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MINISTERSTVO ŠKOLSTVÍ, MLÁDEŽE A TĚLOVÝCHOVY

Image Analysis II

ResNet, DenseNet, MobileNet, SqueezeNet, EfficientNet

Radovan Fusek

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ResNet

Deep Residual Learning for Image Recognition

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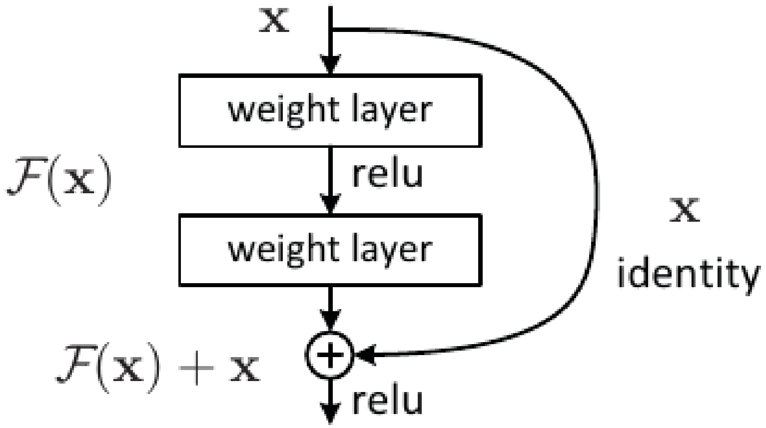


Figure 2. Residual learning: a building block.

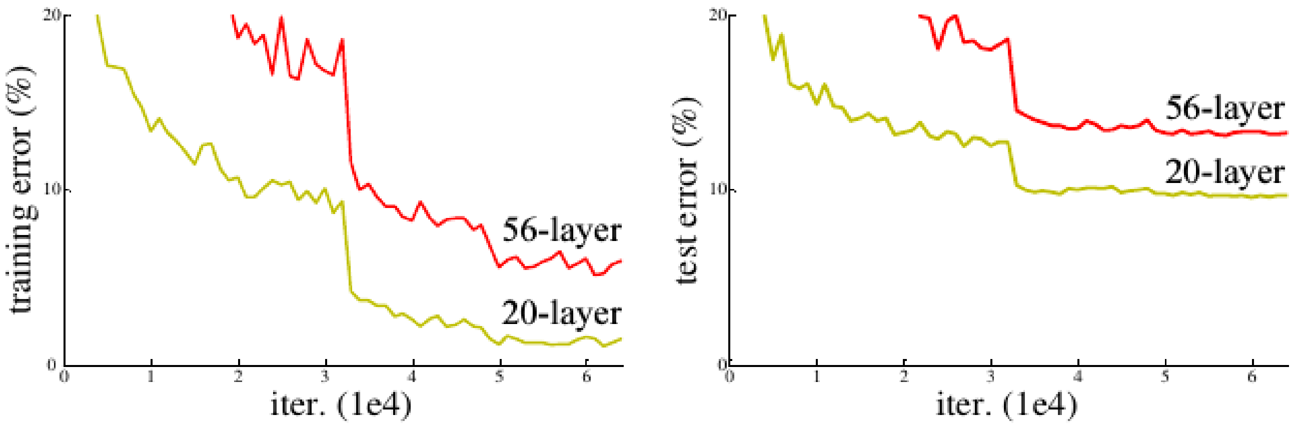


Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer "plain" networks. The deeper network has higher training error, and thus test error. Similar phenomena on ImageNet is presented in Fig. 4.

https://arxiv.org/pdf/1512.03385.pdf

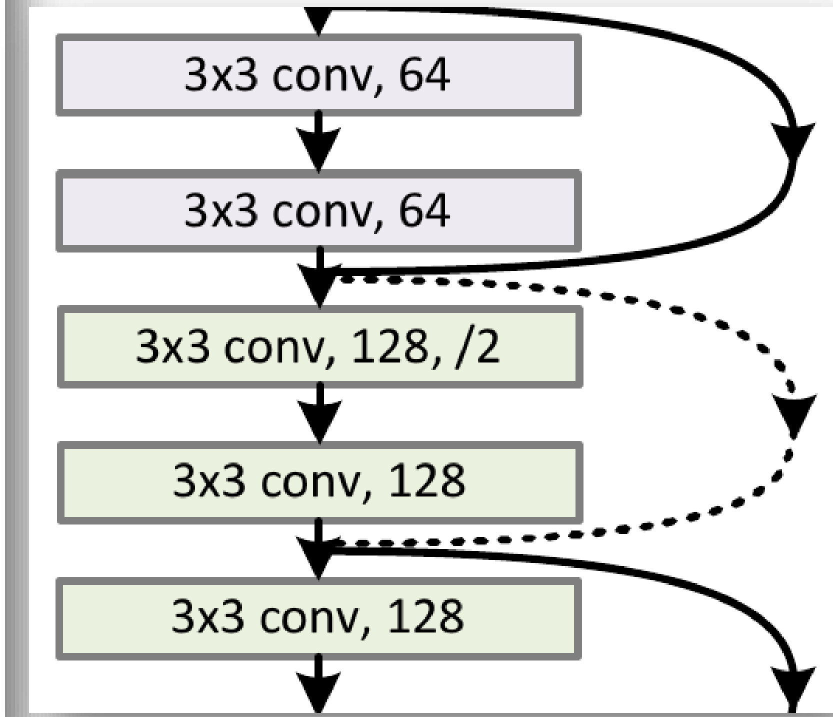
ResNet

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

https://arxiv.org/pdf/1512.03385.pdf

ResNet

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.



