《神经网络与深度学习》

卷积神经网络

https://nndl.github.io/

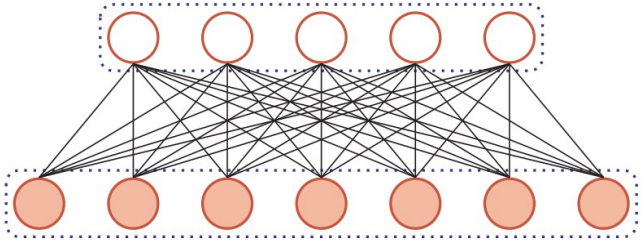
内容

- 卷积神经网络
  - 卷积
  - 卷积神经网络
  - 卷积神经网络的简单实现
  - 其他种类的卷积
- 卷积神经网络的扩展
  - 典型的卷积神经网络(*LeNet, AlexNet, VGG, NiN, ...*)
  - 卷积神经网络的应用

卷积

全连接前馈神经网络

- 权重矩阵的参数非常多

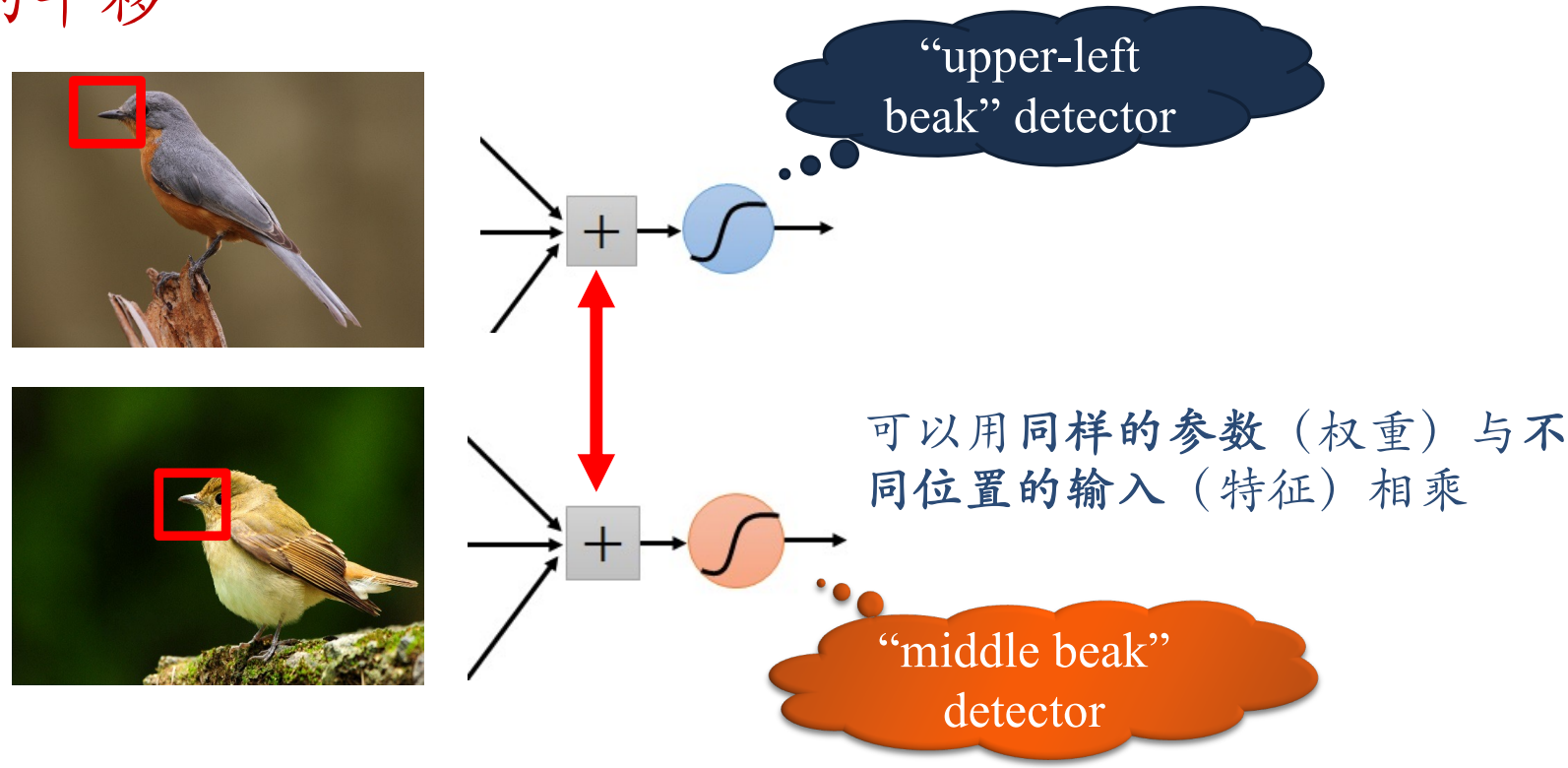


动机

- 局部不变性特征
  - 自然图像中的物体都具有局部不变性特征
    - 尺度缩放、平移、旋转等操作不影响其语义信息。
  - 全连接前馈网络很难提取这些局部不变特征

动机

- 特征的平移


"upper-left beak" detector
"middle beak" detector
可以用同样的参数（权重）与不同位置的输入（特征）相乘

动机

- 特征向下/次采样(sub-sampling)

我们可以次采样像素点，用**更少的参数**（权重）去处理图像

卷积神经网络

- 卷积神经网络（Convolutional Neural Networks，CNN）
  - 一种前馈神经网络
  - 受生物学上感受野（Receptive Field）的机制而提出的
    - 在视觉神经系统中，一个神经元的感受野是指视网膜上的特定区域，只有这个区域内的刺激才能够激活该神经元。

- 卷积神经网络有三个结构上的特性：
  - 局部连接
  - 权重共享
  - 空间或时间上的次采样

卷积

- 卷积经常用在信号处理中，用于计算信号的延迟累积。
- 假设一个信号发生器每个时刻t产生一个信号x_t，其信息的衰减率为w_k，即在k−1个时间步长后，信息为原来的w_k倍
  - 假设$w_1 = 1, w_2 = 1/2, w_3 = 1/4$
- 时刻t收到的信号y_t为当前时刻产生的信息和以前时刻延迟信息的叠加。

卷积

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- 时刻t收到的信号y_t为当前时刻产生的信息和以前时刻延迟信息的叠加。

$$
\begin{aligned}
y_t &= 1 \times x_t + 1/2 \times x_{t-1} + 1/4 \times x_{t-2} \\
&= w_1 \times x_t + w_2 \times x_{t-1} + w_3 \times x_{t-2} \\
&= \sum_{k=1}^{3} w_k \cdot x_{t-k+1}.
\end{aligned}
$$

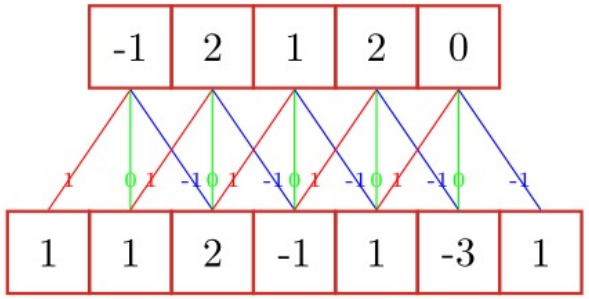
滤波器（filter）或卷积核（convolution kernel）

卷积

- 给定一个输入信号序列x和滤波器w,卷积的输出为:

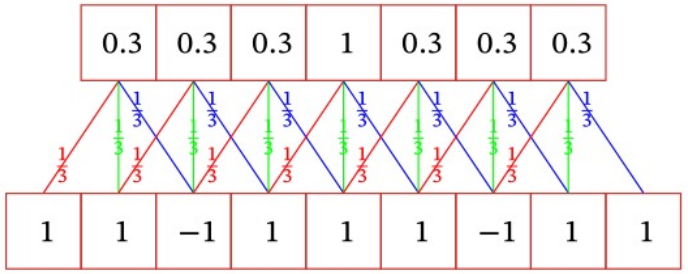
$$y_t = \sum_{k=1}^{K} w_k x_{t-k+1}$$

Filter: [-1,0,1]



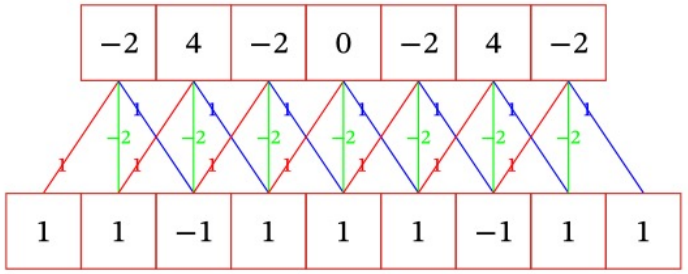
卷积

- 不同的滤波器来提取信号序列中的不同特征



(a) 滤波器 [1/3, 1/3, 1/3]

低频信息

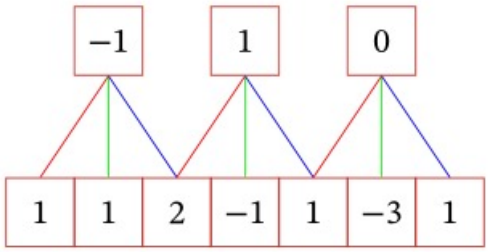


(b) 滤波器 [1, −2, 1]

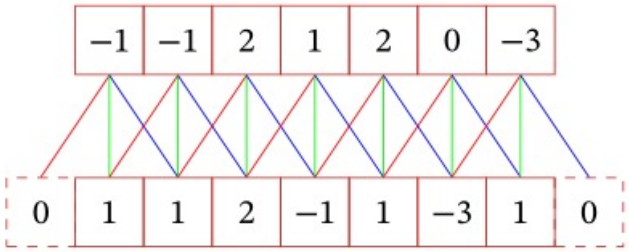
高频信息

卷积扩展

- 引入滤波器的滑动步长S和零填充P



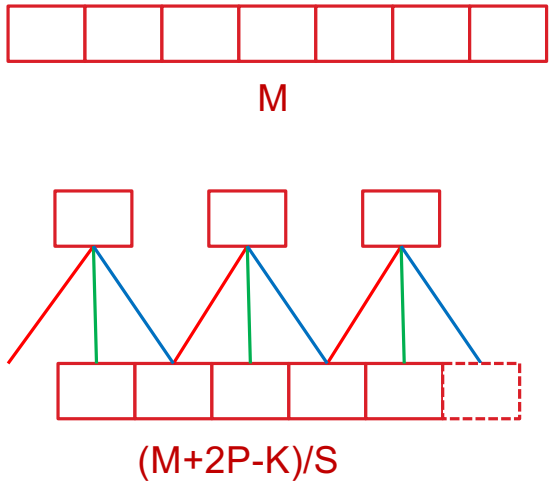
(a) 步长 $S = 2$

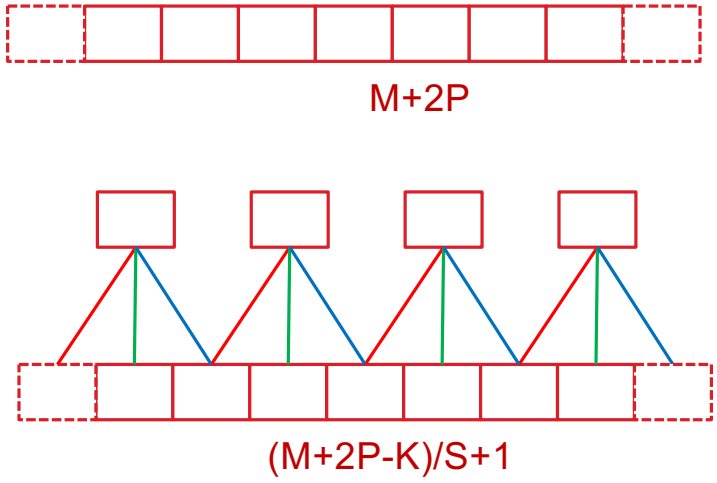


(b) 零填充 $P = 1$

卷积输出长度

- 假设卷积的输入长度为M，卷积大小为K，步长为S，再输入两端各填补P个0，那么该卷积输出长度为(M−K+2P)/S+1





选择合适的卷积大小使得(M−K+2P)/S+1为整数

卷积类型

- 卷积的结果按输出长度不同可以分为三类： (M+2P-K)/S+1
  - 窄卷积：步长 $S=1$，两端不补零 $P=0$，卷积后输出长度为 $M-K+1$
  - 宽卷积：步长 $S=1$，两端补零 $P=K-1$，卷积后输出长度 $M+K-1$
  - 等宽卷积：步长 $S=1$，两端补零 $P=(K-1)/2$，卷积后输出长度 M

- 在早期的文献中，卷积一般默认为窄卷积。
- 而目前的文献中，卷积一般默认为等宽卷积。

二维卷积

- 在图像处理中，图像是以二维矩阵的形式输入到神经网络中，因此我们需要二维卷积。

一个输入信息 $\boldsymbol{X}$ 和滤波器 $\boldsymbol{W}$ 的二维卷积定义为

$$\boldsymbol{Y} = \boldsymbol{W} * \boldsymbol{X},$$

$$y_{ij} = \sum_{u=1}^{U} \sum_{v=1}^{V} w_{uv} x_{i-u+1, j-v+1}.$$

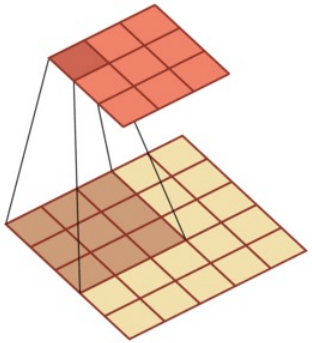
1	1	1 ×−1	1 ×0	1 ×0
−1	0	−3 ×0	0 ×0	1 ×0
2	1	1 ×0	−1 ×0	0 ×1
0	−1	1	2	1
1	2	1	1	1

*

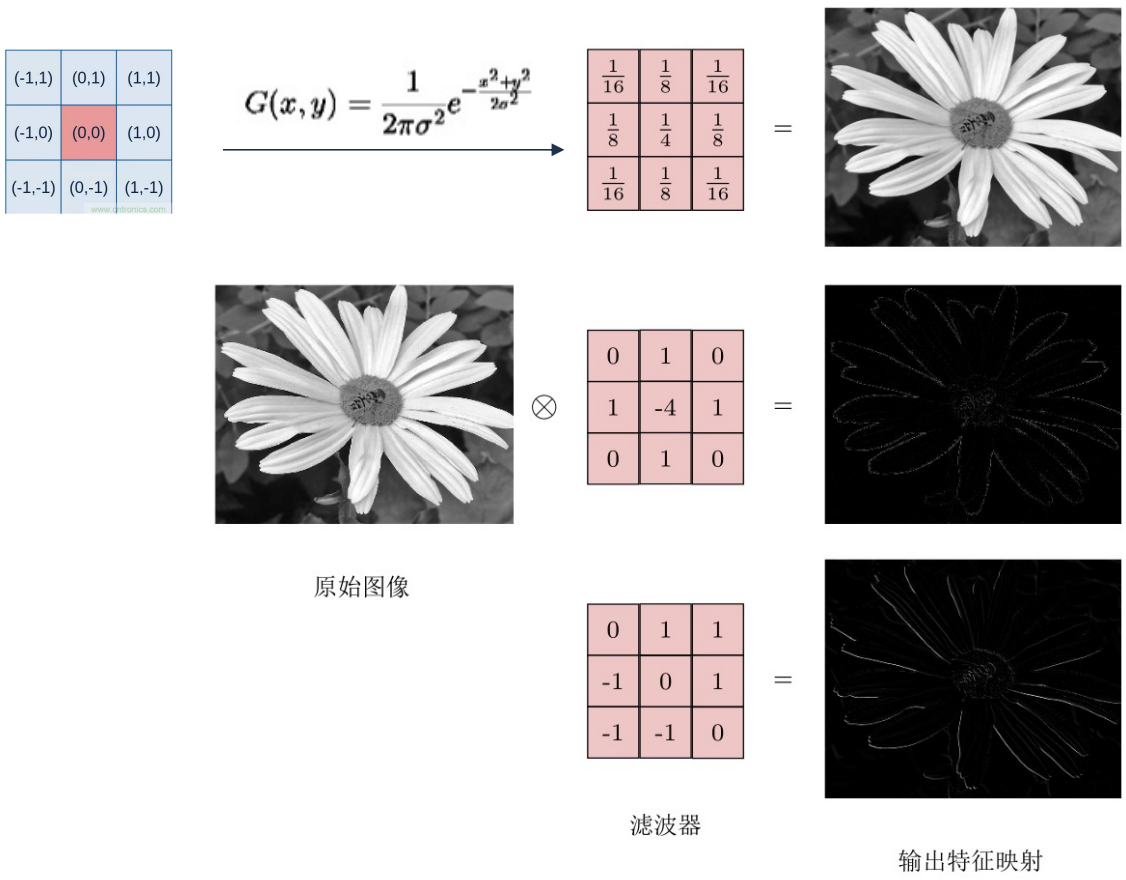
1	0	0
0	0	0
0	0	−1

=

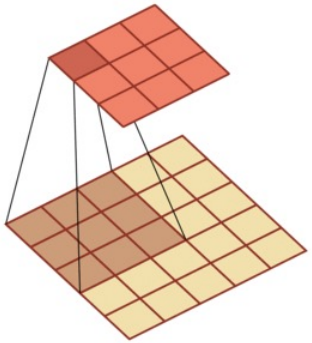
0	−2	−1
2	2	4
−1	0	0



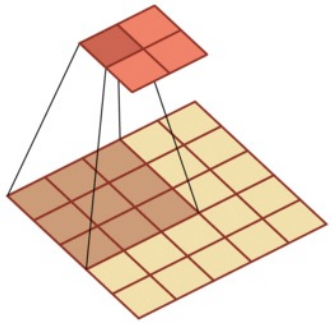
卷积作为特征提取器


(-1,1) (0,1) (1,1)
(-1,0) (0,0) (1,0)
(-1,-1) (0,-1) (1,-1)
$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$
$\frac{1}{16}$ $\frac{1}{8}$ $\frac{1}{16}$
$\frac{1}{8}$ $\frac{1}{4}$ $\frac{1}{8}$
$\frac{1}{16}$ $\frac{1}{8}$ $\frac{1}{16}$
=
⊗
0 1 0
1 -4 1
0 1 0
=
原始图像
0 1 1
-1 0 1
-1 -1 0
=
滤波器
输出特征映射

