Deep Residual Learning for Image Recognition

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优点：RestNet更容易优化，准确度随深度提升，误差率低，且具有较低的复杂性。
适应不同种类型数据集，具有泛化性。

Abstract

Deeper neural networks are more difficult to train. We present a residual learning framework to ease the training of networks that are substantially deeper than those used previously. We explicitly reformulate the layers as learning residual functions with reference to the layer inputs, instead of learning unreferenced functions. We provide comprehensive empirical evidence showing that these residual networks are easier to optimize, and can gain accuracy from considerably increased depth. On the ImageNet dataset we evaluate residual nets with a depth of up to 152 layers—8× deeper than VGG nets [40] but still having lower complexity. An ensemble of these residual nets achieves 3.57% error on the ImageNet test *set. This result won the 1st place on the ILSVRC 2015 classification task. We also present analysis on CIFAR-10 with 100 and 1000 layers.*

The depth of representations is of central importance for many visual recognition tasks. Solely due to our extremely deep representations, we obtain a 28% relative improvement on the COCO object detection dataset. Deep residual nets are foundations of our submissions to ILSVRC & COCO 2015 competitions[1], where we also won the 1st places on the tasks of ImageNet detection, ImageNet localization, COCO detection, and COCO segmentation.

1. Introduction

Deep convolutional neural networks [22, 21] have led to a series of breakthroughs for image classification [21, 49, 39]. Deep networks naturally integrate low/mid/high-level features [49] and classifiers in an end-to-end multi-layer fashion, and the "levels" of features can be enriched by the number of stacked layers (depth). Recent evidence [40, 43] reveals that network depth is of crucial importance, and the leading results [40, 43, 12, 16] on the challenging ImageNet dataset [35] all exploit "very deep" [40] models, with a depth of sixteen [40] to thirty [16]. Many other non-trivial visual recognition tasks [7, 11, 6, 32, 27] have also greatly benefited from very deep models.

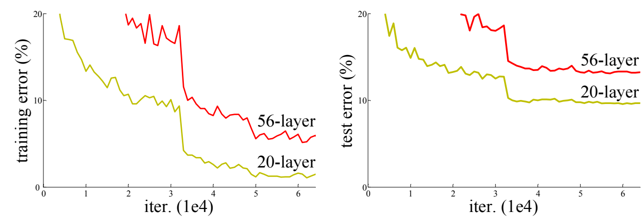

Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer "plain" networks. The deeper network has higher training error, and thus test error. Similar phenomena on ImageNet is presented in Fig. 4.

CIFAR-10数据集，训练集误差（左），测试集误差（右）。20层/56层普通网络，越深的网络错误率越高，imagenet数据集也是这样。

Driven by the significance of depth, a question arises: *Is learning better networks as easy as stacking more layers?* An obstacle to answering this question was the notorious problem of vanishing/exploding gradients [14, 1, 8], which hamper convergence from the beginning. This problem, however, has been largely addressed by normalized initialization [23, 8, 36, 12] and intermediate normalization layers [16], which enable networks with tens of layers to start converging for stochastic gradient descent (SGD) with back-propagation [22].

本间面对的退化问题：随着网络深度的增加，精度会饱和，然后迅速退化。且并不是由过拟合引起的。

关于梯度爆炸：它从一开始就阻碍了收敛，但很大程度上可以通过标准初始化和正则化来解决（SGD+反向传播）

When deeper networks are able to start converging, a *degradation* problem has been exposed: with the network depth increasing, accuracy gets saturated (which might be unsurprising) and then degrades rapidly. Unexpectedly, such degradation is *not caused by overfitting*, and adding more layers to a suitably deep model leads to *higher training error*, as reported in [10, 41] and thoroughly verified by our experiments. Fig. 1 shows a typical example.

The degradation (of training accuracy) indicates that not all systems are similarly easy to optimize. Let us consider a shallower architecture and its deeper counterpart that adds more layers onto it. There exists a solution *by construction* to the deeper model: the added layers are *identity* mapping, and the other layers are copied from the learned shallower model. The existence of this constructed solution indicates that a deeper model should produce no higher training error than its shallower counterpart. But experiments show that our current solvers on hand are unable to find solutions that

但是理论上说，添加的层是自身映射，其他层从是训练好的浅模型中复制而来。理论上网络越深不会导致训练误差越高，所以必有方法解决

[1] http://image-net.org/challenges/LSVRC/2015/ and http://mscoco.org/dataset/#detections-challenge2015.

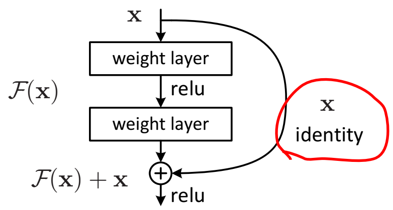

Figure 2. Residual learning: a building block.

改为让一些层去吻合残差映射。用H(X)来表示最优解映射，但我们让堆叠的非线性层去拟合另一个映射F(X)=H(X) - X, 原始映射被重新转换为F(x)+x。把残差推至0和把此映射逼近另一个非线性层相比要容易的多。

are comparably good or better than the constructed solution (or unable to do so in feasible time).

In this paper, we address the degradation problem by introducing a *deep residual learning* framework. Instead of hoping each few stacked layers directly fit a desired underlying mapping, we explicitly let these layers fit a residual mapping. Formally, denoting the desired underlying mapping as $\mathcal{H}(\mathbf{x})$, we let the stacked nonlinear layers fit another mapping of $\mathcal{F}(\mathbf{x}) := \mathcal{H}(\mathbf{x}) - \mathbf{x}$. The original mapping is recast into $\mathcal{F}(\mathbf{x}) + \mathbf{x}$. We hypothesize that it is easier to optimize the residual mapping than to optimize the original, unreferenced mapping. To the extreme, if an identity mapping were optimal, it would be easier to push the residual to zero than to fit an identity mapping by a stack of nonlinear layers.

