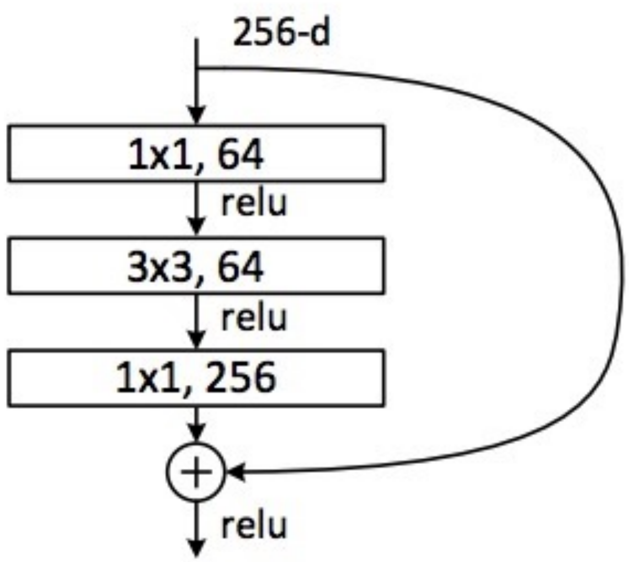
ResNet

Deeper residual module (bottleneck)



- Directly performing 3×3 convolutions with 256 feature maps at input and output: $256\times256\times3\times3 \approx 600K$ operations
- Using 1×1 convolutions to reduce 256 to 64 feature maps, followed by 3×3 convolutions, followed by 1×1 convolutions to expand back to 256 maps:
  $256\times64\times1\times1 \approx 16K$
  $64\times64\times3\times3 \approx 36K$
  $64\times256\times1\times1 \approx 16K$
  Total $\approx 70K$

K. He, X. Zhang, S. Ren, and J. Sun, [Deep Residual Learning for Image Recognition](), CVPR 2016 (Best Paper)

ResNet

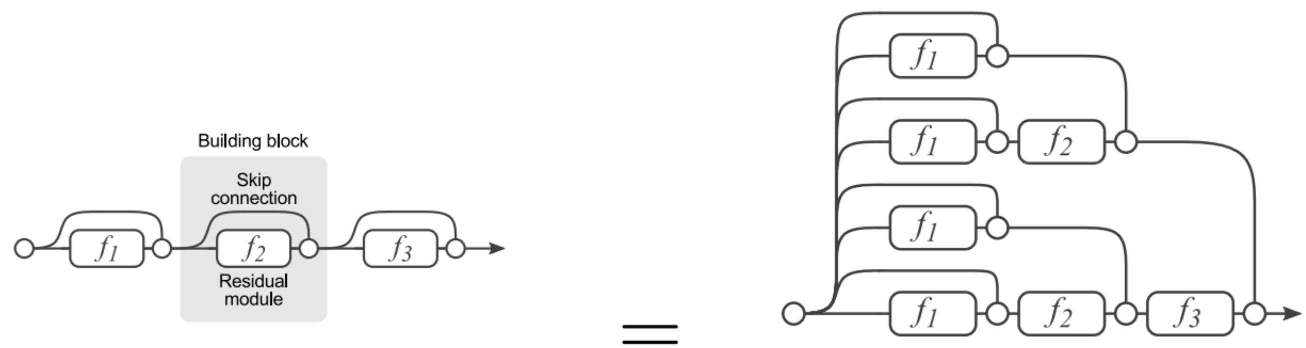
- Architectures for ImageNet:

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

K. He, X. Zhang, S. Ren, and J. Sun, [Deep Residual Learning for Image Recognition](), CVPR 2016 (Best Paper)

Why do ResNets work?

- ResNets are collections of many paths of different length, and shorter paths predominantly contribute to training



(a) Conventional 3-block residual network (b) Unraveled view of (a)

Figure 1: Residual Networks are conventionally shown as (a), which is a natural representation of Equation (1). When we expand this formulation to Equation (6), we obtain an *unraveled view* of a 3-block residual network (b). Circular nodes represent additions. From this view, it is apparent that residual networks have $O(2^n)$ implicit paths connecting input and output and that adding a block doubles the number of paths.