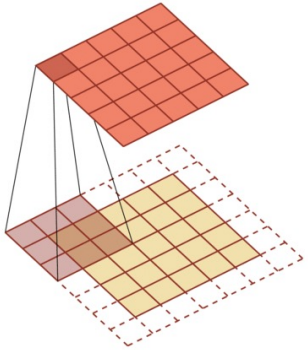
二维卷积



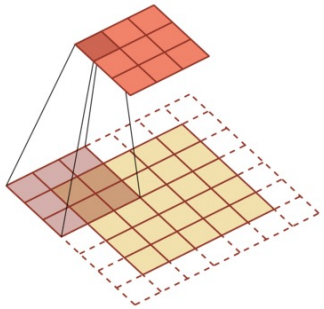
步长1，零填充0



步长2，零填充0



步长1，零填充1

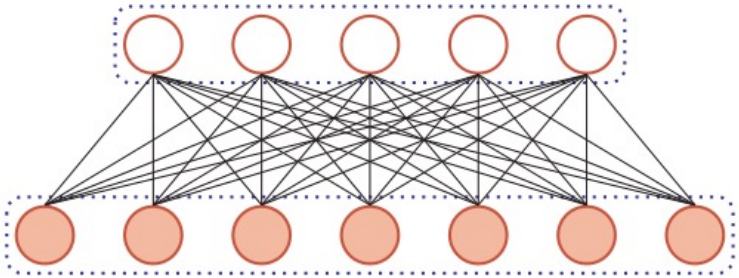


步长2，零填充1

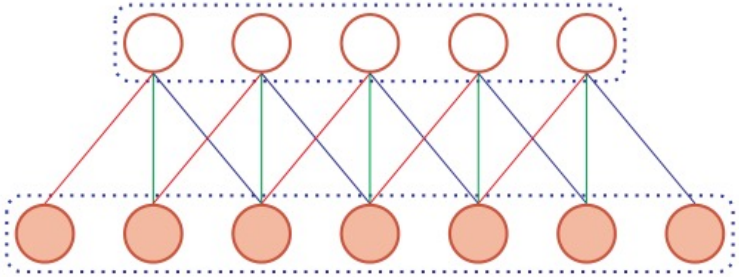
卷积神经网络

卷积神经网络

- 用卷积层代替全连接层



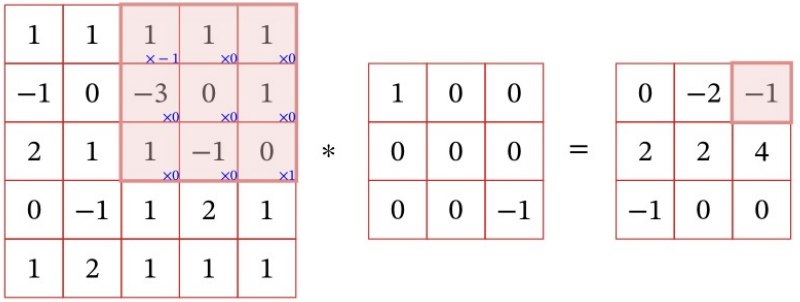
(a) 全连接层



(b) 卷积层

互相关

- 计算卷积需要进行卷积核翻转。
- 在神经网络中卷积操作的目标：提取特征，因此翻转是不必要的！



- 互相关

$$y_{ij} = \sum_{u=1}^{m}\sum_{v=1}^{n} w_{uv} \cdot x_{i+u-1,j+v-1}$$

$$\begin{aligned} \boldsymbol{Y} &= \boldsymbol{W} \otimes \boldsymbol{X} \\ &= \mathrm{rot180}(\boldsymbol{W}) * \boldsymbol{X}, \end{aligned}$$

除非特别声明，卷积一般指“互相关”。

互相关

- 计算卷积需要进行卷积核翻转。
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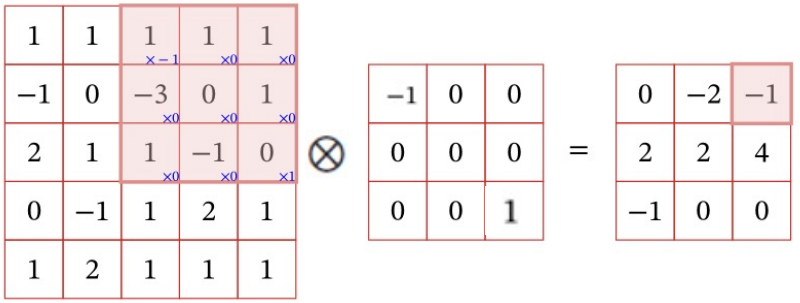


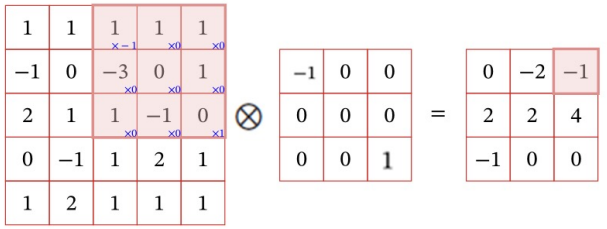
- 互相关

$$y_{ij} = \sum_{u=1}^{m}\sum_{v=1}^{n} w_{uv} \cdot x_{i+u-1,j+v-1}$$

$$\boldsymbol{Y} = \boldsymbol{W} \otimes \boldsymbol{X}$$
$$= \text{rot180}(\boldsymbol{W}) * \boldsymbol{X},$$

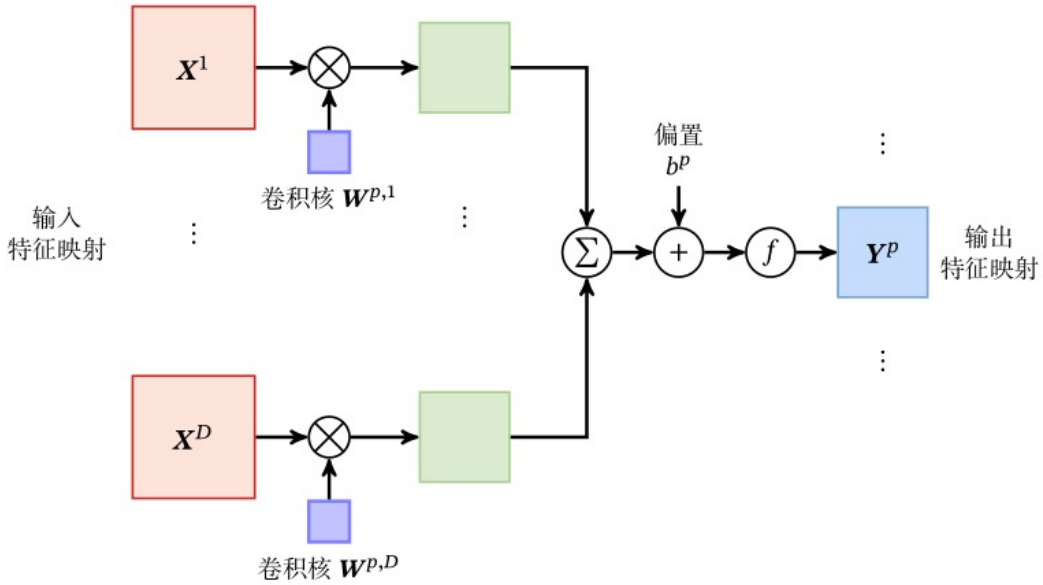
除非特别声明，卷积一般指“互相关”。

多个卷积核



- 特征映射（Feature Map）
  - 图像经过卷积后得到的特征。卷积核可看成一个特征提取器
- 感受野(Receptive Field)
  - 影响元素x(某数组或矩阵中的成员)的前向计算的所有可能的输入区域叫做x的感受野
- 卷积层
  - 输入：D个特征映射 M×N×D
  - 输出：P个特征映射 M′×N′×P
  - 大小为D的这一维称为输入通道(in channel)维，大小为P的这一维称为输出通道(out channel)维

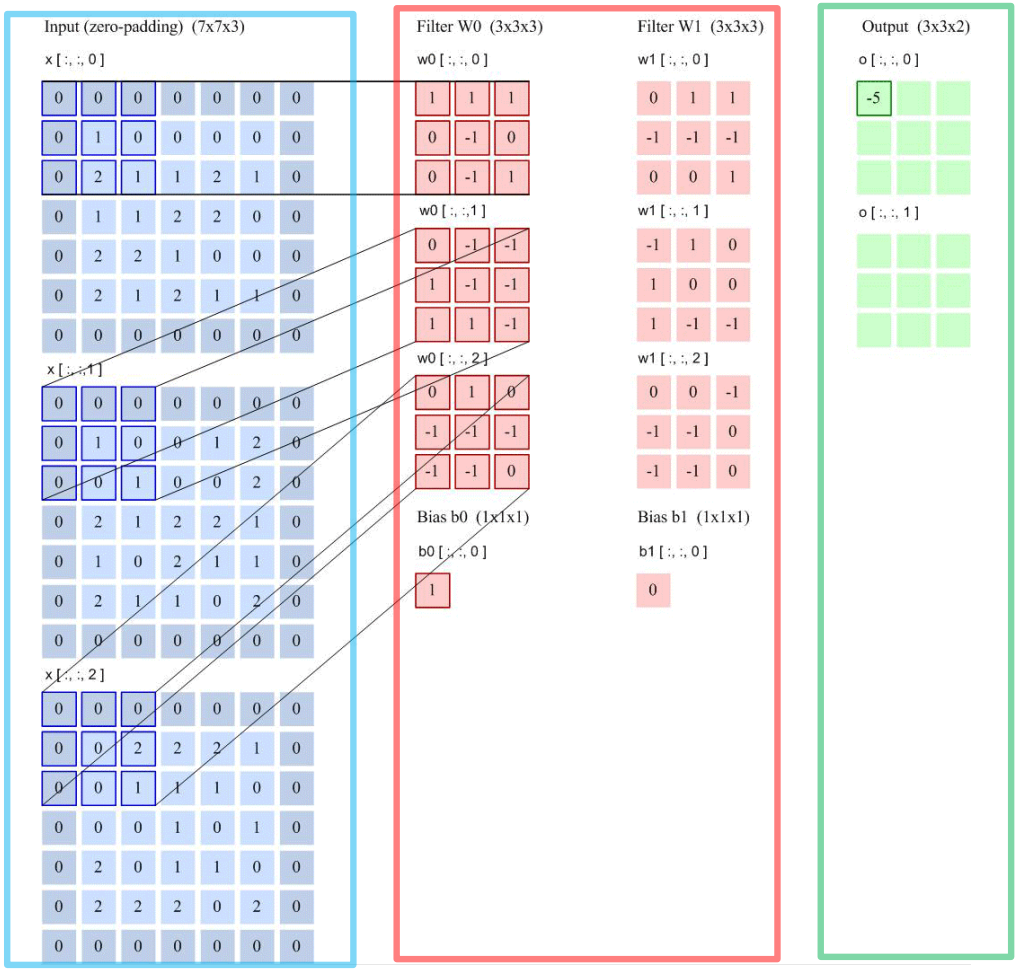
卷积层的映射关系



$$Z^p = W^p \otimes X + b^p = \sum_{d=1}^{D} W^{p,d} \otimes X^d + b^p,$$

$$Y^p = f(Z^p).$$

https://cs231n.github.io/convolutional-networks/#conv



卷积核(convolutional kernel)

三/二维卷积核

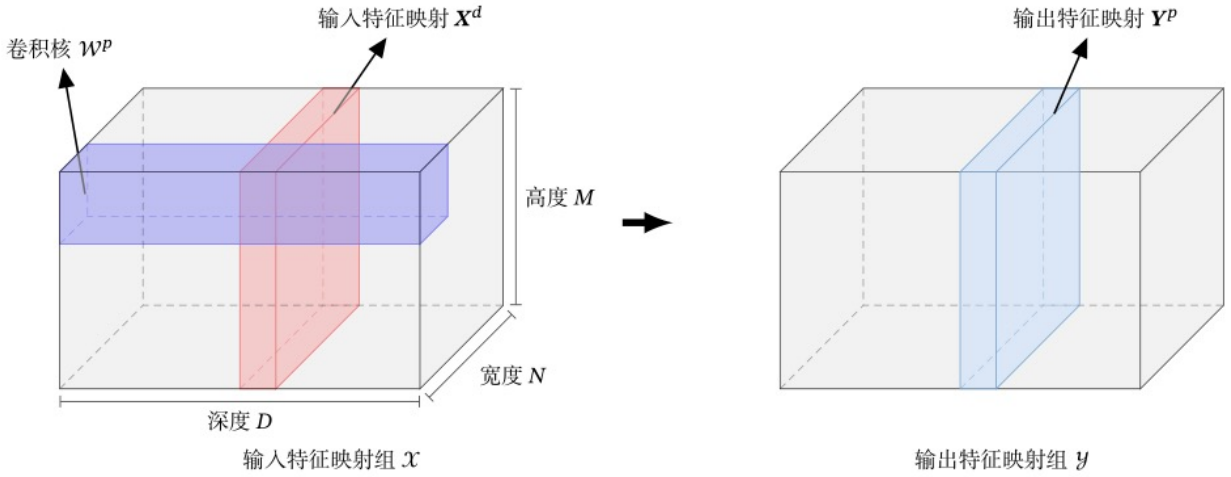
滤波器(filter)

核(kernel)

步长2
filter 3*3*3
filter个数~~6~~ 2
零填充 1

卷积层

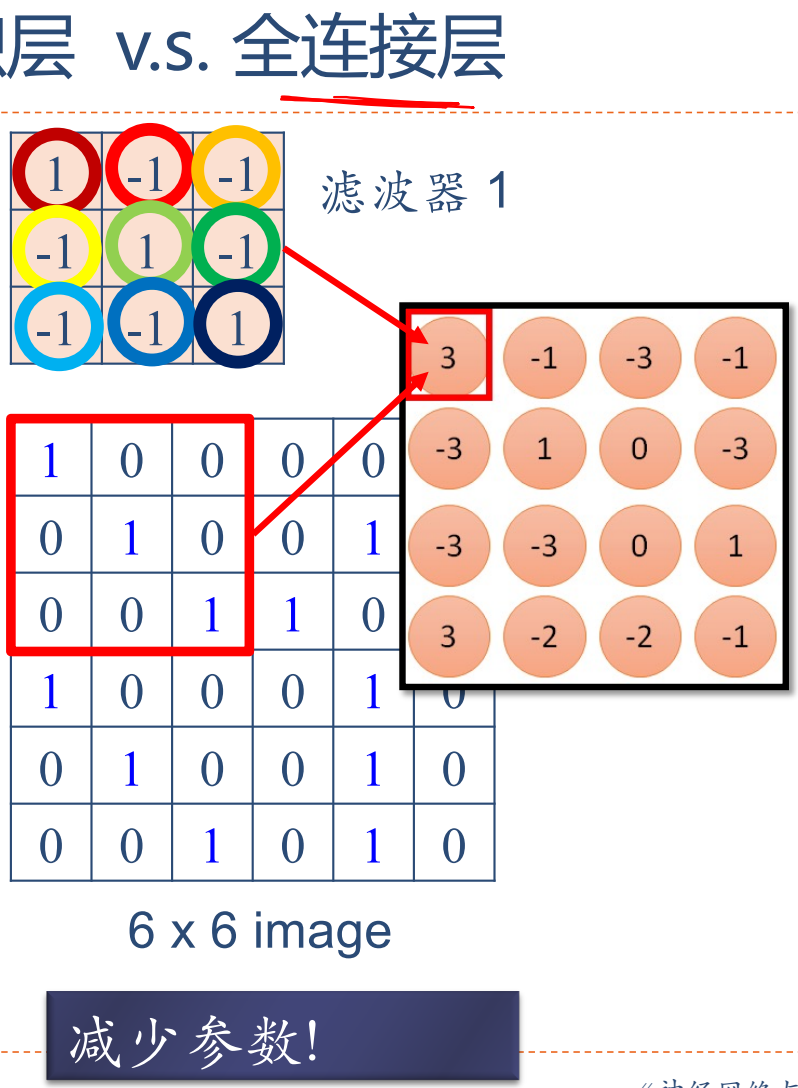
- 典型的卷积层为3维结构



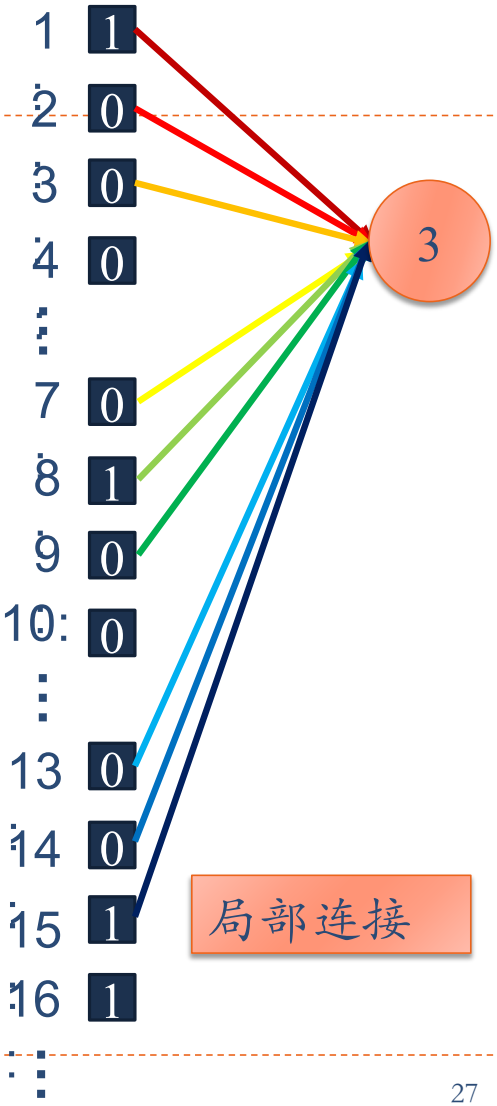
$$Z^p = W^p \otimes X + b^p = \sum_{d=1}^{D} W^{p,d} \otimes X^d + b^p,$$