F(x)+ x的公式可以通过具有快捷连接的前馈神经网络来实现，快捷连接跳过一个或多个层。且不增加参数和复杂性。

The formulation of $\mathcal{F}(\mathbf{x}) + \mathbf{x}$ can be realized by feedforward neural networks with "shortcut connections" (Fig. 2). Shortcut connections [2, 33, 48] are those skipping one or more layers. In our case, the shortcut connections simply perform *identity* mapping, and their outputs are added to the outputs of the stacked layers (Fig. 2). Identity shortcut connections add neither extra parameter nor computational complexity. The entire network can still be trained end-to-end by SGD with backpropagation, and can be easily implemented using common libraries (*e.g.*, Caffe [19]) without modifying the solvers.

We present comprehensive experiments on ImageNet [35] to show the degradation problem and evaluate our method. We show that: 1) Our extremely deep residual nets are easy to optimize, but the counterpart "plain" nets (that simply stack layers) exhibit higher training error when the depth increases; 2) Our deep residual nets can easily enjoy accuracy gains from greatly increased depth, producing results substantially better than previous networks.

Similar phenomena are also shown on the CIFAR-10 set [20], suggesting that the optimization difficulties and the effects of our method are not just akin to a particular dataset. We present successfully trained models on this dataset with over 100 layers, and explore models with over 1000 layers.

On the ImageNet classification dataset [35], we obtain excellent results by extremely deep residual nets. Our 152-layer residual net is the deepest network ever presented on ImageNet, while still having lower complexity than VGG nets [40]. Our ensemble has **3.57%** top-5 error on the ImageNet *test* set, and *won the 1st place in the ILSVRC 2015 classification competition*. The extremely deep representations also have excellent generalization performance on other recognition tasks, and lead us to further *win the 1st places on: ImageNet detection, ImageNet localization, COCO detection, and COCO segmentation* in ILSVRC & COCO 2015 competitions. This strong evidence shows that the residual learning principle is generic, and we expect that it is applicable in other vision and non-vision problems.

2. Related Work

Residual Representations. In image recognition, VLAD [18] is a representation that encodes by the residual vectors with respect to a dictionary, and Fisher Vector [30] can be formulated as a probabilistic version [18] of VLAD. Both of them are powerful shallow representations for image retrieval and classification [4, 47]. For vector quantization, encoding residual vectors [17] is shown to be more effective than encoding original vectors.

In low-level vision and computer graphics, for solving Partial Differential Equations (PDEs), the widely used Multigrid method [3] reformulates the system as subproblems at multiple scales, where each subproblem is responsible for the residual solution between a coarser and a finer scale. An alternative to Multigrid is hierarchical basis preconditioning [44, 45], which relies on variables that represent residual vectors between two scales. It has been shown [3, 44, 45] that these solvers converge much faster than standard solvers that are unaware of the residual nature of the solutions. These methods suggest that a good reformulation or preconditioning can simplify the optimization.

在[3,44,45]中证明了这些用了残差的解法收敛速度都比不用残差的普通解法要快的多。这些研究表明，一个好的模型重构或者预处理手段是能简化优化过程的。

Shortcut Connections. Practices and theories that lead to shortcut connections [2, 33, 48] have been studied for a long time. An early practice of training multi-layer perceptrons (MLPs) is to add a linear layer connected from the network input to the output [33, 48]. In [43, 24], a few intermediate layers are directly connected to auxiliary classifiers for addressing vanishing/exploding gradients. The papers of [38, 37, 31, 46] propose methods for centering layer responses, gradients, and propagated errors, implemented by shortcut connections. In [43], an "inception" layer is composed of a shortcut branch and a few deeper branches.

早期快捷连接：添加一个线性层（从网络的输入直连到输出[33,48]），在[43,24]中提到，少量中间层被直接连到附加的分类层解决梯度消失/爆炸问题

Concurrent with our work, "highway networks" [41, 42] present shortcut connections with gating functions [15]. These gates are data-dependent and have parameters, in contrast to our identity shortcuts that are parameter-free. When a gated shortcut is "closed" (approaching zero), the layers in highway networks represent *non-residual* functions. On the contrary, our formulation always learns residual functions; our identity shortcuts are never closed, and all information is always passed through, with additional residual functions to be learned. In addition, high-

对比[41,42]提出的高速公路网络，本论文快捷连接（恒等捷径）1无参数的。总是学习残差方程，2快捷连接是永不关闭的，借此学习残差函数。3多出精度随深度增加的特性（比如超过100层后）。

优点：针对ImageNet的数据集
1.残差网络很容易习得映射关系，因而比普通深层网络更容易训练。
2.深度增加精度也可增加，效果良好。CIFAR-10数据集，超过100层的网络表现很成功，还可以扩展到1000层。
3.ImageNet对象分类数据集比赛，152层的残差网络参赛网络中最深的，然而却拥有比VGG更低的复杂度。3.57%的错误率，第一名。
4.在其他识别任务中也有良好的泛化能力，多个比赛的第一名（有ImageNet detection, Imagenet localization,COCOdetection COCOsegmentation），证明残差学习的原则是可泛化的。

way networks have not demonstrated accuracy gains with extremely increased depth (*e.g.*, over 100 layers).

