TensorFlow

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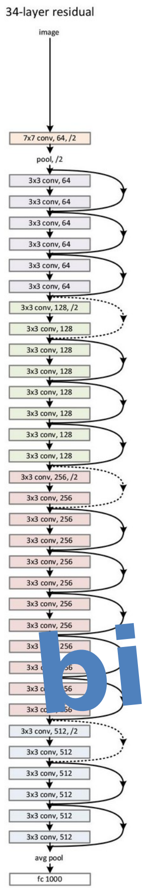
PYTORCH

深度学习 - 图像处理篇

作者：神秘的wz

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)

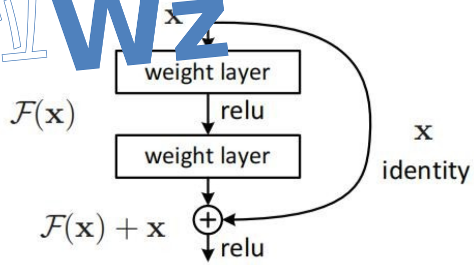
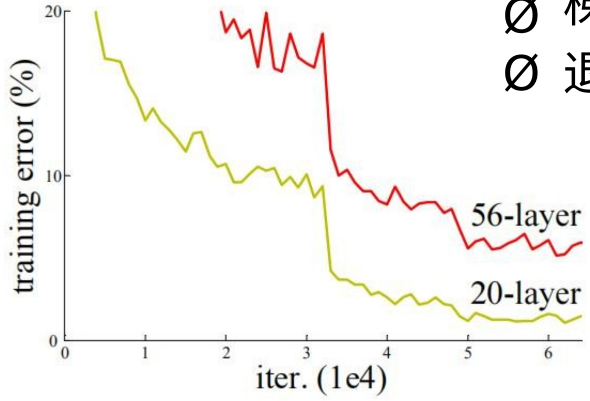
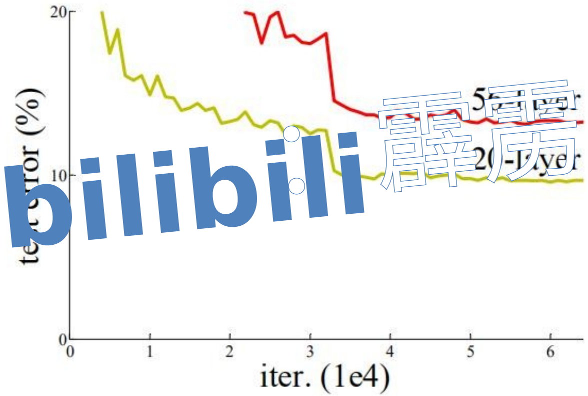


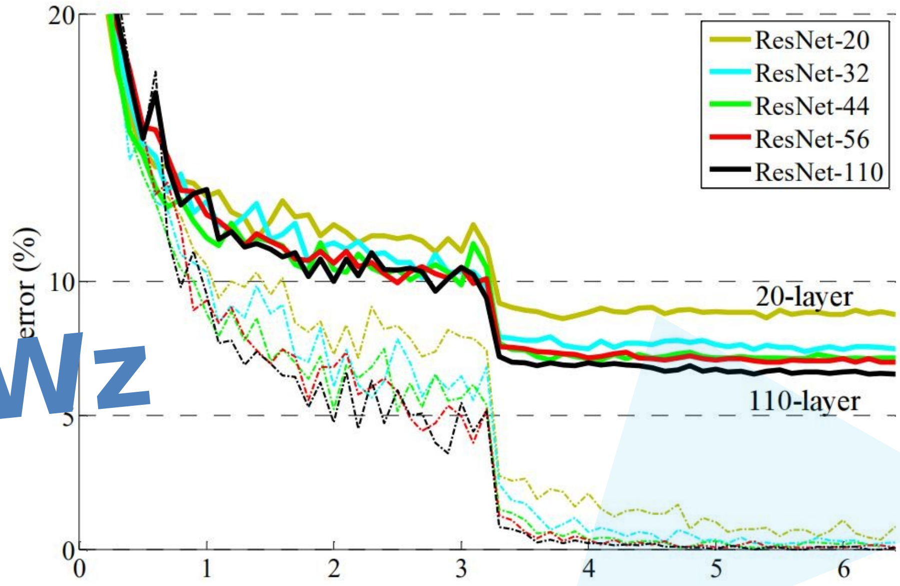
Figure 2. Residual learning: a building block.

