

ResNet详解

ResNet在2015年由微软实验室提出，斩获当年ImageNet竞赛中分类任务第一名，目标检测第一名。获得COCO数据集中目标检测第一名，图像分割第一名。（啥也别说了，就是NB）

Deep Residual Learning for Image Recognition

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网络中的亮点：

- 超深的网络结构(突破1000层)
- 提出residual模块
- 使用Batch Normalization加速训练(丢弃dropout)

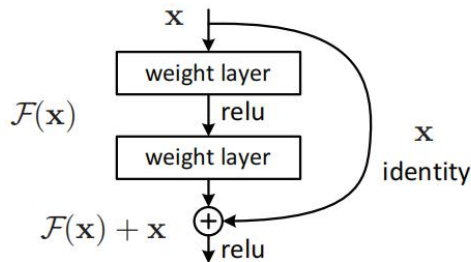
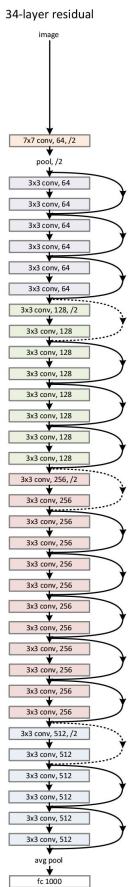
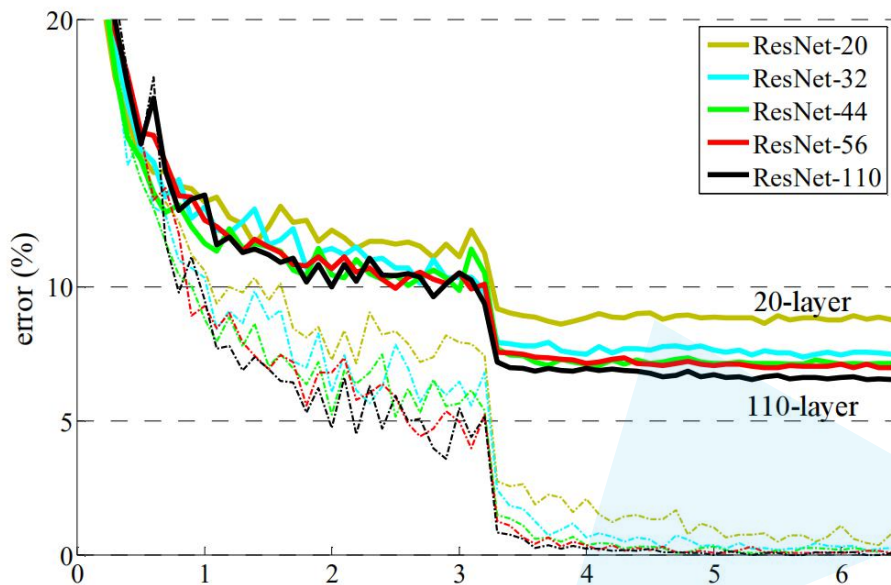
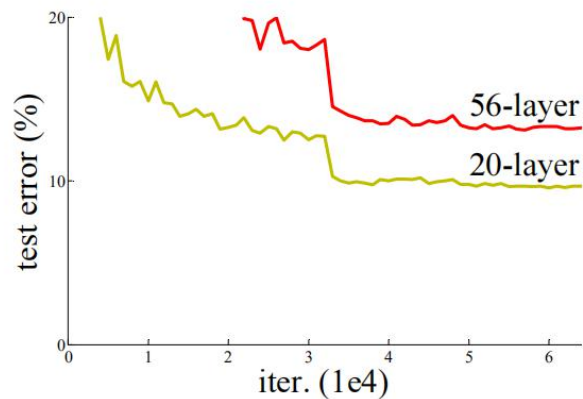
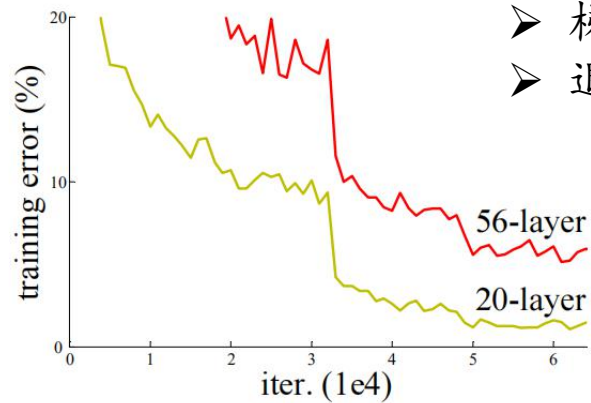