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ResNet

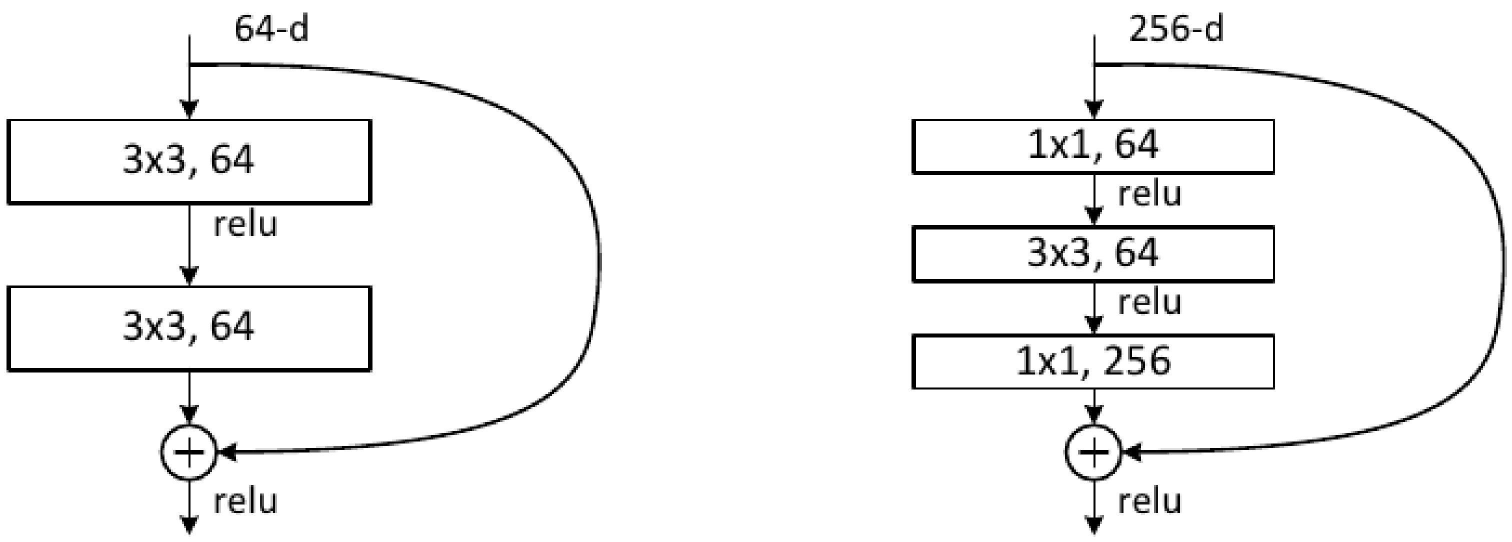


Figure 5. A deeper residual function $\mathcal{F}$ for ImageNet. Left: a building block (on 56×56 feature maps) as in Fig. 3 for ResNet-34. Right: a “bottleneck” building block for ResNet-50/101/152.

https://arxiv.org/pdf/1512.03385.pdf

ResNet

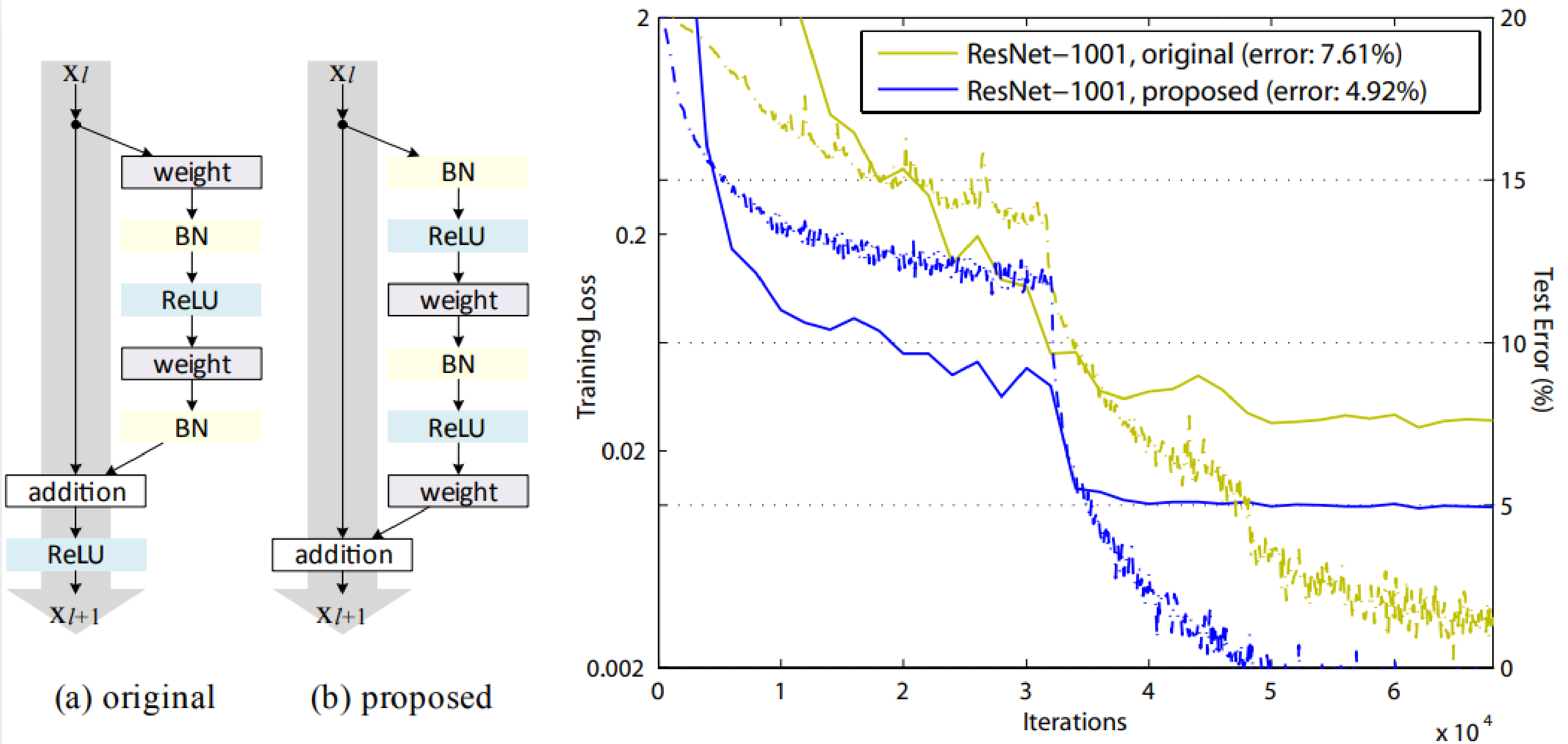


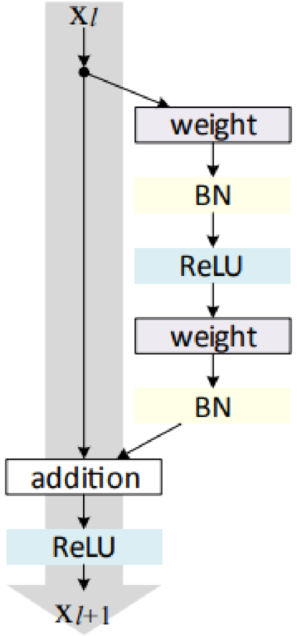
Figure 1. Left: (a) original Residual Unit in [1]; (b) proposed Residual Unit. The grey arrows indicate the easiest paths for the information to propagate, corresponding to the additive term "$\mathbf{x}_l$" in Eqn.(4) (forward propagation) and the additive term "1" in Eqn.(5) (backward propagation). **Right**: training curves on CIFAR-10 of **1001-layer** ResNets. Solid lines denote test error (y-axis on the right), and dashed lines denote training loss (y-axis on the left). The proposed unit makes ResNet-1001 easier to train.