ResNet 详解

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

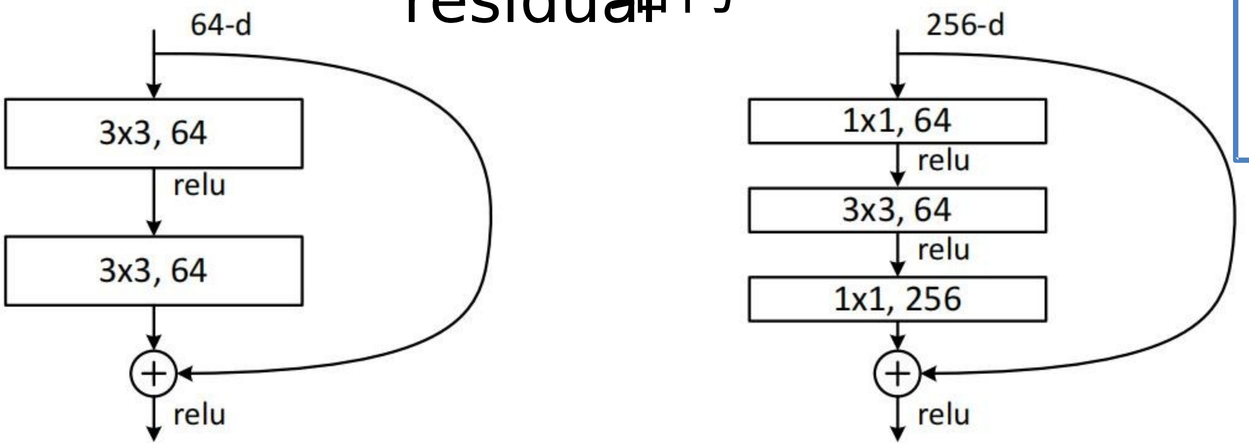






ResNet 详解

residual结构



1x1的卷积核用来降维和升维

3 3 256 256 3 3 256 256 1,179,648

1 1 256 64 3 3 64 64 1 1 64 256 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