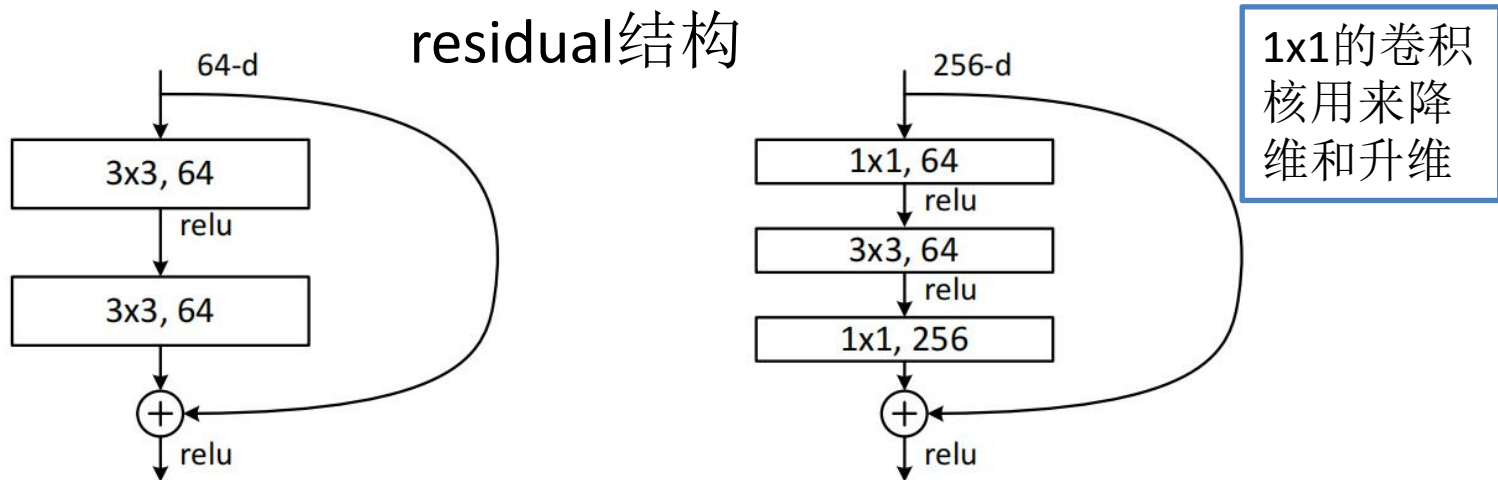
Figure 2. Residual learning: a building block.

ResNet详解

- 梯度消失或梯度爆炸
- 退化问题(degradation problem)



ResNet详解



$$3 \times 3 \times 256 \times 256 + 3 \times 3 \times 256 \times 256 = 1,179,648$$

$$1 \times 1 \times 256 \times 64 + 3 \times 3 \times 64 \times 64 + 1 \times 1 \times 64 \times 256 = 69,632$$

Figure 5. A deeper residual function \mathcal{F} for ImageNet. Left: a building block (on 56×56 feature maps) as in Fig. 3 for ResNet-34. Right: a “bottleneck” building block for ResNet-50/101/152.

