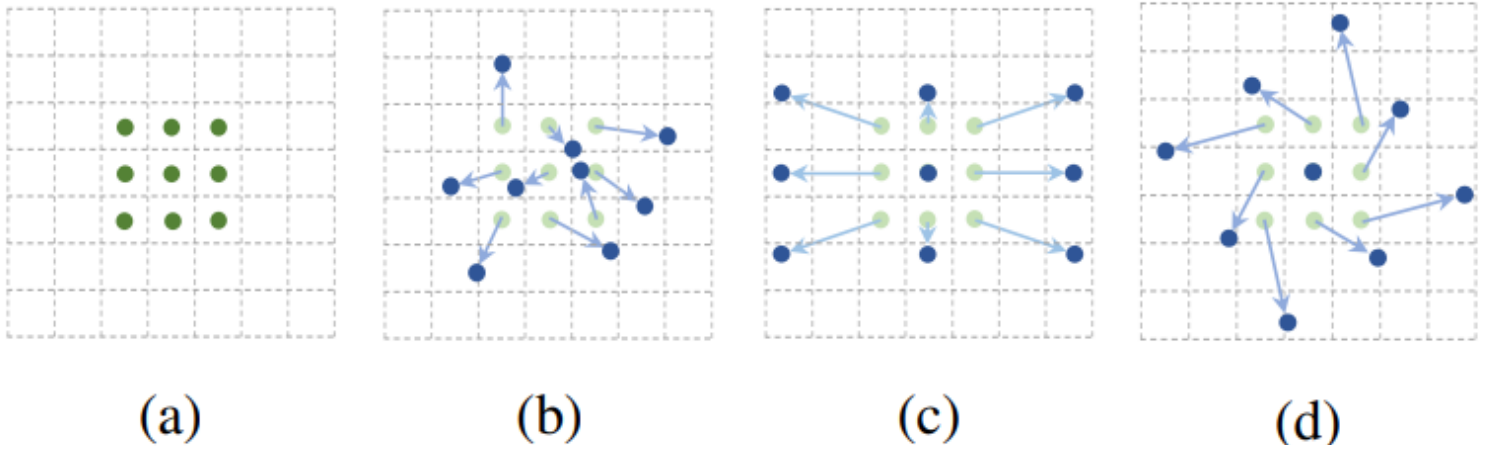
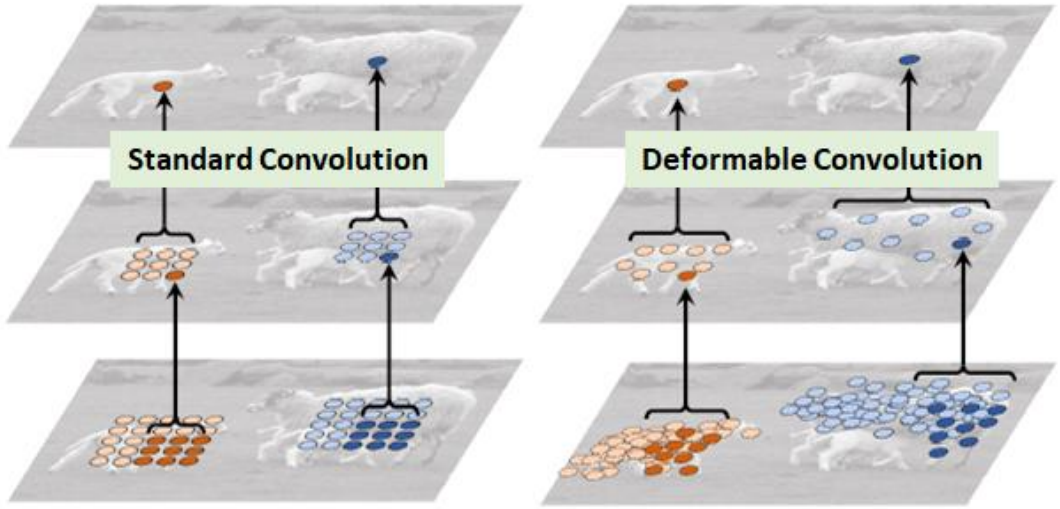
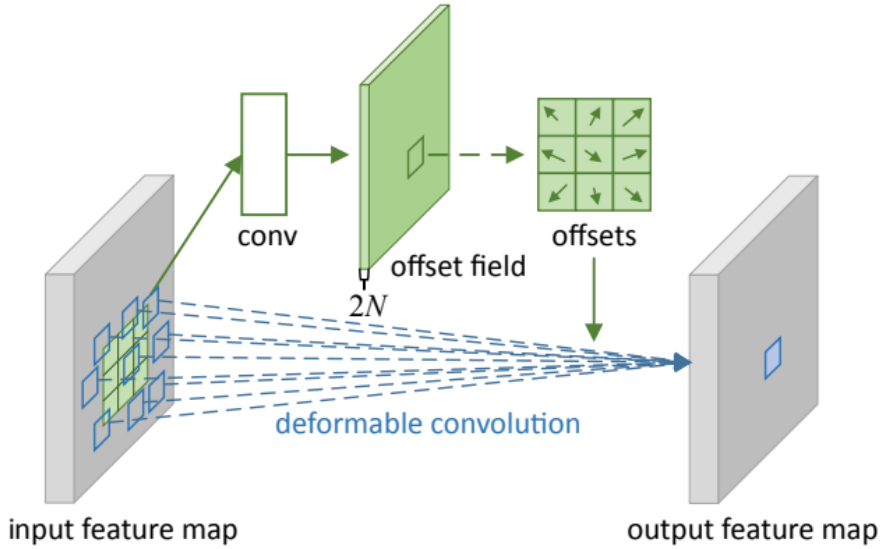
可变形卷积







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- 下节课：卷积神经网络架构