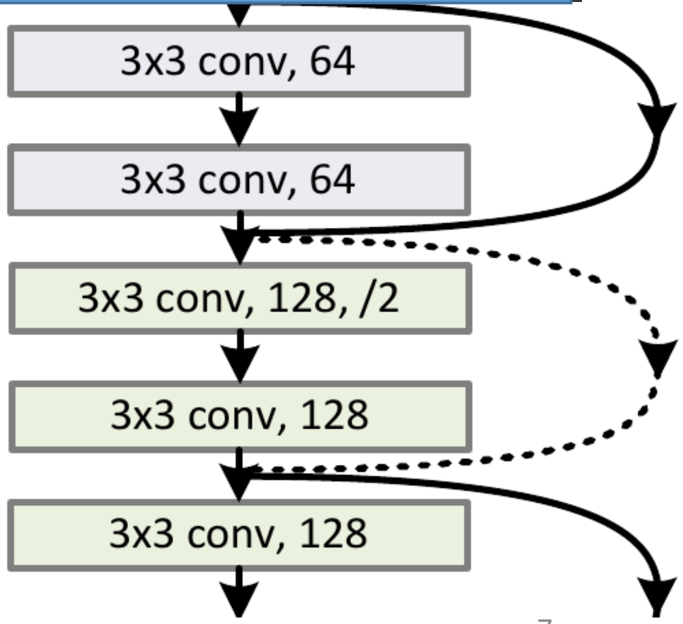
https://arxiv.org/abs/1603.05027
https://arxiv.org/pdf/1512.03385.pdf

ResNet

```
class ResidualBlockExample(nn.Module):
    def __init__(self, in_channels, out_channels, stride, use_1x1conv=False):

    def forward(self, X):
```





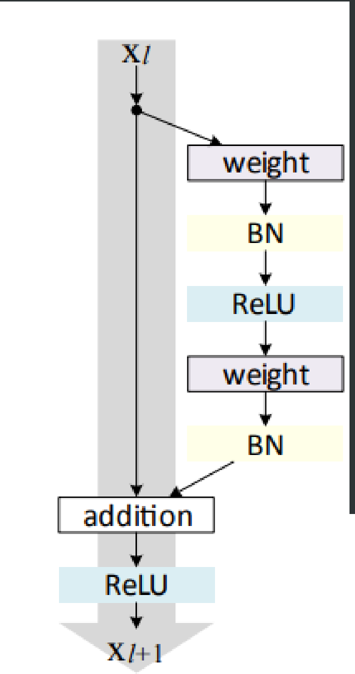
https://arxiv.org/abs/1603.05027

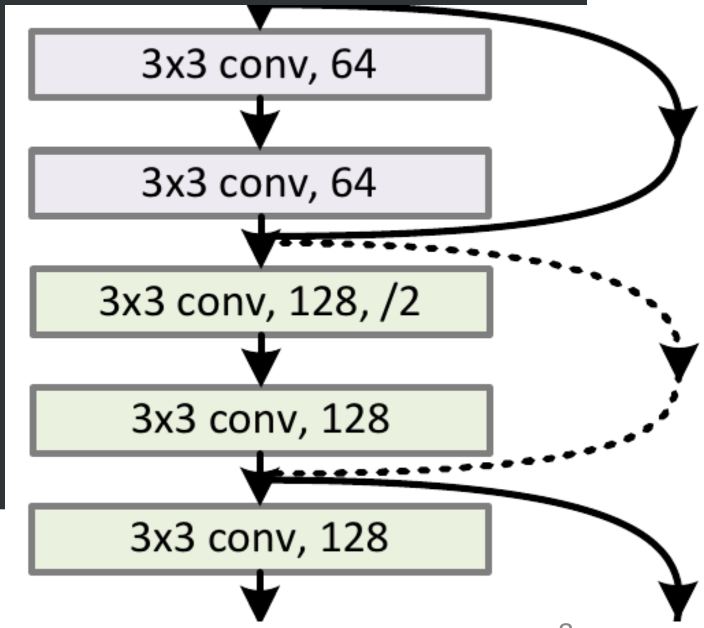
https://arxiv.org/pdf/1512.03385.pdf

ResNet

```
class ResidualBlockExample(nn.Module):
    def __init__(self,  in_channels, out_channels, stride, use_1x1conv=False):
        super().__init__()
        self.conv1 = nn.Conv2d(in_channels, out_channels, 3, stride=stride, padding=1)
        self.conv2 = nn.Conv2d(out_channels, out_channels, 3, stride=1, padding=1)
        self.relu = nn.ReLU()
        self.bn = nn.LazyBatchNorm2d()
        self.conv3 = None
        if use_1x1conv:
            self.conv3 = nn.Conv2d(in_channels, out_channels, kernel_size=1, stride=stride, padding=0)

    def forward(self, X):
        out = self.relu(self.bn(self.conv1(X)))
        out = self.bn(self.conv2(out))
        if self.conv3:
            X = self.conv3(X)
        print("forward out.shape", out.shape)
        print("forward X.shape", X.shape)
        out += X
        out = self.relu(out)
        return out
```





http://d2l.ai/chapter_convolutional-modern/resnet.html
https://arxiv.org/abs/1603.05027
https://arxiv.org/pdf/1512.03385.pdf

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DenseNet

Densely Connected Convolutional Networks

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Abstract

Recent work has shown that convolutional networks can be substantially deeper, more accurate, and efficient to train if they contain shorter connections between layers close to the input and those close to the output. In this paper, we embrace this observation and introduce the Dense Convolutional Network (DenseNet), which connects each layer to every other layer in a feed-forward fashion. Whereas traditional convolutional networks with L layers have L connections—one between each layer and its subsequent layer—our network has $\frac{L(L+1)}{2}$ direct connections. For each layer, the feature-maps of all preceding layers are used as inputs, and its own feature-maps are used as inputs into all subsequent layers. DenseNets have several compelling advantages: they alleviate the vanishing-gradient problem, strengthen feature propagation, encourage feature reuse, and substantially reduce the number of parameters. We evaluate our proposed architecture on four highly competitive object recognition benchmark tasks (CIFAR-10, CIFAR-100, SVHN, and ImageNet). DenseNets obtain significant improvements over the state-of-the-art on most of them, whilst requiring less computation to achieve high performance. Code and pre-trained models are available at https://github.com/liuzhuang13/DenseNet.