$$Y^p = f(Z^p).$$

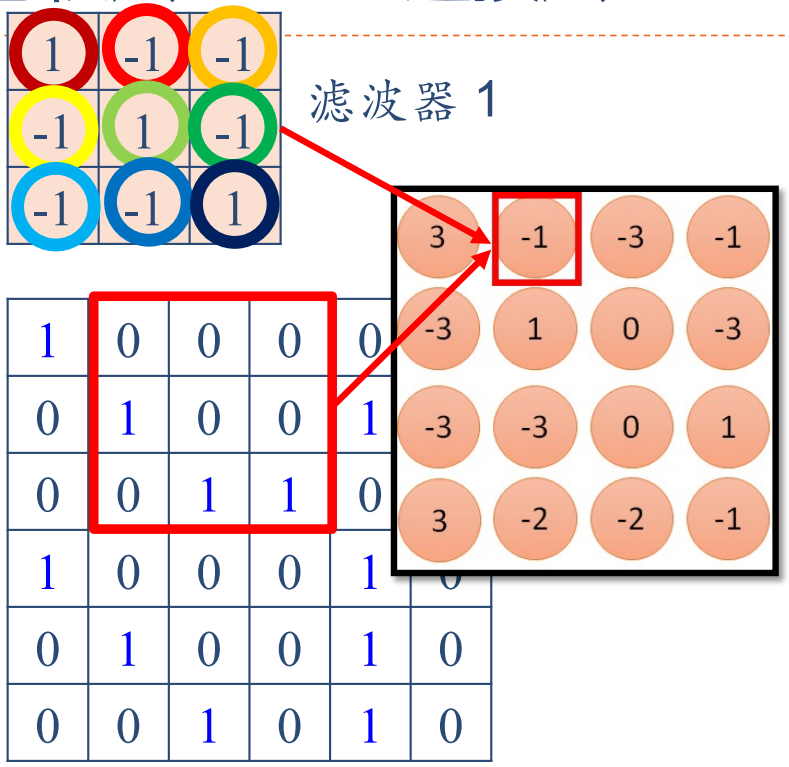
卷积层 v.s. 全连接层



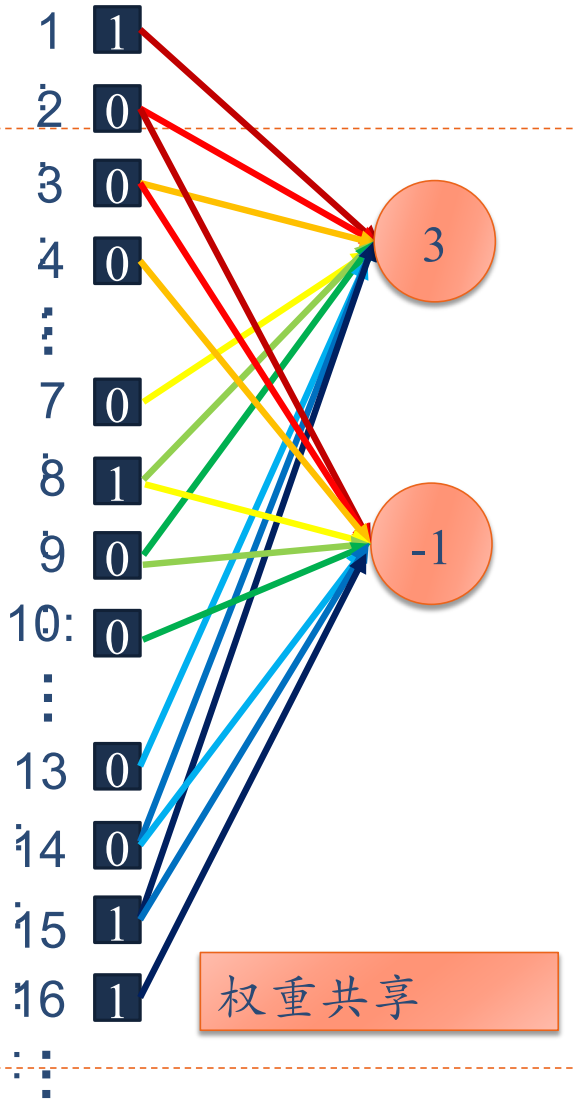
减少参数!



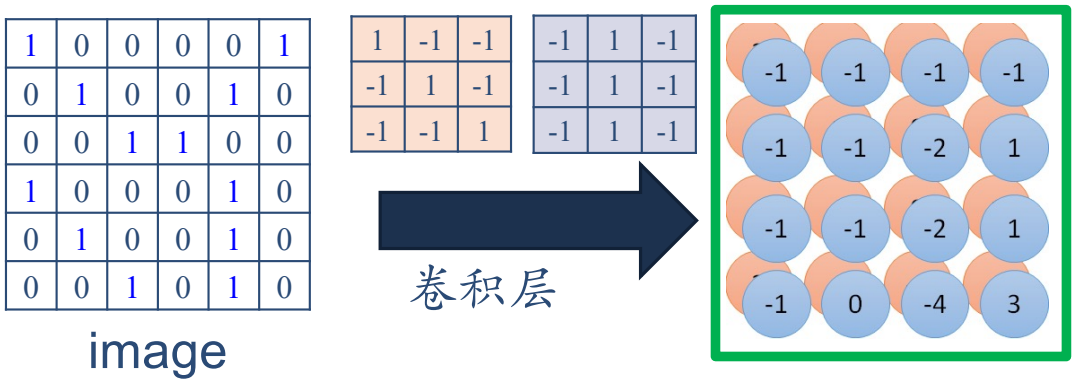
卷积层 v.s. 全连接层



进一步减少参数!



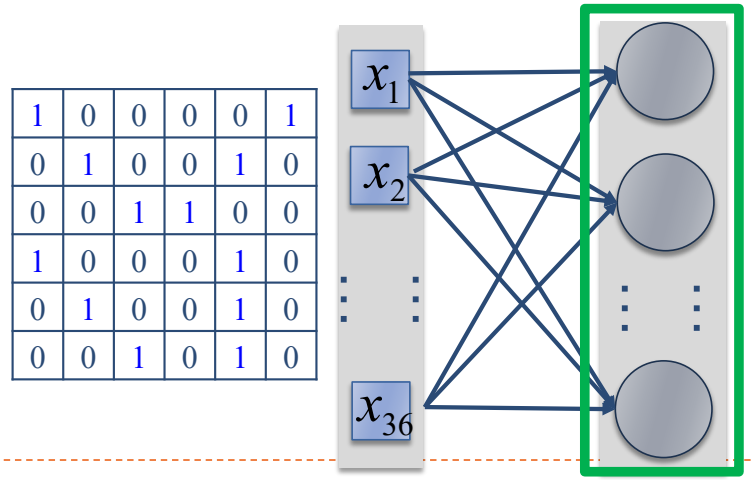
卷积层 v.s. 全连接层



想象输入图像大小为6*6

带两个滤波器的卷积层参数个数
（3*3+1）*2

全连接层



全连接层两个神经元参数个数
（6*6+1）*2

卷积的导数

- $Y = W \otimes X$，其中$X \in R^{M \times N}$, W$\in R^{U \times V}$, Y$\in R^{(M-U+1)\times(N-V+1)}$。函数$f(Y) \in R$为一个标量函数

- $f(Y)$关于W的偏导数为X和$\frac{\partial f(Y)}{\partial Y}$的卷积

$$\frac{\partial f(\mathbf{Y})}{\partial w_{uv}} = \sum_{i=1}^{M-U+1}\sum_{j=1}^{N-V+1} \frac{\partial y_{ij}}{\partial w_{uv}} \frac{\partial f(\mathbf{Y})}{\partial y_{ij}}$$

$$= \sum_{i=1}^{M-U+1}\sum_{j=1}^{N-V+1} x_{i+u-1,j+v-1} \frac{\partial f(\mathbf{Y})}{\partial y_{ij}}$$

$$= \sum_{i=1}^{M-U+1}\sum_{j=1}^{N-V+1} \frac{\partial f(\mathbf{Y})}{\partial y_{ij}} x_{u+i-1,v+j-1}.$$

$$y_{ij} = \sum_{u,v} w_{uv} x_{i+u-1,j+v-1}.$$

$$\frac{\partial f(\mathbf{Y})}{\partial \mathbf{W}} = \frac{\partial f(\mathbf{Y})}{\partial \mathbf{Y}} \otimes \mathbf{X}.$$

卷积的导数

$f(Y)$关于X的偏导数为W和$\frac{\partial f(Y)}{\partial Y}$的真实卷积(非自相关)

$$\frac{\partial f(\mathbf{Y})}{\partial x_{st}} = \sum_{i=1}^{M-U+1} \sum_{j=1}^{N-V+1} \frac{\partial y_{ij}}{\partial x_{st}} \frac{\partial f(\mathbf{Y})}{\partial y_{ij}} \qquad y_{ij} = \sum_{s,t} x_{s,t} w_{s-i+1,t-j+1}$$

$$= \sum_{i=1}^{M-U+1} \sum_{j=1}^{N-V+1} w_{s-i+1,t-j+1} \frac{\partial f(\mathbf{Y})}{\partial y_{ij}},$$

$$\frac{\partial f(Y)}{X} = \mathrm{W} * \frac{\partial f(Y)}{Y}$$

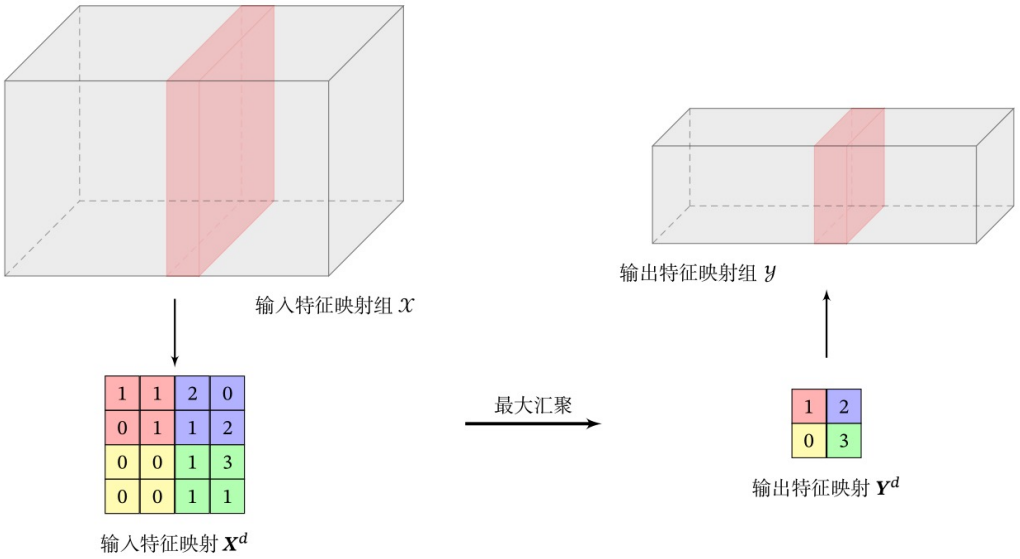
汇聚层

- 卷积层虽然可以显著减少连接的个数，但是每一个特征映射的神经元个数并没有显著减少

- 为了对特征进一步进行选择，降低特征数量，减少参数数量，引入汇聚层对特征进行次采样
  - 最大汇聚(max-pooling) $y_{m,n}^{d} = \max_{i \in R_{m,n}^{d}} x_i$
  - 平均汇聚(mean-pooling) $y_{m,n}^{d} = \frac{1}{|R_{m,n}^{d}|} \sum_{i \in R_{m,n}^{d}} x_i$

- 一般情况下，汇聚层不含任何参数

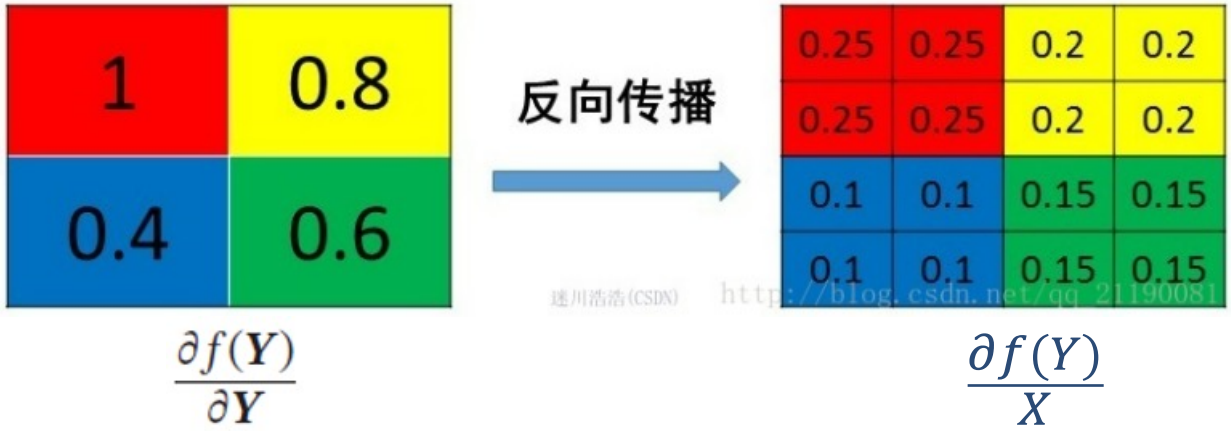
汇聚层



- 汇聚层也可以看作一个特殊的卷积层，卷积核大小为$K\times K$，卷积核为max函数或mean函数

Mean-pooling的导数

- $Y = \text{Mean} - \text{pooling}(X)$,其中$X \in R^{M \times N}$, $\text{Y} \in R^{(M-U+1) \times (N-V+1)}$
- 可看作向上采样(up sampling)

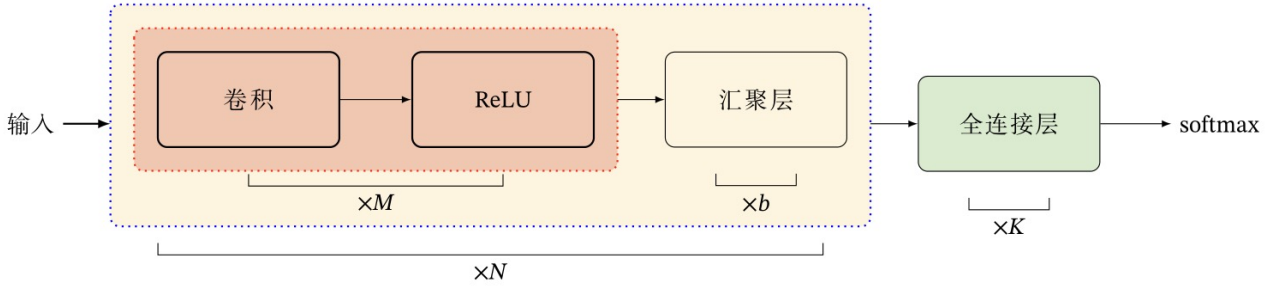


Max-pooling的导数

- $Y = \text{Max} - \text{pooling}(X)$,其中$X \in R^{M \times N}$, $\text{Y} \in R^{(M-U+1)\times(N-V+1)}$

卷积网络结构

- 卷积网络是由卷积层、汇聚层、全连接层交叉堆叠而成。
  - 趋向于小卷积、大深度
  - 汇聚层比例逐渐降低，趋向于全卷积
- 典型结构



- 一个卷积块为连续M 个卷积层和b个汇聚层（M通常设置为2～5，b为0或1）。一个卷积网络中可以堆叠N 个连续的卷积块，然后在接着K 个全连接层（N 的取值区间比较大，比如1～100或者更大；K一般为0～2）。