3. Deep Residual Learning

3.1. Residual Learning

Let us consider $\mathcal{H}(\mathbf{x})$ as an underlying mapping to be fit by a few stacked layers (not necessarily the entire net), with $\mathbf{x}$ denoting the inputs to the first of these layers. If one hypothesizes that multiple nonlinear layers can asymptotically approximate complicated functions[2], then it is equivalent to hypothesize that they can asymptotically approximate the residual functions, *i.e.*, $\mathcal{H}(\mathbf{x}) - \mathbf{x}$ (assuming that the input and output are of the same dimensions). So rather than expect stacked layers to approximate $\mathcal{H}(\mathbf{x})$, we explicitly let these layers approximate a residual function $\mathcal{F}(\mathbf{x}) := \mathcal{H}(\mathbf{x}) - \mathbf{x}$. The original function thus becomes $\mathcal{F}(\mathbf{x})+\mathbf{x}$. Although both forms should be able to asymptotically approximate the desired functions (as hypothesized), the ease of learning might be different.

动机源于退化问题(图1，左)。如果添加的层可以构造为恒等映射，那么较深的模型的训练误差应该不大于较浅的模型。

通过残差学习重构，如果恒等映射是最优的，求解器可以简单地将多个非线性层的权值趋近于零来逼近恒等映射。

This reformulation is motivated by the counterintuitive phenomena about the degradation problem (Fig. 1, left). As we discussed in the introduction, if the added layers can be constructed as identity mappings, a deeper model should have training error no greater than its shallower counterpart. The degradation problem suggests that the solvers might have difficulties in approximating identity mappings by multiple nonlinear layers. With the residual learning reformulation, if identity mappings are optimal, the solvers may simply drive the weights of the multiple nonlinear layers toward zero to approach identity mappings.

In real cases, it is unlikely that identity mappings are optimal, but our reformulation may help to precondition the problem. If the optimal function is closer to an identity mapping than to a zero mapping, it should be easier for the solver to find the perturbations with reference to an identity mapping, than to learn the function as a new one. We show by experiments (Fig. 7) that the learned residual functions in general have small responses, suggesting that identity mappings provide reasonable preconditioning.

3.2. Identity Mapping by Shortcuts

We adopt residual learning to every few stacked layers. A building block is shown in Fig. 2. Formally, in this paper we consider a building block defined as:

$$\mathbf{y} = \mathcal{F}(\mathbf{x}, \{W_i\}) + \mathbf{x}. \tag{1}$$

Here $\mathbf{x}$ and $\mathbf{y}$ are the input and output vectors of the layers considered. The function $\mathcal{F}(\mathbf{x}, \{W_i\})$ represents the residual mapping to be learned. For the example in Fig. 2 that has two layers, $\mathcal{F} = W_2\sigma(W_1\mathbf{x})$ in which σ denotes ReLU [29] and the biases are omitted for simplifying notations. The operation $\mathcal{F} + \mathbf{x}$ is performed by a shortcut connection and element-wise addition. We adopt the second nonlinearity after the addition (*i.e.*, $\sigma(\mathbf{y})$, see Fig. 2).

快捷连接不引入额外的参数和复杂度。不仅在实践中很有吸引力，而且方便比较纯网络和残差网络，同时具有相同数量的参数、深度、宽度和计算成本(可忽略的元素相加除外)。

The shortcut connections in Eqn.(1) introduce neither extra parameter nor computation complexity. This is not only attractive in practice but also important in our comparisons between plain and residual networks. We can fairly compare plain/residual networks that simultaneously have the same number of parameters, depth, width, and computational cost (except for the negligible element-wise addition).

The dimensions of $\mathbf{x}$ and $\mathcal{F}$ must be equal in Eqn.(1). If this is not the case (*e.g.*, when changing the input/output channels), we can perform a linear projection W_s by the shortcut connections to match the dimensions:

匹配维度

$$\mathbf{y} = \mathcal{F}(\mathbf{x}, \{W_i\}) + W_s\mathbf{x}. \tag{2}$$

We can also use a square matrix W_s in Eqn.(1). But we will show by experiments that the identity mapping is sufficient for addressing the degradation problem and is economical, and thus W_s is only used when matching dimensions.

The form of the residual function $\mathcal{F}$ is flexible. Experiments in this paper involve a function $\mathcal{F}$ that has two or three layers (Fig. 5), while more layers are possible. But if $\mathcal{F}$ has only a single layer, Eqn.(1) is similar to a linear layer: $\mathbf{y} = W_1\mathbf{x} + \mathbf{x}$, for which we have not observed advantages.

只有一个层（公式1）等价：y = W1x + x，无优势。

We also note that although the above notations are about fully-connected layers for simplicity, they are applicable to convolutional layers. The function $\mathcal{F}(\mathbf{x}, \{W_i\})$ can represent multiple convolutional layers. The element-wise addition is performed on two feature maps, channel by channel.

3.3. Network Architectures

We have tested various plain/residual nets, and have observed consistent phenomena. To provide instances for discussion, we describe two models for ImageNet as follows.

设计：
1.对于相同的尺寸的输出特征图谱，每层必须含有相同数量的过滤器。
2.如果特征图谱的尺寸减半，则过滤器的数量必须翻倍，以保持每层的时间复杂度。
3.卷积层（stride=2）进行下采样，网络末端以全局的均值池化层结束，1000的全连接层（Softmax激活）。共34层（见图3中）。
计算量远小于VGG

Plain Network. Our plain baselines (Fig. 3, middle) are mainly inspired by the philosophy of VGG nets [40] (Fig. 3, left). The convolutional layers mostly have 3×3 filters and follow two simple design rules: (i) for the same output feature map size, the layers have the same number of filters; and (ii) if the feature map size is halved, the number of filters is doubled so as to preserve the time complexity per layer. We perform downsampling directly by convolutional layers that have a stride of 2. The network ends with a global average pooling layer and a 1000-way fully-connected layer with softmax. The total number of weighted layers is 34 in Fig. 3 (middle).

