动手一天学深度学习

1 基础 · 2 卷积网络 · 3 计算 · 4 计算机视觉

深度学习实训营 2019

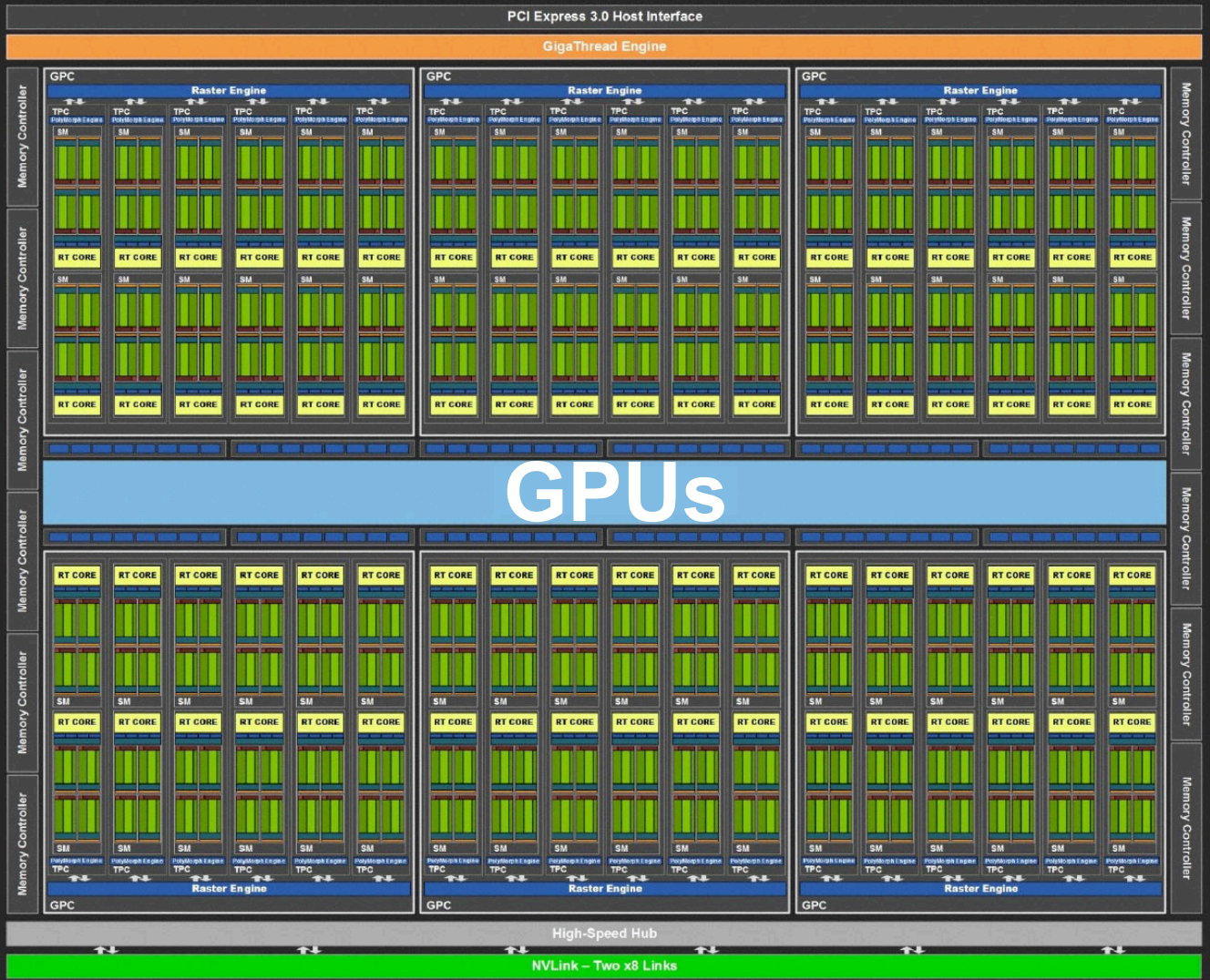
李沐

http://1day-zh.d2l.ai

aws

大纲

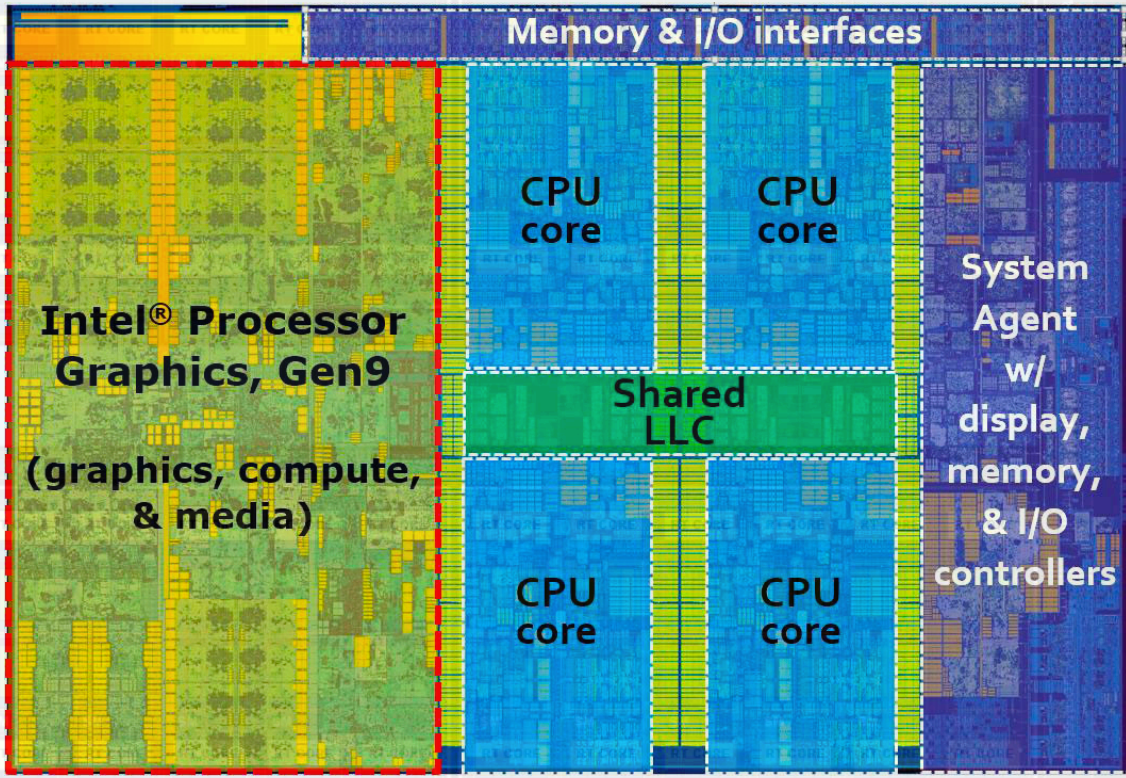
- GPUs
- 卷积，填充，步幅，池化
- 卷积神经网络 (LeNet)
- 深度卷积神经网络 (AlexNet)
- 使用重复元素 (VGG)
- 残差网络 (ResNet)



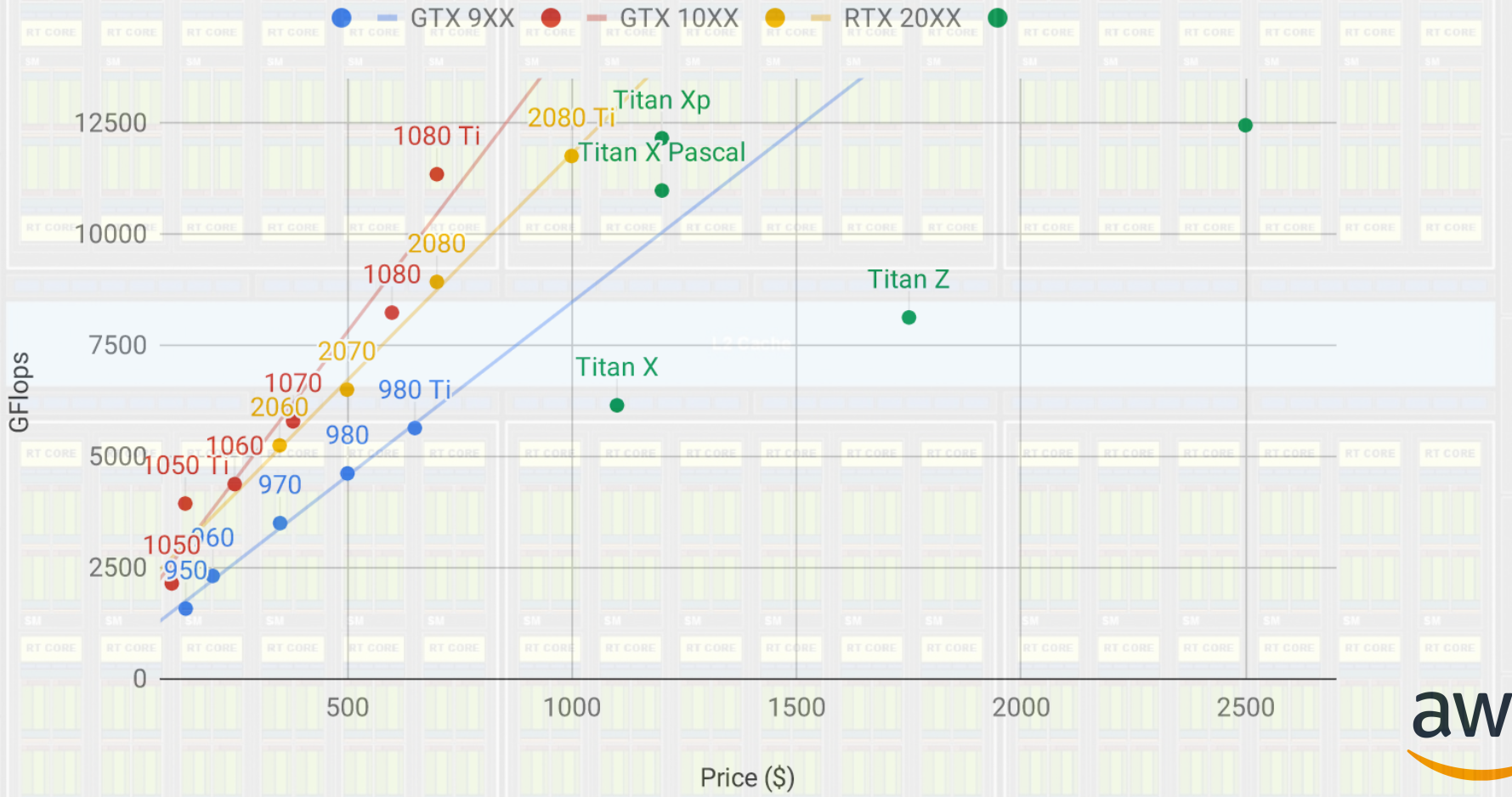
NVIDIA Turing TU102

Intel i7-6700K

- 4 物理核
- 每个核
  - 64KB L1 缓存
  - 256KB L2 缓存
- 共享的 8MB L3 缓存
- 30 GB/s 内存带宽

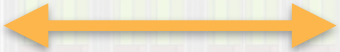


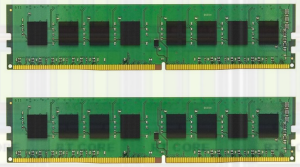
GPU 性能


GTX 9XX
GTX 10XX
RTX 20XX
12500
10000
7500
5000
2500
0
GFlops
500
1000
1500
2000
2500
Price ($)
Titan Xp
2080 Ti
1080 Ti
Titan X Pascal
2080
1080
Titan Z
2070
1070
Titan X
980 Ti
2060
980
1060
1050 Ti
970
1050
960
950

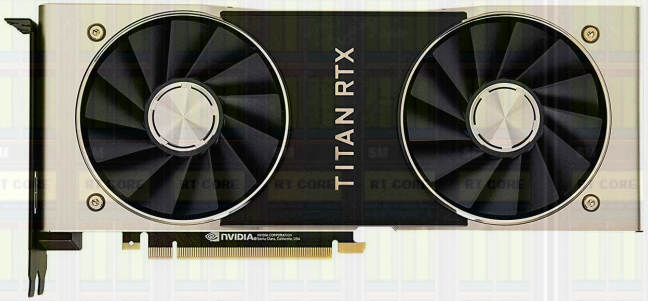
高端游戏、深度学习PC

Intel i7
0.15 TFLOPS





DDR4
32 GB



Nvidia Titan RTX
12 TFLOPS (130TF for FP16 TensorCores)
24 GB

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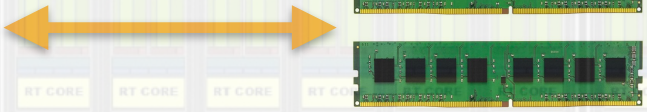
Highend Gaming / DeepLearning PC

Intel i7
0.15 TFLOPS



DDR4
32 GB

```
ctx = npx.cpu()
```

```
x.copyto(ctx)
```

Nvidia Titan RTX
12 TFLOPS (130TF for FP16 TensorCores)
24 GB

```
ctx = npx.gpu(0)
```

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GPU Notebook

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从全连接网络到卷积网络

区分猫和狗图片

- 使用一个还可以的摄像头
- RGB 图片有 36M 元素
- 单100输出的隐藏层模型有 36 亿元素
- 超过了地球上所有的猫和狗 (9亿狗 + 6亿猫)

Dual

12MP

wide-angle and telephoto cameras

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倒叙 — 单隐藏层网络

Output layer

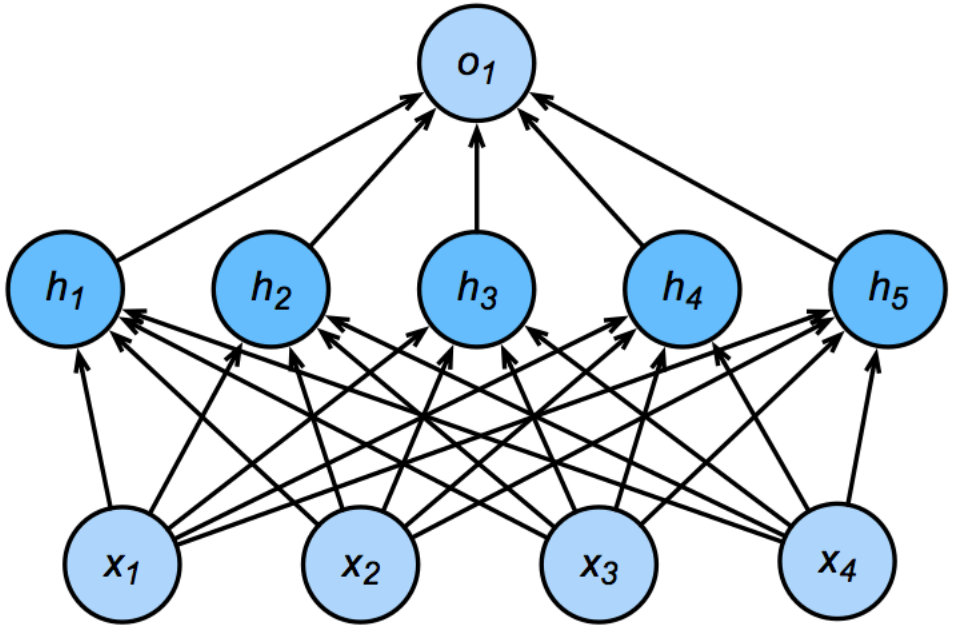
100 输出单元

Hidden layer

3.6B 参数 = 14GB

36M 特征

Input layer



$$\mathbf{h} = \sigma(\mathbf{W}\mathbf{x} + \mathbf{b})$$

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Waldo 在哪里?