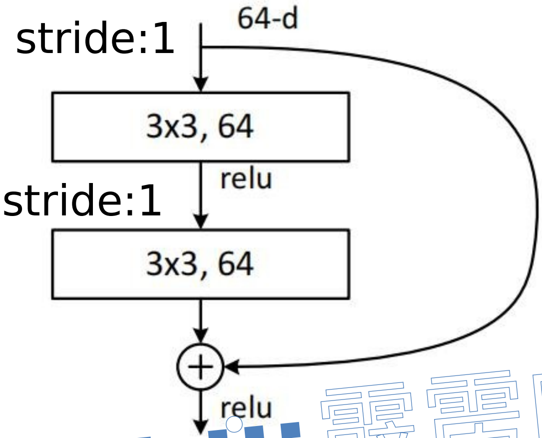
ResNet 详解

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				
		[3×3, 64 3×3, 64] ×2	[3×3, 64 3×3, 64] ×3	[1×1, 64 3×3, 64 1×1, 256] ×3	[1×1, 64 3×3, 64 1×1, 256] ×3	[1×1, 64 3×3, 64 1×1, 256] ×3
conv3_x	28×28	[3×3, 128 3×3, 128] ×2	[3×3, 128 3×3, 128] ×4	[1×1, 128 3×3, 128 1×1, 512] ×4	[1×1, 128 3×3, 128 1×1, 512] ×4	[1×1, 128 3×3, 128 1×1, 512] ×8
conv4_x	14×14	[3×3, 256 3×3, 256] ×2	[3×3, 256 3×3, 256] ×6	[1×1, 256 3×3, 256 1×1, 1024] ×6	[1×1, 256 3×3, 256 1×1, 1024] ×23	[1×1, 256 3×3, 256 1×1, 1024] ×36
conv5_x	7×7	[3×3, 512 3×3, 512] ×2	[3×3, 512 3×3, 512] ×3	[1×1, 512 3×3, 512 1×1, 2048] ×3	[1×1, 512 3×3, 512 1×1, 2048] ×3	[1×1, 512 3×3, 512 1×1, 2048] ×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

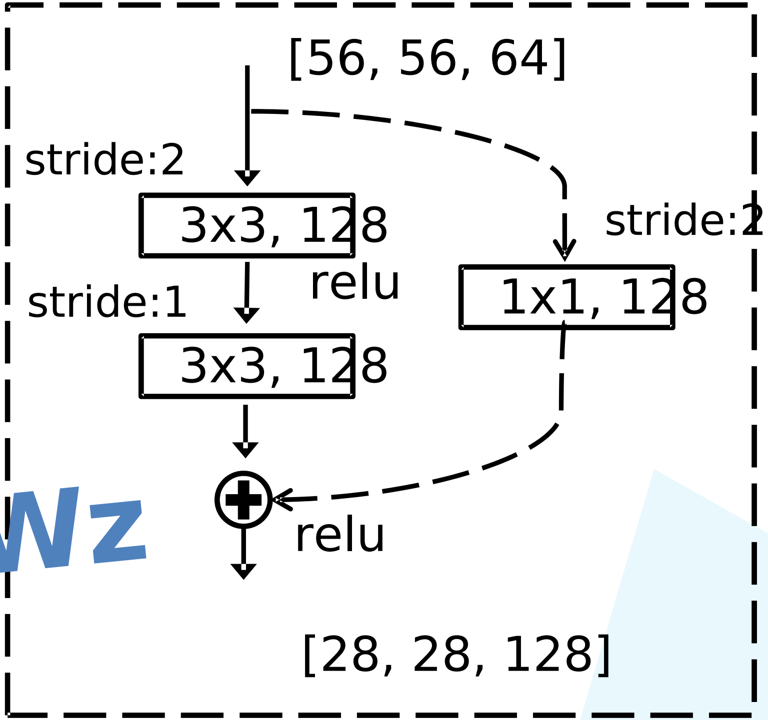
Table 1. Architectures for ImageNet. Building blocks are shown in brackets (see also Fig. 5), with the numbers of blocks stacked. Down-sampling is performed by conv3_1, conv4_1, and conv5_1 with a stride of 2.