It is worth noticing that our model has *fewer* filters and *lower* complexity than VGG nets [40] (Fig. 3, left). Our 34-layer baseline has 3.6 billion FLOPs (multiply-adds), which is only 18% of VGG-19 (19.6 billion FLOPs).

[2]This hypothesis, however, is still an open question. See [28].

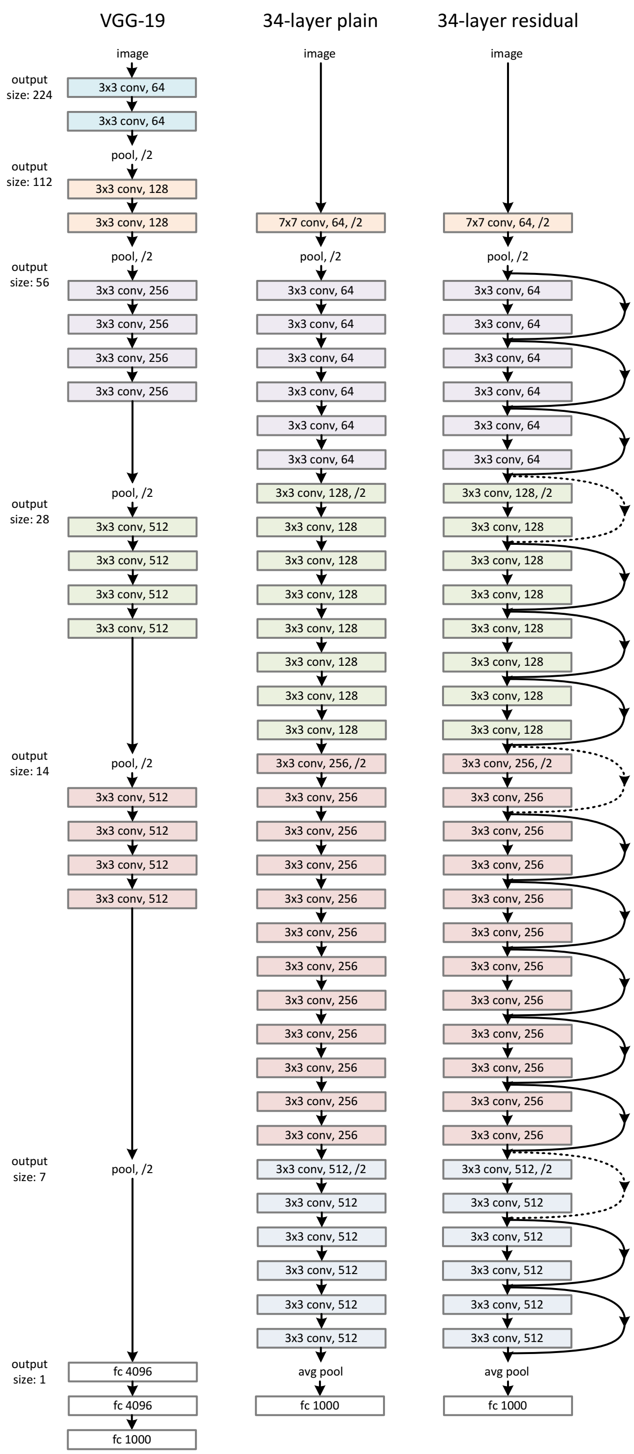

Figure 3. Example network architectures for ImageNet. **Left**: the VGG-19 model [40] (19.6 billion FLOPs) as a reference. **Middle**: a plain network with 34 parameter layers (3.6 billion FLOPs). **Right**: a residual network with 34 parameter layers (3.6 billion FLOPs). The dotted shortcuts increase dimensions. **Table 1** shows more details and other variants.

Residual Network. Based on the above plain network, we insert shortcut connections (Fig. 3, right) which turn the network into its counterpart residual version. The identity shortcuts (Eqn.(1)) can be directly used when the input and output are of the same dimensions (solid line shortcuts in Fig. 3). When the dimensions increase (dotted line shortcuts in Fig. 3), we consider two options: (A) The shortcut still performs identity mapping, with extra zero entries padded for increasing dimensions. This option introduces no extra parameter; (B) The projection shortcut in Eqn.(2) is used to match dimensions (done by 1×1 convolutions). For both options, when the shortcuts go across feature maps of two sizes, they are performed with a stride of 2.

设计：
基于普通网络，插入快捷连接。虚线的快捷连接尺寸变化处理：
a快捷连接仍然使用identity mapping，对于维度的增加用零来填补空缺。不引入额外的参数
b.projection shortcut（公式2）被用来匹配尺寸（1×1卷积）
大小不同图谱用stride=2来处理。

3.4. Implementation

Our implementation for ImageNet follows the practice in [21, 40]. The image is resized with its shorter side randomly sampled in $[256, 480]$ for scale augmentation [40]. A 224×224 crop is randomly sampled from an image or its horizontal flip, with the per-pixel mean subtracted [21]. The standard color augmentation in [21] is used. We adopt batch normalization (BN) [16] right after each convolution and before activation, following [16]. We initialize the weights as in [12] and train all plain/residual nets from scratch. We use SGD with a mini-batch size of 256. The learning rate starts from 0.1 and is divided by 10 when the error plateaus, and the models are trained for up to 60×10^4 iterations. We use a weight decay of 0.0001 and a momentum of 0.9. We do not use dropout [13], following the practice in [16].