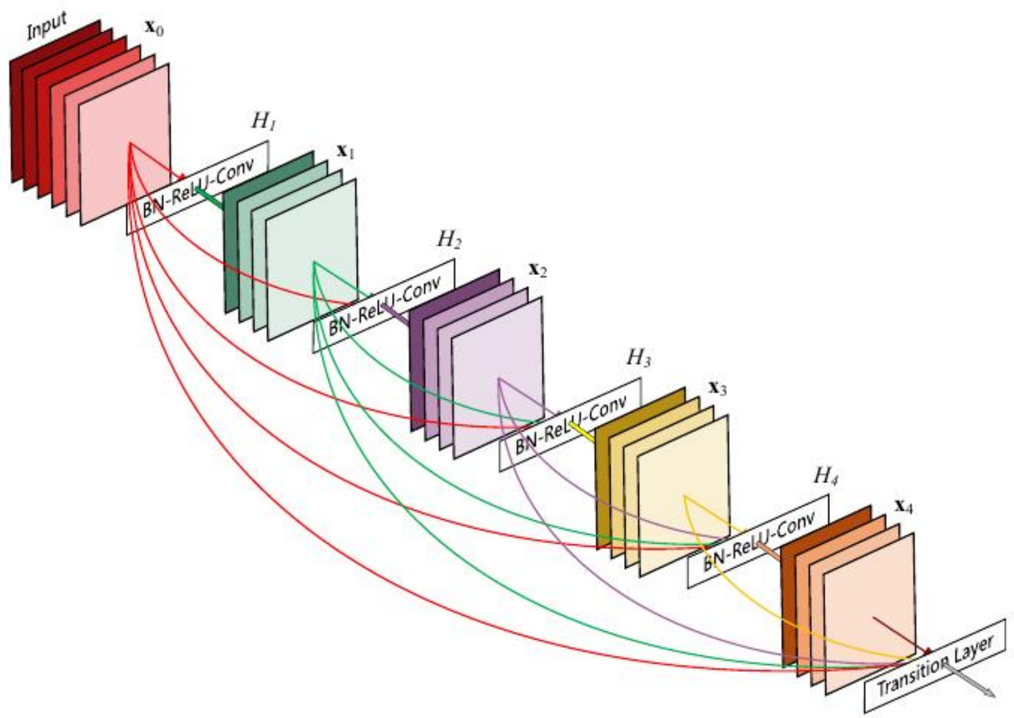

Figure 1: A 5-layer dense block with a growth rate of $k = 4$. Each layer takes all preceding feature-maps as input.

https://arxiv.org/abs/1608.06993

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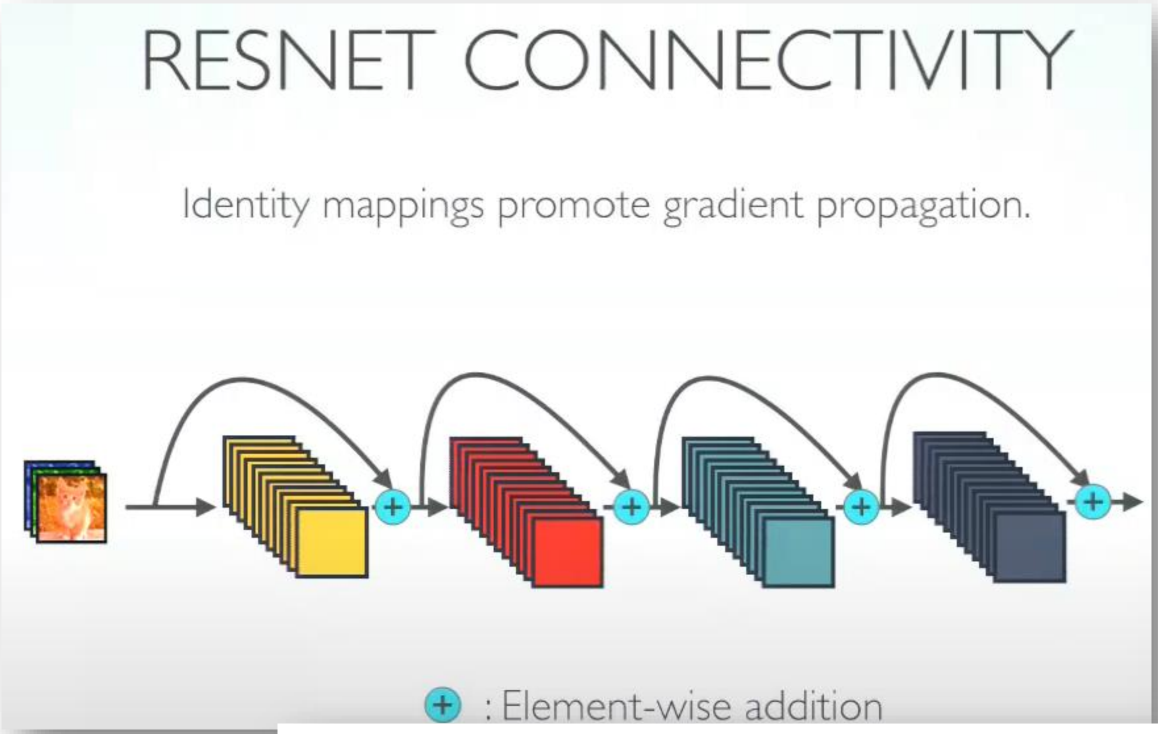
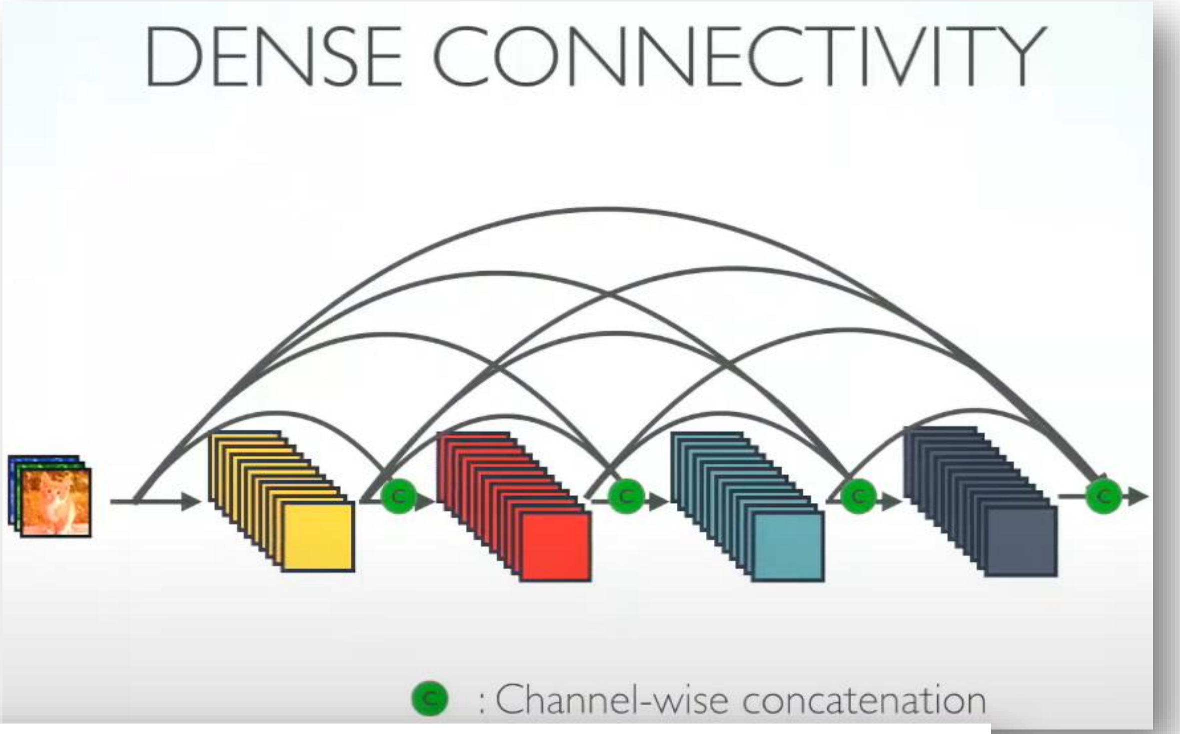
DenseNet





