TUGAS BESAR MACHINE LEARNING

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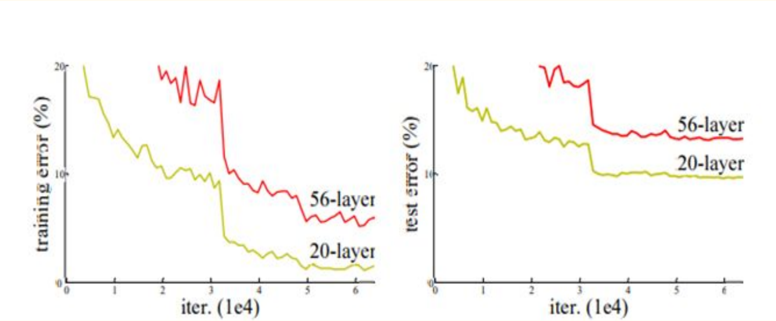
RESIDUAL NETWORKS (ResNet)

INTRODUCTION

Deep networks naturally integrate low/mid/highmlevel features and classifiers in an end-to-end multilayer fashion, and the “levels” of features can be enriched by the number of stacked layers (depth).

Recent evidence reveals that network depth is of crucial importance, and the leading results on the challenging. ImageNet dataset ll exploit “very deep” models, with a depth of sixteen to thirty.



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.

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.

Formally, denoting the desired underlying mapping as H(x), we let the stacked nonlinear layers fit another mapping of F(x) := H(x)−x. The original mapping is recast into F(x)+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.

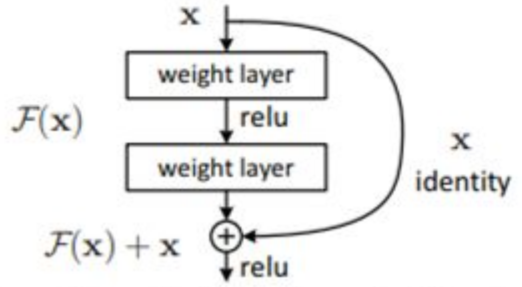


Figure 2. Residual learning: a building block.

RELATED WORK

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

DEEP RESIDUAL LEARNING

Residual Learning

- Stacked nonlinear layers fit another mapping of $F(x) := H(x) - x$.
- 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.

Identity Mapping by Shortcuts

A building block is shown in Fig. 2. Formally, in this paper we consider a building block defined as:

$$y = F(x, \{W_{saya}\}) + x.$$

Here x and y are the input and output vectors of the layers considered. The function F(x, {Wi}) represents the residual mapping to be learned. For the example in Fig. 2 that has two layers, F = W2σ(W1x) in which σ denotes 2This hypothesis, however, is still an open question. See [28]. ReLU [29] and the biases are omitted for simplifying notations. The operation F + x is performed by a shortcut connection and element-wise addition.

Network Architectures

Plain Network. Our plain baselines (Fig. 3, middle) are mainly inspired by the philosophy of VGG nets (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.

It is worth noticing that our model has fewer filters and lower complexity than VGG nets [41] (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).

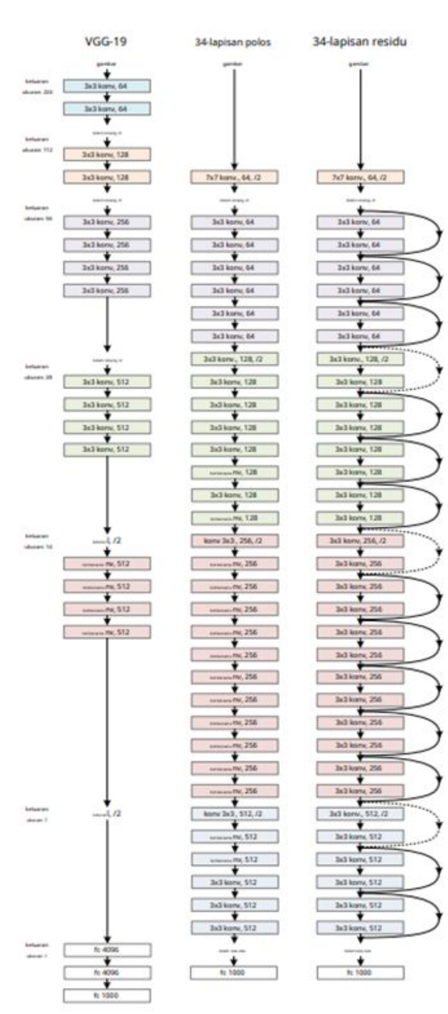


Figure 3. Example network architectures for ImageNet. Left: the VGG-19 model [41] (19.6 billion FLOPs) as a reference. Middle: a plain network with 34 parameter layers (3.6 billion FLOPs). Right: a residual network with 34 parameter layers (3.6 billion FLOPs). The dotted shortcuts increase dimensions. Table 1 shows more details and other variants.

EXPERIMENT

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

The 152-layer ResNet (11.3 billion FLOPs) still has lower complexity than VGG -16/19 nets (15.3/19.6 billion FLOPs).

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