基于ImageNet，图片被根据短边等比缩放，按照[256,480]区间的尺寸随机采样进行尺度增强。一个224x224的裁切是随机抽样的图像或其水平翻转，并将裁剪结果减去它的平均像素值，标准颜色的增强。批量正则化用在了每个卷积层和激活层之间，初始化权重为0。

In testing, for comparison studies we adopt the standard 10-crop testing [21]. For best results, we adopt the fully-convolutional form as in [40, 12], and average the scores at multiple scales (images are resized such that the shorter side is in $\{224, 256, 384, 480, 640\}$).

4. Experiments

4.1. ImageNet Classification

We evaluate our method on the ImageNet 2012 classification dataset [35] that consists of 1000 classes. The models are trained on the 1.28 million training images, and evaluated on the 50k validation images. We also obtain a final result on the 100k test images, reported by the test server. We evaluate both top-1 and top-5 error rates.

1000个类的ImageNet 2012分类数据集。训练集：128万；测试集50k

Plain Networks. We first evaluate 18-layer and 34-layer plain nets. The 34-layer plain net is in Fig. 3 (middle). The 18-layer plain net is of a similar form. See Table 1 for detailed architectures.

The results in Table 2 show that the deeper 34-layer plain net has higher validation error than the shallower 18-layer plain net. To reveal the reasons, in Fig. 4 (left) we compare their training/validation errors during the training procedure. We have observed the degradation problem - the

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				
		$\begin{bmatrix}3\times3, 64\\3\times3, 64\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 64\\3\times3, 64\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 64\\3\times3, 64\\1\times1, 256\end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix}3\times3, 128\\3\times3, 128\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 128\\3\times3, 128\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times4$	$\begin{bmatrix}1\times1, 128\\3\times3, 128\\1\times1, 512\end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix}3\times3, 256\\3\times3, 256\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 256\\3\times3, 256\end{bmatrix}\times6$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times6$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times23$	$\begin{bmatrix}1\times1, 256\\3\times3, 256\\1\times1, 1024\end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix}3\times3, 512\\3\times3, 512\end{bmatrix}\times2$	$\begin{bmatrix}3\times3, 512\\3\times3, 512\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$	$\begin{bmatrix}1\times1, 512\\3\times3, 512\\1\times1, 2048\end{bmatrix}\times3$
	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. Downsampling is performed by conv3_1, conv4_1, and conv5_1 with a stride of 2.

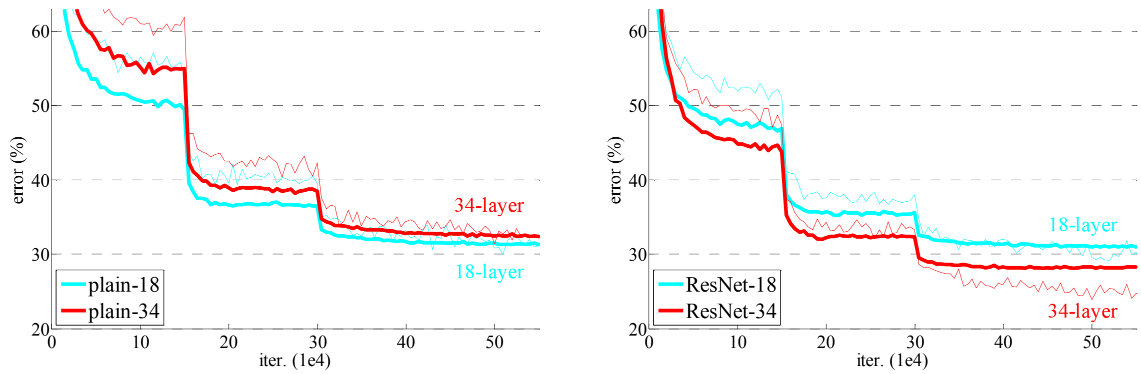

Figure 4. Training on **ImageNet**. Thin curves denote training error, and bold curves denote validation error of the center crops. Left: plain networks of 18 and 34 layers. Right: ResNets of 18 and 34 layers. In this plot, the residual networks have no extra parameter compared to their plain counterparts. 图4：Imagenet的训练，细的曲线表示训练集误差，粗的曲线表示验证集误差。左：普通网络（18/34层），右：残差网络（18/34层）

	plain	ResNet
18 layers	27.94	27.88
34 layers	28.54	**25.03**

Table 2. Top-1 error (%, 10-crop testing) on ImageNet validation. Here the ResNets have no extra parameter compared to their plain counterparts. Fig. 4 shows the training procedures.

34-layer plain net has higher *training* error throughout the whole training procedure, even though the solution space of the 18-layer plain network is a subspace of that of the 34-layer one.

We argue that this optimization difficulty is *unlikely* to be caused by vanishing gradients. These plain networks are trained with BN [16], which ensures forward propagated signals to have non-zero variances. We also verify that the backward propagated gradients exhibit healthy norms with BN. So neither forward nor backward signals vanish. In fact, the 34-layer plain net is still able to achieve competitive accuracy (Table 3), suggesting that the solver works to some extent. We conjecture that the deep plain nets may have exponentially low convergence rates, which impact the reducing of the training error[3]. The reason for such optimization difficulties will be studied in the future.

原因尚不明了，深的普通网络可能指数级的降低的收敛速度，训练误差的降低产生影响。

Residual Networks. Next we evaluate 18-layer and 34-layer residual nets (*ResNets*). The baseline architectures are the same as the above plain nets, expect that a shortcut connection is added to each pair of 3×3 filters as in Fig. 3 (right). In the first comparison (Table 2 and Fig. 4 right), we use identity mapping for all shortcuts and zero-padding for increasing dimensions (option A). So they have *no extra parameter* compared to the plain counterparts.

所有的短连接使用恒等映射，对增加的维度使用零填充(选项A)。

We have three major observations from Table 2 and Fig. 4. First, the situation is reversed with residual learning – the 34-layer ResNet is better than the 18-layer ResNet (by 2.8%). More importantly, the 34-layer ResNet exhibits considerably lower training error and is generalizable to the validation data. This indicates that the degradation problem is well addressed in this setting and we manage to obtain accuracy gains from increased depth.