注意：主分支与shortcut的输出特征矩阵shape必须相同

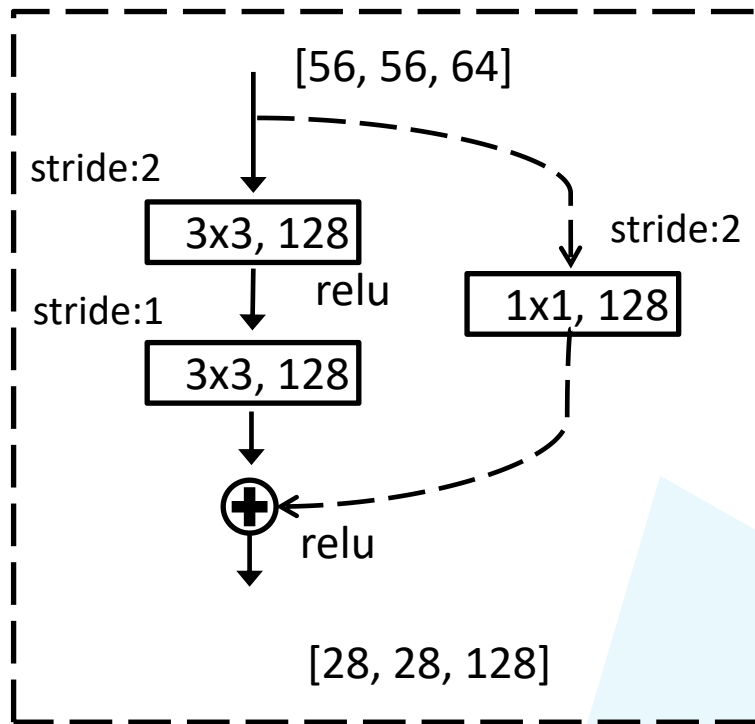
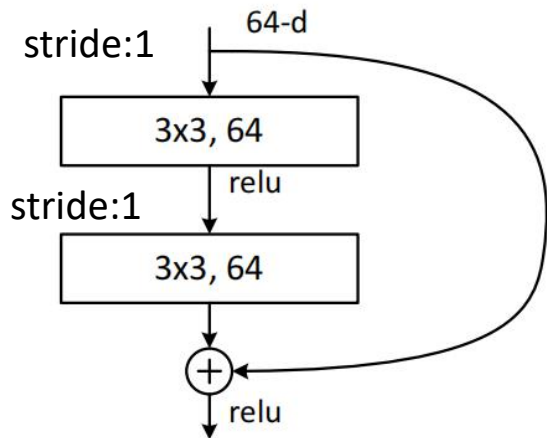
ResNet详解

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix} 3 \times 3, 64 \\ 3 \times 3, 64 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3, 64 \\ 3 \times 3, 64 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 64 \\ 3 \times 3, 64 \\ 1 \times 1, 256 \end{bmatrix} \times 3$
conv3_x	28×28	$\begin{bmatrix} 3 \times 3, 128 \\ 3 \times 3, 128 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3, 128 \\ 3 \times 3, 128 \end{bmatrix} \times 4$	$\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix} \times 4$	$\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix} \times 4$	$\begin{bmatrix} 1 \times 1, 128 \\ 3 \times 3, 128 \\ 1 \times 1, 512 \end{bmatrix} \times 8$
conv4_x	14×14	$\begin{bmatrix} 3 \times 3, 256 \\ 3 \times 3, 256 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3, 256 \\ 3 \times 3, 256 \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{bmatrix} \times 23$	$\begin{bmatrix} 1 \times 1, 256 \\ 3 \times 3, 256 \\ 1 \times 1, 1024 \end{bmatrix} \times 36$
conv5_x	7×7	$\begin{bmatrix} 3 \times 3, 512 \\ 3 \times 3, 512 \end{bmatrix} \times 2$	$\begin{bmatrix} 3 \times 3, 512 \\ 3 \times 3, 512 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} 1 \times 1, 512 \\ 3 \times 3, 512 \\ 1 \times 1, 2048 \end{bmatrix} \times 3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

Table 1. Architectures for ImageNet. Building blocks are shown in brackets (see also Fig. 5), with the numbers of blocks stacked. Down-sampling is performed by conv3_1, conv4_1, and conv5_1 with a stride of 2.