两个原则

- 变化无关
- 本地性

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重新考虑全连接层

- 将输入和输出变形成矩阵 (宽，高)
- 将权重变形成 4-D 张量

$$h_{i,j} = \sum_{k,l} w_{i,j,k,l} x_{k,l} = \sum_{a,b} v_{i,j,a,b} x_{i+a,j+b}$$

这里 W 是 V 的元素重新排列：

$$v_{i,j,a,b} = w_{i,j,i+a,j+b}$$

想法1：变化无关

$$h_{i,j} = \sum_{a,b} v_{i,j,a,b} x_{i+a,j+b}$$

- 在 x 中的偏移会导致 h 中的偏移和数值变化
- v 不应该跟 (i,j) 相关联。修改 $v_{i,j,a,b} = v_{a,b}$

$$h_{i,j} = \sum_{a,b} v_{a,b} x_{i+a,j+b}$$

这是 2-D ~~卷积~~

互相关

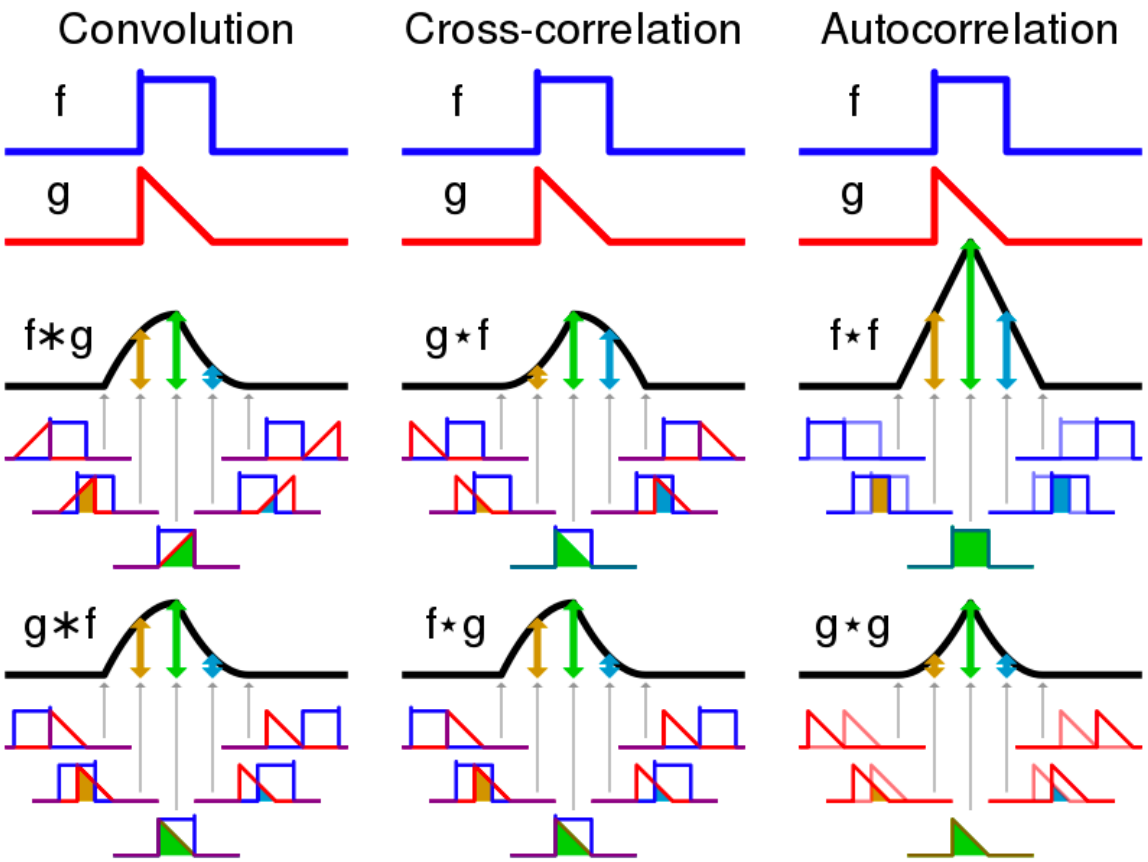
想法 2 — 本地性

$$h_{i,j} = \sum_{a,b} v_{a,b} x_{i+a,j+b}$$

- 我们不应该看离 x(i,j) 太远的来计算 h(i,j)
- 在区间 $|a|, |b| > \Delta$ 外的权重置零 $v_{a,b} = 0$

$$h_{i,j} = \sum_{a=-\Delta}^{\Delta} \sum_{b=-\Delta}^{\Delta} v_{a,b} x_{i+a,j+b}$$

卷积层



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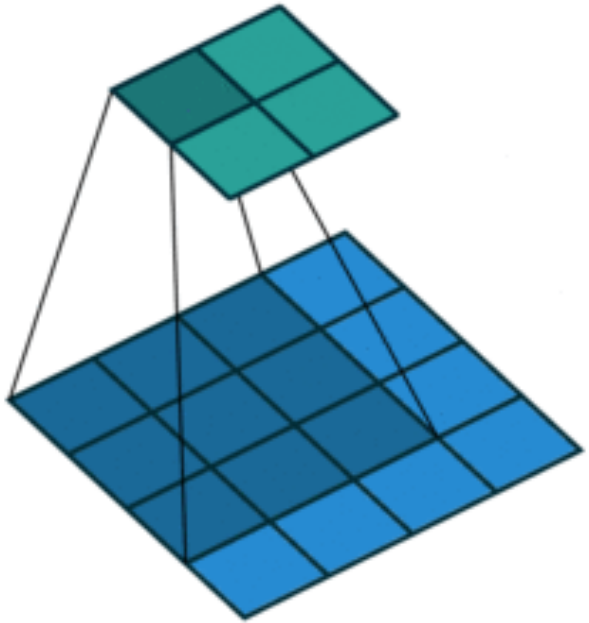
2-D 互相关

Input			*	Kernel		=	Output	
0	1	2		0	1		19	25
3	4	5		2	3		37	43
6	7	8						

$$0\times0+1\times1+3\times2+4\times3=19,$$
$$1\times0+2\times1+4\times2+5\times3=25,$$
$$3\times0+4\times1+6\times2+7\times3=37,$$
$$4\times0+5\times1+7\times2+8\times3=43.$$



(vdumoulin@ Github)

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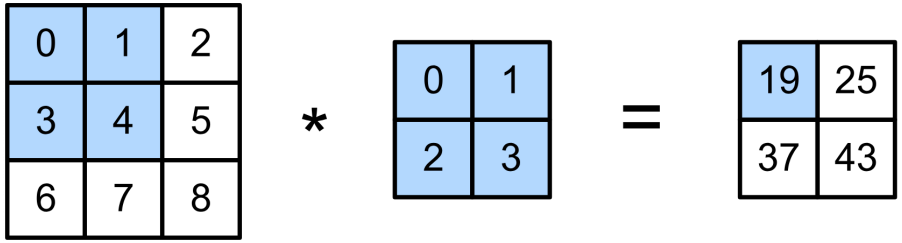
2-D 卷积层

- $\mathbf{X}: n_h \times n_w$：输入矩阵
- $\mathbf{W}: k_h \times k_w$：核矩阵
- b: scalar bias
- $\mathbf{Y}: (n_h - k_h + 1) \times (n_w - k_w + 1)$：输出矩阵



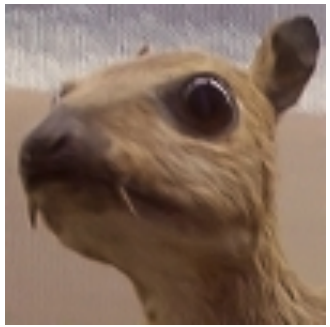
$$\mathbf{Y} = \mathbf{X} \star \mathbf{W} + b$$

- **W** 和 *b* 是可以学习的参数

例子

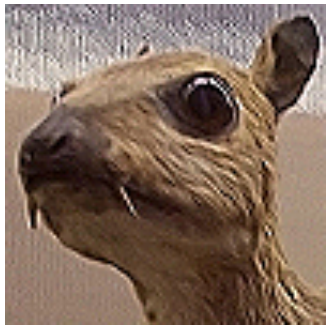
$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

边缘检测



(wikipedia)

$$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$



锐化

$$\frac{1}{16}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$$

高斯模糊

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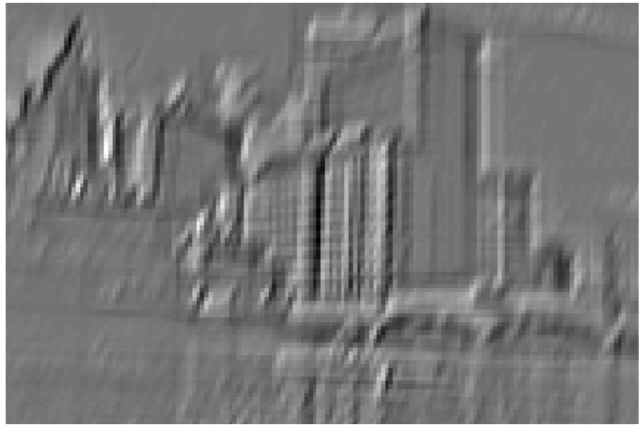
例子



(Rob Fergus)

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Convolutions Notebook

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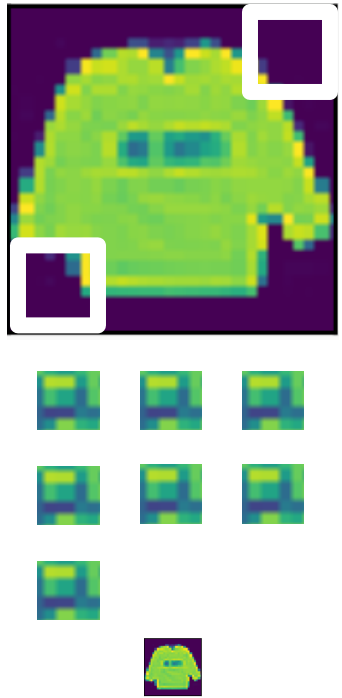
填充和步幅

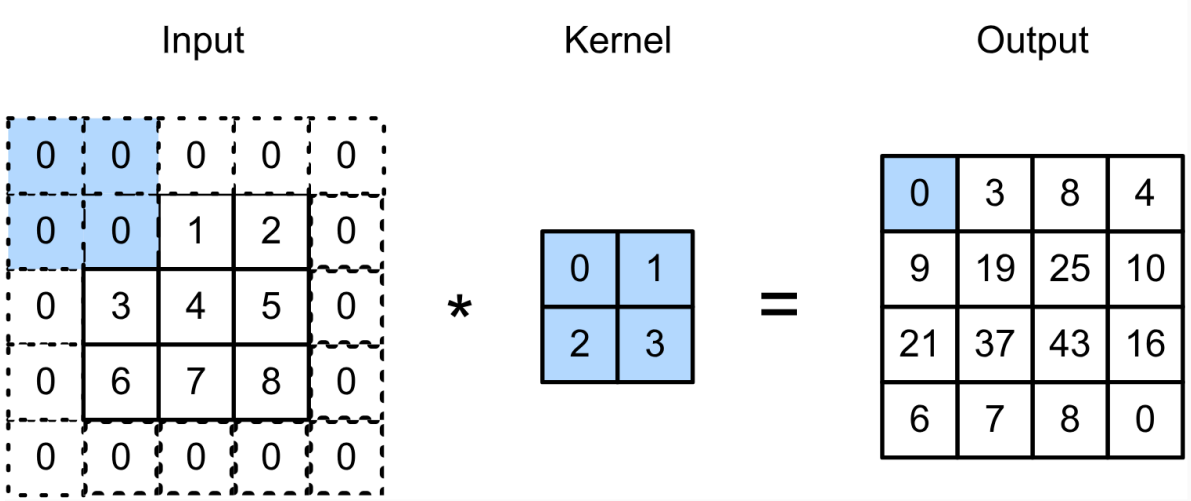
填充

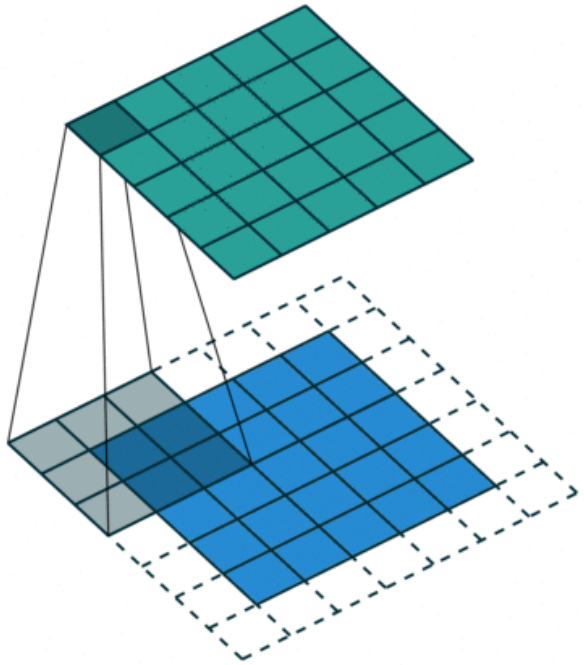
- 给定一张 32 x 32 输入图片
- 使用 5 x 5 核卷积
  - 使用一层：输出为 28 x 28
  - 使用七层：输出为 4 x 4
- 大尺寸的核导致形状大小锐减
  - 从 $n_h \times n_w$ 变成 $(n_h - k_h + 1) \times (n_w - k_w + 1)$



填充

在输入的四周填充行和列，通常填充值为0





$$0 \times 0 + 0 \times 1 + 0 \times 2 + 0 \times 3 = 0$$

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填充

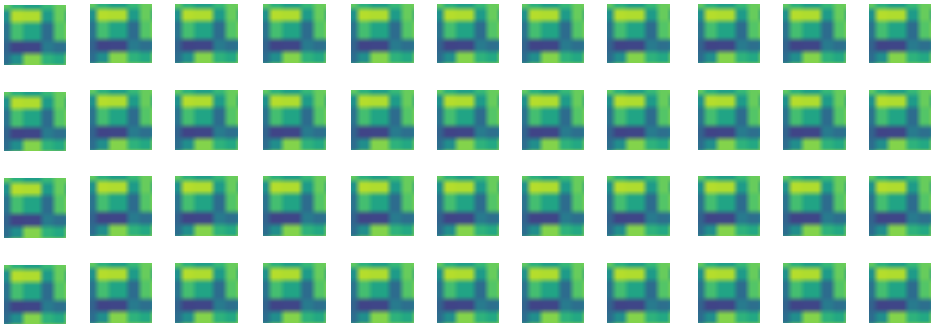
- 填充 p_h 行和 p_w 列，输出形状为

$$(n_h - k_h + p_h + 1) \times (n_w - k_w + p_w + 1)$$

- 通常使用 $p_h = k_h - 1$ 和 $p_w = k_w - 1$
  - 奇数 k_h：在两边填充 $p_h/2$
  - 偶数 k_h：上面填充 $\lceil p_h/2 \rceil$，下面 $\lfloor p_h/2 \rfloor$