结果对比：
1.消除退化问题，并且可推广到验证数据。
2.对比普通网络，34层ResNet将错误降低了3.5，验证了在深度网络上残差学习的有效性。
3.收敛更快，ResNet在早期提供更快的收敛速度。

Second, compared to its plain counterpart, the 34-layer

[3] We have experimented with more training iterations (3×) and still observed the degradation problem, suggesting that this problem cannot be feasibly addressed by simply using more iterations.

model	top-1 err.	top-5 err.
VGG-16 [40]	28.07	9.33
GoogLeNet [43]	-	9.15
PReLU-net [12]	24.27	7.38
plain-34	28.54	10.02
ResNet-34 A	25.03	7.76
ResNet-34 B	24.52	7.46
ResNet-34 C	24.19	7.40
ResNet-50	22.85	6.71
ResNet-101	21.75	6.05
ResNet-152	**21.43**	**5.71**

Table 3. Error rates (%, **10-crop** testing) on ImageNet validation. VGG-16 is based on our test. ResNet-50/101/152 are of option B that only uses projections for increasing dimensions.

method	top-1 err.	top-5 err.
VGG [40] (ILSVRC'14)	-	8.43†
GoogLeNet [43] (ILSVRC'14)	-	7.89
VGG [40] (v5)	24.4	7.1
PReLU-net [12]	21.59	5.71
BN-inception [16]	21.99	5.81
ResNet-34 B	21.84	5.71
ResNet-34 C	21.53	5.60
ResNet-50	20.74	5.25
ResNet-101	19.87	4.60
ResNet-152	**19.38**	**4.49**

与其他最先进技术的比较。34层已经很好。深度增加后，152层top-5的验证错误率4.49%。结果优于所有以前的综合模型

Table 4. Error rates (%) of **single-model** results on the ImageNet validation set (except † reported on the test set).

method	top-5 err. (**test**)
VGG [40] (ILSVRC'14)	7.32
GoogLeNet [43] (ILSVRC'14)	6.66
VGG [40] (v5)	6.8
PReLU-net [12]	4.94
BN-inception [16]	4.82
ResNet (ILSVRC'15)	**3.57**

Table 5. Error rates (%) of **ensembles**. The top-5 error is on the test set of ImageNet and reported by the test server.

ResNet reduces the top-1 error by 3.5% (Table 2), resulting from the successfully reduced training error (Fig. 4 right *vs*. left). This comparison verifies the effectiveness of residual learning on extremely deep systems.

Last, we also note that the 18-layer plain/residual nets are comparably accurate (Table 2), but the 18-layer ResNet converges faster (Fig. 4 right *vs*. left). When the net is "not overly deep" (18 layers here), the current SGD solver is still able to find good solutions to the plain net. In this case, the ResNet eases the optimization by providing faster convergence at the early stage.

Identity *vs*. Projection Shortcuts. We have shown that

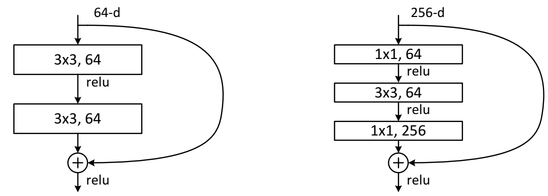

Figure 5. A deeper residual function $\mathcal{F}$ for ImageNet. Left: a building block (on 56×56 feature maps) as in Fig. 3 for ResNet-34. Right: a "bottleneck" building block for ResNet-50/101/152.

先用1x1降维，3x3进行卷积，再用1x1进行升维。

parameter-free, identity shortcuts help with training. Next we investigate projection shortcuts (Eqn.(2)). In Table 3 we compare three options: (A) zero-padding shortcuts are used for increasing dimensions, and all shortcuts are parameter-free (the same as Table 2 and Fig. 4 right); (B) projection shortcuts are used for increasing dimensions, and other shortcuts are identity; and (C) all shortcuts are projections.

Table 3 shows that all three options are considerably better than the plain counterpart. B is slightly better than A. We argue that this is because the zero-padded dimensions in A indeed have no residual learning. C is marginally better than B, and we attribute this to the extra parameters introduced by many (thirteen) projection shortcuts. But the small differences among A/B/C indicate that projection shortcuts are not essential for addressing the degradation problem. So we do not use option C in the rest of this paper, to reduce memory/time complexity and model sizes. Identity shortcuts are particularly important for not increasing the complexity of the bottleneck architectures that are introduced below.

表3，C>B>A，但采用B+深度瓶颈架构加快训练时间，如图5。152层的ResNet比VGG16/19 复杂度少得多

Deeper Bottleneck Architectures. Next we describe our deeper nets for ImageNet. Because of concerns on the training time that we can afford, we modify the building block as a *bottleneck* design[4]. For each residual function $\mathcal{F}$, we use a stack of 3 layers instead of 2 (Fig. 5). The three layers are 1×1, 3×3, and 1×1 convolutions, where the 1×1 layers are responsible for reducing and then increasing (restoring) dimensions, leaving the 3×3 layer a bottleneck with smaller input/output dimensions. Fig. 5 shows an example, where both designs have similar time complexity.

The parameter-free identity shortcuts are particularly important for the bottleneck architectures. If the identity shortcut in Fig. 5 (right) is replaced with projection, one can show that the time complexity and model size are doubled, as the shortcut is connected to the two high-dimensional ends. So identity shortcuts lead to more efficient models for the bottleneck designs.