ResNet 详解

residual结构



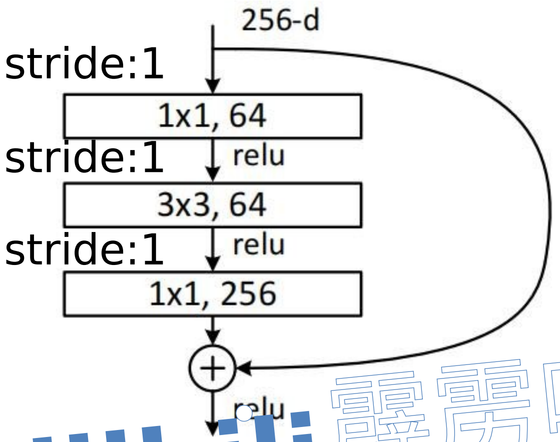
Option B

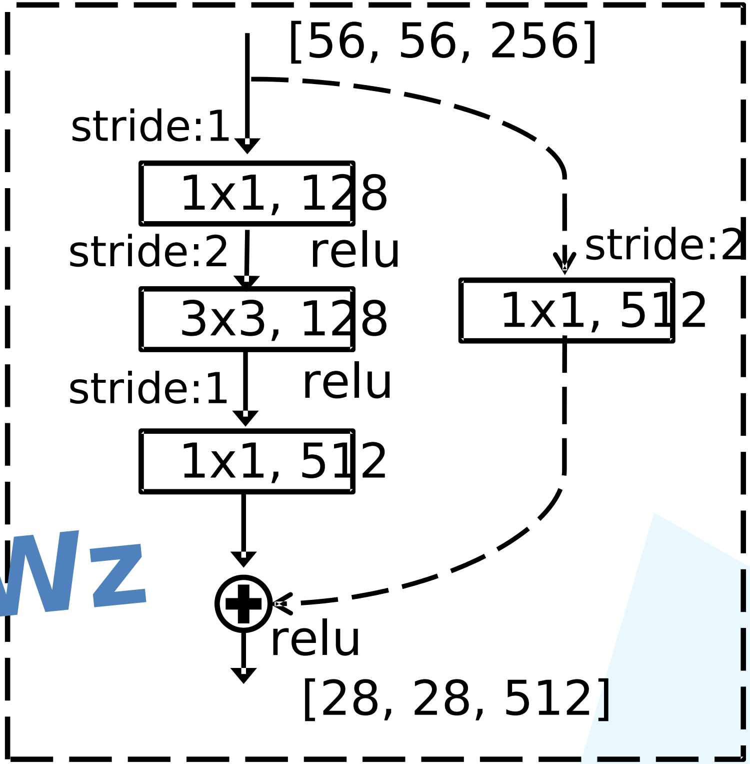


注意：主分支与**shortcut**的输出特征矩阵**shape**必须相同

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。

2 在正向传播过程中统计得到

在反向传播过程中训练得到

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;
Parameters to be learned: γ, β