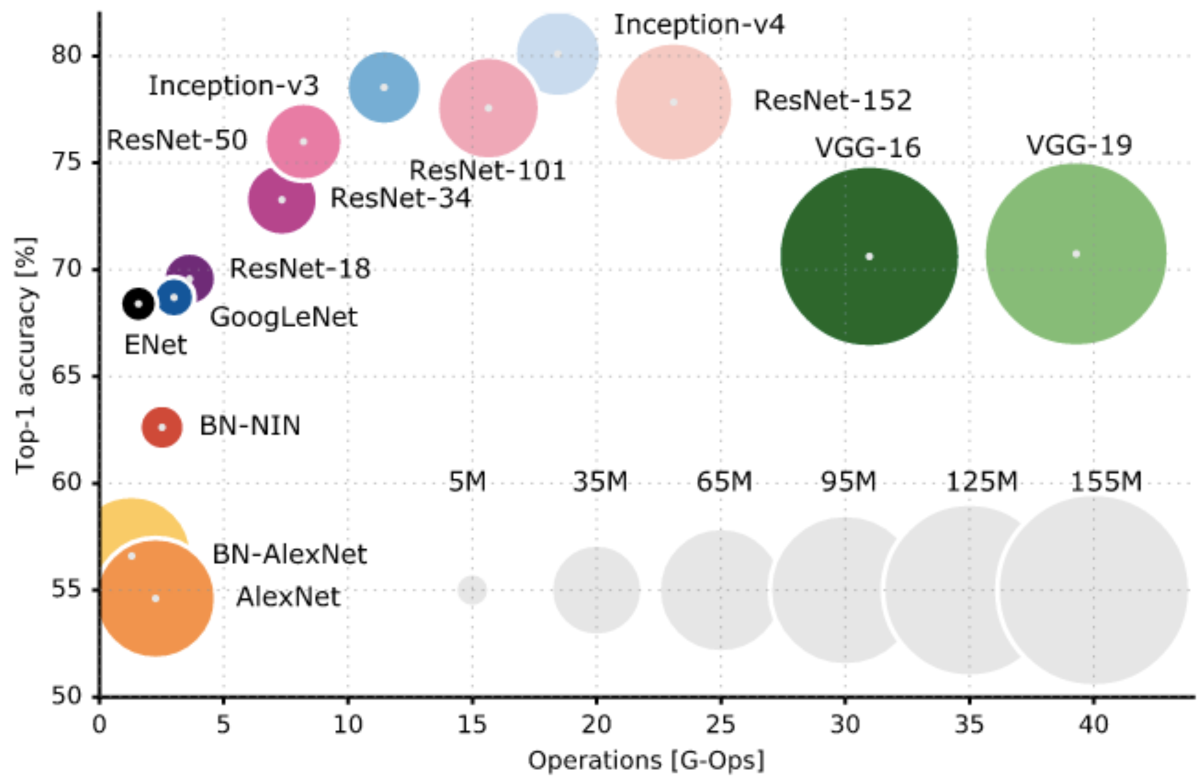
A. Veit, M. Wilber, S. Belongie, [Residual Networks Behave Like Ensembles of Relatively Shallow Networks](), NIPS 2016

Summary: ILSVRC 2012-2015

Team	**Year**	**Place**	**Error (top-5)**	**External data**
SuperVision – Toronto (AlexNet, 7 layers)	2012	-	16.4%	no
SuperVision	2012	1st	15.3%	ImageNet 22k
Clarifai – NYU (7 layers)	2013	-	11.7%	no
Clarifai	2013	1st	11.2%	ImageNet 22k
VGG – Oxford (16 layers)	2014	2nd	7.32%	no
GoogLeNet (19 layers)	2014	1st	6.67%	no
ResNet (152 layers)	2015	1st*	3.57%	

*Officially, there was no longer a classification competition and ResNet-based systems won in localization and detection

Comparing architectures



https://culurciello.github.io/tech/2016/06/04/nets.html

Outline

- AlexNet (2012-2013)
- VGGNet (2014)
- GoogLeNet (2014)
- ResNet (2015)
- Beyond ResNet (2016 and onward): Wide ResNet, ResNeXT, DenseNet

Beyond ResNet: Wide ResNet

- Reduce number of residual blocks, but increase number of feature maps in each block
  - More parallelizable, better feature reuse
  - 16-layer WRN outperforms 1000-layer ResNets, though with much larger # of parameters