一个完整的卷积神经网络

Convolution

Max Pooling

A new image

Convolution

Max Pooling

A new image

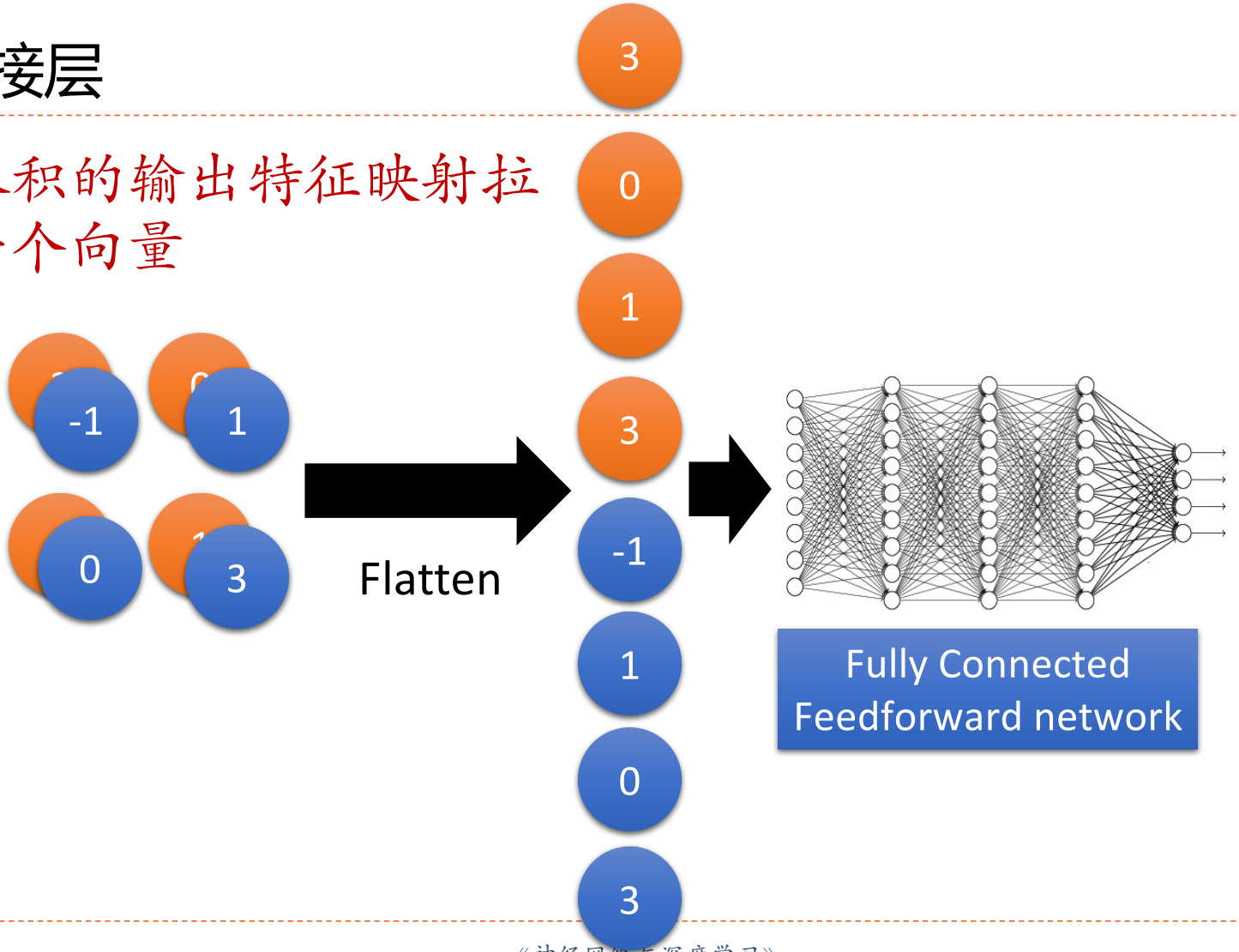
cat dog ……

Fully Connected Feedforward network

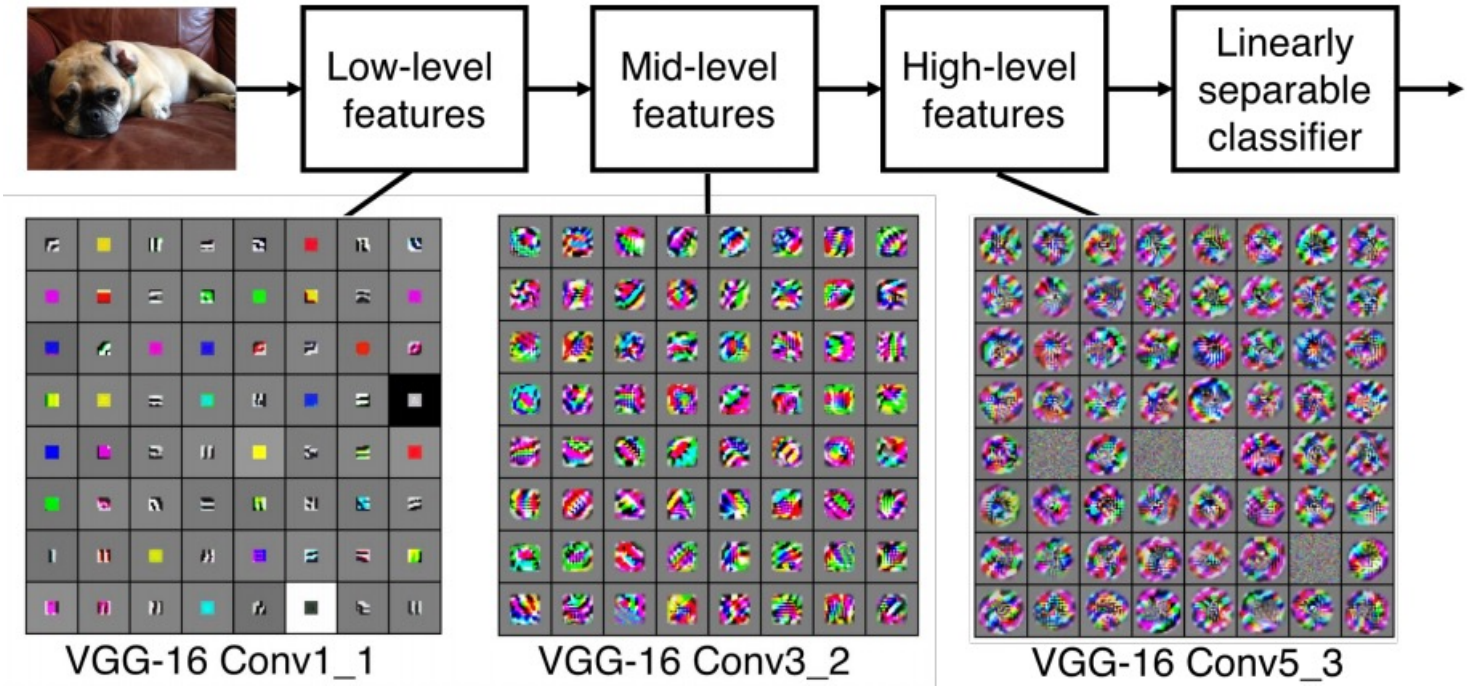
Flatten

全连接层

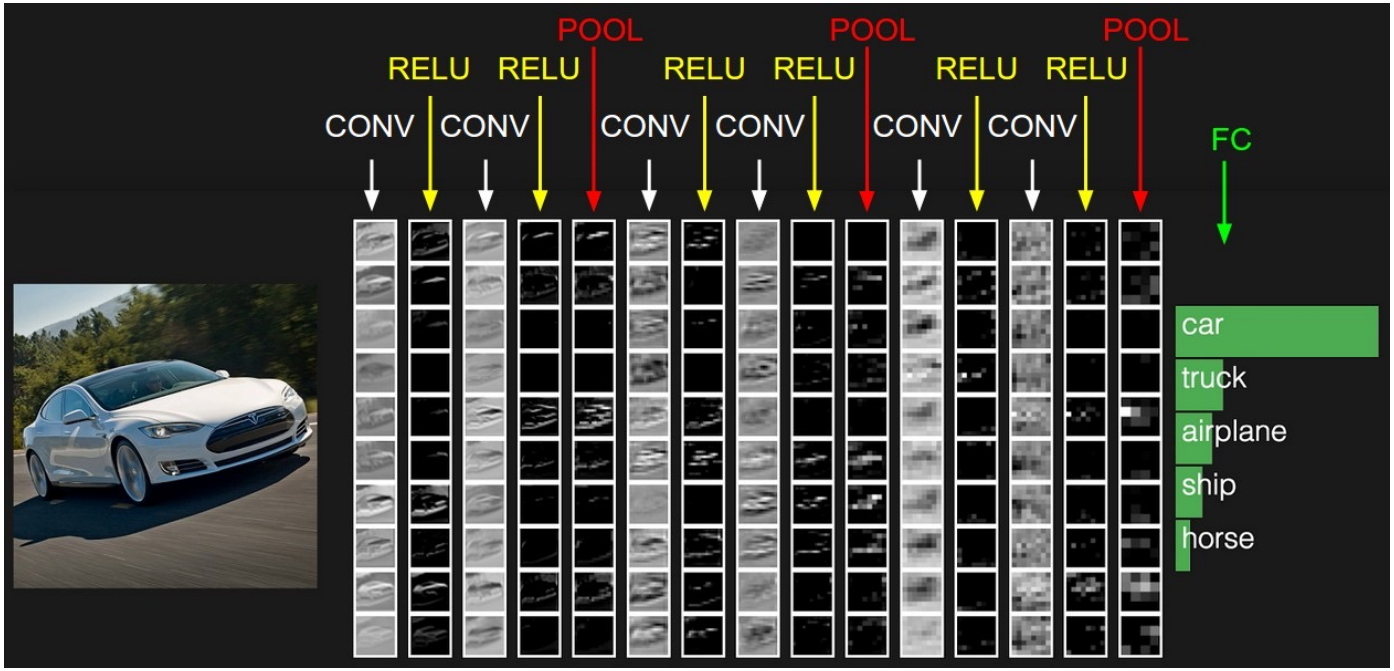
- 将卷积的输出特征映射拉成一个向量



表示学习


Low-level features
Mid-level features
High-level features
Linearly separable classifier
VGG-16 Conv1_1
VGG-16 Conv3_2
VGG-16 Conv5_3

表示学习


POOL
POOL
POOL
RELU
RELU
RELU
RELU
RELU
RELU
CONV
CONV
CONV
CONV
CONV
CONV
FC
car
truck
airplane
ship
horse

卷积神经网络的参数学习

$$Z^{(l,p)} = \sum_{d=1}^{D} W^{(l,p,d)} \otimes X^{(l-1,d)} + b^{(l,p)}$$

- 损失函数关于第l层的卷积核$W^{(l,p,d)}$和偏置$b^{(l,p)}$的偏导数

$$\frac{\partial \mathcal{L}}{\partial W^{(l,p,d)}} = \frac{\partial \mathcal{L}}{\partial Z^{(l,p)}} \otimes X^{(l-1,d)} = \delta^{(l,p)} \otimes X^{(l-1,d)},$$

$$\frac{\partial \mathcal{L}}{\partial b^{(l,p)}} = \sum_{i,j} [\delta^{(l,p)}]_{i,j}.$$

- 反向传播算法误差项
  - 第l+1层为卷积层

$$\delta^{(l,d)} = f_l'(Z^{(l,d)}) \odot \sum_{P=1}^{P} \left(W^{(l+1,p,d)} * \delta^{(l+1,p)} \right),$$

  - 第$l+1$层为汇聚层

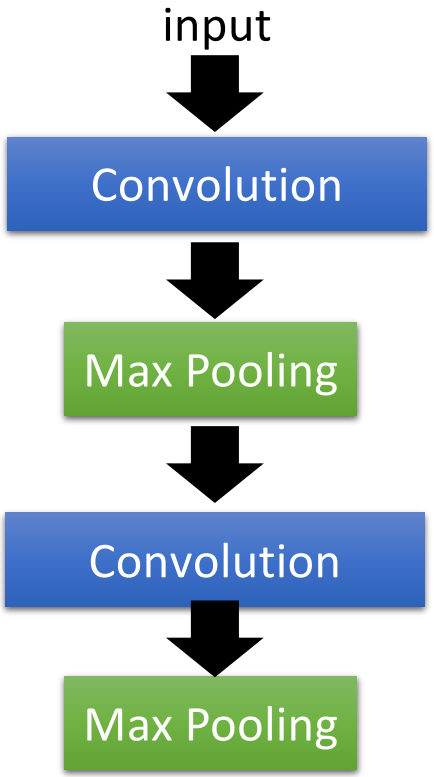
$$\delta^{(l,p)} = f_l'(Z^{(l,p)}) \odot \mathrm{up}(\delta^{(l+1,p)}),$$

卷积神经网络的简单实现

CNN via Pytorch

```
class CNN(nn.Module):
    def __init__(self):
        super(CNN, self).__init__()
        self.conv1 = nn.Sequential( #input shape (1,28,28)
            nn.Conv2d(in_channels=1, #input height
                      out_channels=16, #n_filter
                      kernel_size=5, #filter size
                      stride=1, #filter step
                      padding=2 #con2d出来的图片大小不变
                      ), #output shape (16,28,28)
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2) #2x2采样，output shape (

        )
        self.conv2 = nn.Sequential(nn.Conv2d(16, 32, 5, 1, 2),
                                   nn.ReLU(),
                                   nn.MaxPool2d(2))
        self.out = nn.Linear(32*7*7,10)

    def forward(self, x):
        x = self.conv1(x)
        x = self.conv2(x)
        x = x.view(x.size(0), -1) #flat (batch_size, 32*7*7)
        output = self.out(x)
        return output
```

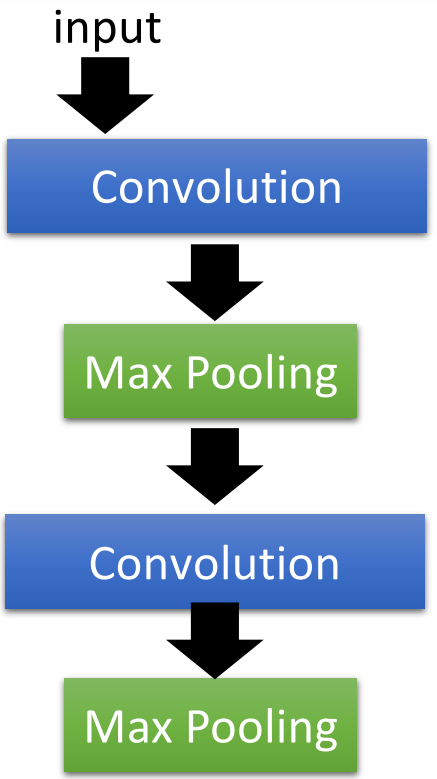
Only modified the ***network structure*** and ***input format (vector -> 3-D tensor)***



CNN via Pytorch

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

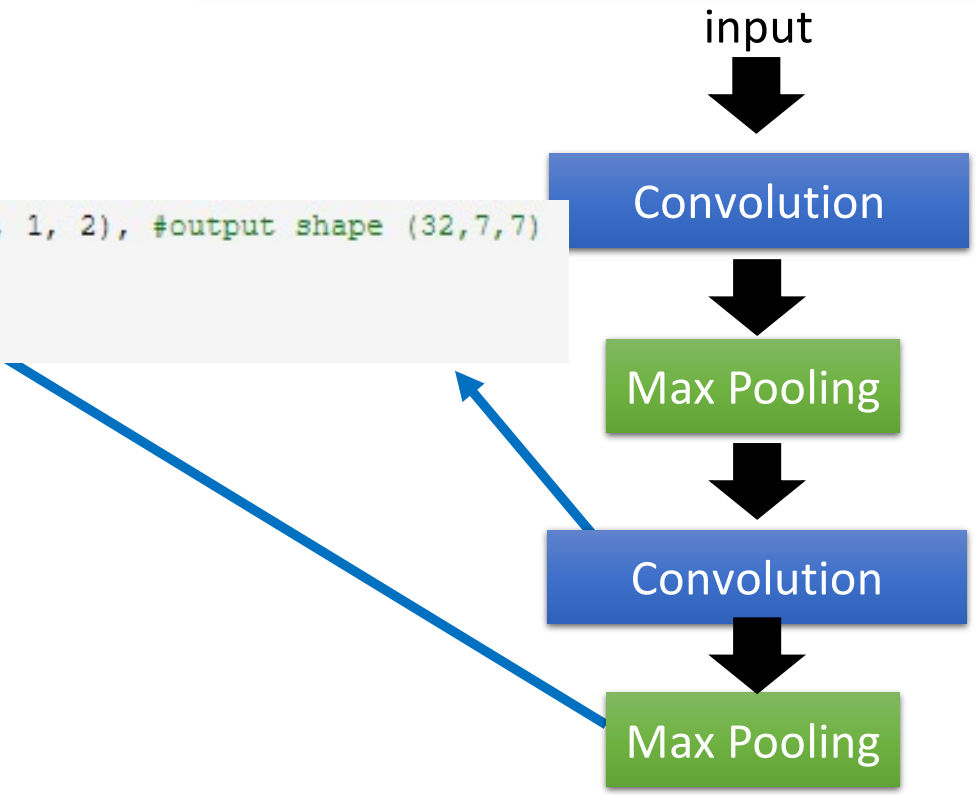
```
self.conv1 = nn.Sequential( #input shape (1,28,28)
    nn.Conv2d(in_channels=1, #input height
              out_channels=16, #n_filter
              kernel_size=5, #filter size
              stride=1, #filter step
              padding=2 #con2d出来的图片大小不变
              ), #output shape (16,28,28)
    nn.ReLU(),
    nn.MaxPool2d(kernel_size=2) #2x2采样，output shape (16,14,14)

)
```



CNN via Pytorch

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

```
self.conv2 = nn.Sequential(nn.Conv2d(16, 32, 5, 1, 2), #output shape (32,7,7)
                           nn.ReLU(),
                           nn.MaxPool2d(2))
```



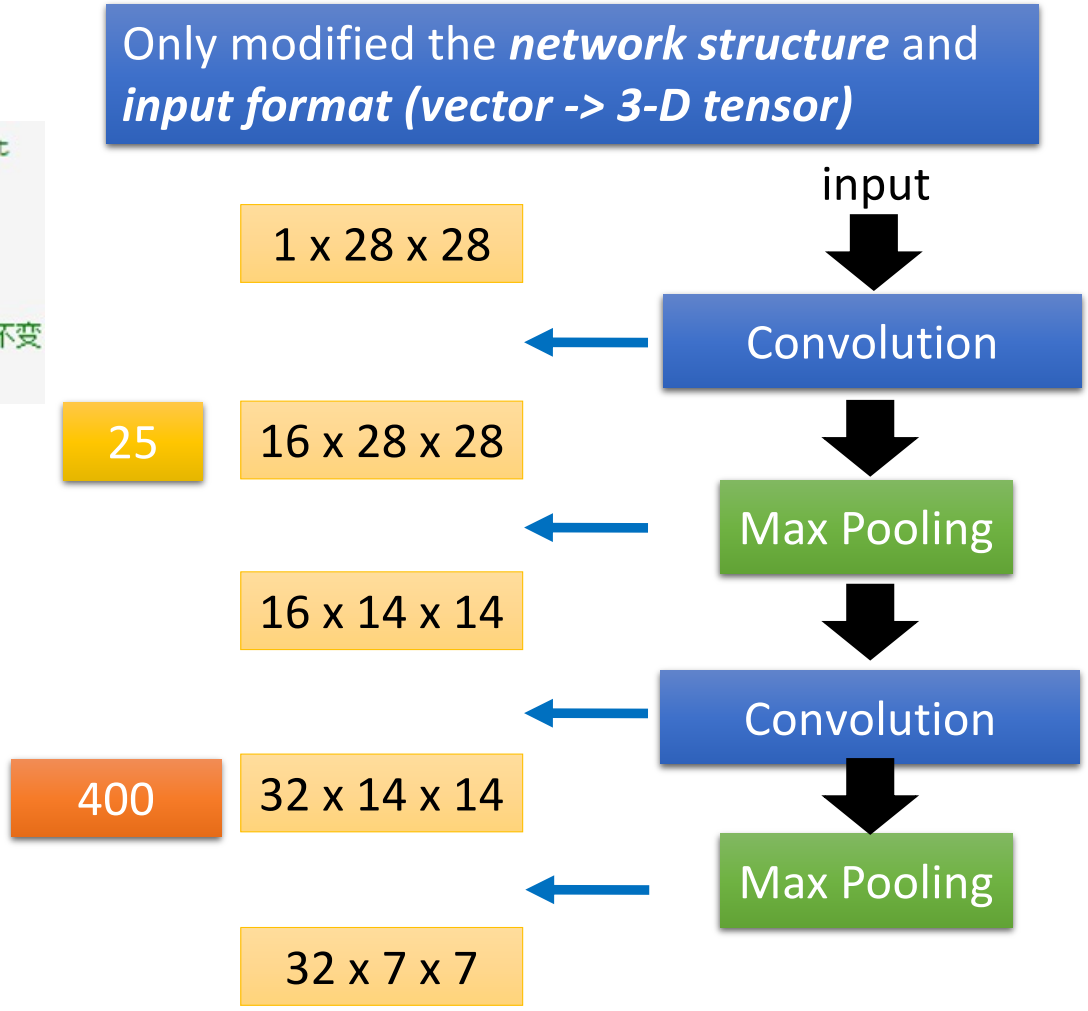
CNN via Pytorch

```
nn.Conv2d(in_channels=1, #input height
          out_channels=16, #n_filter
          kernel_size=5, #filter size
          stride=1, #filter step
          padding=2 #con2d出来的图片大小不变
          ), #output shape (16,28,28)
```

How many parameters for each filter?