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

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

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

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

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

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

https://blog.csdn.net/qq_37541097/article/details/104434557

迁移学习简介

使用迁移学习的优势：

1. 能够快速的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

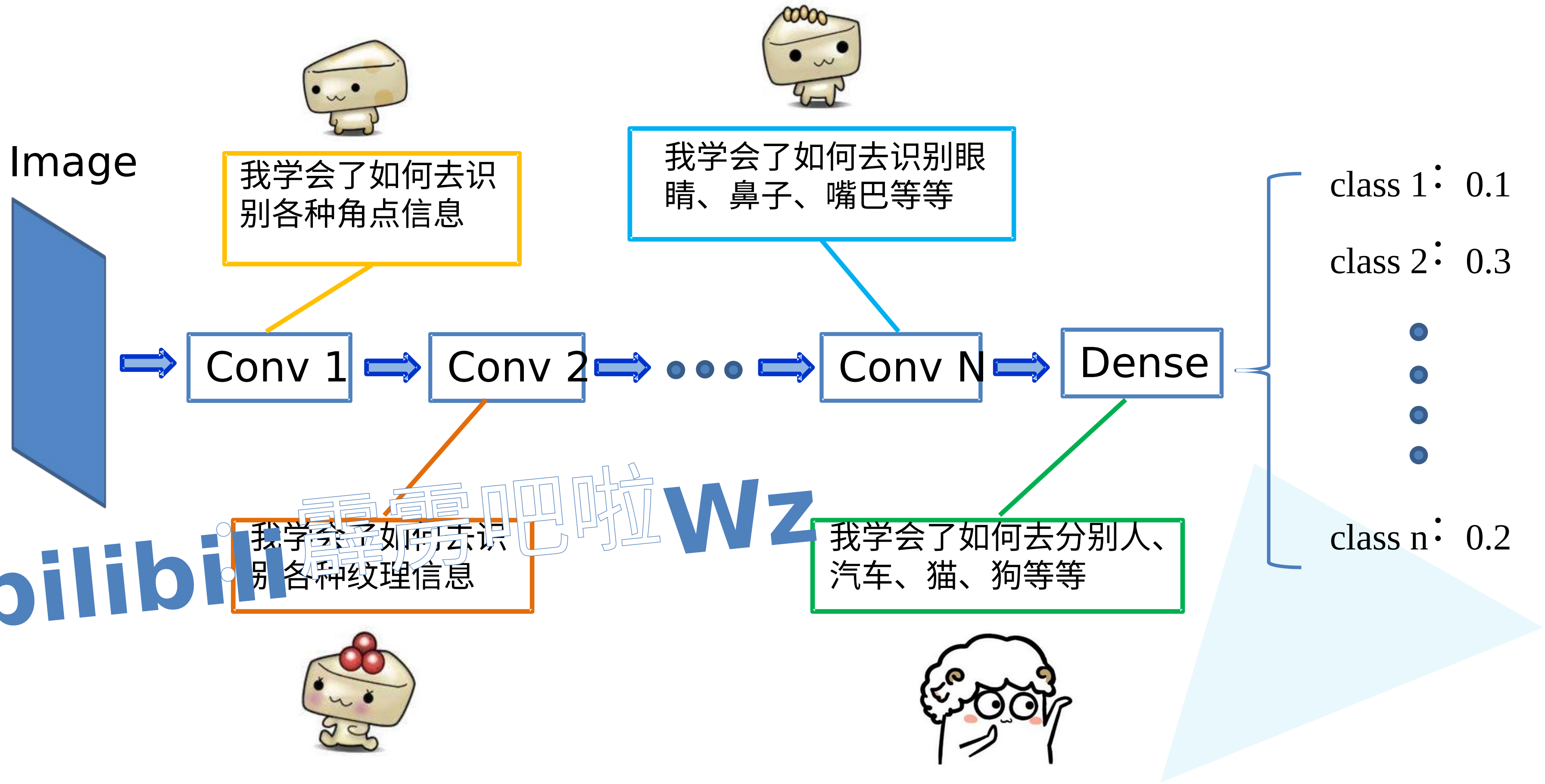
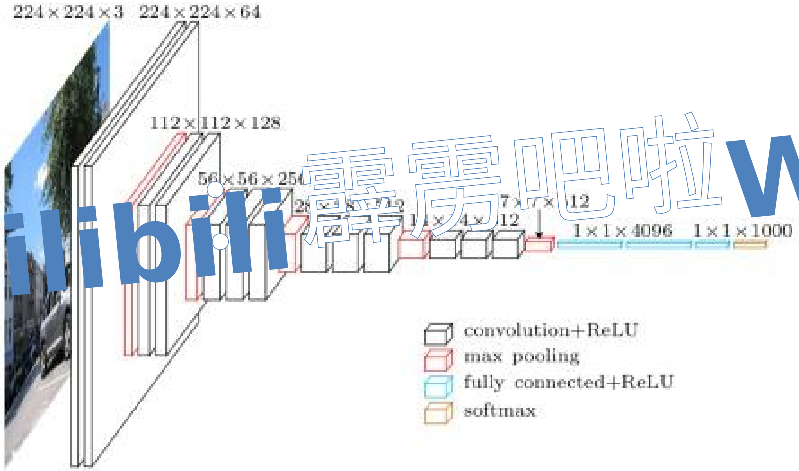


Image
我学会了如何去识别各种角点信息
我学会了如何去识别眼睛、鼻子、嘴巴等等
Conv 1
Conv 2
Conv N
Dense
class 1： 0.1
class 2： 0.3
class n： 0.2
我学会了如何去识别各种纹理信息
我学会了如何去分别人、汽车、猫、狗等等

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



沟通方式

1.github

https://github.com/WZMIAOMIAO/deep-learning-for-image-processing

2.CSDN

https://blog.csdn.net/qq_37541097/article/details/103482003

3.bilibili

https://space.bilibili.com/18161609/channel/index

尽可能每周更新

感谢各位的观看！