步幅

- 填充可以让形状不变或者线性随层数减小
  - 使用 224 x 224 图片和 5 x 5 核卷积，需要 44 层来将输出变成 4 x 4，这样导致大量的计算



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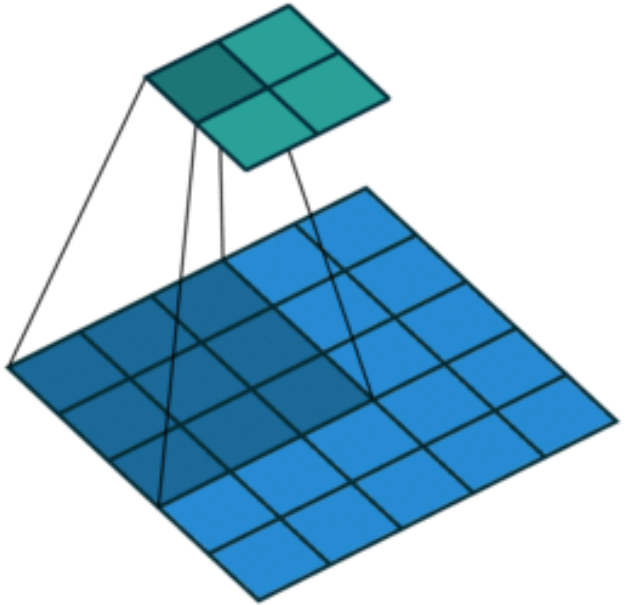
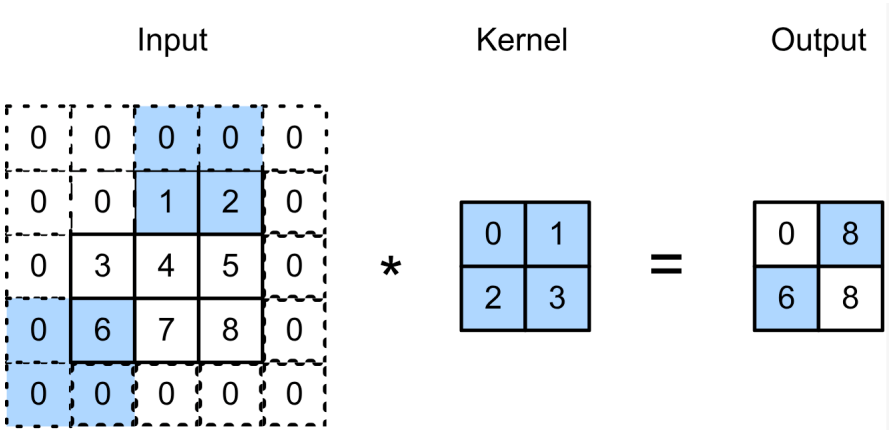
步幅

- 步幅是每次滑动时越过的行、列数



高步幅3，宽步幅2



$$0\times0+0\times1+1\times2+2\times3=8$$
$$0\times0+6\times1+0\times2+0\times3=6$$

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步幅

- 给定高步幅 s_h 和宽步幅 s_w，输出的形状为

$$\lfloor (n_h - k_h + p_h + s_h)/s_h \rfloor \times \lfloor (n_w - k_w + p_w + s_w)/s_w \rfloor$$

- 使用 $p_h = k_h - 1$ 和 $p_w = k_w - 1$

$$\lfloor (n_h + s_h - 1)/s_h \rfloor \times \lfloor (n_w + s_w - 1)/s_w \rfloor$$

如果高和宽可以被步幅整除

$$(n_h/s_h) \times (n_w/s_w)$$


多输入和输出通道

多输入通道

- 彩色图片可能有 RGB 三个通道，转成灰度图片会损失信息

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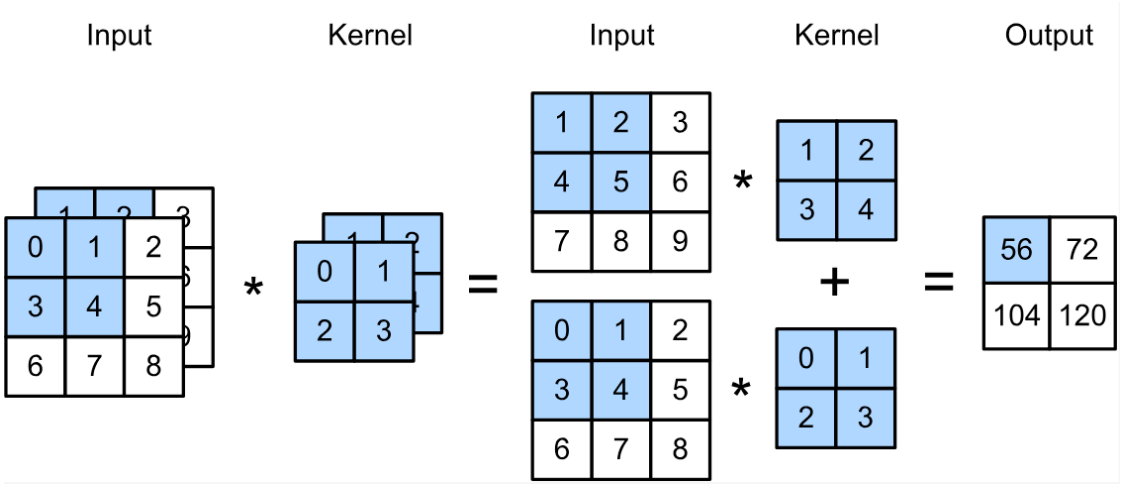
多输入通道

- 彩色图片可能有 RGB 三个通道，转成灰度图片会损失信息

多输入通道

- 每个输出通道使用一个卷积核，然后对结果相加



$$(1\times1+2\times2+4\times3+5\times4)$$
$$+(0\times0+1\times1+3\times2+4\times3)$$
$$=56$$

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多输入通道

- 输入 $\mathbf{X}$：$c_i \times n_h \times n_w$
- 核 $\mathbf{W}$：$c_i \times k_h \times k_w$
- 输出 $\mathbf{Y}$：$m_h \times m_w$

$$\mathbf{Y} = \sum_{i=0}^{c_i} \mathbf{X}_{i,:,:} \star \mathbf{W}_{i,:,:}$$

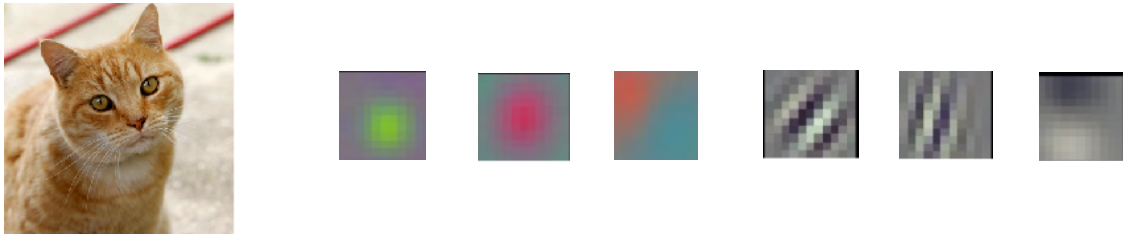
多输出通道

- 不论多少输入通道，输出通道总是1
- 我们可以有多个 3-D 核，每个核产生一个输出通道
- 输入 $\mathbf{X}: c_i \times n_h \times n_w$
- 核 $\mathbf{W}: c_o \times c_i \times k_h \times k_w$
- 输出 $\mathbf{Y}: c_o \times m_h \times m_w$

$$\mathbf{Y}_{i,:,:} = \mathbf{X} \star \mathbf{W}_{i,:,:,:} \quad \text{for } i = 1, \ldots, c_o$$

多输入、输出通道

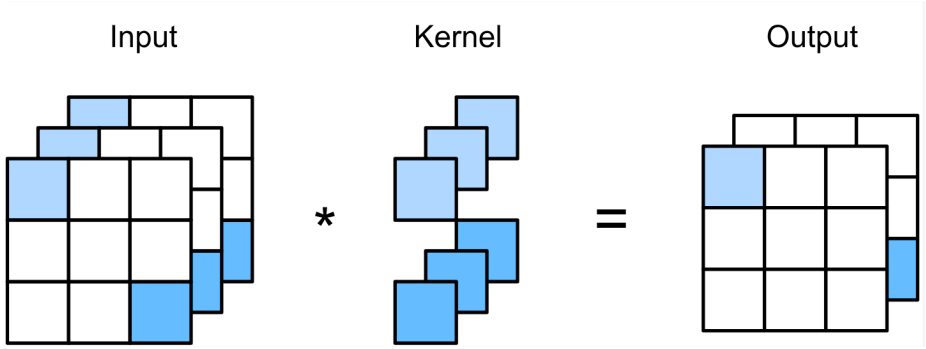
- 每个输出通道可能识别某个模式



- 讲多个输入通道模式合并来识别一个更高层的模式

1 x 1 卷积层

一个常用选择是 $k_h = k_w = 1$。它不识别空间信息，但混合通道



等价一个全连接层，它有 $n_h n_w \times c_i$ 输入，权重为 $c_o \times c_i$

2-D 卷积层总结 Layer Summary

- 输入 $\mathbf{X}: c_i \times n_h \times n_w$
- 核 $\mathbf{W}: c_o \times c_i \times k_h \times k_w$
- 偏移 $\mathbf{B}: c_o \times c_i$
- 输出 $\mathbf{Y}: c_o \times m_h \times m_w$

$$\mathbf{Y} = \mathbf{X} \star \mathbf{W} + \mathbf{B}$$

- 计算复杂度（浮点计算数 FLOP）$O(c_i c_o k_h k_w m_h m_w)$

  $c_i = c_o = 100, k_h = h_w = 5, m_h = m_w = 64$ -> 1GFLOP

- 10 层, 1M 样本: 10PF
  (CPU: 0.15 TF = 18h, GPU: 12 TF = 14min)

池化层

池化层

- 卷积对位置敏感
  - 检测垂直边

X

```
[[1. 1. 0. 0. 0.
 [1. 1. 0. 0. 0.
 [1. 1. 0. 0. 0.
 [1. 1. 0. 0. 0.
```

Y

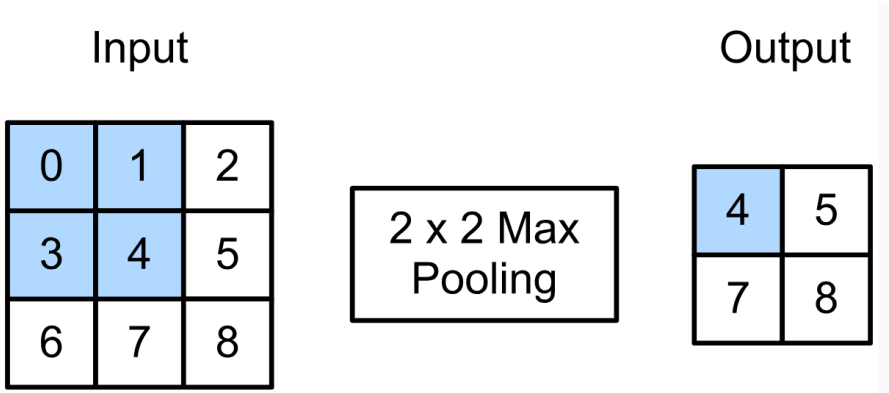
```
[[ 0.  1.  0.  0.
 [ 0.  1.  0.  0.
 [ 0.  1.  0.  0.
 [ 0.  1.  0.  0.
```

1 个像素偏移
导致输出为 0

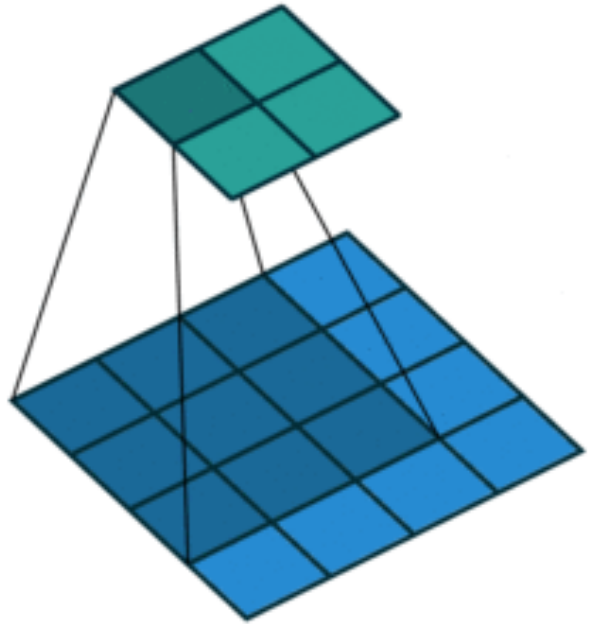
- 我们需要一定程度上变化无关
  - 光照，物体位置，大小，外观变化

2-D 最大池化层

- 返回在一个滑动窗里的最大值



$$\max(0,1,3,4) = 4$$



2-D 最大池化层

- 返回在一个滑动窗里的最大值

检测垂直边

```
[[1. 1. 0. 0. 0.
 [1. 1. 0. 0. 0.
 [1. 1. 0. 0. 0.
 [1. 1. 0. 0. 0.
```

卷积输出

```
[[ 0.  1.  0.  0.
 [ 0.  1.  0.  0.
 [ 0.  1.  0.  0.
 [ 0.  1.  0.  0.
```

2 x 2 最大池化层

```
[[ 1.  1.  1.  0.
 [ 1.  1.  1.  0.
 [ 1.  1.  1.  0.
 [ 1.  1.  1.  0.
```

容忍一个像素偏移

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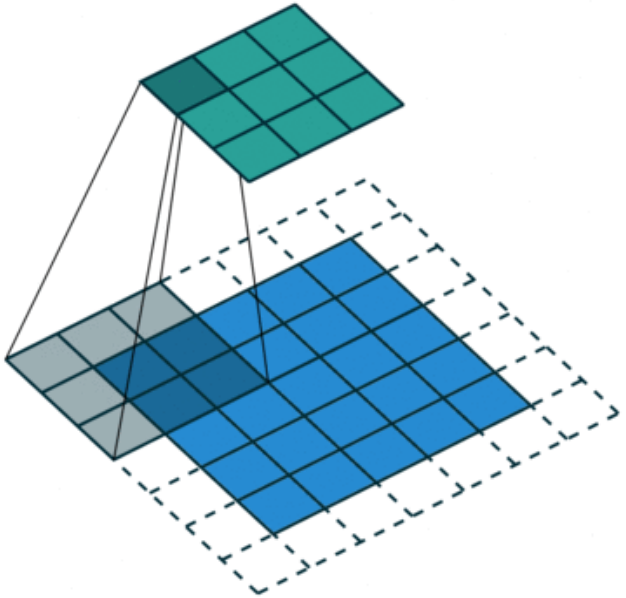
填充、步幅、和多通道