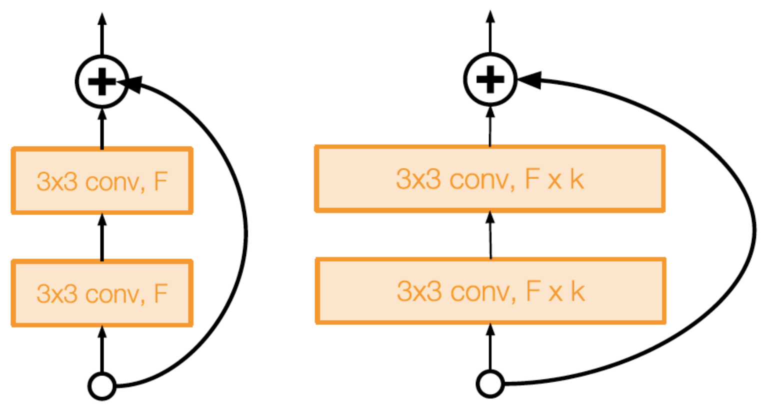


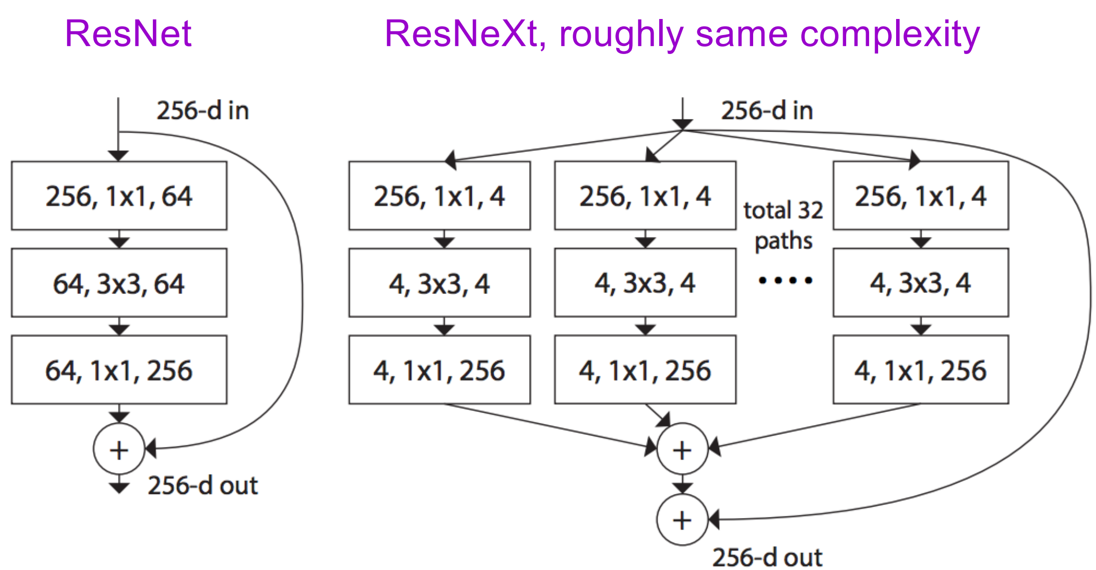
Image source

Basic residual block   Wide residual block

S. Zagoryuko and N. Komodakis, Wide Residual Networks, BMVC 2016

Beyond ResNet: ResNeXt

- Propose "cardinality" as a new factor in network design, apart from depth and width
- Claim that increasing cardinality is a better way to increase capacity than increasing depth or width



S. Xie, R. Girshick, P. Dollar, Z. Tu, and K. He, [Aggregated Residual Transformations for Deep Neural Networks](), CVPR 2017