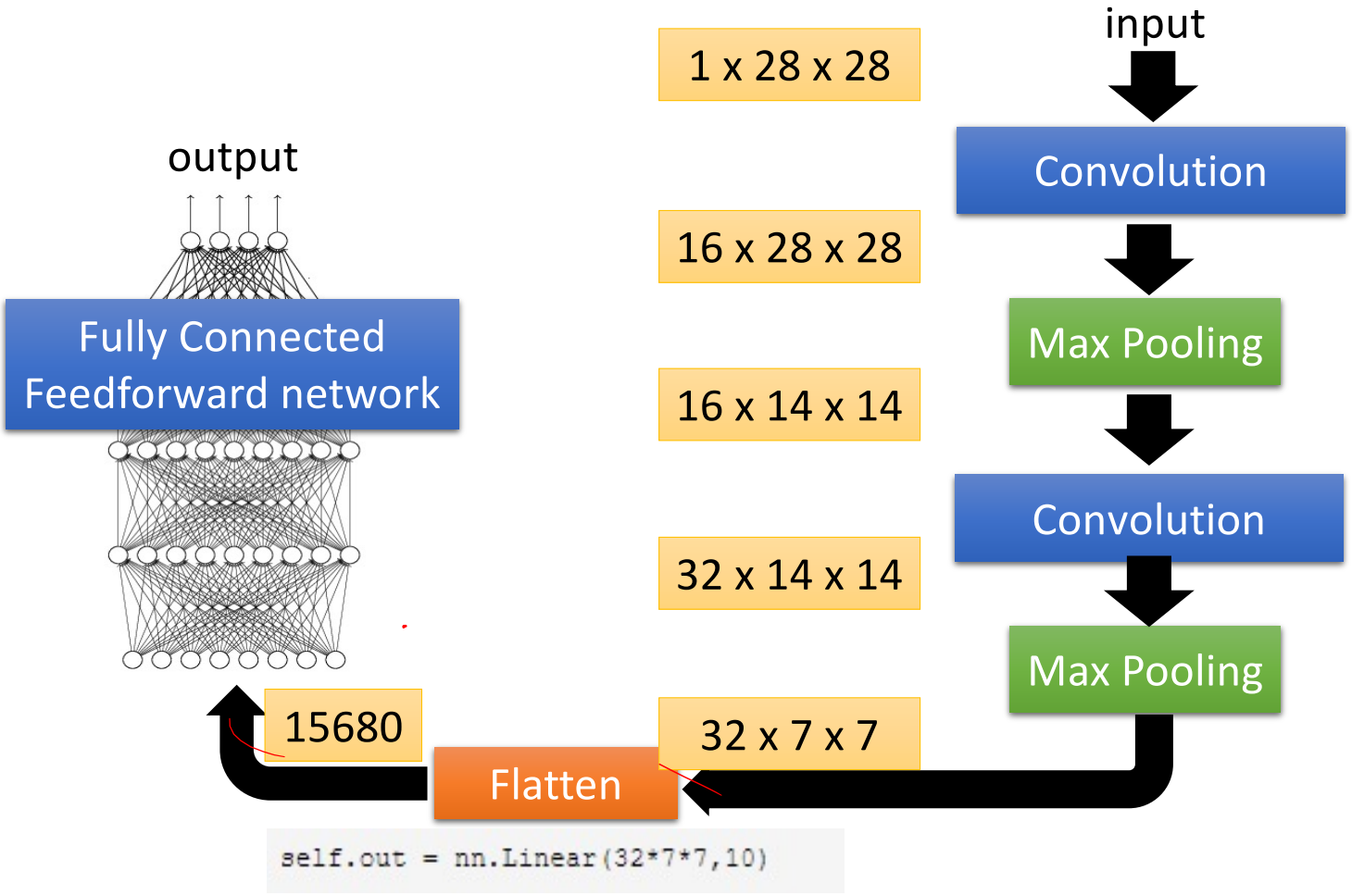
```
(nn.Conv2d(16, 32, 5, 1, 2),
```

How many parameters for each filter?



CNN via Pytorch

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




```
self.out = nn.Linear(32*7*7,10)
```

卷积神经网络的时间复杂度

$$\textbf{Time} \sim O\left(\sum_{l=1}^{L} M_l^2 \cdot K_l^2 \cdot C_{l-1} \cdot C_l\right)$$

- L 神经网络所具有的卷积层数，也即**网络的深度**。
- l 神经网络第 l 个卷积层
- C_l 神经网络第 l 个卷积层的输出通道数 C_{out}
- 对于第 l 个卷积层而言，其输入通道数 C_{in} 就是第 $(l-1)$ 个卷积层的输出通道数。

卷积神经网络的空间复杂度

空间复杂度（访存量），严格来讲包括两部分：总参数量 + 各层输出特征图。

- **参数量**：模型所有带参数的层的权重参数总量（即**模型体积**，下式第一个求和表达式）
- **特征图**：模型在实时运行过程中每层所计算出的输出特征图大小（下式第二个求和表达式）

$$\textbf{Space} \sim O\left(\sum_{l=1}^{L} K_l^2 \cdot C_{l-1} \cdot C_l + \sum_{l=1}^{L} M^2 \cdot C_l\right)$$

- 总参数量只与卷积核的尺寸 K 、通道数 C 、层数 L 相关，而**与输入数据的大小无关。**
- 输出特征图的空间占用比较容易，就是其空间尺寸 M^2 和通道数 C 的连乘。

思考

对于一个输入为100×100×256 的特征映射组，使用3×3 的卷积核，输出为100×100×256 的特征映射组的卷积层，求其时间和空间复杂度．如果引入一个1×1 卷积核，先得到100×100×64 的特征映射，再进行3×3 的卷积，得到100×100×256 的特征映射组，求其时间和空间复杂度．

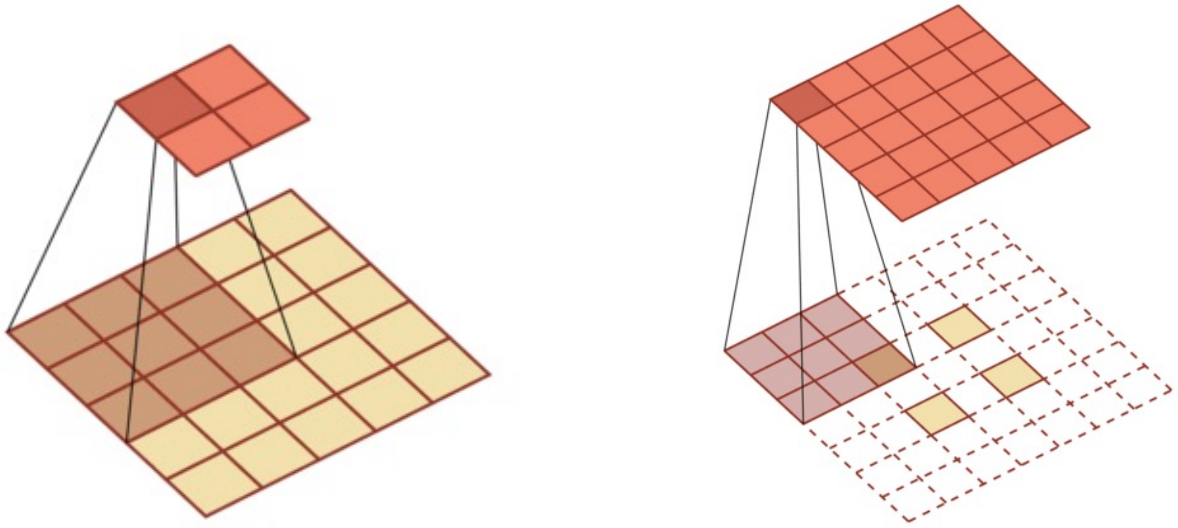
时间复杂度：100*100*256*3*3*256 =
空间复杂度：256*3*3*256 + 100*100*256 =

时间复杂度：100*100*256*64 + 100*100*64*3*3*256=
空间复杂度：1*1*64*256 + 100*100*64 + 3*3*64*256 + 100*100*256 =

其它卷积种类

转置卷积(Transposed Convolution)/微步卷积(Fractionally-Strided Convolution)

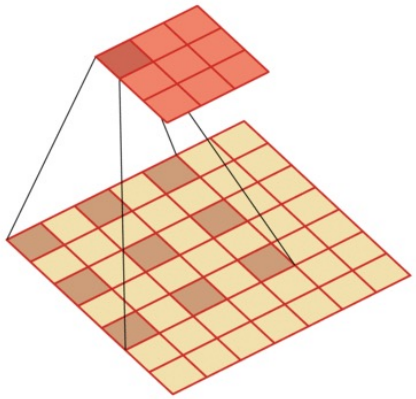
- 低维特征映射到高维特征

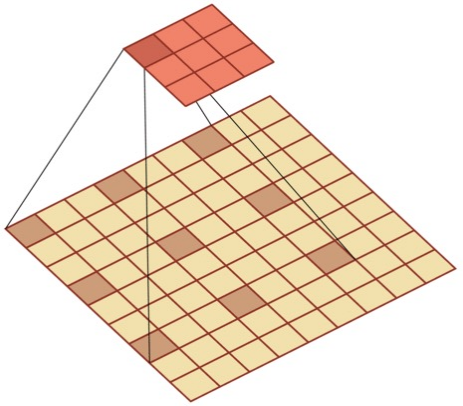


空洞卷积(Atrous Convolution)

- 如何增加输出单元的感受野
  - 增加卷积核的大小
  - 增加层数来实现
  - 在卷积之前进行汇聚操作

- 空洞卷积
  - 通过给卷积核插入“空洞”来变相地增加其大小。





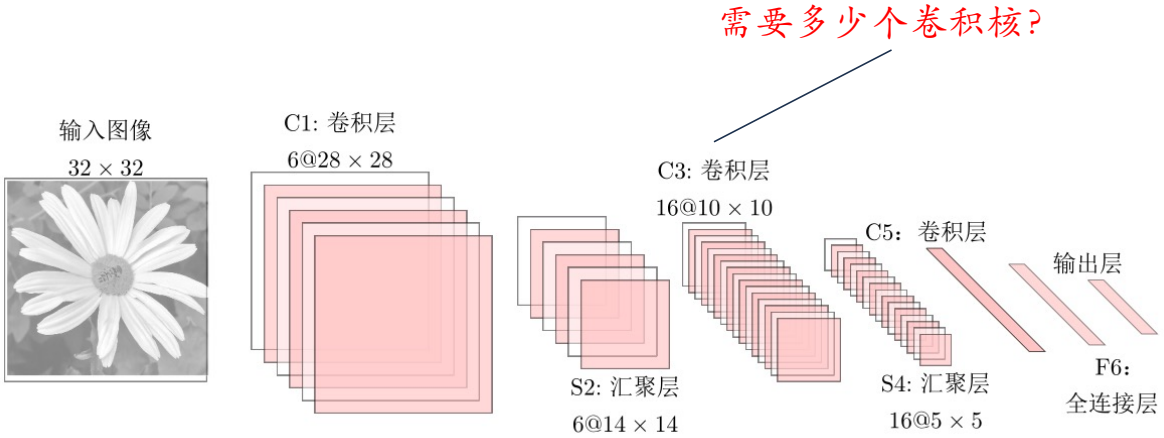
内容

- 卷积神经网络
  - 卷积
  - 卷积神经网络
  - 卷积神经网络的简单实现
  - 其他种类的卷积
- 卷积神经网络的扩展
  - 典型的卷积神经网络(*LeNet, AlexNet, VGG, NiN, ...*)
  - 卷积神经网络的应用

典型的卷积网络

LeNet-5

- LeNet-5 是一个非常成功的神经网络模型。
  - 基于 LeNet-5 的手写数字识别系统在 90 年代被美国很多银行使用，用来识别支票上面的手写数字。
  - LeNet-5 共有 7 层。



[1] LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86(11), 2278-2324.

LeNet的简单实现

```
class LeNet(nn.Module):
    def __init__(self):
        super(LeNet, self).__init__()
        self.conv = nn.Sequential(
            nn.Conv2d(1, 6, 5), # in_channels, out_channels, kernel_size
            nn.Sigmoid(),
            nn.MaxPool2d(2, 2), # kernel_size, stride
            nn.Conv2d(6, 16, 5),
            nn.Sigmoid(),
            nn.MaxPool2d(2, 2)
        )
        self.fc = nn.Sequential(
            nn.Linear(16*4*4, 120),
            nn.Sigmoid(),
            nn.Linear(120, 84),
            nn.Sigmoid(),
            nn.Linear(84, 10)
        )

    def forward(self, img):
        feature = self.conv(img)
        output = self.fc(feature.view(img.shape[0], -1))
        return output
```

Large Scale Visual Recognition Challenge

2012 Teams	%error
Supervision (Toronto)	15.3
ISI (Tokyo)	26.1
VGG (Oxford)	26.9
XRCE/INRIA	27.0
UvA (Amsterdam)	29.6
INRIA/LEAR	33.4

2013 Teams	%error
Clarifai (NYU spinoff)	11.7
NUS (singapore)	12.9
Zeiler-Fergus (NYU)	13.5
A. Howard	13.5
OverFeat (NYU)	14.1
UvA (Amsterdam)	14.2
Adobe	15.2
VGG (Oxford)	15.2
VGG (Oxford)	23.0

2014 Teams	%error
GoogLeNet	6.6
VGG (Oxford)	7.3
MSRA	8.0
A. Howard	8.1
DeeperVision	9.5
NUS-BST	9.7
TTIC-ECP	10.2
XYZ	11.2
UvA	12.1

AlexNet

[1] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. In Advances in neural information processing systems (pp. 1097-1105).

- 2012 ILSVRC winner
  - （top 5 error of 16% compared to runner-up with 26% error）
  - 第一个现代深度卷积网络模型
    - 首次使用了很多现代深度卷积网络的一些技术方法
  - 5个卷积层、3个汇聚层和3个全连接层

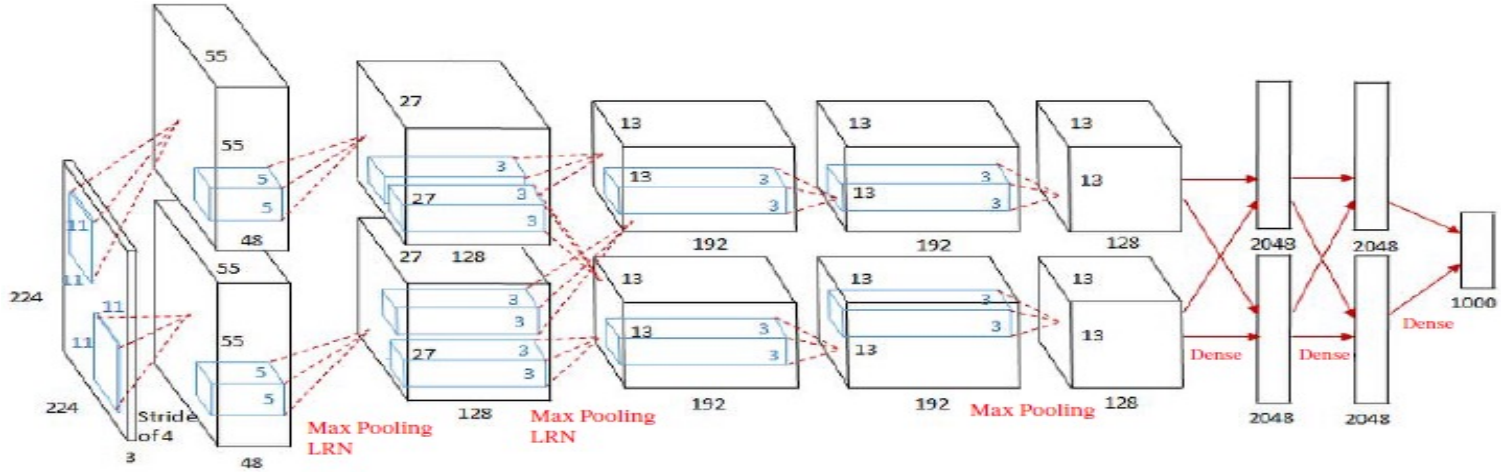


图 5.12　AlexNet 网络结构[1]

AlexNet v.s. LeNet

- AlexNet是更深的神经网络模型
- AlexNet中卷积通道数比LeNet大，AlexNet中全连接层带来近1GB的模型参数
- AlexNet将sigmoid激活函数改成了ReLU激活函数
- AlexNet通过dropout，图像增广(翻转、裁剪和颜色变化)的手段缓解过拟合问题

AlexNet的简单实现

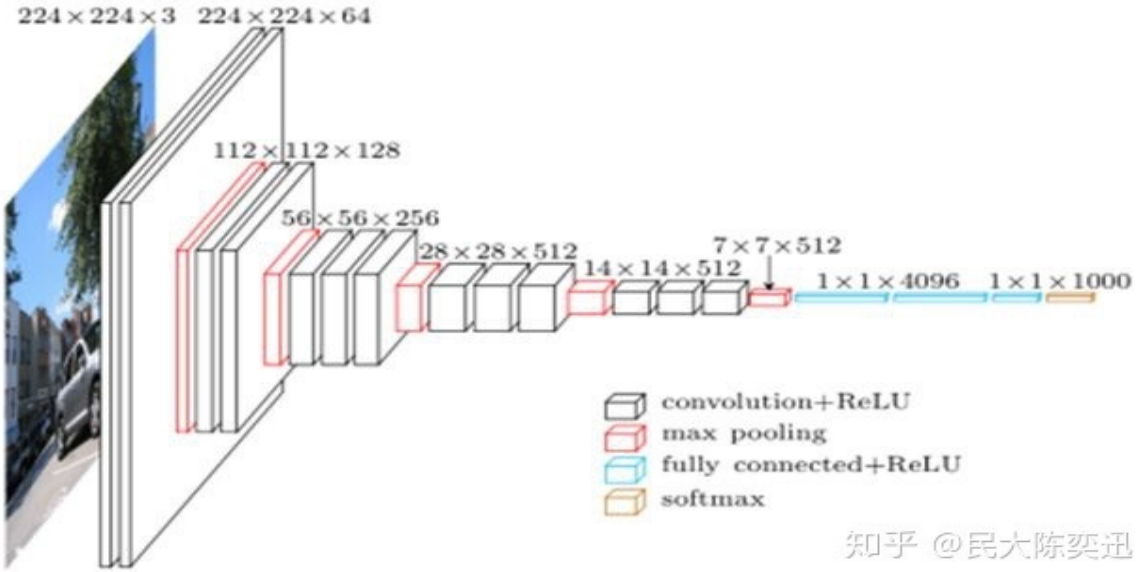
```
class AlexNet(nn.Module):
    def __init__(self):
        super(AlexNet, self).__init__()
        self.conv = nn.Sequential(
            nn.Conv2d(1, 96, 11, 4), # in_channels, out_channels, kernel_size, stride, padding
            nn.ReLU(),
            nn.MaxPool2d(3, 2), # kernel_size, stride
            # 减小卷积窗口，使用填充为2来使得输入与输出的高和宽一致，且增大输出通道数
            nn.Conv2d(96, 256, 5, 1, 2),
            nn.ReLU(),
            nn.MaxPool2d(3, 2),
            # 连续3个卷积层，且使用更小的卷积窗口。除了最后的卷积层外，进一步增大了输出通道数。
            # 前两个卷积层后不使用池化层来减小输入的高和宽
            nn.Conv2d(256, 384, 3, 1, 1),
            nn.ReLU(),
            nn.Conv2d(384, 384, 3, 1, 1),
            nn.ReLU(),
            nn.Conv2d(384, 256, 3, 1, 1),
            nn.ReLU(),
            nn.MaxPool2d(3, 2)
        )
```

```
        # 这里全连接层的输出个数比LeNet中的大数倍。使用丢弃层来缓解过拟合
        self.fc = nn.Sequential(
            nn.Linear(256*5*5, 4096),
            nn.ReLU(),
            nn.Dropout(0.5),
            nn.Linear(4096, 4096),
            nn.ReLU(),
            nn.Dropout(0.5),
            # 输出层。由于这里使用Fashion-MNIST，所以用类别数为10，而非论文中的1000
            nn.Linear(4096, 10),
        )
```

VGG

[1] Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556.