- 池化层的填充和步幅与卷积层类似
- 没有可学习的参数
- 对每个输入通道应用池化得到对应输出通道结果

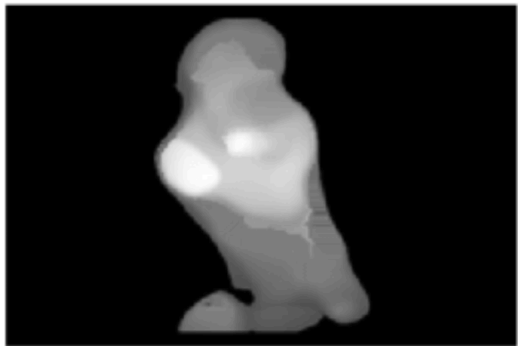
输出通道数 = 输入通道数



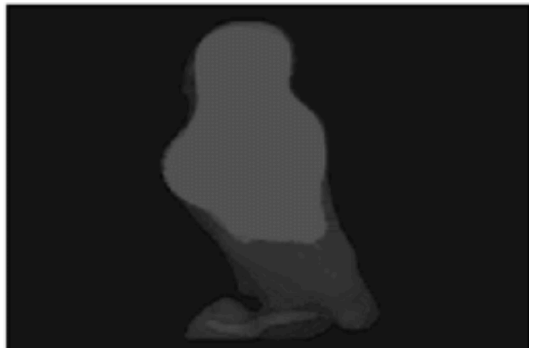
平均池化

- 最大池化：滑动窗里的最大信号值
- 平均池化：将 max 变成 mean
  - 窗口里的平均信号值

Max pooling



Average pooling



Pooling Notebook

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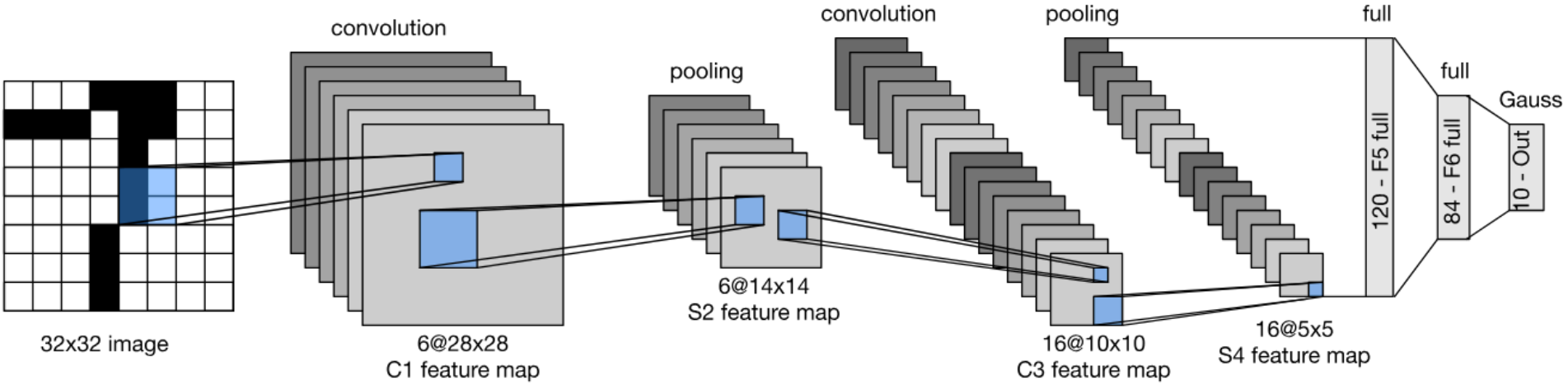
LeNet



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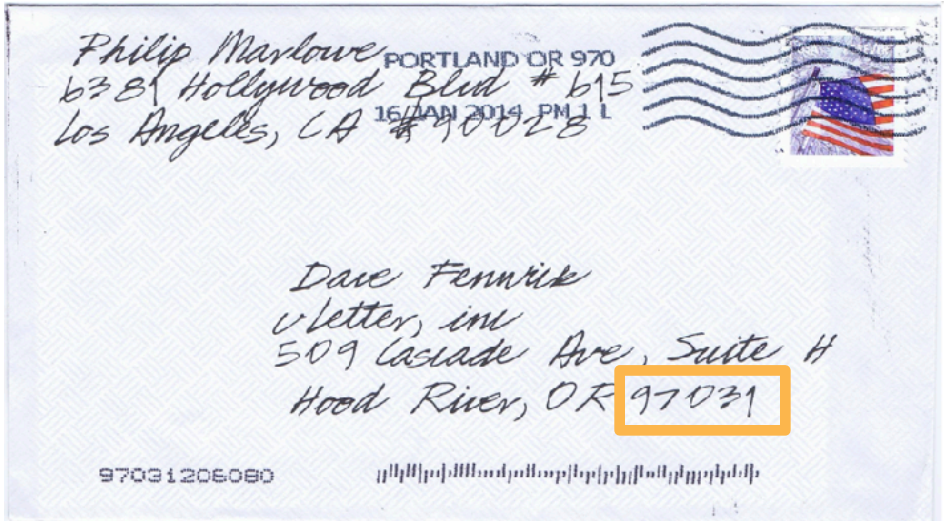
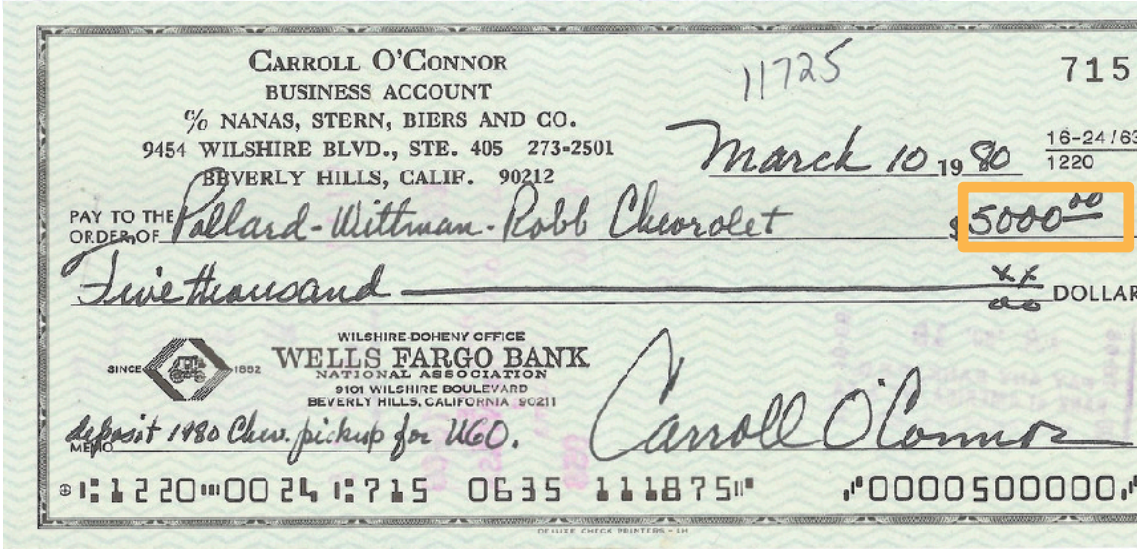
手写数字识别





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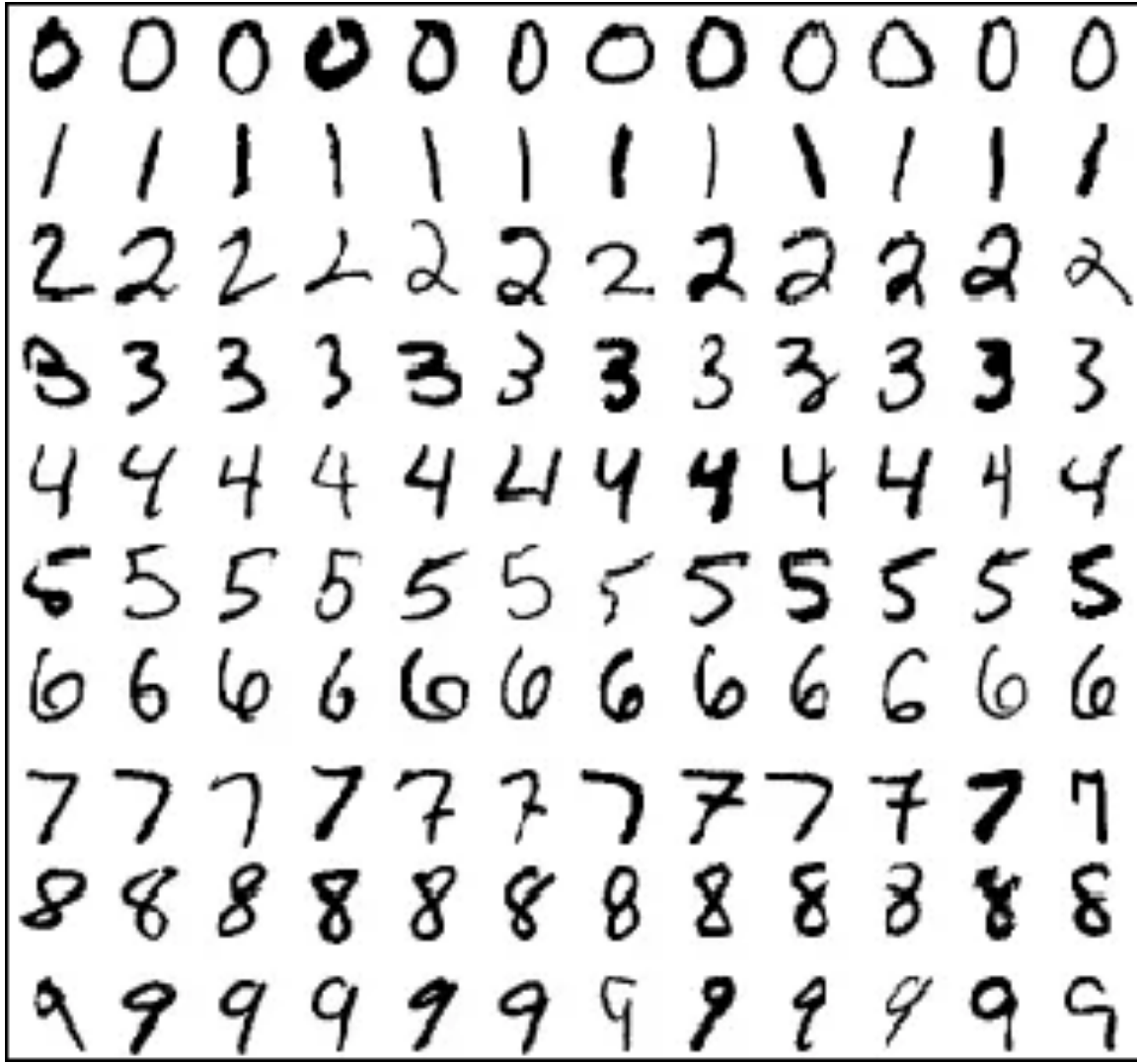
MNIST

- 居中且剪裁了
- 50,000 训练样本
- 10,000 测试样本
- 28 x 28 灰度图片
- 10 类



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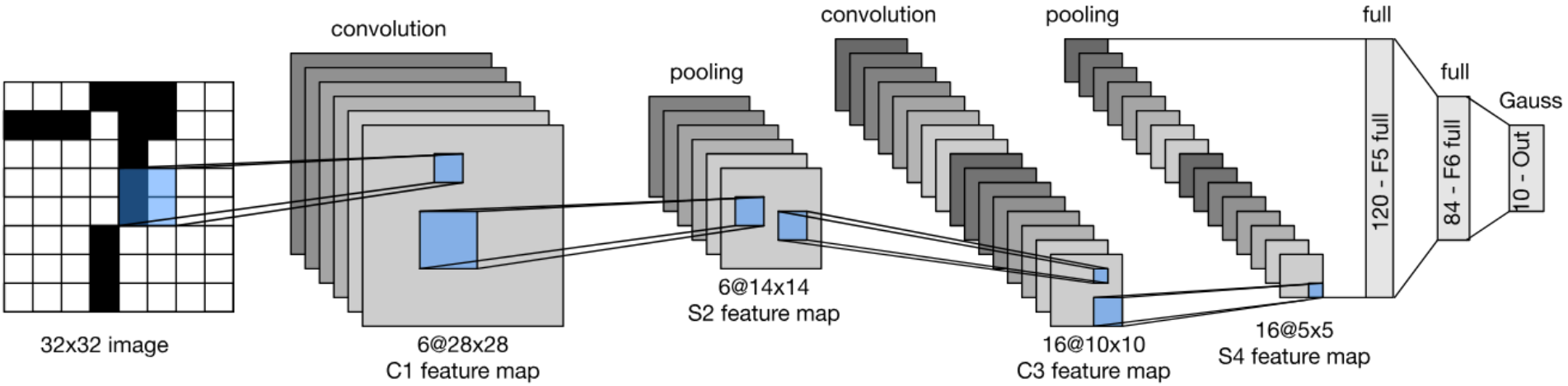
Y. LeCun, L. Bottou, Y. Bengio, P. Haffner, 1998 Gradient-based learning applied to document recognition

aws



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LeNet Notebook

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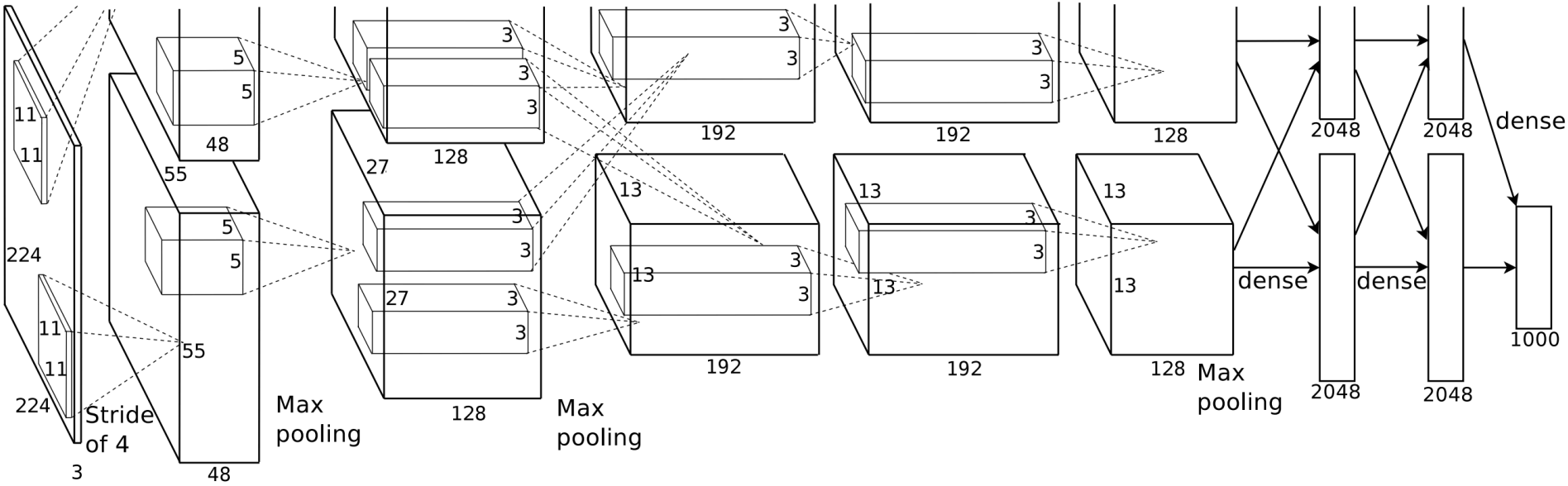
AlexNet