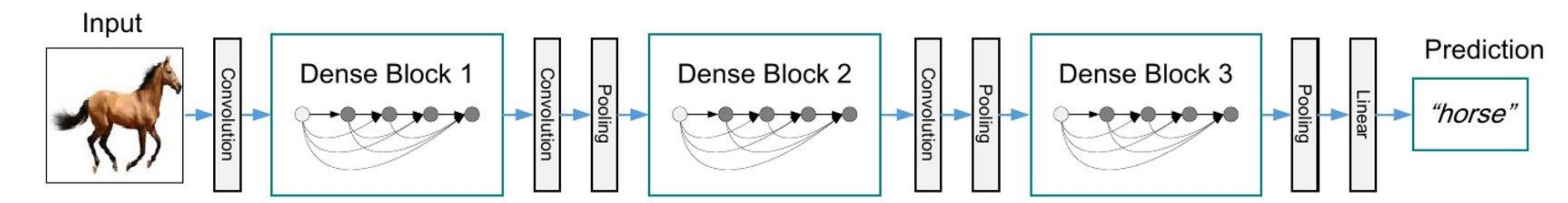
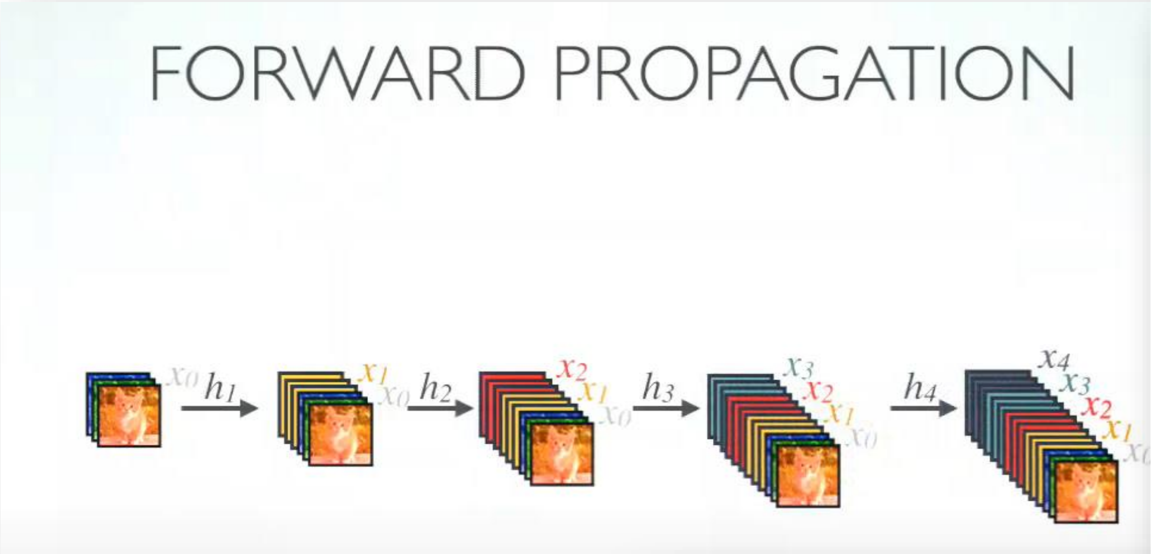
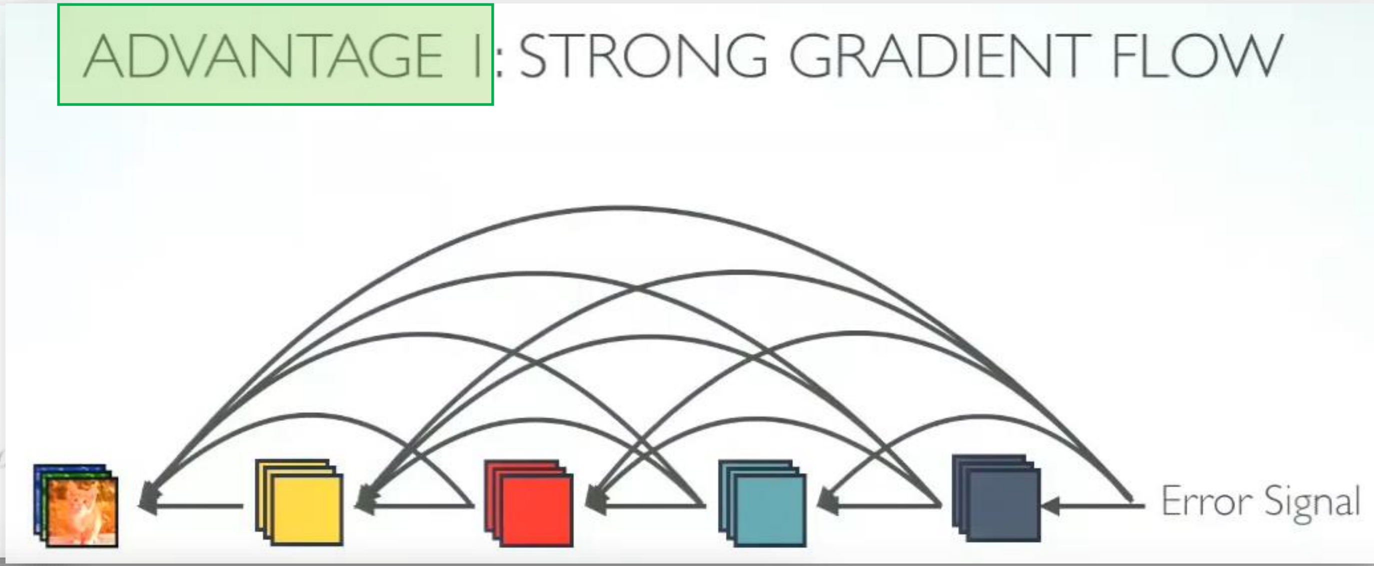