- ILSVRC 2014 runner-up
  - Top 5 error of 7.3%
  - 使用重复元素的网络
  - 展示了网络的深度是算法优良性能的关键部分



VGG

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

VGG的简单实现

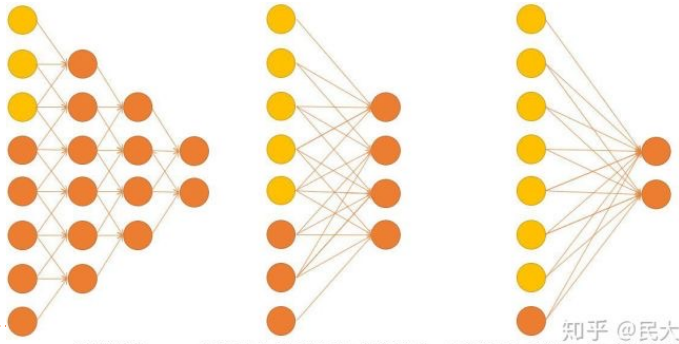
```
def vgg_block(num_convs, in_channels, out_channels):
    blk = []
    for i in range(num_convs):
        if i == 0:
            blk.append(nn.Conv2d(in_channels, out_channels, kernel_size=3, padding=1))
        else:
            blk.append(nn.Conv2d(out_channels, out_channels, kernel_size=3, padding=1))
        blk.append(nn.ReLU())
    blk.append(nn.MaxPool2d(kernel_size=2, stride=2)) # 这里会使宽高减半
    return nn.Sequential(*blk)
```

```
def vgg(conv_arch, fc_features, fc_hidden_units=4096):
    net = nn.Sequential()
    # 卷积层部分
    for i, (num_convs, in_channels, out_channels) in enumerate(conv_arch):
        # 每经过一个vgg_block都会使宽高减半
        net.add_module("vgg_block_" + str(i+1), vgg_block(num_convs, in_channels, out_channels))
    # 全连接层部分
    net.add_module("fc", nn.Sequential(d2l.FlattenLayer(),
                                       nn.Linear(fc_features, fc_hidden_units),
                                       nn.ReLU(),
                                       nn.Dropout(0.5),
                                       nn.Linear(fc_hidden_units, fc_hidden_units),
                                       nn.ReLU(),
                                       nn.Dropout(0.5),
                                       nn.Linear(fc_hidden_units, 10)
                                      ))
    return net
```

```
conv_arch = ((1, 1, 64), (1, 64, 128), (2, 128, 256), (2, 256, 512), (2, 512, 512))
# 经过5个vgg_block，宽高会减半5次，变成 224/32 = 7
fc_features = 512 * 7 * 7 # c * w * h
fc_hidden_units = 4096 # 任意
```

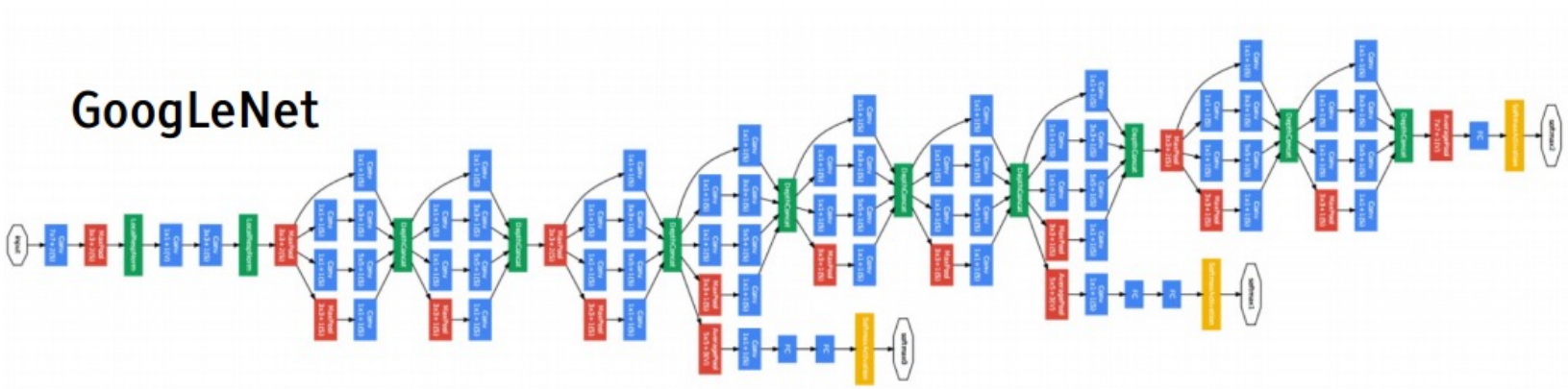
VGG的优点

- 小卷积核
  - 多个小卷积堆叠在分类精度上比单个大卷积要好
- 小汇聚核
  - 相比AlexNet的3*3的汇聚核，VGG全部为2*2的汇聚核
- 层数更深
  - 作者通过6个实验证明，最后两个实验层数最深，效果也最好
- 卷积核堆叠的感受野
  - 两个3*3的卷积堆叠在一起获得的感受野相当于一个5*5卷积；3个3x3卷积的堆叠获取到的感受野相当于一个7x7的卷积



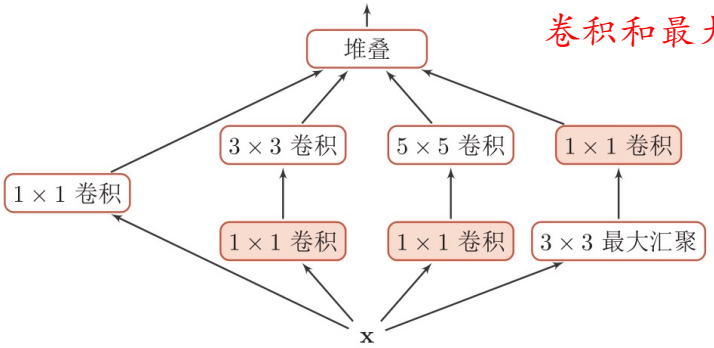
Inception网络

- 2014 ILSVRC winner （22层）
  - 参数：GoogLeNet：4M VS AlexNet：60M
  - 错误率：6.7%
  - 含并行结构
  - Inception网络是由多个inception模块和少量的汇聚层堆叠而成。



Inception模块 v1

- 在卷积网络中，如何设置卷积层的卷积核大小是一个十分关键的问题。
  - 在Inception网络中，一个卷积层包含多个不同大小的卷积操作，称为Inception模块。
  - Inception模块同时使用1×1、3×3、5×5等不同大小的卷积核，并将得到的特征映射在深度上拼接（堆叠）起来作为输出特征映射。



卷积和最大汇聚都是等宽的。

Inception模块 v3

- 用多层**小卷积核**替换**大卷积核**，以减少计算量和参数量。
  - 使用两层3x3的卷积来替换v1中的5x5的卷积
  - 使用连续的nx1和1xn来替换nxn的卷积。

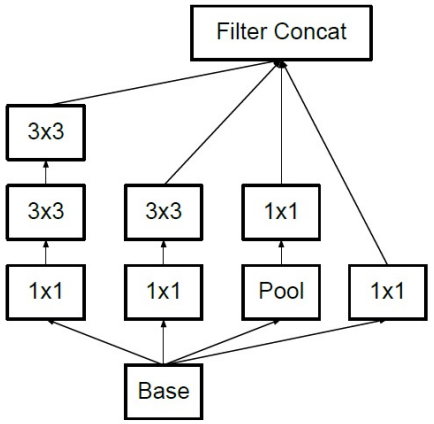


Figure 5. Inception modules where each 5×5 convolution is replaced by two 3×3 convolution, as suggested by principle 3 of Section 2.

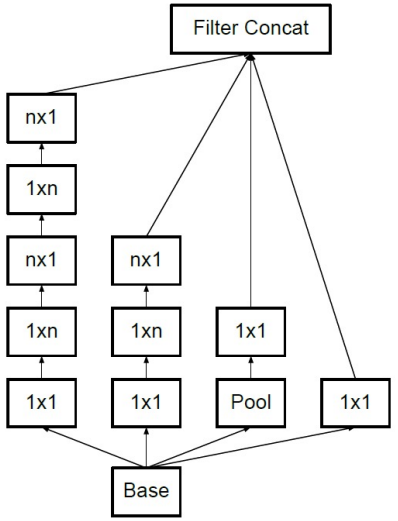


Figure 6. Inception modules after the factorization of the $n \times n$ convolutions. In our proposed architecture, we chose $n = 7$ for the 17×17 grid. (The filter sizes are picked using principle 3)

Inception的简单实现

```
class Inception(nn.Module):
    # c1 - c4为每条线路里的层的输出通道数
    def __init__(self, in_c, c1, c2, c3, c4):
        super(Inception, self).__init__()
        # 线路1，单1 x 1卷积层
        self.p1_1 = nn.Conv2d(in_c, c1, kernel_size=1)
        # 线路2，1 x 1卷积层后接3 x 3卷积层
        self.p2_1 = nn.Conv2d(in_c, c2[0], kernel_size=1)
        self.p2_2 = nn.Conv2d(c2[0], c2[1], kernel_size=3, padding=1)
        # 线路3，1 x 1卷积层后接5 x 5卷积层
        self.p3_1 = nn.Conv2d(in_c, c3[0], kernel_size=1)
        self.p3_2 = nn.Conv2d(c3[0], c3[1], kernel_size=5, padding=2)
        # 线路4，3 x 3最大池化层后接1 x 1卷积层
        self.p4_1 = nn.MaxPool2d(kernel_size=3, stride=1, padding=1)
        self.p4_2 = nn.Conv2d(in_c, c4, kernel_size=1)

    def forward(self, x):
        p1 = F.relu(self.p1_1(x))
        p2 = F.relu(self.p2_2(F.relu(self.p2_1(x))))
        p3 = F.relu(self.p3_2(F.relu(self.p3_1(x))))
        p4 = F.relu(self.p4_2(self.p4_1(x)))
        return torch.cat((p1, p2, p3, p4), dim=1)  # 在通道维上连结输出
```

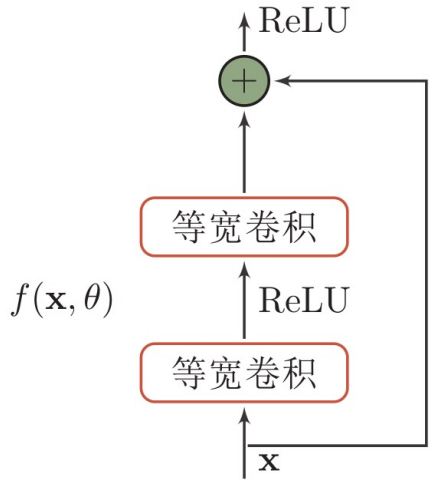
残差网络

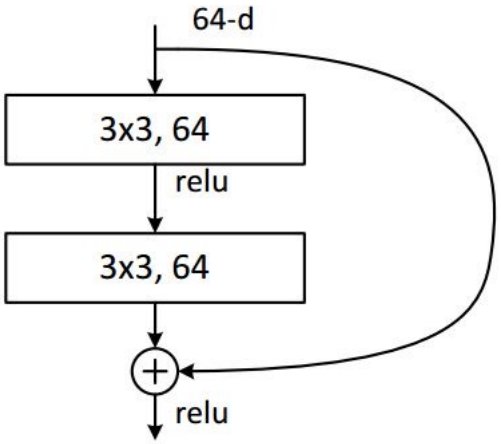
[1] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778)

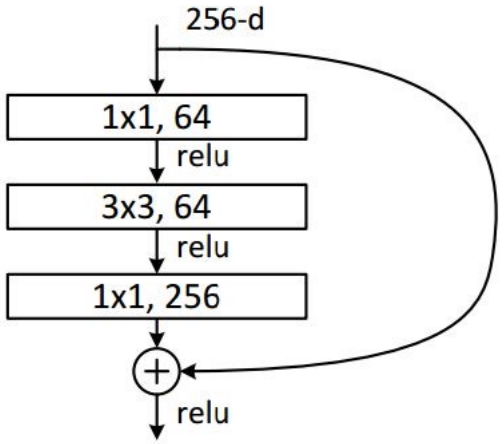
- 残差网络（Residual Network，ResNet）是通过给非线性的卷积层增加**直连边**的方式来提高信息的传播效率。
  - 假设在一个深度网络中，我们期望一个非线性单元（可以为一层或多层的卷积层）f(x,θ)去逼近一个目标函数为h(x)。
  - 将目标函数拆分成两部分：恒等函数和残差函数

$$h(\mathbf{x}) = \underbrace{\mathbf{x}}_{\text{恒等函数}} + \underbrace{\big(h(\mathbf{x}) - \mathbf{x}\big)}_{\text{残差函数}} \rightarrow f(\mathbf{x}, \theta)$$