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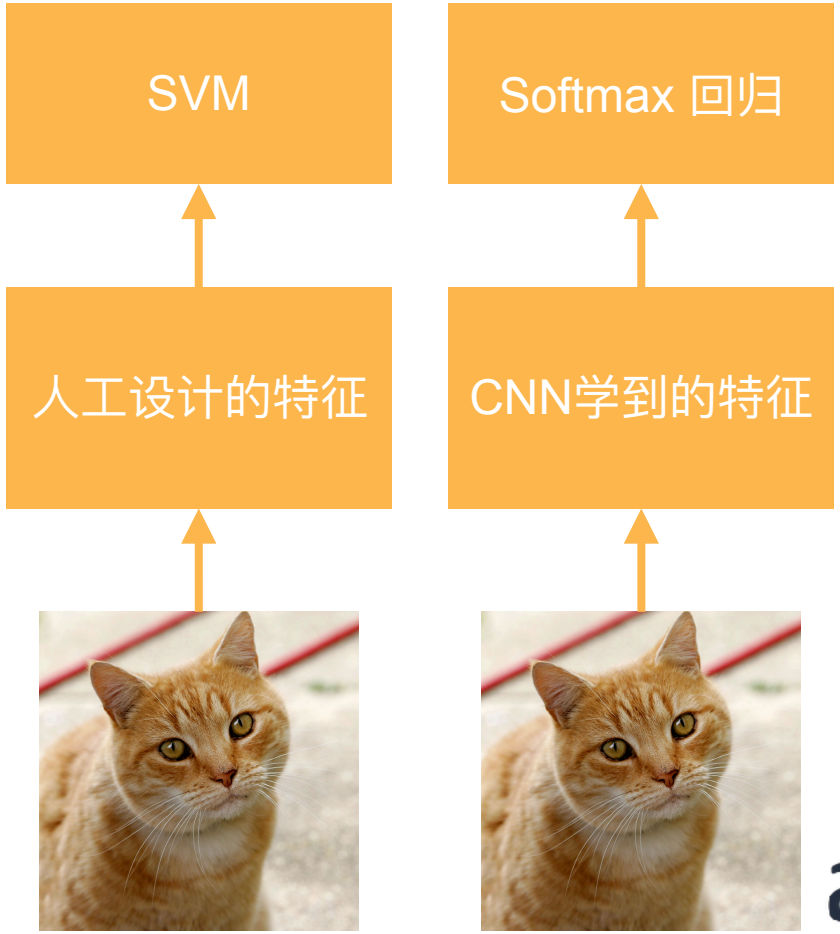
AlexNet

- AlexNet 在 ImageNet 2012 竞赛中获得了冠军
- 更深更大的LeNet
- 关键改动
  - Dropout
  - ReLu
  - MaxPooling
- 观点上的改变



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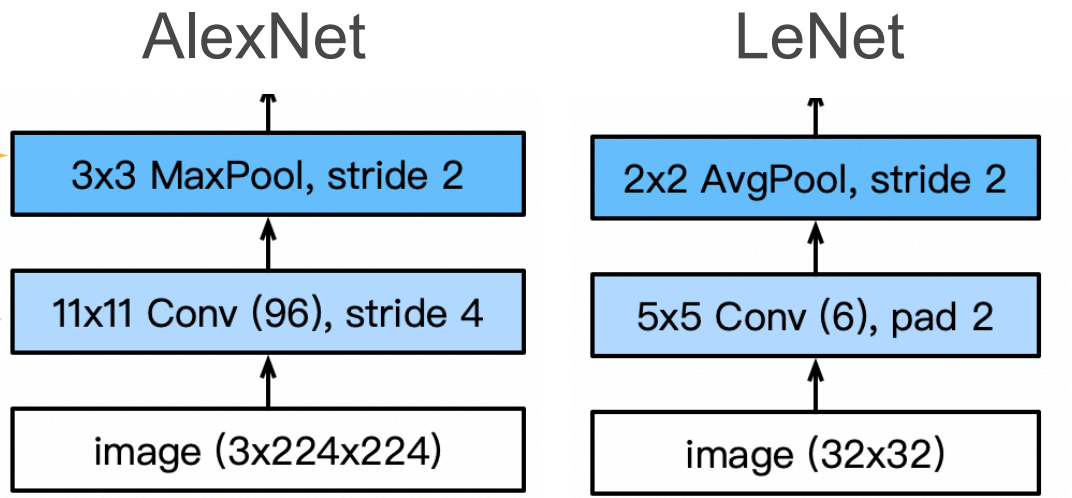
AlexNet 架构

更大的池化窗口

更大的卷积窗和步幅，更多通道。因为输入更大了



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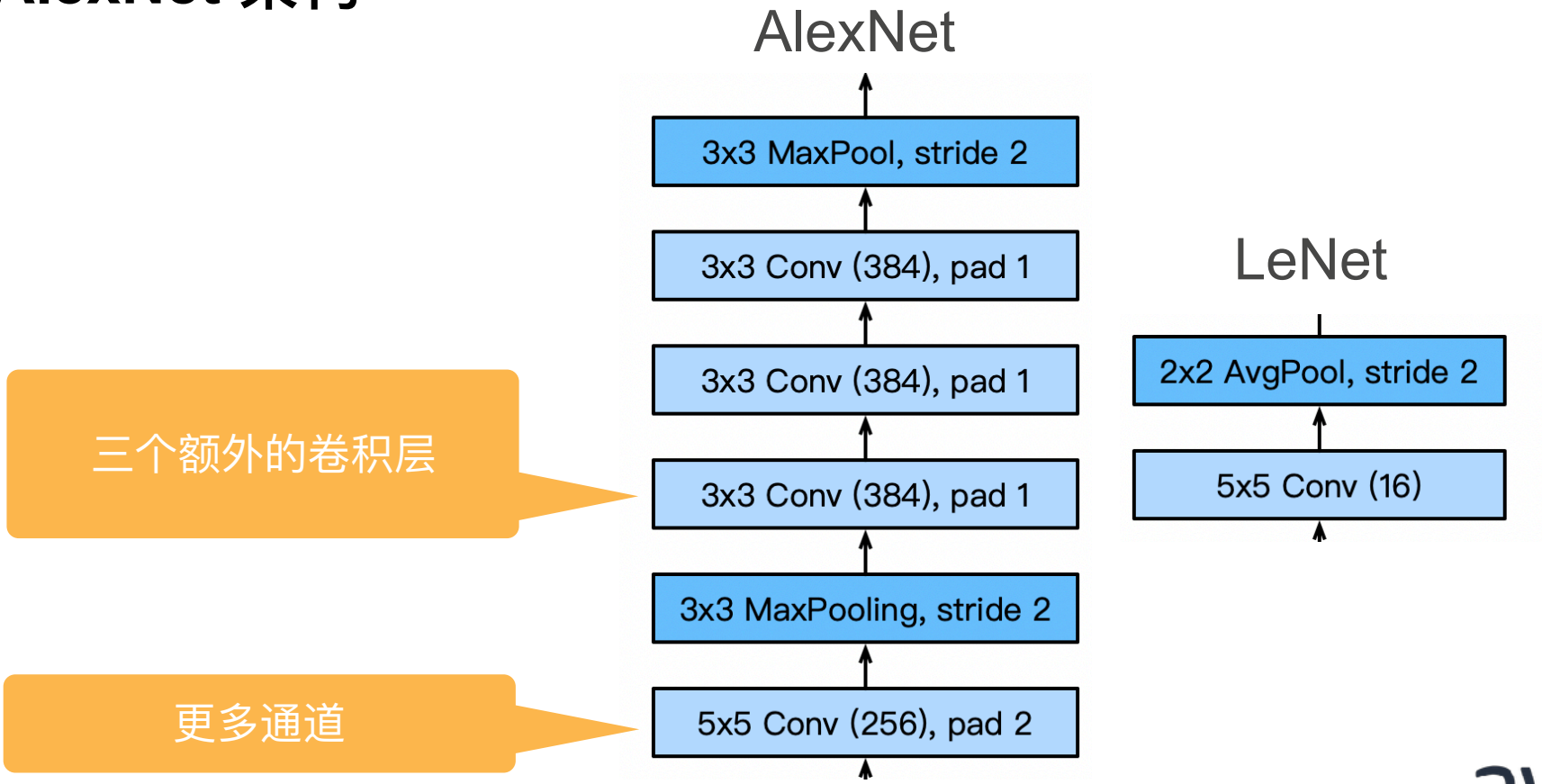
AlexNet 架构



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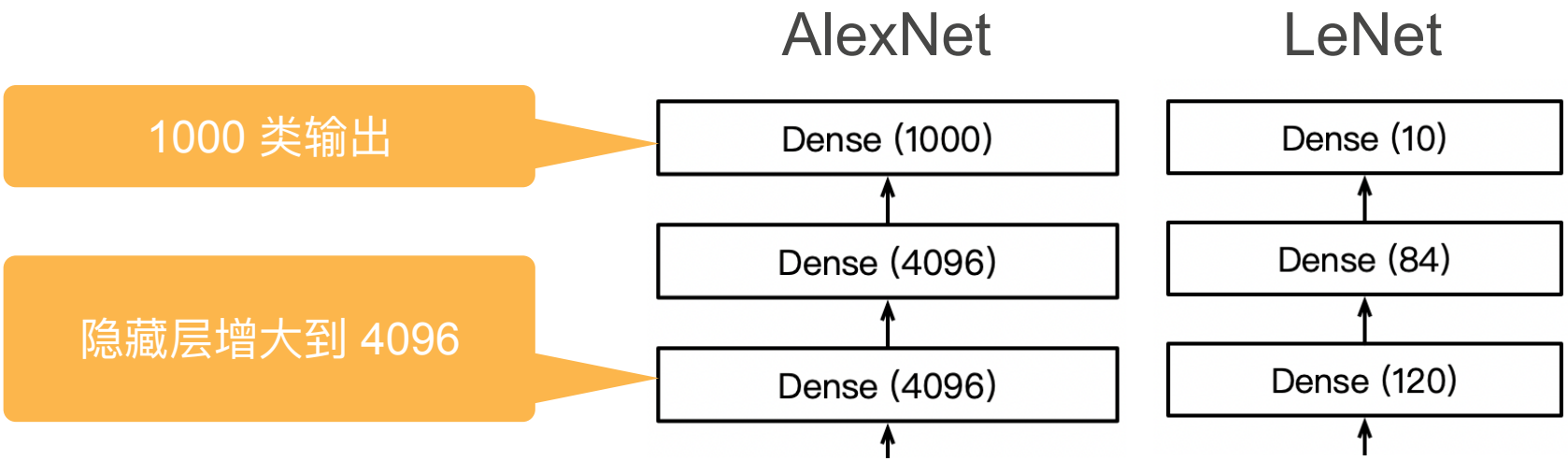
AlexNet 架构



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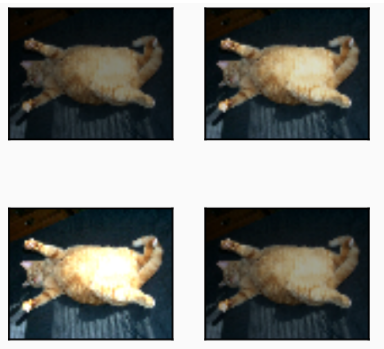
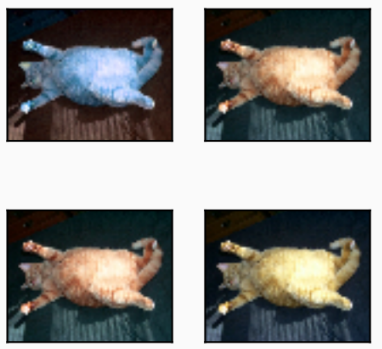
更多技巧

- 激活函数从 sigmoid 变成 ReLu (没有梯度消失)
- 增加 dropout 层 (更鲁棒)
- 数据增强





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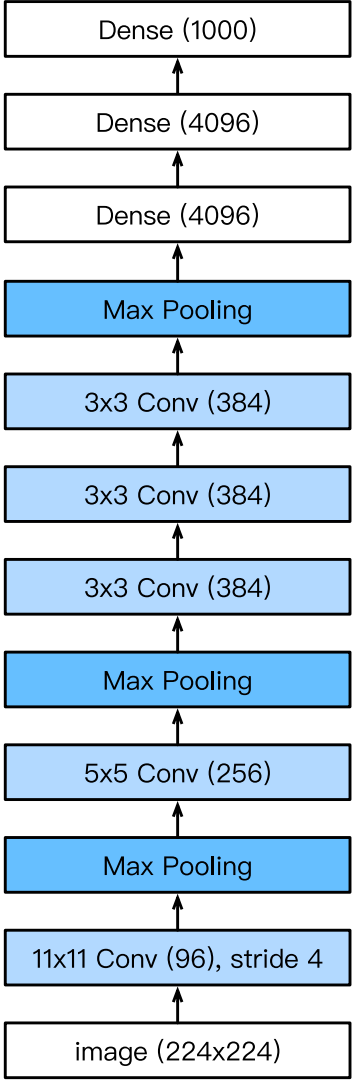
复杂度

	参数数量		FLOP	
	AlexNet	LeNet	AlexNet	LeNet
Conv1	35K	150	101M	1.2M
Conv2	614K	2.4K	415M	2.4M
Conv3-5	3M		445M	
Dense1	26M	0.48M	26M	0.48M
Dense2	16M	0.1M	16M	0.1M
Total	46M	0.6M	1G	4M
Increase	11x	1x	250x	1x