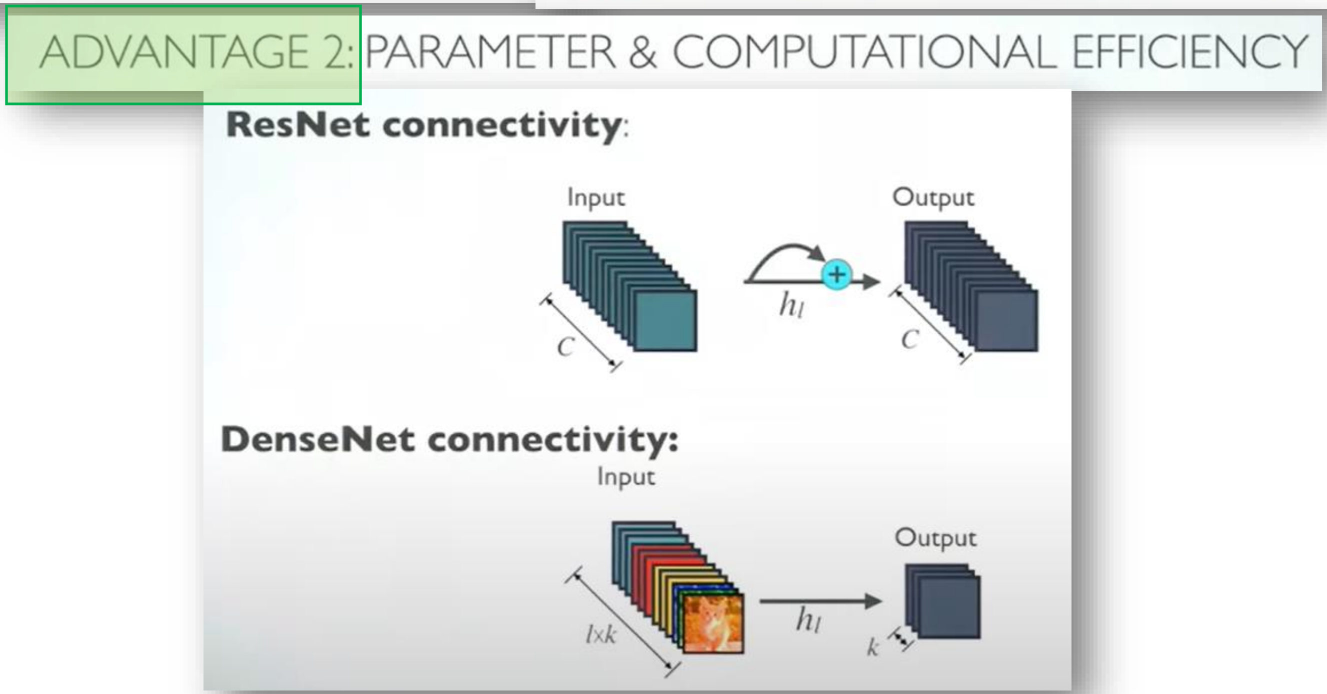
Figure 2: A deep DenseNet with three dense blocks. The layers between two adjacent blocks are referred to as transition layers and change feature-map sizes via convolution and pooling.

https://www.youtube.com/watch?v=-W6y8xnd--U
https://arxiv.org/abs/1608.06993

DenseNet







https://www.youtube.com/watch?v=-W6y8xnd--U
https://arxiv.org/abs/1608.06993

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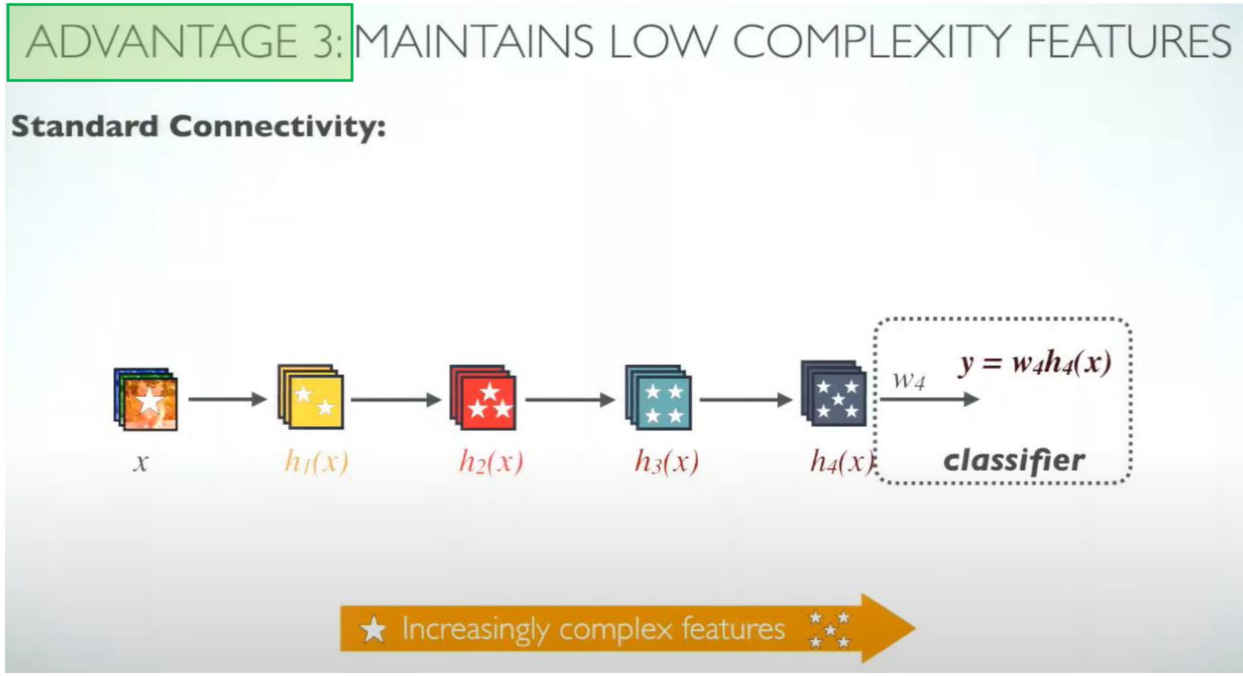
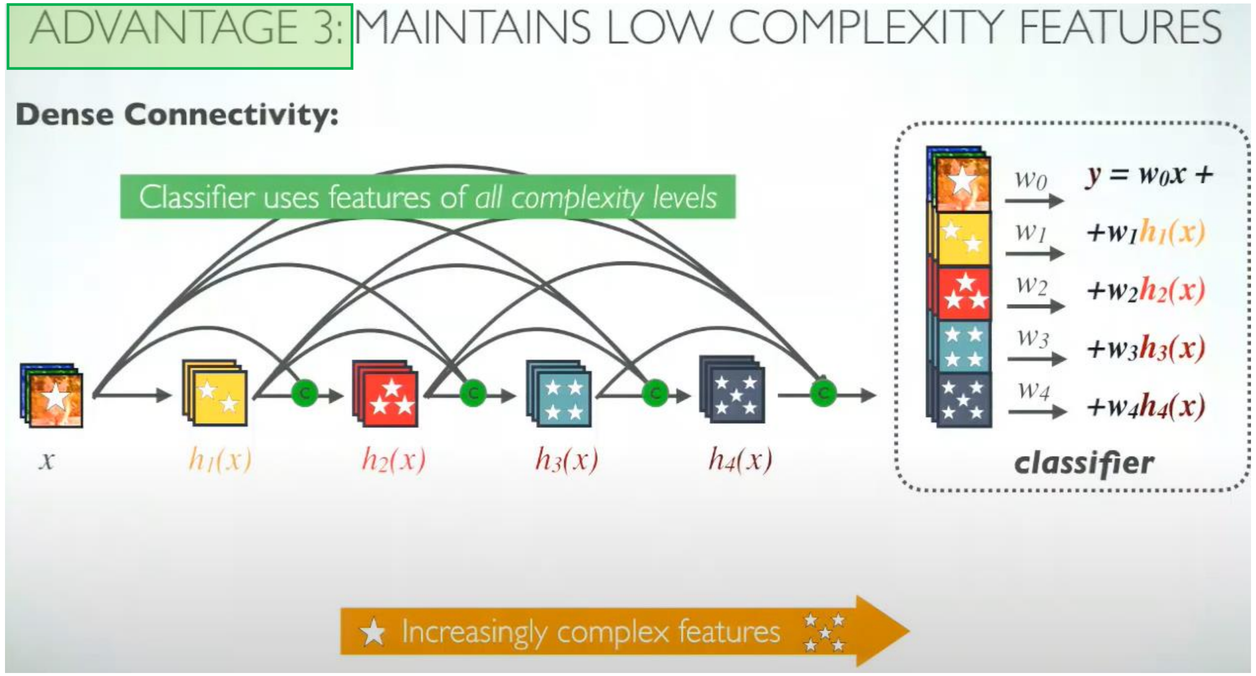
DenseNet