残差单元

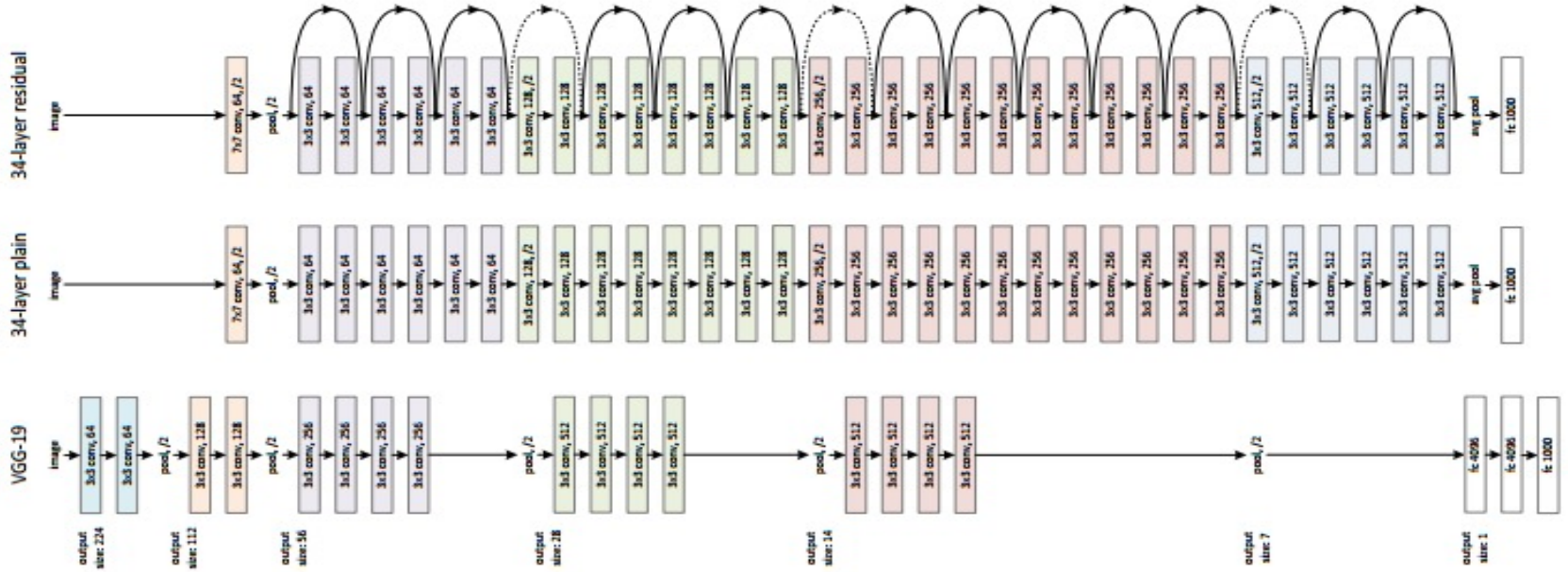

ReLU
等宽卷积
$f(\mathbf{x},\theta)$
ReLU
等宽卷积
x


64-d
3x3, 64
relu
3x3, 64
relu


256-d
1x1, 64
relu
3x3, 64
relu
1x1, 256
relu

ResNet

- 2015 ILSVRC winner （152层）
  - 错误率： 3.57%

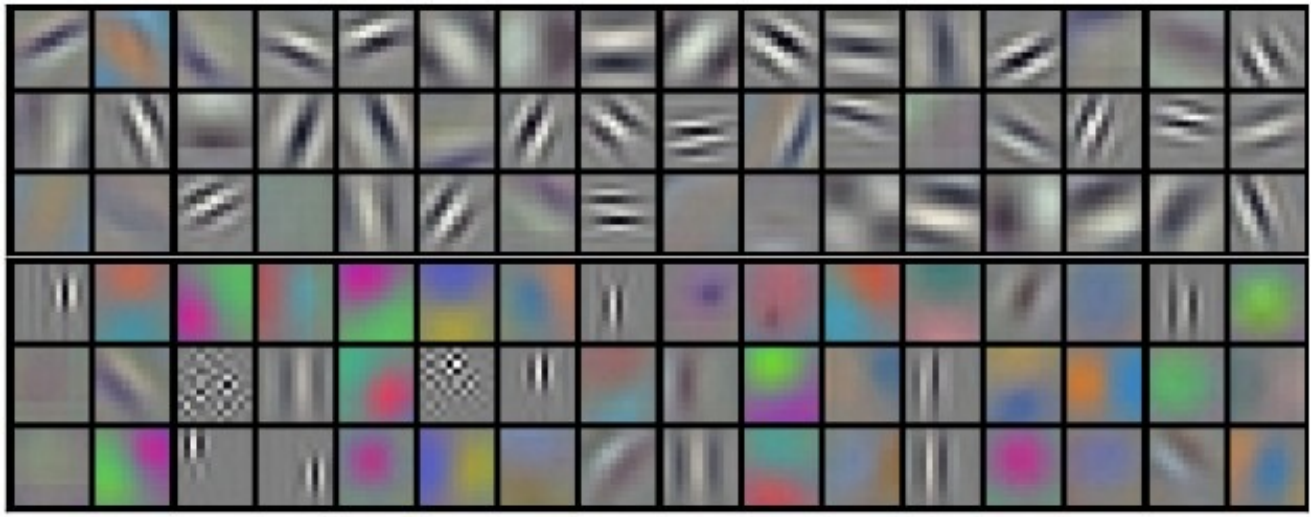


ResNet的简单实现

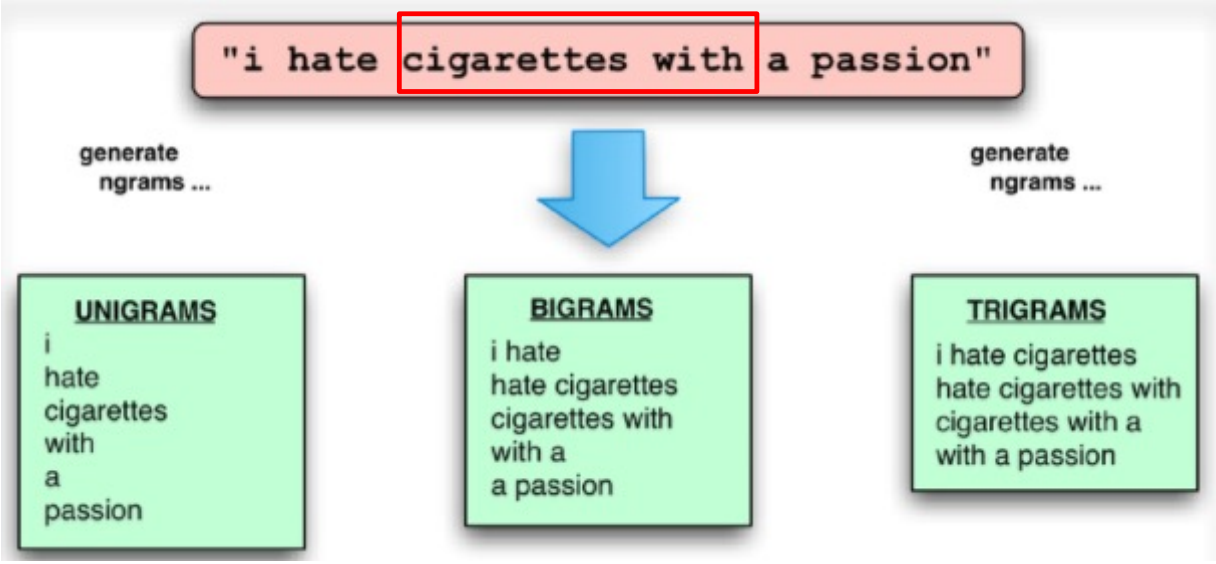
```
class Residual(nn.Module):  # 本类已保存在d2lzh_pytorch包中方便以后使用
    def __init__(self, in_channels, out_channels, use_1x1conv=False, stride=1):
        super(Residual, self).__init__()
        self.conv1 = nn.Conv2d(in_channels, out_channels, kernel_size=3, padding=1, stride=stride)
        self.conv2 = nn.Conv2d(out_channels, out_channels, kernel_size=3, padding=1)
        if use_1x1conv:
            self.conv3 = nn.Conv2d(in_channels, out_channels, kernel_size=1, stride=stride)
        else:
            self.conv3 = None
        self.bn1 = nn.BatchNorm2d(out_channels)
        self.bn2 = nn.BatchNorm2d(out_channels)

    def forward(self, X):
        Y = F.relu(self.bn1(self.conv1(X)))
        Y = self.bn2(self.conv2(Y))
        if self.conv3:
            X = self.conv3(X)
        return F.relu(Y + X)
```

CNN 可视化：滤波器

- AlexNet中的滤波器（96 filters [11x11x3]）

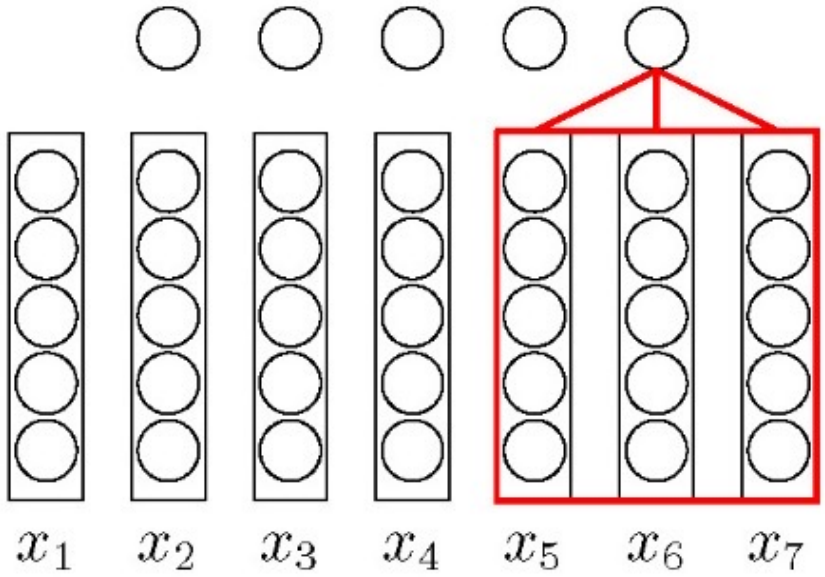


Ngram特征与卷积

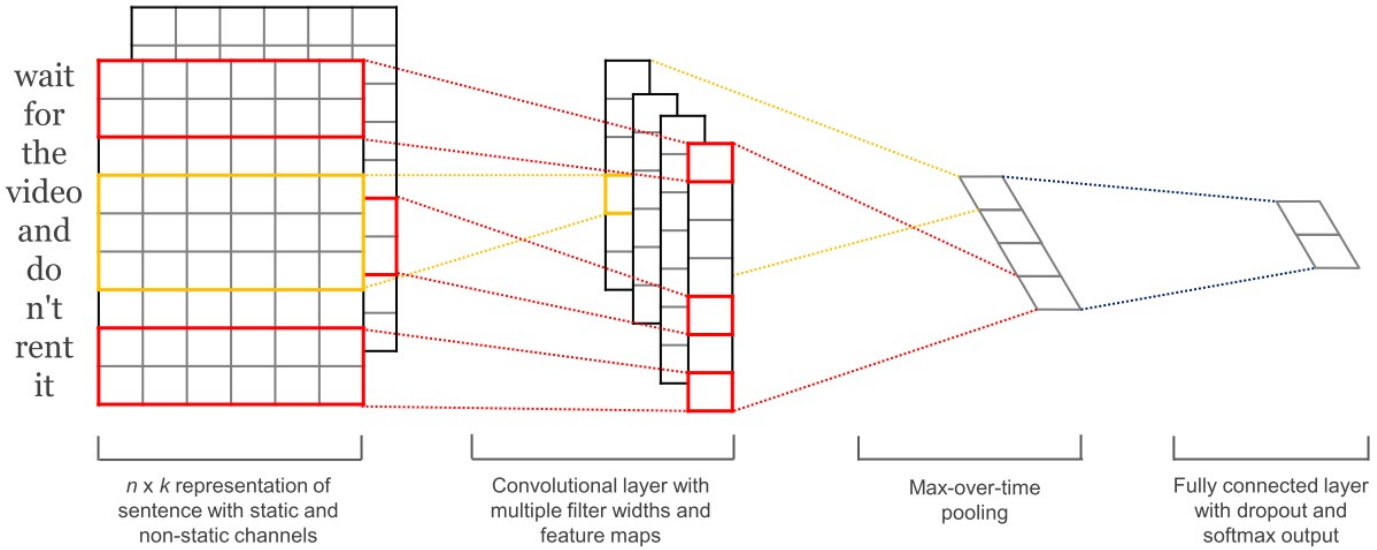


如何用卷积操作来实现?