ResNet详解

residual结构

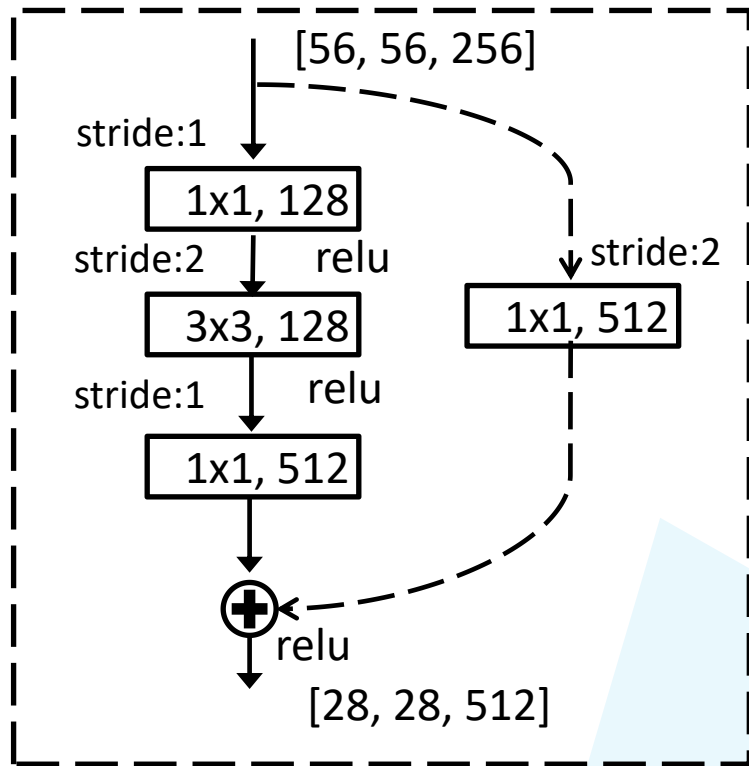
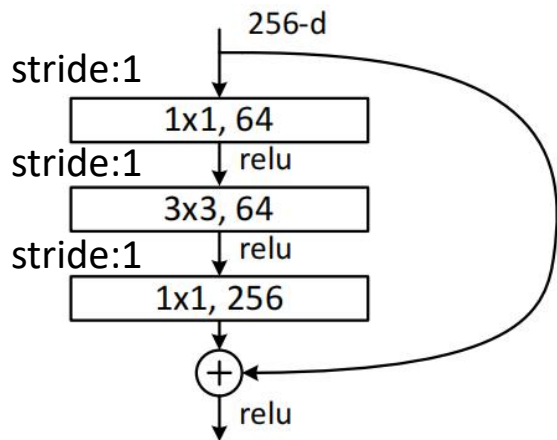


Option B

注意：主分支与shortcut的输出特征矩阵shape必须相同

ResNet详解

residual结构



Option B

注意：主分支与shortcut的输出特征矩阵shape必须相同

Batch Normalization详解

Batch Normalization

Batch Normalization的目的是使我们的一批（Batch）feature map满足均值为0，方差为1的分布规律。

μ σ^2 在正向传播过程中统计得到

γ β 在反向传播过程中训练得到

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_1 \dots x_m\}$;
Parameters to be learned: γ, β

Output: $\{y_i = \text{BN}_{\gamma, \beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m} \sum_{i=1}^m x_i \quad // \text{ mini-batch mean}$$

$$\sigma_{\mathcal{B}}^2 \leftarrow \frac{1}{m} \sum_{i=1}^m (x_i - \mu_{\mathcal{B}})^2 \quad // \text{ mini-batch variance}$$

$$\hat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} \quad // \text{ normalize}$$

$$y_i \leftarrow \gamma \hat{x}_i + \beta \equiv \text{BN}_{\gamma, \beta}(x_i) \quad // \text{ scale and shift}$$

Algorithm 1: Batch Normalizing Transform, applied to activation x over a mini-batch.