https://www.youtube.com/watch?v=-W6y8xnd--U
https://arxiv.org/abs/1608.06993

DenseNet

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			

Table 1: DenseNet architectures for ImageNet. The growth rate for all the networks is $k = 32$. Note that each "conv" layer shown in the table corresponds the sequence BN-ReLU-Conv.

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DenseNet

Model	top-1	top-5
DenseNet-121	25.02 / 23.61	7.71 / 6.66
DenseNet-169	23.80 / 22.08	6.85 / 5.92
DenseNet-201	22.58 / 21.46	6.34 / 5.54
DenseNet-264	22.15 / 20.80	6.12 / 5.29

Table 3: The top-1 and top-5 error rates on the ImageNet validation set, with single-crop / 10-crop testing.

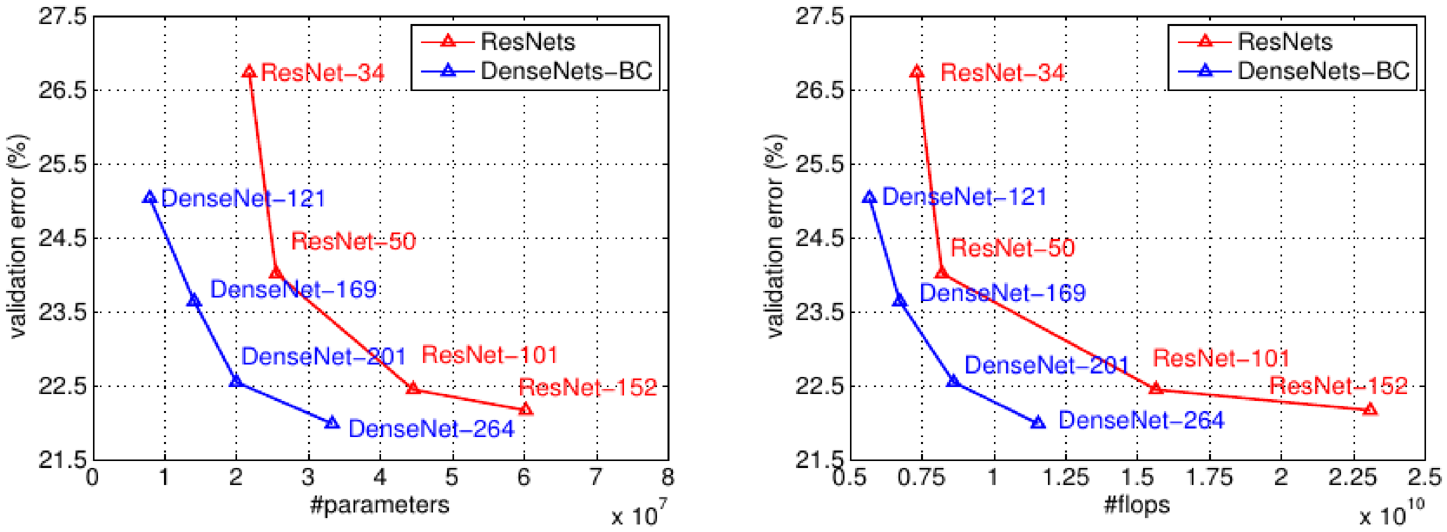

Figure 3: Comparison of the DenseNets and ResNets top-1 error rates (single-crop testing) on the ImageNet validation dataset as a function of learned parameters (*left*) and FLOPs during test-time (*right*).

https://arxiv.org/abs/1608.06993

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MobileNet

MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications

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Abstract

We present a class of efficient models called MobileNets for mobile and embedded vision applications. MobileNets are based on a streamlined architecture that uses depth-wise separable convolutions to build light weight deep neural networks. We introduce two simple global hyper-parameters that efficiently trade off between latency and accuracy. These hyper-parameters allow the model builder to choose the right sized model for their application based on the constraints of the problem. We present extensive experiments on resource and accuracy tradeoffs and show strong performance compared to other popular models on ImageNet classification. We then demonstrate the effectiveness of MobileNets across a wide range of applications and use cases including object detection, finegrain classification, face attributes and large scale geo-localization.

1. Introduction

models. Section 3 describes the MobileNet architecture and two hyper-parameters width multiplier and resolution multiplier to define smaller and more efficient MobileNets. Section 4 describes experiments on ImageNet as well a variety of different applications and use cases. Section 5 closes

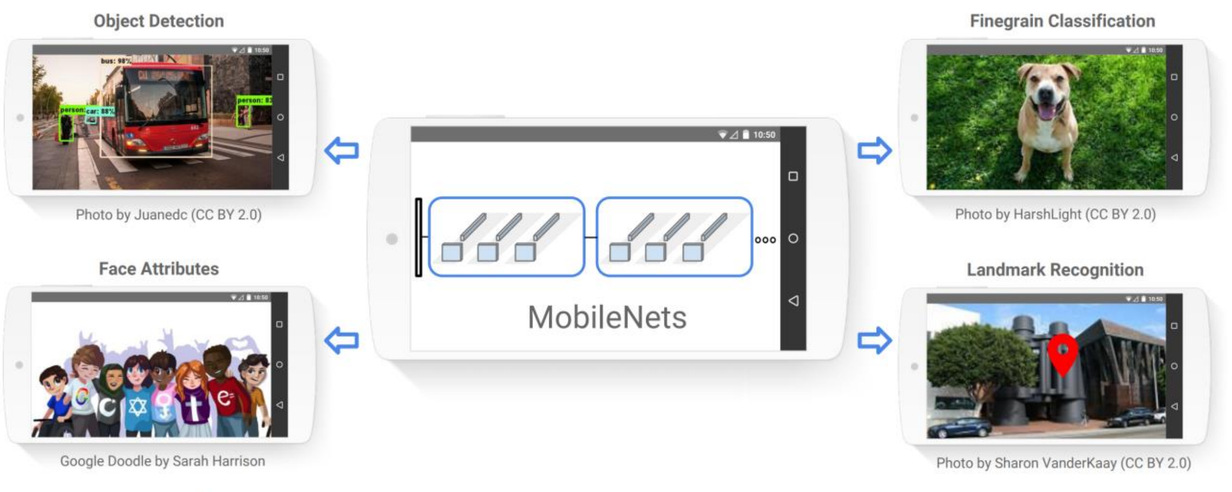

Figure 1. MobileNet models can be applied to various recognition tasks for efficient on device intelligence.