文本序列的卷积

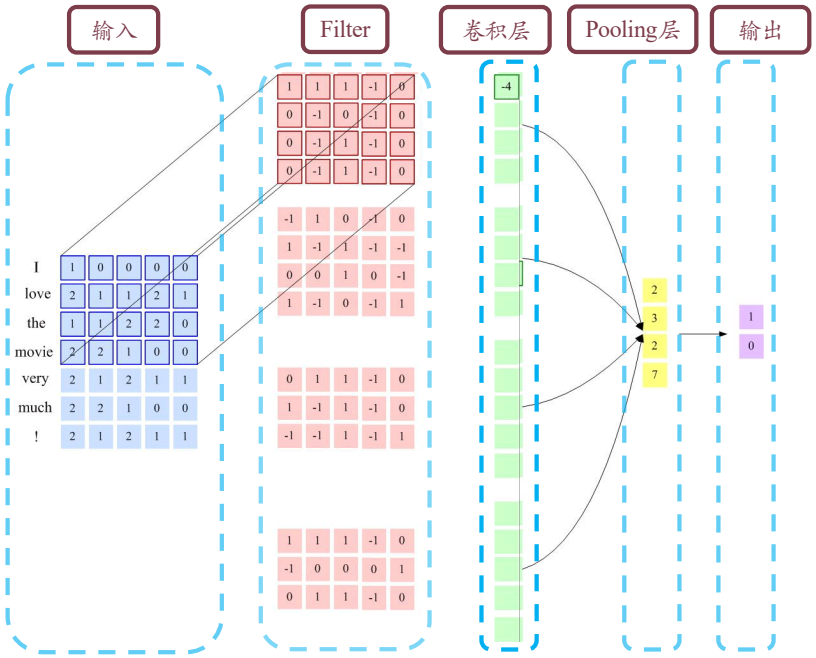


基于卷积模型的句子表示

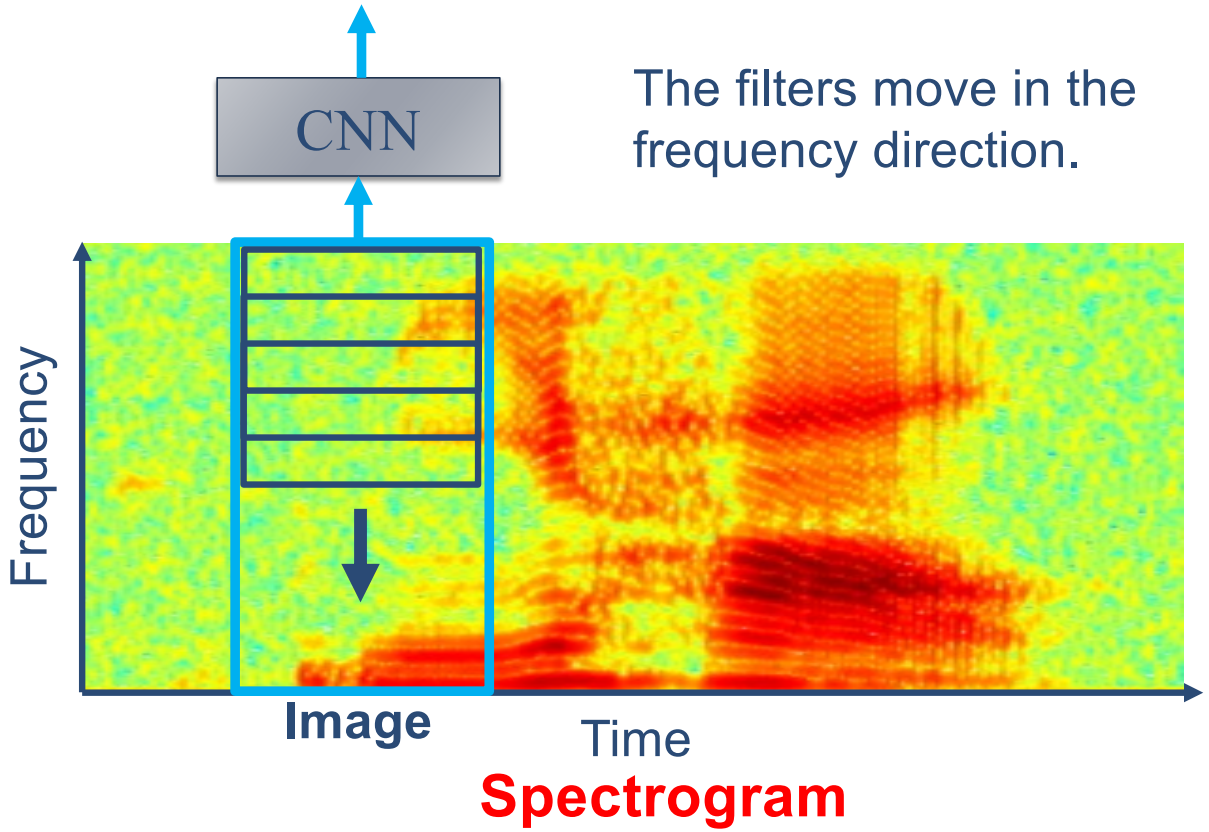


Y. Kim. "Convolutional neural networks for sentence classification". In: *arXiv preprint arXiv:1408.5882* (2014).

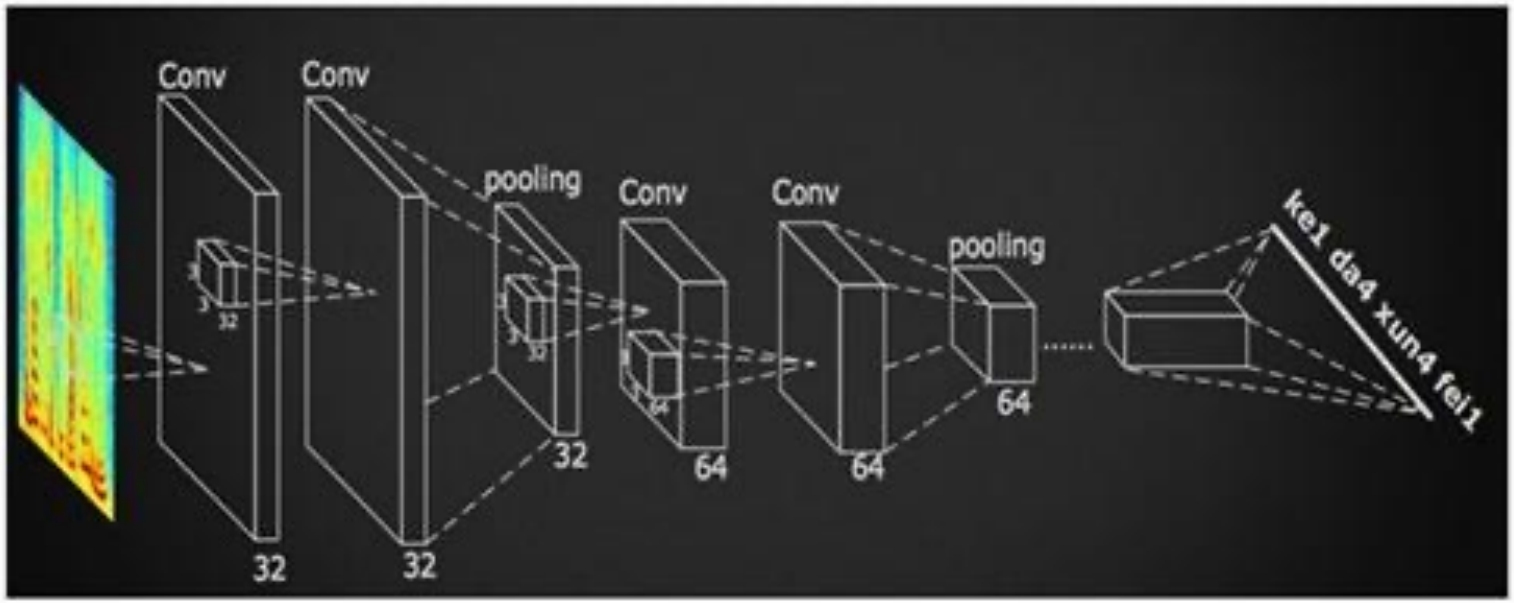
文本序列的卷积模型



基于卷积模型的语音表示

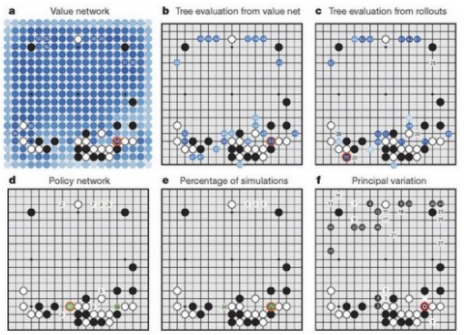


语音识别的DFCNN框架



卷积的应用

AlphaGo

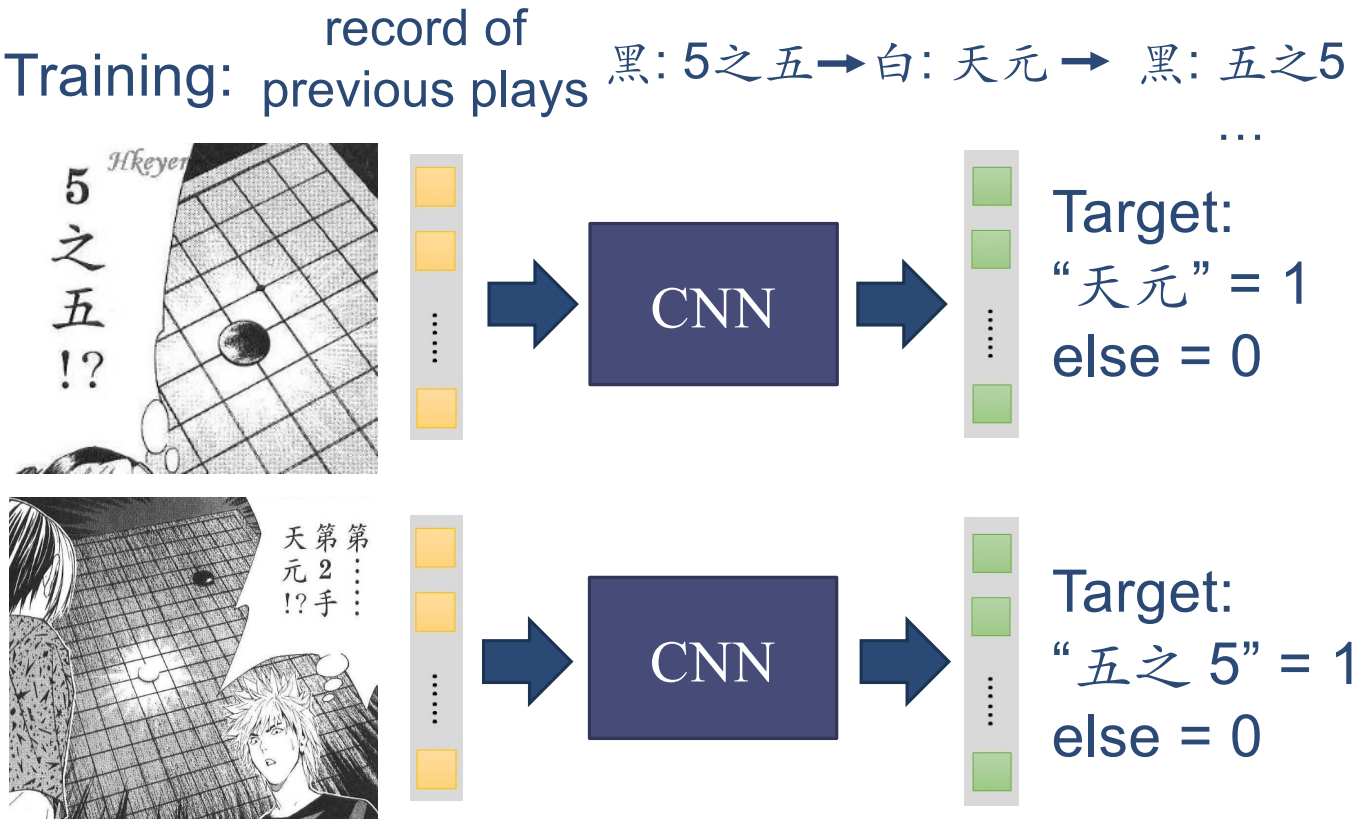


The input to the policy network is a 19 × 19 × 48 image stack consisting of 48 feature planes. The first hidden layer zero pads the input into a 23 × 23 image, then convolves *k* filters of kernel size 5 × 5 with stride 1 with the input image and applies a rectifier nonlinearity. Each of the subsequent hidden layers 2 to 12 zero pads the respective previous hidden layer into a 21 × 21 image, then convolves *k* filters of kernel size 3 × 3 with stride 1, again followed by a rectifier nonlinearity. The final layer convolves 1 filter of kernel size 1 × 1 with stride 1, with a different bias for each position, and applies a softmax function. The match version of AlphaGo used *k* = 192 filters; Fig. 2b and Extended Data Table 3 additionally show the results of training with *k* = 128, 256 and 384 filters.

policy network:
[19x19x48] Input
CONV1: 192 5x5 filters , stride 1, pad 2 => [19x19x192]
CONV2..12: 192 3x3 filters, stride 1, pad 1 => [19x19x192]
CONV: 1 1x1 filter, stride 1, pad 0 => [19x19] *(probability map of promising moves)*

分布式系统：1202 个CPU 和176 块GPU
单机版：48 个CPU 和8 块GPU
走子速度：3 毫秒-2 微秒

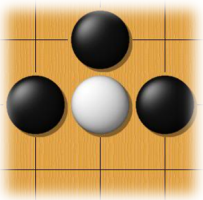
Playing Go


Training:
record of previous plays
黑: 5之五→白: 天元→ 黑: 五之5
…
5之五!?
CNN
Target:
“天元” = 1
else = 0
第…… 第2手 天元!?
CNN
Target:
“五之 5” = 1
else = 0

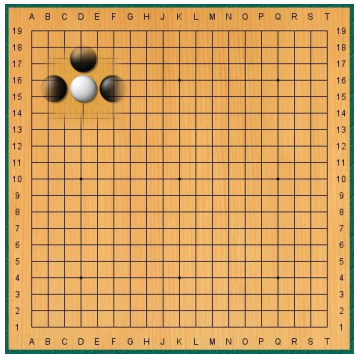
Why CNN for playing Go?

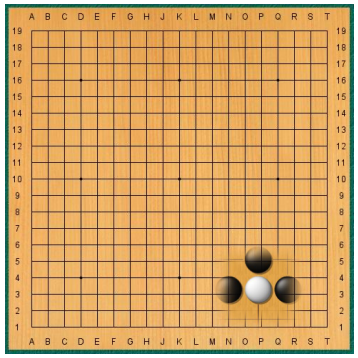
- Some patterns are much smaller than the whole image

  Alpha Go uses 5 x 5 for first layer

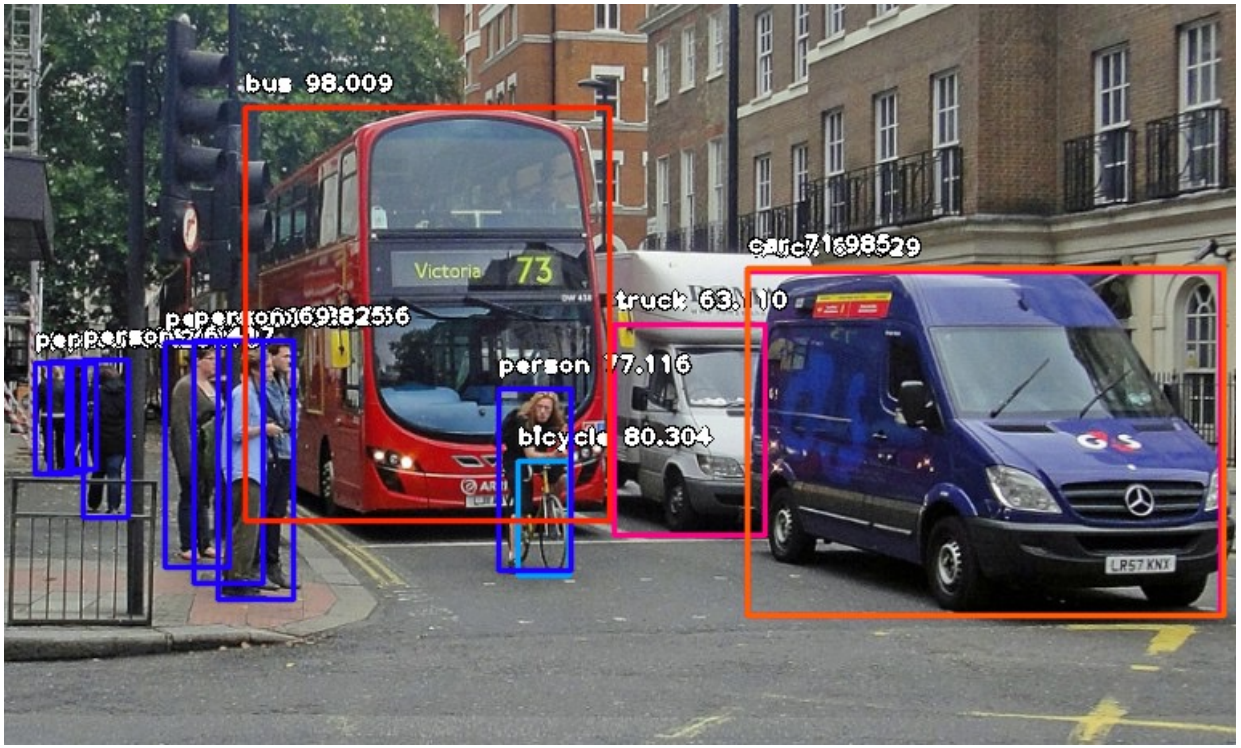


- The same patterns appear in different regions.





目标检测（Object Detection）

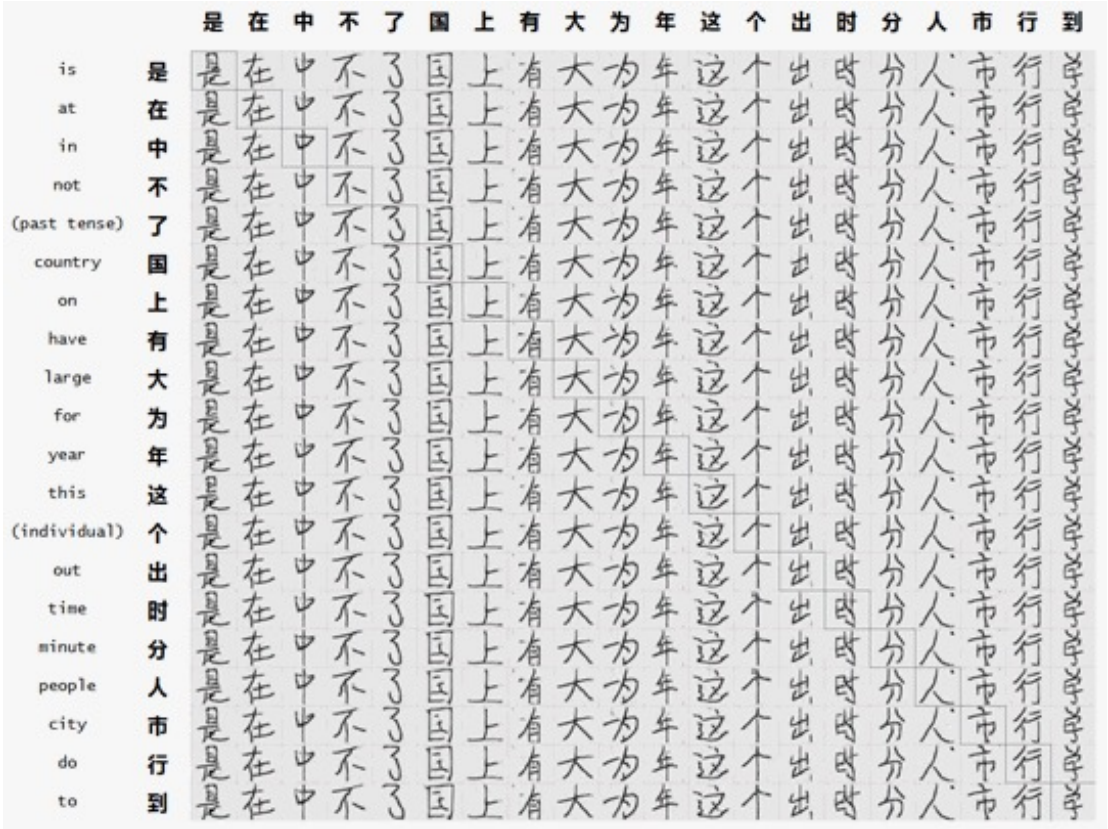


语义分割(Semantic Segmentation)

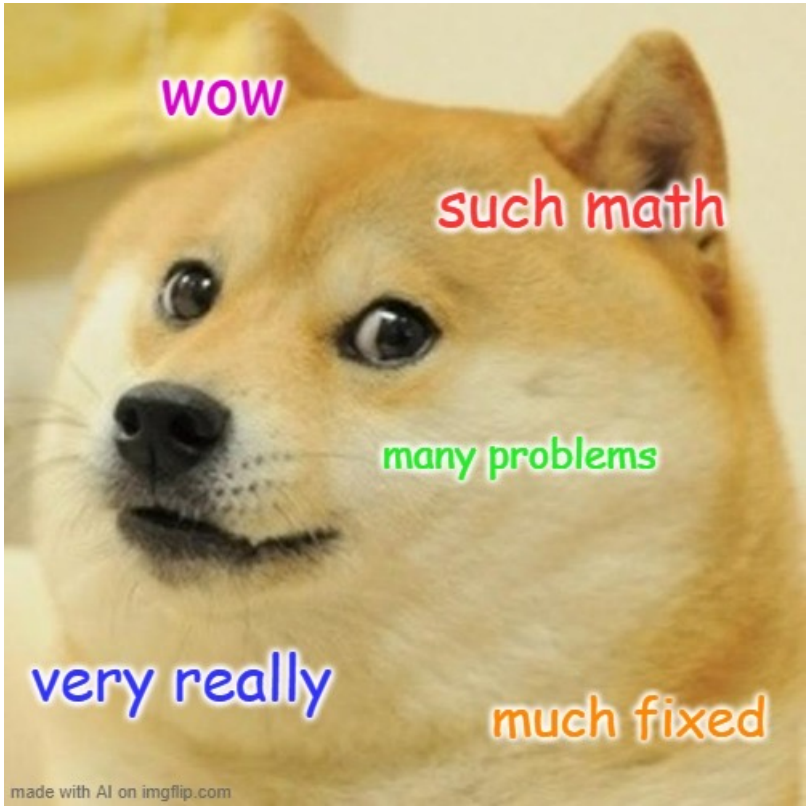
Figure 4. More results of **Mask R-CNN** on COCO test images, using ResNet-101-FPN and running at 5 fps, with 35.7 mask AP (Table 1).

OCR(optical character recognition)

图像生成(image generation)



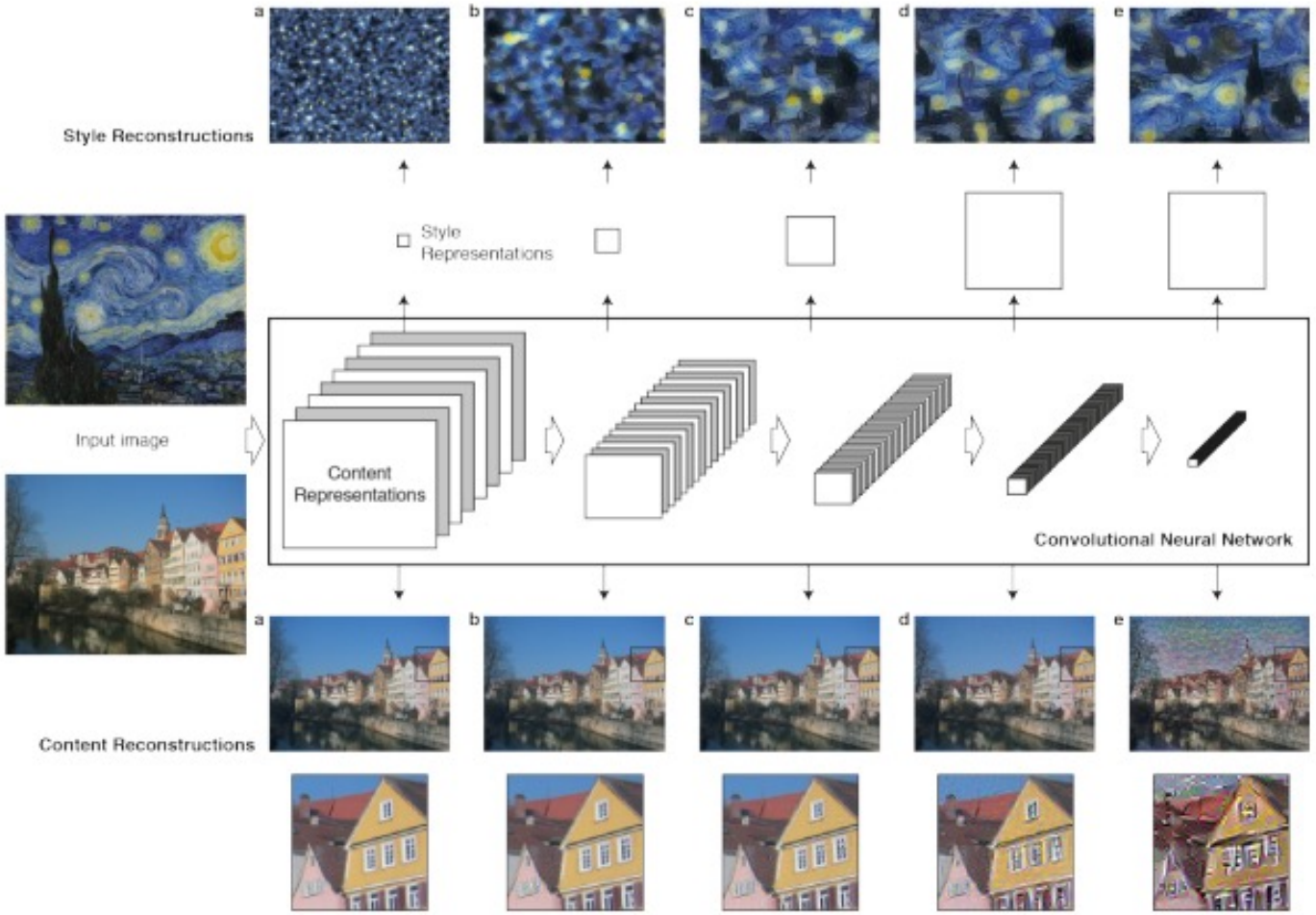
表情包生成(meme generation)



https://imgflip.com/ai-meme

画风迁移(image style transfer)

画风迁移


a
b
c
d
e
Style Reconstructions
Style Representations
Input image
Content Representations
Convolutional Neural Network
Content Reconstructions