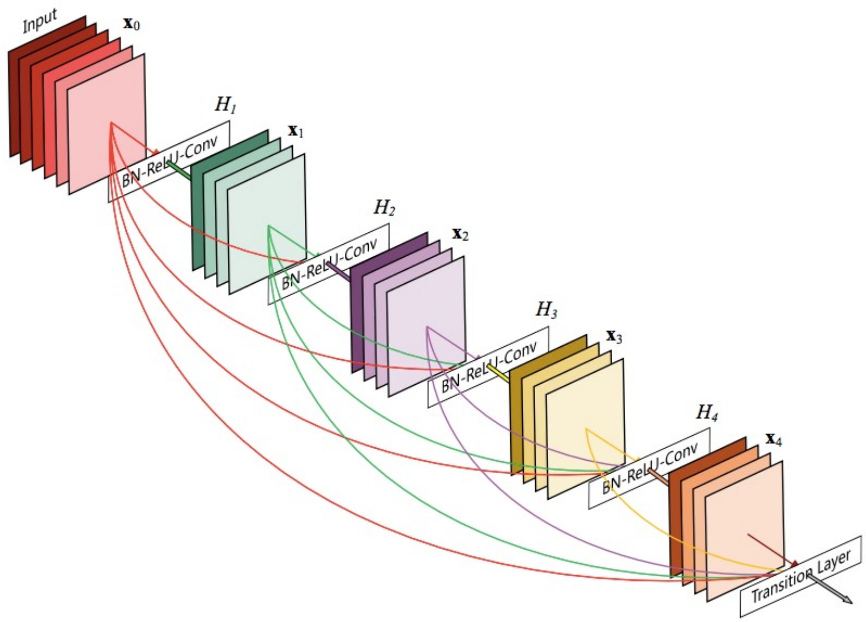
Beyond ResNet: ResNeXt

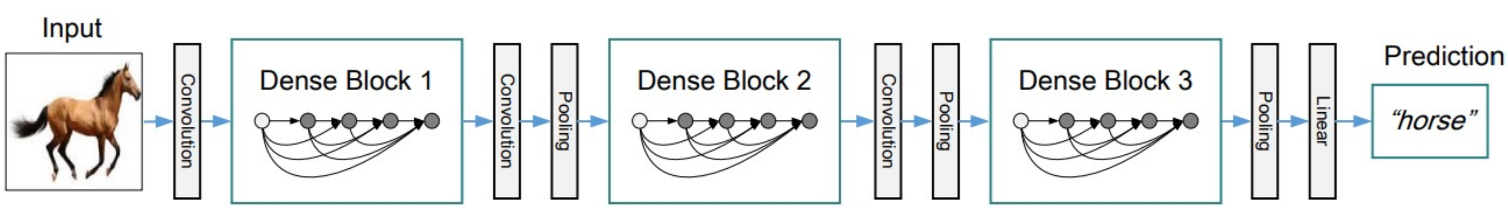
	setting	top-1 error (%)
ResNet-50	$1 \times 64d$	23.9
ResNeXt-50	$2 \times 40d$	23.0
ResNeXt-50	$4 \times 24d$	22.6
ResNeXt-50	$8 \times 14d$	22.3
ResNeXt-50	$32 \times 4d$	**22.2**
ResNet-101	$1 \times 64d$	22.0
ResNeXt-101	$2 \times 40d$	21.7
ResNeXt-101	$4 \times 24d$	21.4
ResNeXt-101	$8 \times 14d$	21.3
ResNeXt-101	$32 \times 4d$	**21.2**

Table 3. Ablation experiments on ImageNet-1K. (**Top**): ResNet-50 with preserved complexity (~4.1 billion FLOPs); (**Bottom**): ResNet-101 with preserved complexity (~7.8 billion FLOPs). The error rate is evaluated on the single crop of 224×224 pixels.

S. Xie, R. Girshick, P. Dollar, Z. Tu, and K. He, Aggregated Residual Transformations for Deep Neural Networks, CVPR 2017

Beyond ResNet: DenseNets





G. Huang, Z. Liu, and L. van der Maaten, [Densely Connected Convolutional Networks](), CVPR 2017 (Best Paper Award)

DenseNets

Layers	Output Size	DenseNet-121	DenseNet-169	DenseNet-201	DenseNet-264
Convolution	112×112	7×7 conv, stride 2			
Pooling	56×56	3×3 max pool, stride 2			
Dense Block (1)	56×56	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$
Transition Layer (1)	56×56	1×1 conv			
	28×28	2×2 average pool, stride 2			
Dense Block (2)	28×28	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$
Transition Layer (2)	28×28	1×1 conv			
	14×14	2×2 average pool, stride 2			
Dense Block (3)	14×14	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 24$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 48$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 64$
Transition Layer (3)	14×14	1×1 conv			
	7×7	2×2 average pool, stride 2			
Dense Block (4)	7×7	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 16$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 48$
Classification Layer	1×1	7×7 global average pool			
		1000D fully-connected, softmax			

G. Huang, Z. Liu, and L. van der Maaten, Densely Connected Convolutional Networks, CVPR 2017 (Best Paper Award)