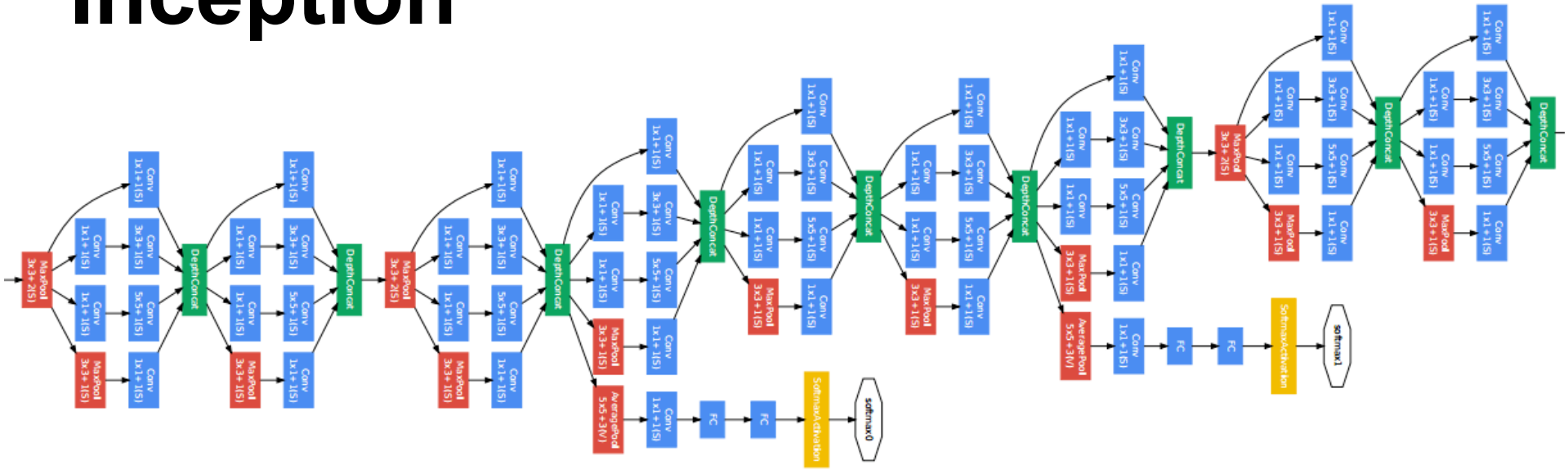


http://1day-zh.gluon.ai

AlexNet Notebook

http://1day-zh.gluon.ai

Inception



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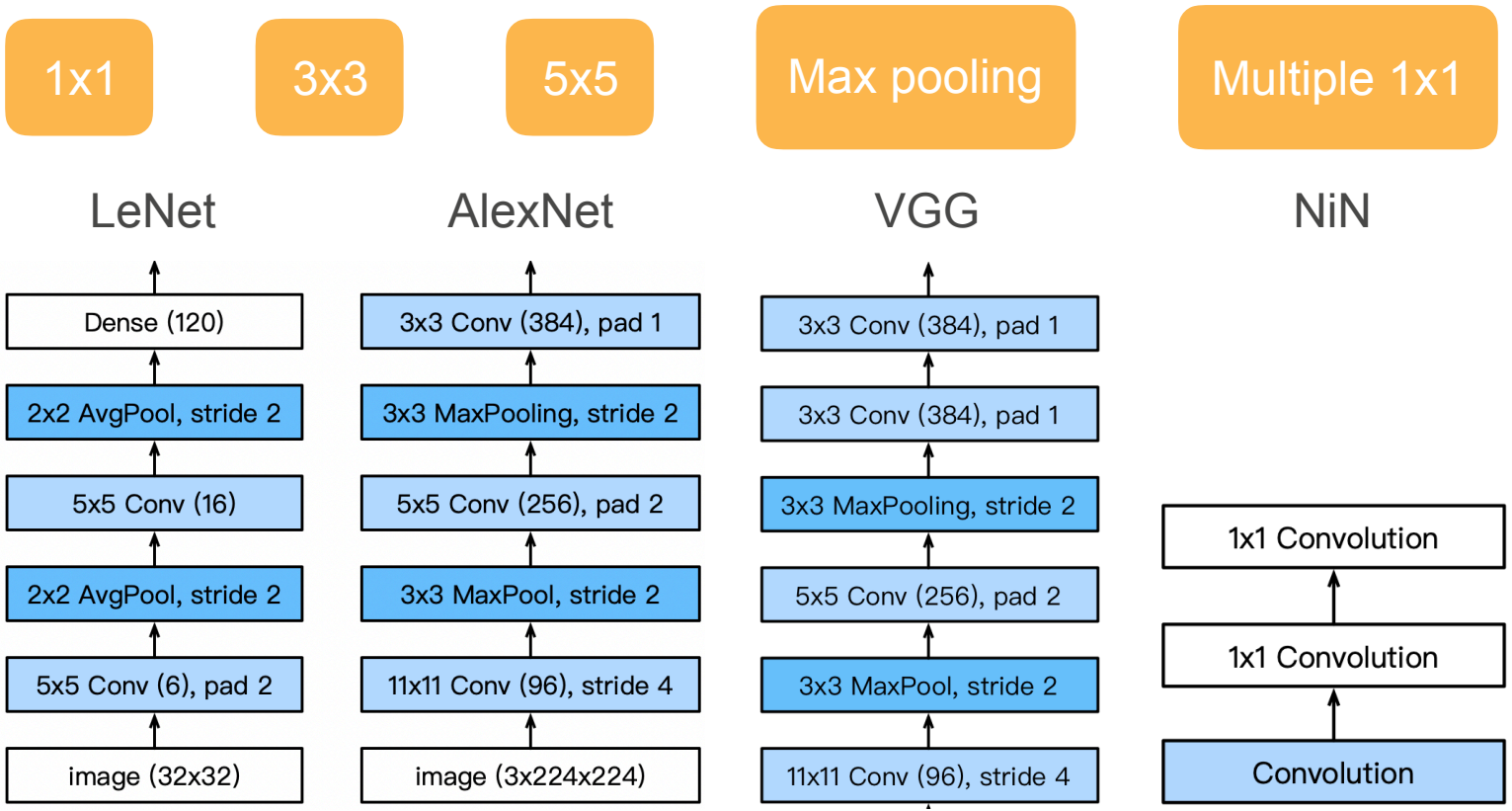
如何选取最好的卷积层

1x1 | 3x3 | 5x5 | Max pooling | Multiple 1x1



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只有别人做选择。我要全部

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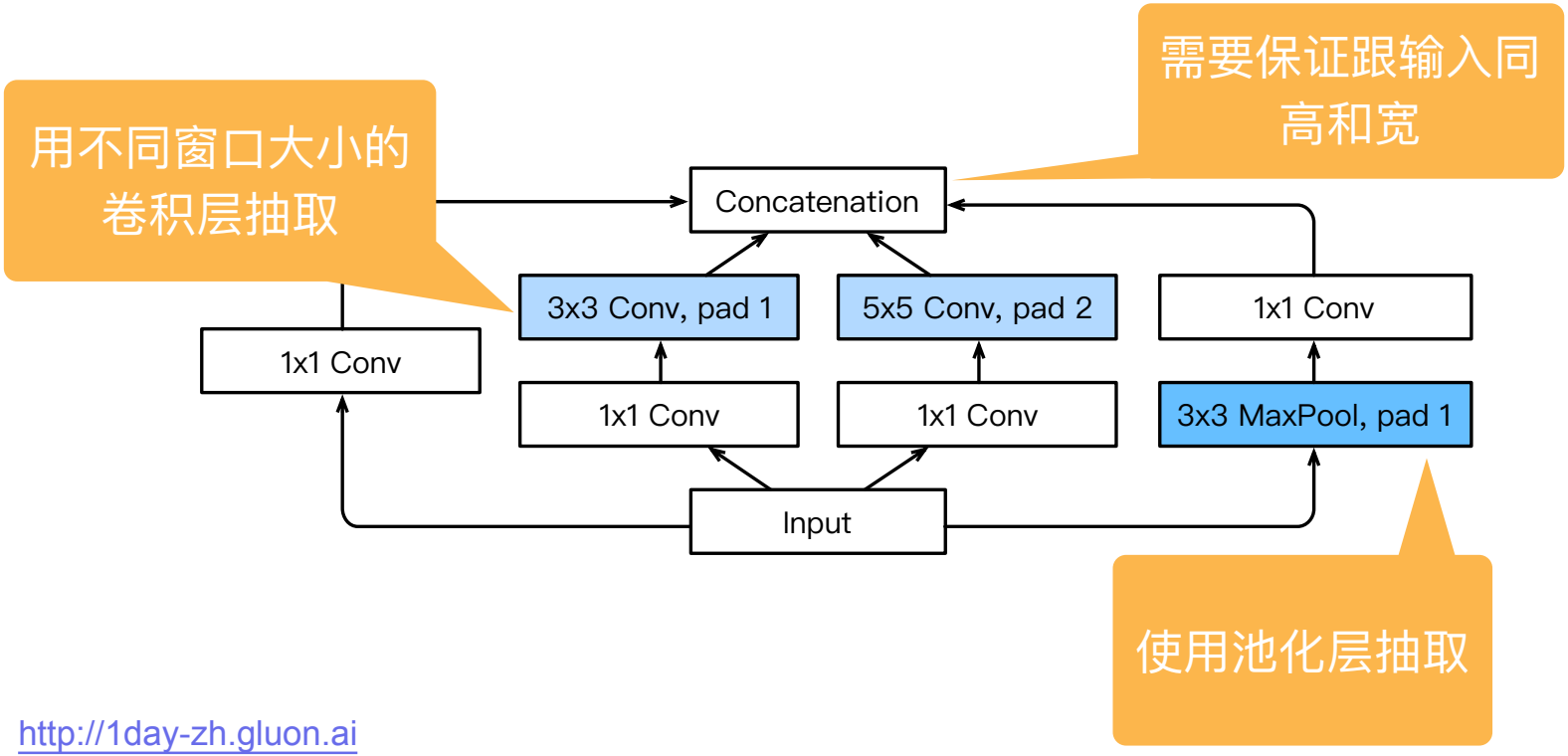
Inception 块

4 条通道分别抽取不同的方面信息，然后在通道维上合并



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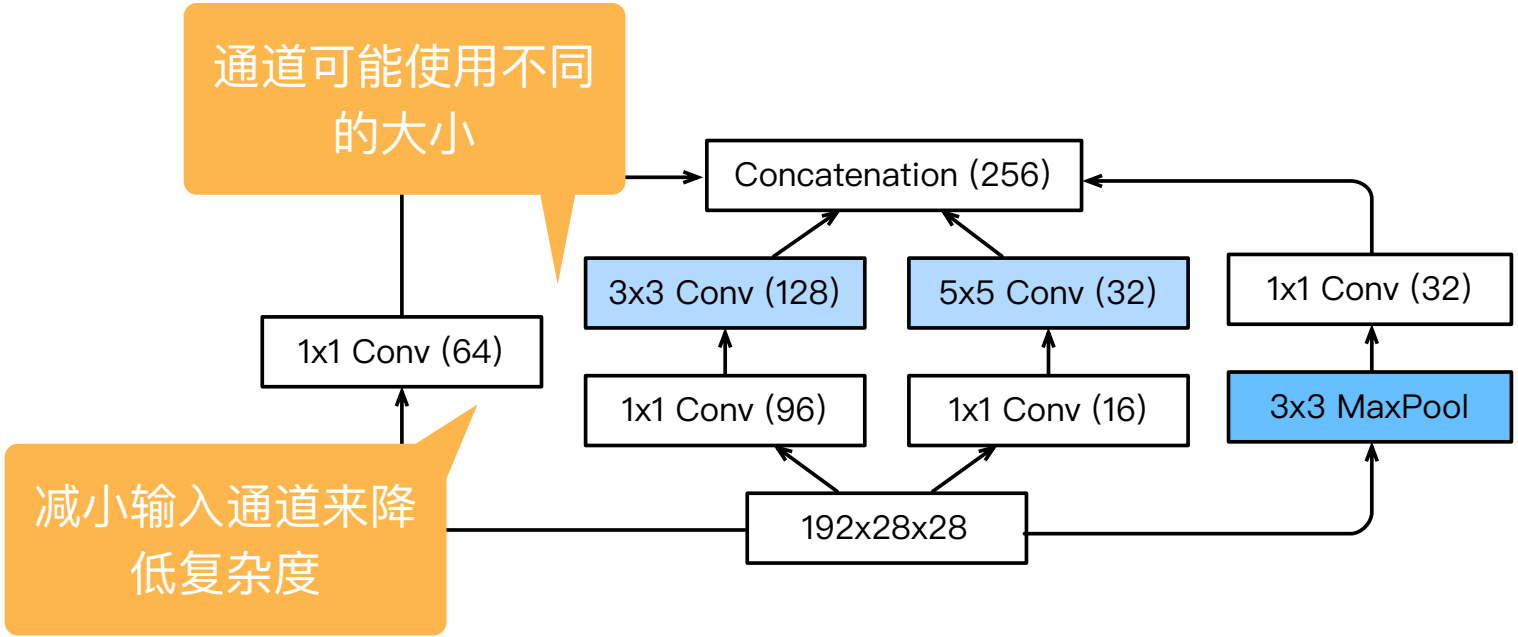
Inception 块

第一个 Inception 块，以及每个通道的大小



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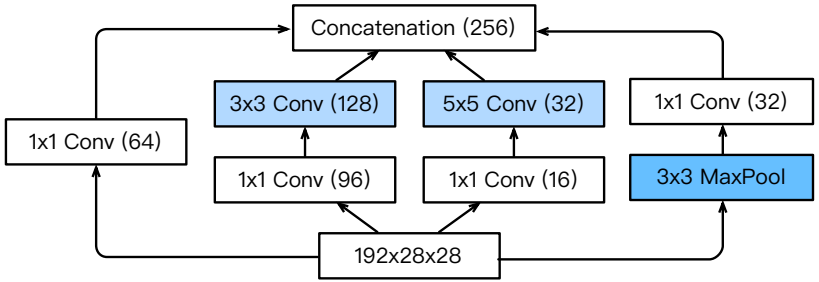
Inception 块

Inception 块通常比单 3x3 或 5x5 卷积层设计有更少的可学习参数和计算量

- 混合不同的函数
- 内存和计算有效

	#parameters	FLOPS
Inception	0.16 M	128 M
3x3 Conv	0.44 M	346 M
5x5 Conv	1.22 M	963 M



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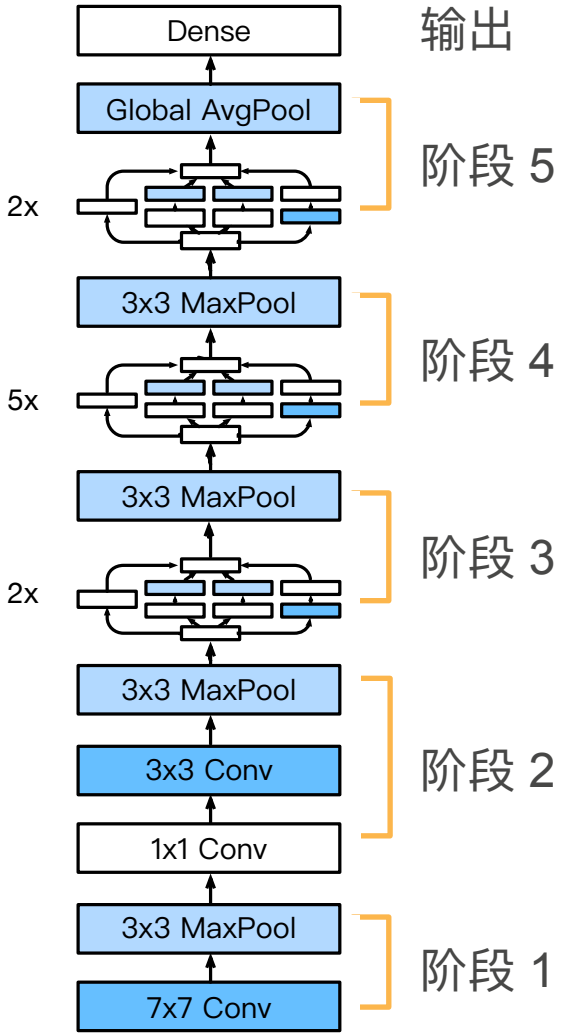
GoogLeNet