50-layer ResNet: We replace each 2-layer block in the

[4]Deeper *non*-bottleneck ResNets (*e.g*., Fig. 5 left) also gain accuracy from increased depth (as shown on CIFAR-10), but are not as economical as the bottleneck ResNets. So the usage of bottleneck designs is mainly due to practical considerations. We further note that the degradation problem of plain nets is also witnessed for the bottleneck designs.

三种选择：
（A）zero-padding shortcuts对不足的特征维数直接进行补零。
（B）projection shortcuts利用1x1卷积核进行升降维。其他的shortcut都是恒等映射（identity）类型。
（C）所有的shortcut都是使用projection shortcuts。

34-layer net with this 3-layer bottleneck block, resulting in a 50-layer ResNet (Table 1). We use option B for increasing dimensions. This model has 3.8 billion FLOPs.

101-layer and 152-layer ResNets: We construct 101-layer and 152-layer ResNets by using more 3-layer blocks (Table 1). Remarkably, although the depth is significantly increased, the 152-layer ResNet (11.3 billion FLOPs) still has *lower complexity* than VGG-16/19 nets (15.3/19.6 billion FLOPs).

The 50/101/152-layer ResNets are more accurate than the 34-layer ones by considerable margins (Table 3 and 4). We do not observe the degradation problem and thus enjoy significant accuracy gains from considerably increased depth. The benefits of depth are witnessed for all evaluation metrics (Table 3 and 4).

Comparisons with State-of-the-art Methods. In Table 4 we compare with the previous best single-model results. Our baseline 34-layer ResNets have achieved very competitive accuracy. Our 152-layer ResNet has a single-model top-5 validation error of 4.49%. This single-model result outperforms all previous ensemble results (Table 5). We combine six models of different depth to form an ensemble (only with two 152-layer ones at the time of submitting). This leads to **3.57%** top-5 error on the test set (Table 5). *This entry won the 1st place in ILSVRC 2015.*

4.2. CIFAR-10 and Analysis

We conducted more studies on the CIFAR-10 dataset [20], which consists of 50k training images and 10k testing images in 10 classes. We present experiments trained on the training set and evaluated on the test set. Our focus is on the behaviors of extremely deep networks, but not on pushing the state-of-the-art results, so we intentionally use simple architectures as follows.

The plain/residual architectures follow the form in Fig. 3 (middle/right). The network inputs are 32×32 images, with the per-pixel mean subtracted. The first layer is 3×3 convolutions. Then we use a stack of $6n$ layers with 3×3 convolutions on the feature maps of sizes $\{32, 16, 8\}$ respectively, with $2n$ layers for each feature map size. The numbers of filters are $\{16, 32, 64\}$ respectively. The subsampling is performed by convolutions with a stride of 2. The network ends with a global average pooling, a 10-way fully-connected layer, and softmax. There are totally $6n$+2 stacked weighted layers. The following table summarizes the architecture:

output map size	32×32	16×16	8×8
# layers	1+$2n$	$2n$	$2n$
# filters	16	32	64

When shortcut connections are used, they are connected to the pairs of 3×3 layers (totally $3n$ shortcuts). On this dataset we use identity shortcuts in all cases (*i.e.*, option A), so our residual models have exactly the same depth, width, and number of parameters as the plain counterparts.

method			error (%)
Maxout [9]			9.38
NIN [25]			8.81
DSN [24]			8.22
	# layers	# params	
FitNet [34]	19	2.5M	8.39
Highway [41, 42]	19	2.3M	7.54 (7.72±0.16)
Highway [41, 42]	32	1.25M	8.80
ResNet	20	0.27M	8.75
ResNet	32	0.46M	7.51
ResNet	44	0.66M	7.17
ResNet	56	0.85M	6.97
ResNet	110	1.7M	**6.43** (6.61±0.16)
ResNet	1202	19.4M	7.93

Table 6. Classification error on the **CIFAR-10** test set. All methods are with data augmentation. For ResNet-110, we run it 5 times and show "best (mean±std)" as in [42].

We use a weight decay of 0.0001 and momentum of 0.9, and adopt the weight initialization in [12] and BN [16] but with no dropout. These models are trained with a mini-batch size of 128 on two GPUs. We start with a learning rate of 0.1, divide it by 10 at 32k and 48k iterations, and terminate training at 64k iterations, which is determined on a 45k/5k train/val split. We follow the simple data augmentation in [24] for training: 4 pixels are padded on each side, and a 32×32 crop is randomly sampled from the padded image or its horizontal flip. For testing, we only evaluate the single view of the original 32×32 image.

We compare $n = \{3, 5, 7, 9\}$, leading to 20, 32, 44, and 56-layer networks. Fig. 6 (left) shows the behaviors of the plain nets. The deep plain nets suffer from increased depth, and exhibit higher training error when going deeper. This phenomenon is similar to that on ImageNet (Fig. 4, left) and on MNIST (see [41]), suggesting that such an optimization difficulty is a fundamental problem.

Fig. 6 (middle) shows the behaviors of ResNets. Also similar to the ImageNet cases (Fig. 4, right), our ResNets manage to overcome the optimization difficulty and demonstrate accuracy gains when the depth increases.

We further explore $n = 18$ that leads to a 110-layer ResNet. In this case, we find that the initial learning rate of 0.1 is slightly too large to start converging[5]. So we use 0.01 to warm up the training until the training error is below 80% (about 400 iterations), and then go back to 0.1 and continue training. The rest of the learning schedule is as done previously. This 110-layer network converges well (Fig. 6, middle). It has *fewer* parameters than other deep and thin

[5] With an initial learning rate of 0.1, it starts converging (<90% error) after several epochs, but still reaches similar accuracy.