迁移学习简介

使用迁移学习的优势：

1. 能够快速训练出一个理想的结果
2. 当数据集较小时也能训练出理想的效果

弟弟，我来教你如何
辨别渣男和渣女，姐
我阅人无数

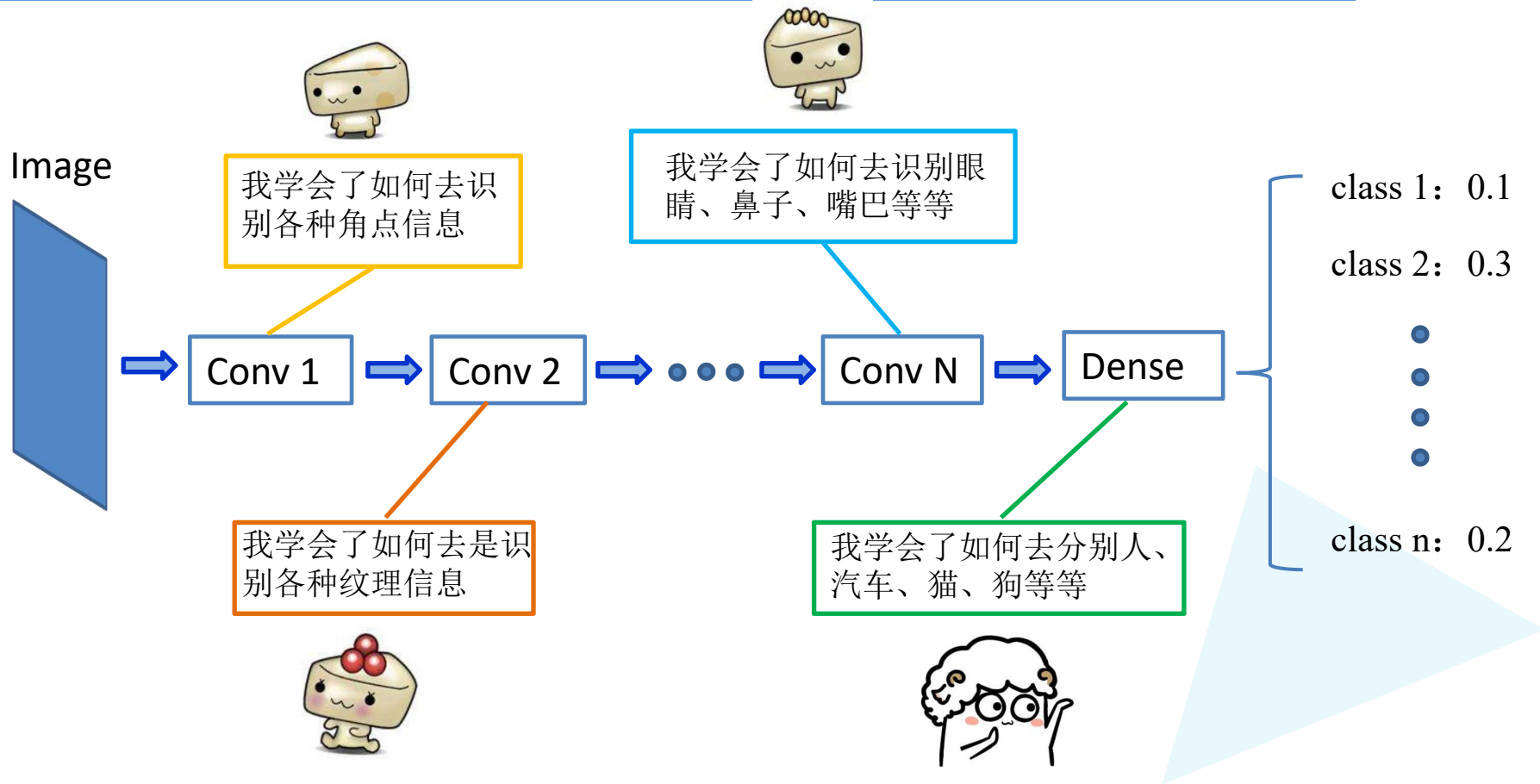


好呀，老姐，快快快
教我



注意：使用别人预训练模型参数时，要注意别人的预处理方式。

迁移学习简介



迁移学习简介

常见的迁移学习方式:

1. 载入权重后训练所有参数
2. 载入权重后只训练最后几层参数
3. 载入权重后在原网络基础上再添加一层全连接层，仅训练最后一个全连接层