- 5 阶段，共 9 个 inception 块



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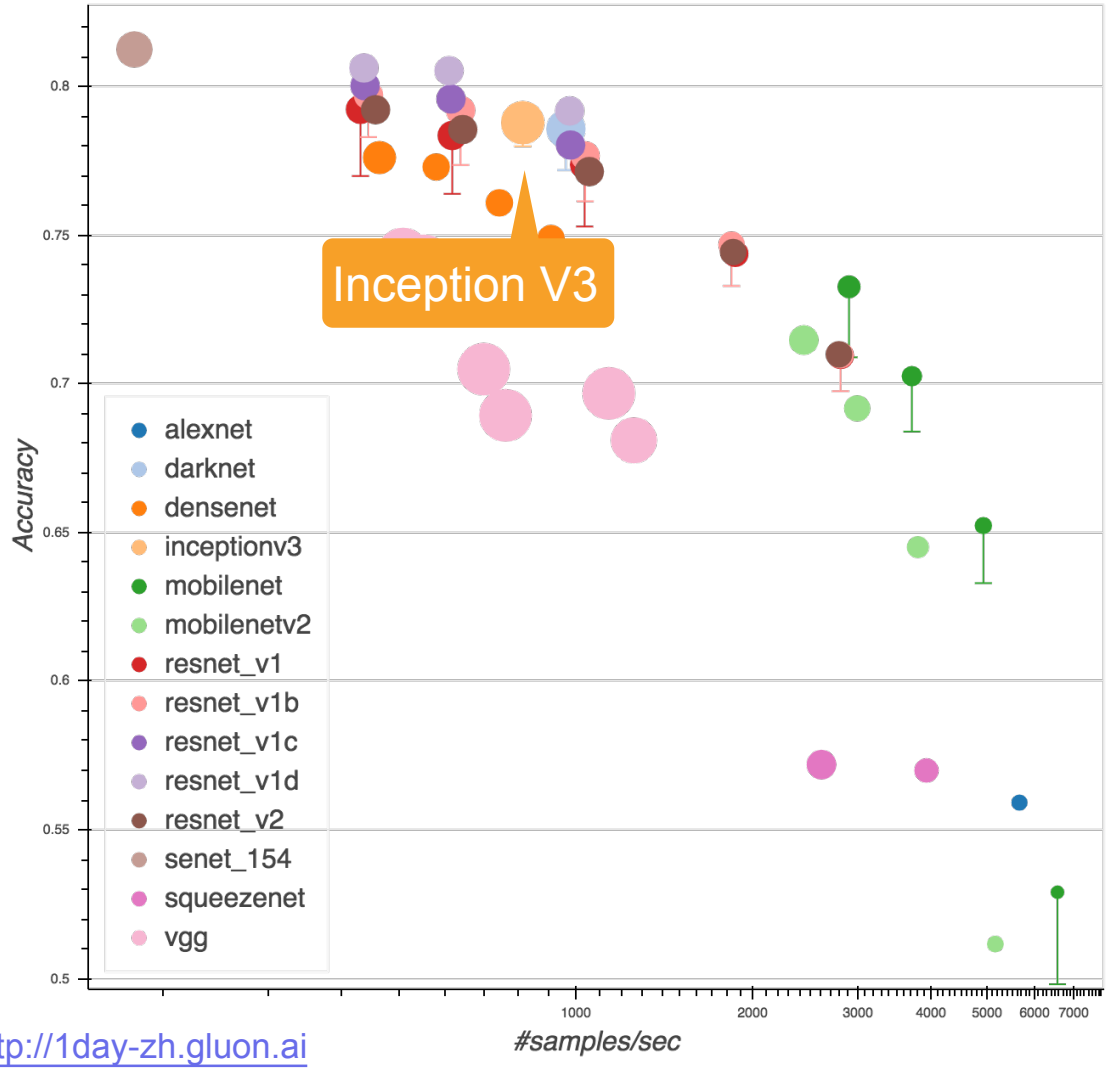
不同的 Inception 架构

- Inception-BN (v2) — 使用批量归一化
- Inception-V3 — 修改了 inception 块
  - 替换 5x5 成多个 3x3 卷积层
  - 替换 5x5 成 1x7 和 7x1 卷积层
  - 替换 3x3 成 1x3 和 3x1 卷积层
  - 更深
- Inception-V4 — 加了残差连接



GluonCV Model Zoo

https://gluon-cv.mxnet.io/model_zoo/classification.html

http://1day-zh.gluon.ai

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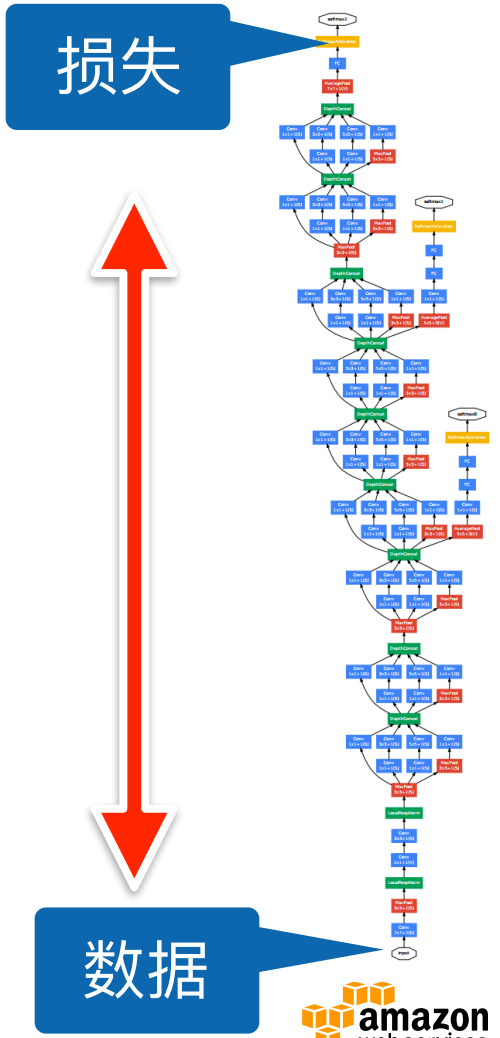
http://1day-zh.gluon.ai

批量归一化

- 损失通常在最后一层
  - 顶部层通常学习更快
- 数据是从底部进入
  - 底部层变化会改变所有层
  - 顶部层需要重新学习很多次
  - 收敛更慢
- 我们能不能在更新底部层的时候不要改变太多顶部层



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批量归一化

- 我们能不能在更新底部层的时候不要改变太多顶部层
- 固定均值和方差

$$\mu_B = \frac{1}{|B|}\sum_{i\in B} x_i \text{ and } \sigma_B^2 = \frac{1}{|B|}\sum_{i\in B}(x_i - \mu_B)^2 + \epsilon$$

然后分别调整

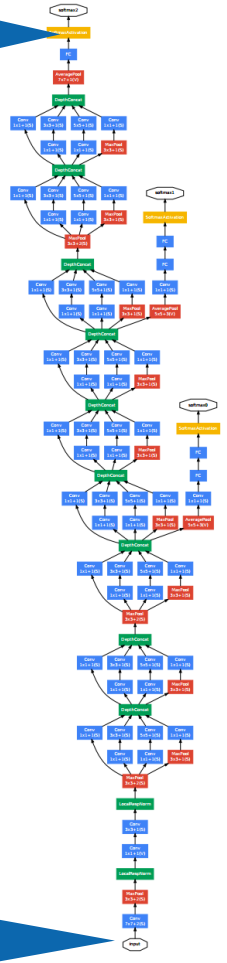
$$x_{i+1} = \gamma\frac{x_i - \mu_B}{\sigma_B} + \beta$$

均值

方差

损失

数据



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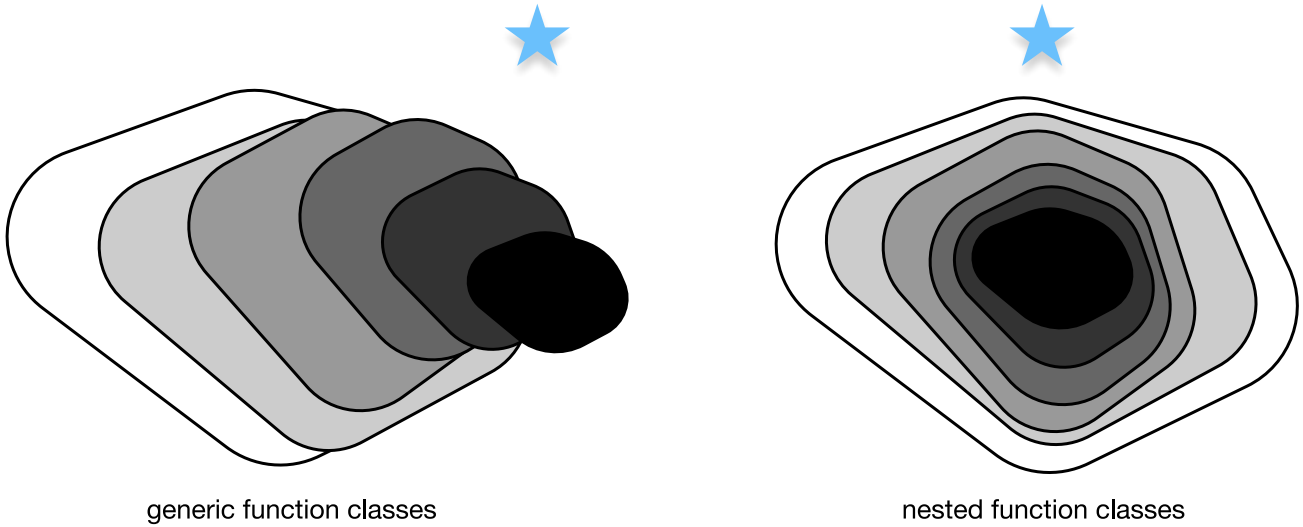
amazon web services

残差网络



generic function classes

nested function classes

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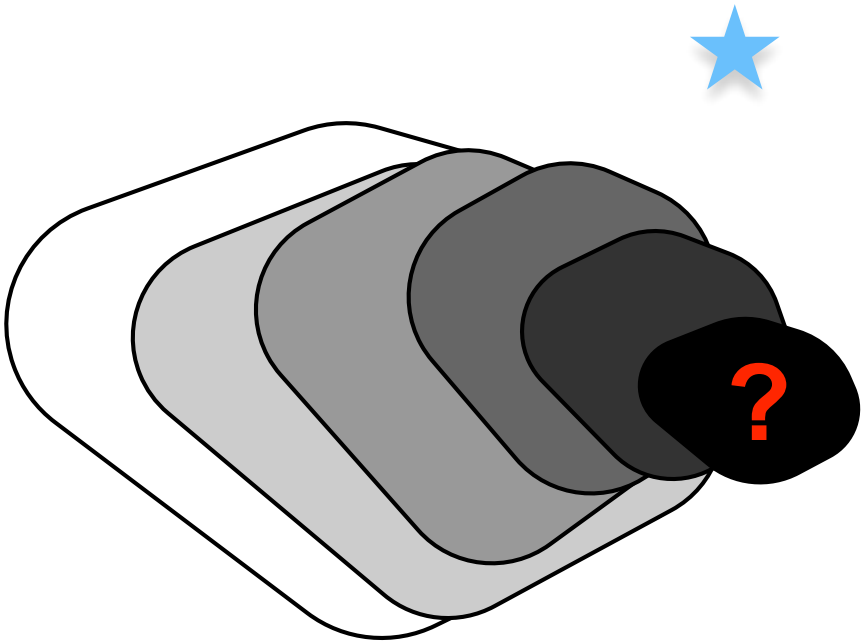
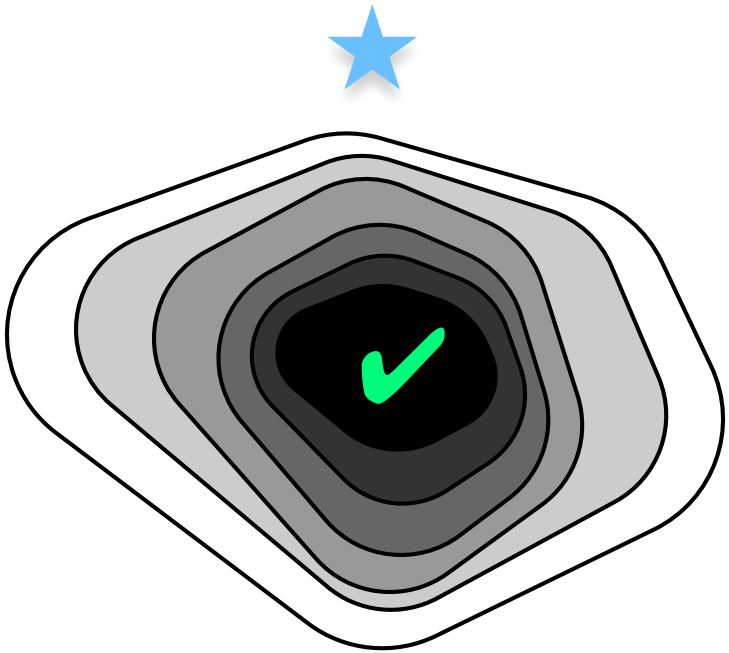
加层总是能提升精度吗?



generic function classes



nested function classes

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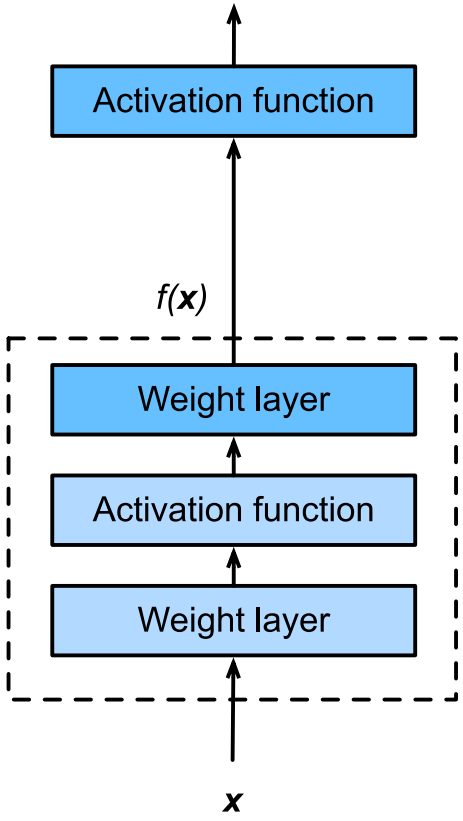
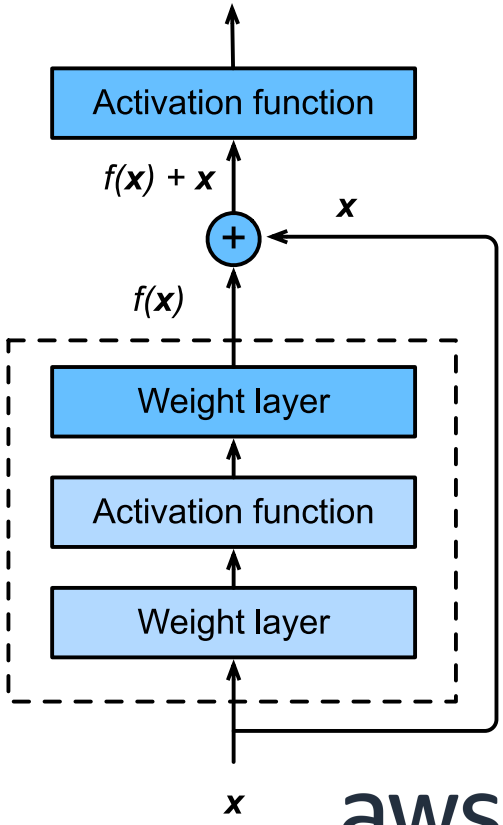
残差网络