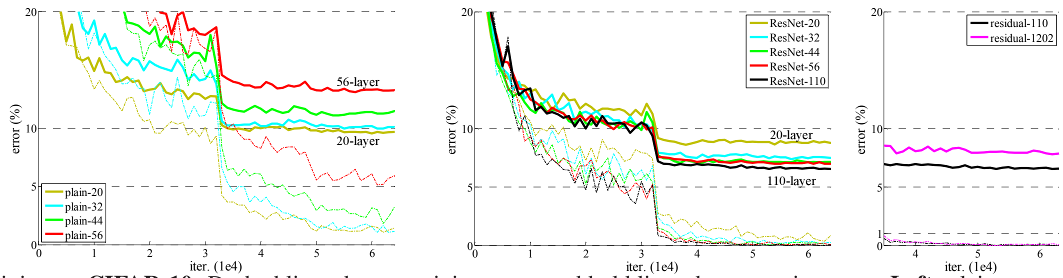

Figure 6. Training on **CIFAR-10**. Dashed lines denote training error, and bold lines denote testing error. **Left**: plain networks. The error of plain-110 is higher than 60% and not displayed. **Middle**: ResNets. **Right**: ResNets with 110 and 1202 layers.

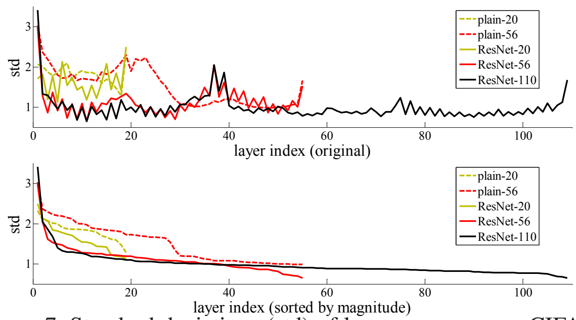

Figure 7. Standard deviations (std) of layer responses on CIFAR-10. The responses are the outputs of each 3×3 layer, after BN and before nonlinearity. **Top**: the layers are shown in their original order. **Bottom**: the responses are ranked in descending order.

networks such as FitNet [34] and Highway [41] (Table 6), yet is among the state-of-the-art results (6.43%, Table 6).

残差函数的响应强度（图7），残差函数通常比非残差函数更接近于零。更深的ResNet具有更小的响应量。当有更多的层时，单个层的ResNets倾向于较少地修改信号。

Analysis of Layer Responses. Fig. 7 shows the standard deviations (std) of the layer responses. The responses are the outputs of each 3×3 layer, after BN and before other nonlinearity (ReLU/addition). For ResNets, this analysis reveals the response strength of the residual functions. Fig. 7 shows that ResNets have generally smaller responses than their plain counterparts. These results support our basic motivation (Sec.3.1) that the residual functions might be generally closer to zero than the non-residual functions. We also notice that the deeper ResNet has smaller magnitudes of responses, as evidenced by the comparisons among ResNet-20, 56, and 110 in Fig. 7. When there are more layers, an individual layer of ResNets tends to modify the signal less.

1000层没有显示出优化的困难，误差率增加可能是过拟合。

Exploring Over 1000 layers. We explore an aggressively deep model of over 1000 layers. We set $n = 200$ that leads to a 1202-layer network, which is trained as described above. Our method shows *no optimization difficulty*, and this 10^3-layer network is able to achieve *training error* <0.1% (Fig. 6, right). Its test error is still fairly good (7.93%, Table 6).

But there are still open problems on such aggressively deep models. The testing result of this 1202-layer network is worse than that of our 110-layer network, although both have similar training error. We argue that this is because of overfitting. The 1202-layer network may be unnecessarily large (19.4M) for this small dataset. Strong regularization such as maxout [9] or dropout [13] is applied to obtain the best results ([9, 25, 24, 34]) on this dataset. In this paper, we use no maxout/dropout and just simply impose regularization via deep and thin architectures by design, without distracting from the focus on the difficulties of optimization. But combining with stronger regularization may improve results, which we will study in the future.

未来要研究的方向：如何实施了正规化来配合增大/减少网络深度架构设计，结合更强的正规化手段进一步提升结果。

training data	07+12	07++12
test data	VOC 07 test	VOC 12 test
VGG-16	73.2	70.4
ResNet-101	**76.4**	**73.8**

Table 7. Object detection mAP (%) on the PASCAL VOC 2007/2012 test sets using **baseline** Faster R-CNN. See also appendix for better results.

metric	mAP@.5	mAP@[.5, .95]
VGG-16	41.5	21.2
ResNet-101	**48.4**	**27.2**

Table 8. Object detection mAP (%) on the COCO validation set using **baseline** Faster R-CNN. See also appendix for better results.

4.3. Object Detection on PASCAL and MS COCO

泛化：PASCAL VOC 2007、2012[5]、COCO[26]的目标检测基线，COCO 2015竞赛:ImageNet检测、ImageNet定位、COCO检测、COCO分割

Our method has good generalization performance on other recognition tasks. Table 7 and 8 show the object detection baseline results on PASCAL VOC 2007 and 2012 [5] and COCO [26]. We adopt *Faster R-CNN* [32] as the detection method. Here we are interested in the improvements of replacing VGG-16 [40] with ResNet-101. The detection implementation (see appendix) of using both models is the same, so the gains can only be attributed to better networks. Most remarkably, on the challenging COCO dataset we obtain a 6.0% increase in COCO's standard metric (mAP@[.5, .95]), which is a 28% relative improvement. This gain is solely due to the learned representations.

Based on deep residual nets, we won the 1st places in several tracks in ILSVRC & COCO 2015 competitions: ImageNet detection, ImageNet localization, COCO detection, and COCO segmentation. The details are in the appendix.

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