- 加一层会改变函数类
- 我们想加一个函数
- ‘Taylor 展开’ 风格

$$f(x) = x + g(x)$$

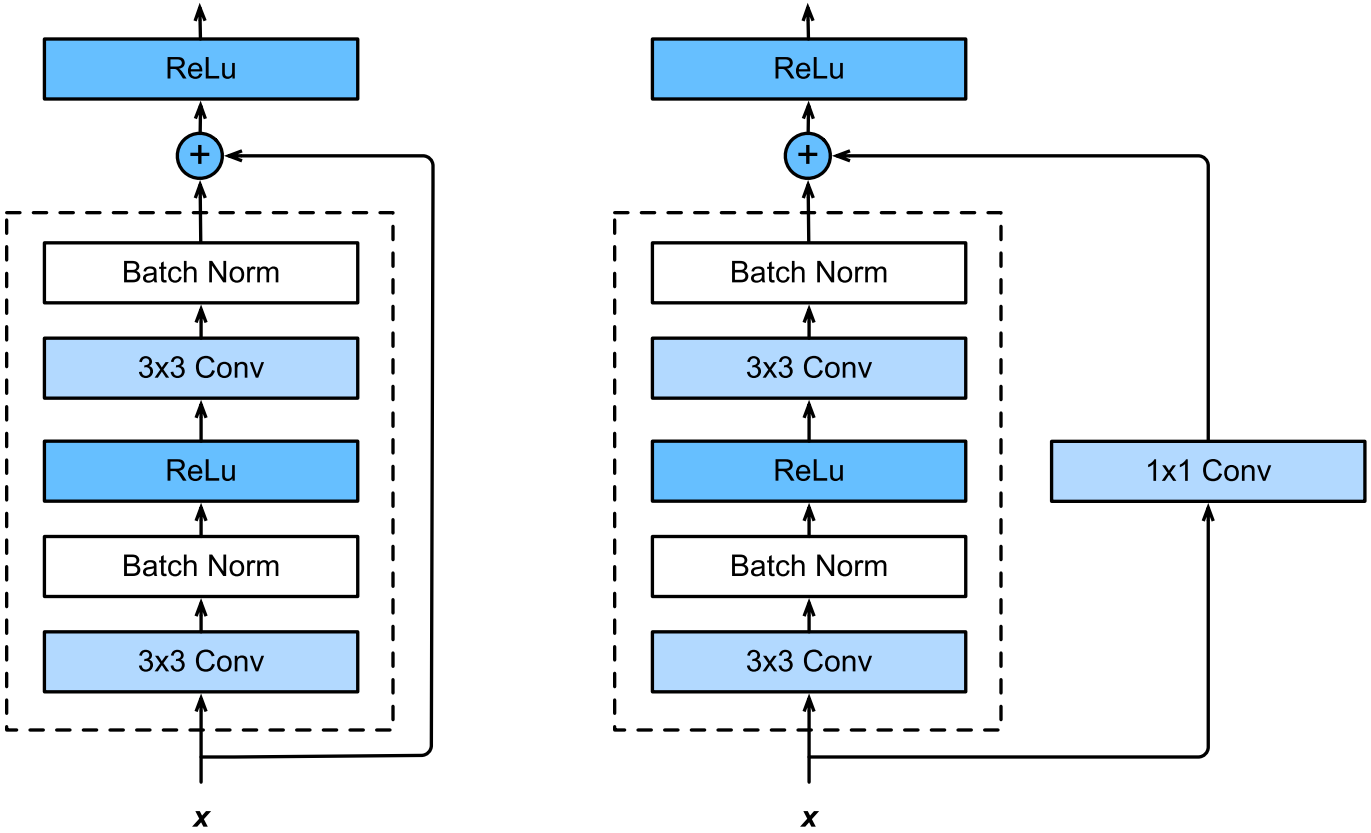




He et al., 2015

http://1day-zh.gluon.ai

残差块细节



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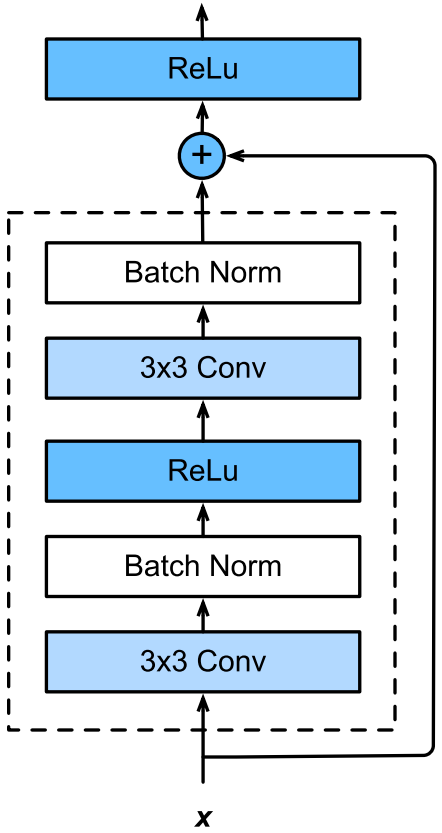
代码实现




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

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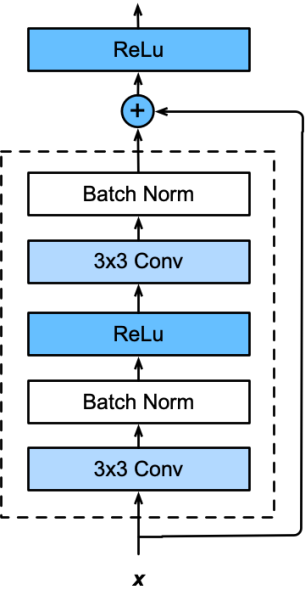
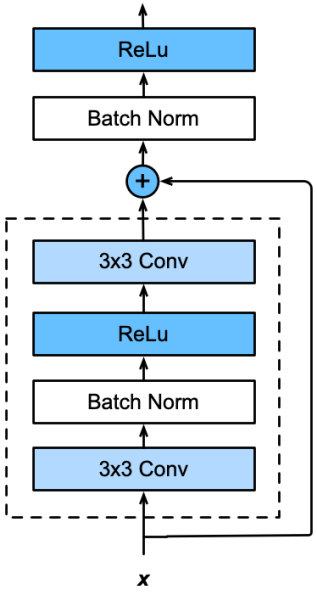
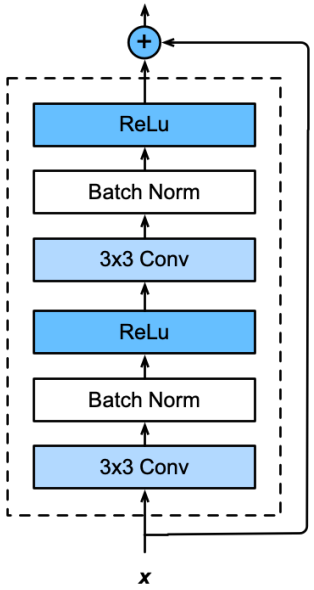
残差块有很多方式



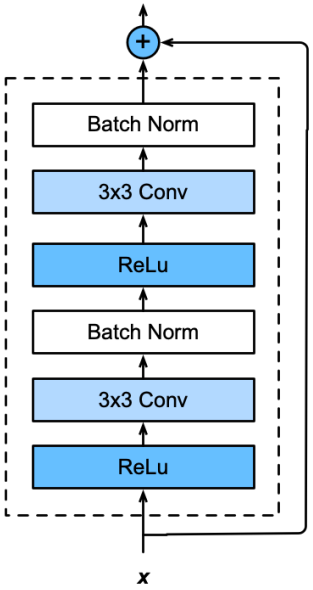
original



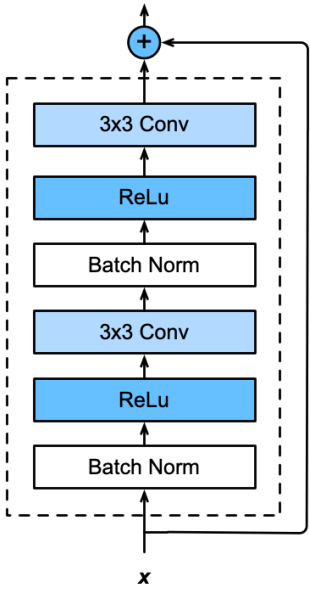
Batch Norm after addition



ReLu last



Batch Norm last



Pre-activation

使用各种不同排列

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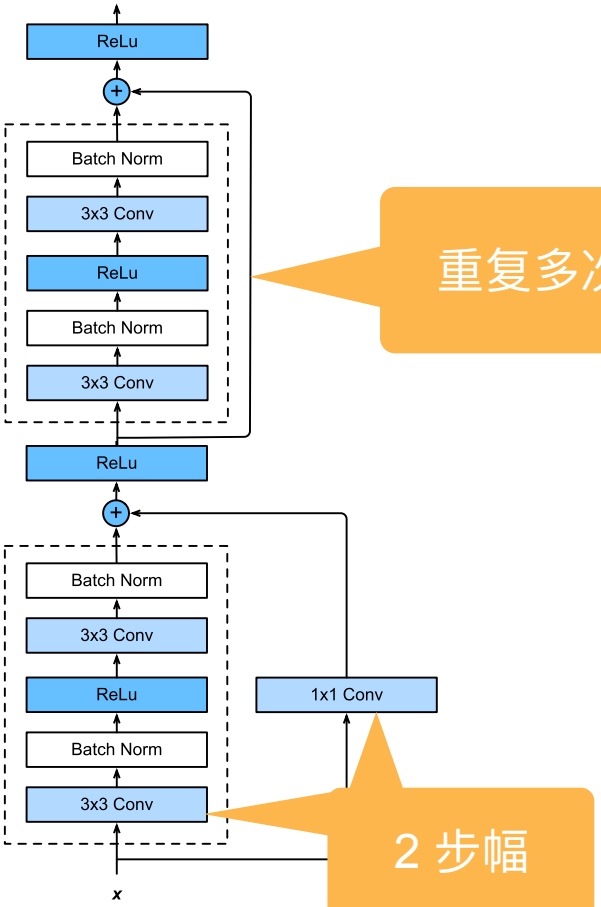
ResNet 块



- 每块里面先减半高宽 (stride=2)
- 累加残差块

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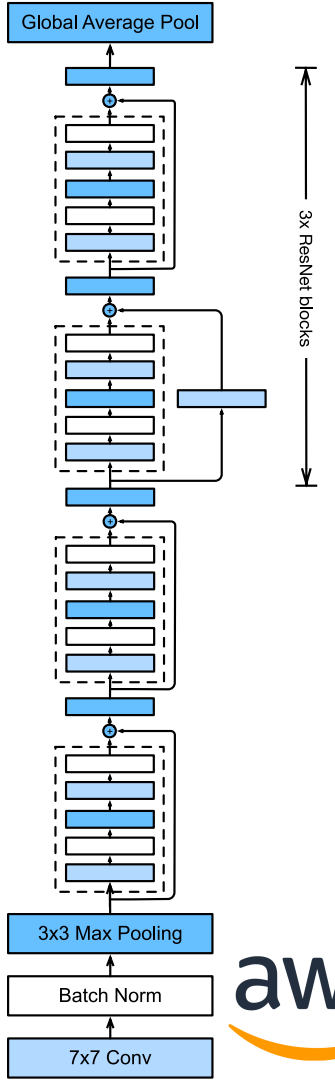
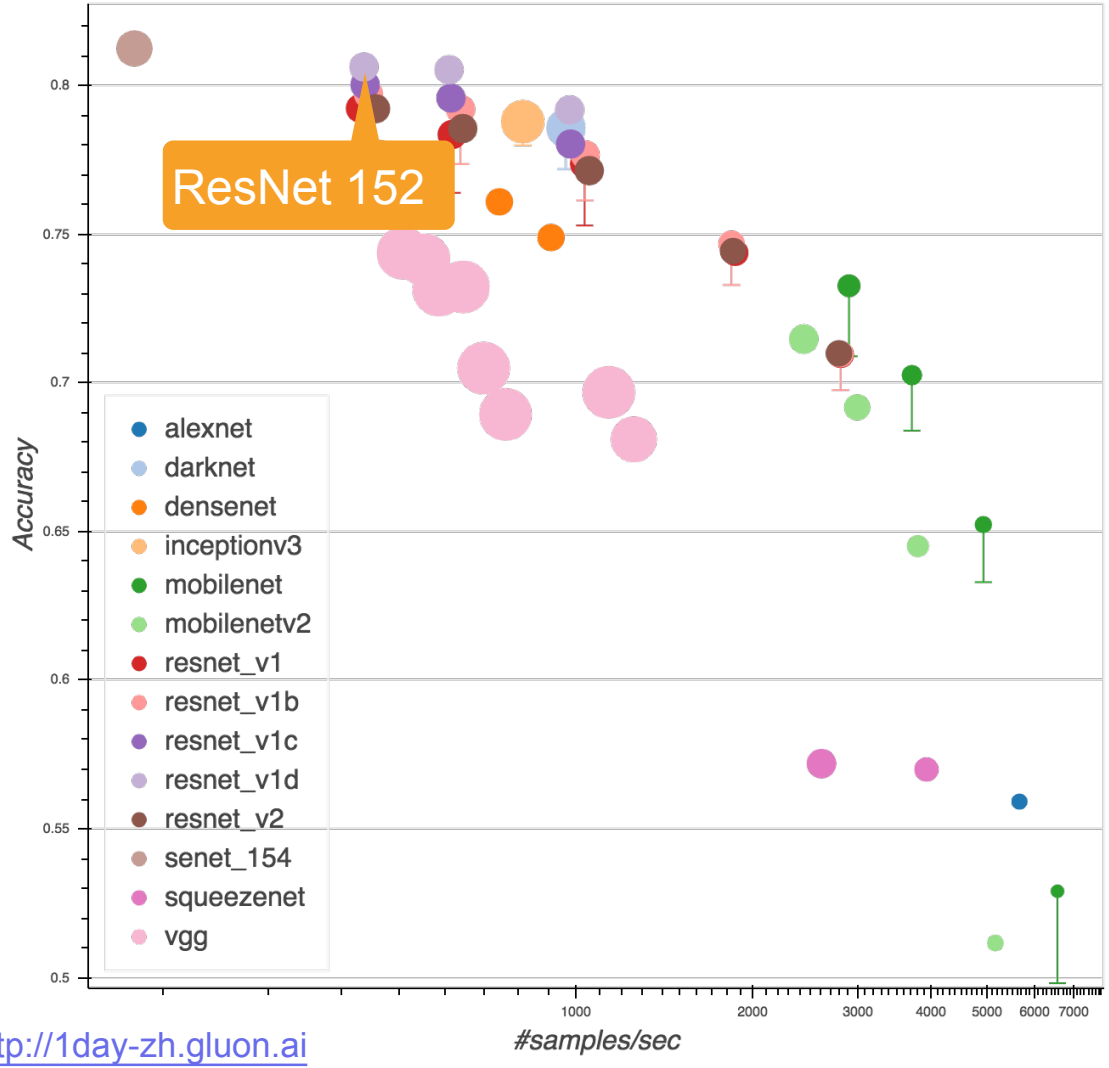
ResNet 架构

- 跟 VGG 和 GoogleNet 一样的总体架构
- 通过残差连接来增加表达性
- 池化和步幅来降低复杂度
- 批量归一化来做正则



http://1day-zh.gluon.ai



GluonCV Model Zoo

https://gluon-cv.mxnet.io/model_zoo/classification.html

http://1day-zh.gluon.ai

Jupyter Notebook

http://1day-zh.gluon.ai

总结

- GPUs
- 卷积，填充，步幅，池化
- 卷积神经网络 (LeNet)
- 深度卷积神经网络 (AlexNet)
- 使用重复元素 (VGG)
- 残差网络 (ResNet)