https://arxiv.org/pdf/1704.04861v1

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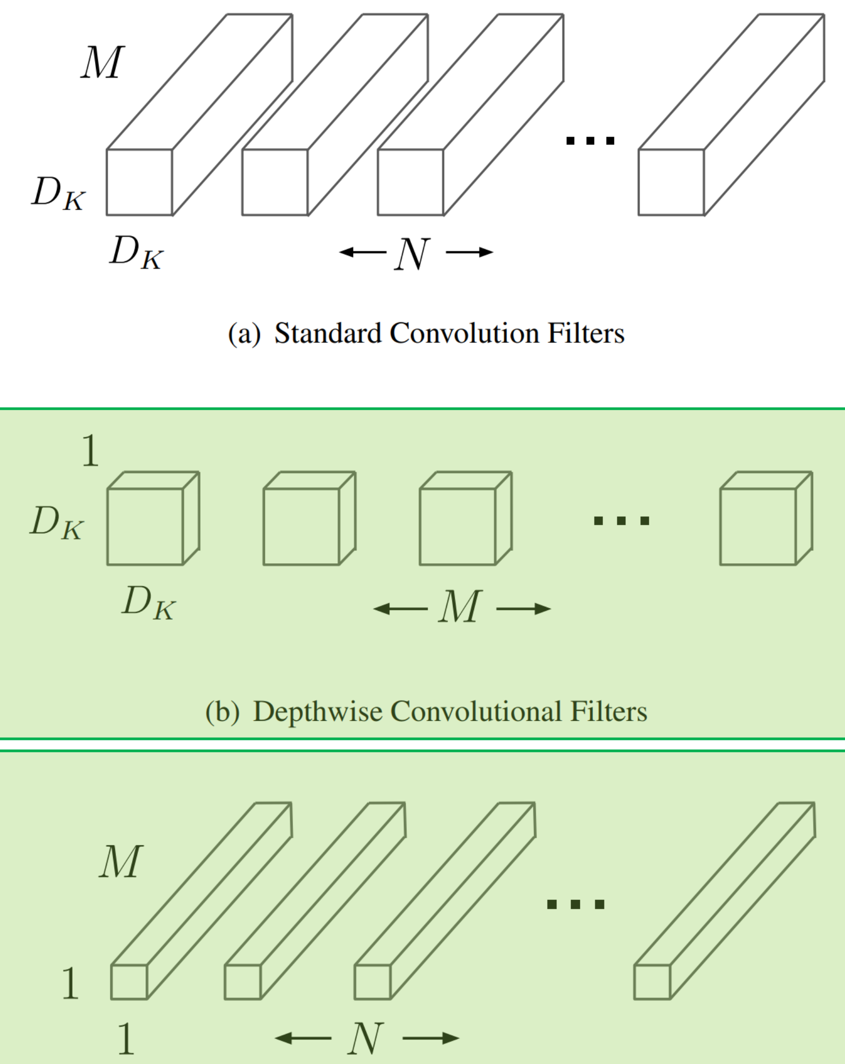
MobileNet

3. MobileNet Architecture

In this section we first describe the core layers that MobileNet is built on which are depthwise separable filters. We then describe the MobileNet network structure and conclude with descriptions of the two model shrinking hyperparameters width multiplier and resolution multiplier.

3.1. Depthwise Separable Convolution

The MobileNet model is based on depthwise separable convolutions which is a form of factorized convolutions which factorize a standard convolution into a depthwise convolution and a 1×1 convolution called a pointwise convolution. For MobileNets the depthwise convolution applies a single filter to each input channel. The pointwise convolution then applies a 1×1 convolution to combine the outputs the depthwise convolution. A standard convolution both filters and combines inputs into a new set of outputs in one step. The depthwise separable convolution splits this into two layers, a separate layer for filtering and a separate layer for combining. This factorization has the effect of drastically reducing computation and model size. Figure 2 shows how a standard convolution 2(a) is factorized into a depthwise convolution 2(b) and a 1×1 pointwise convolution 2(c).



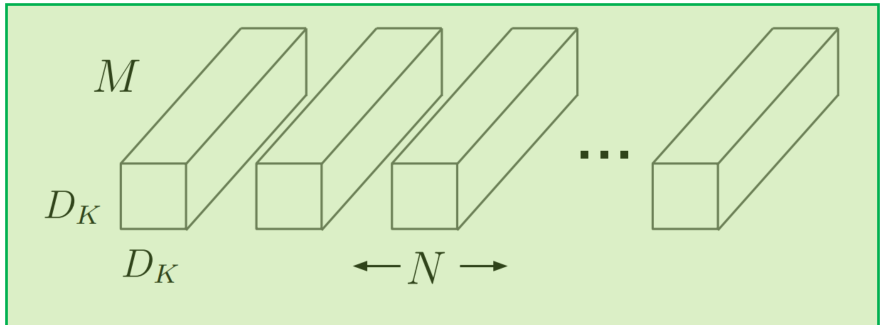
(a) Standard Convolution Filters

(b) Depthwise Convolutional Filters

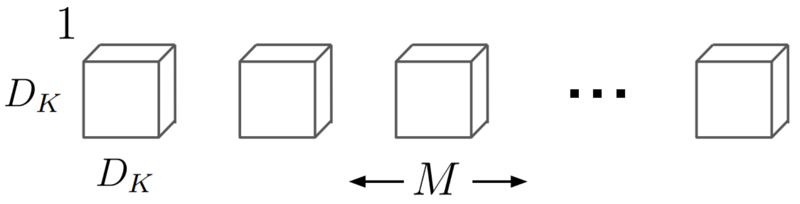
(c) 1×1 Convolutional Filters called Pointwise Convolution in the context of Depthwise Separable Convolution

https://arxiv.org/pdf/1704.04861v1

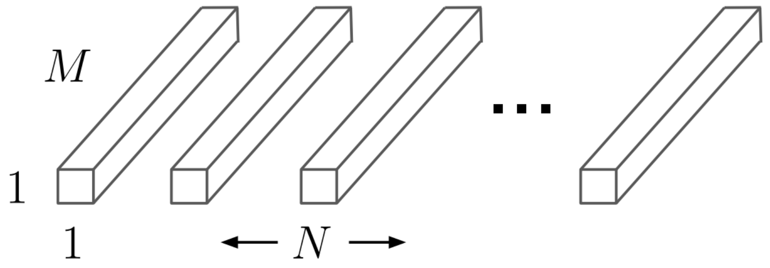
MobileNet



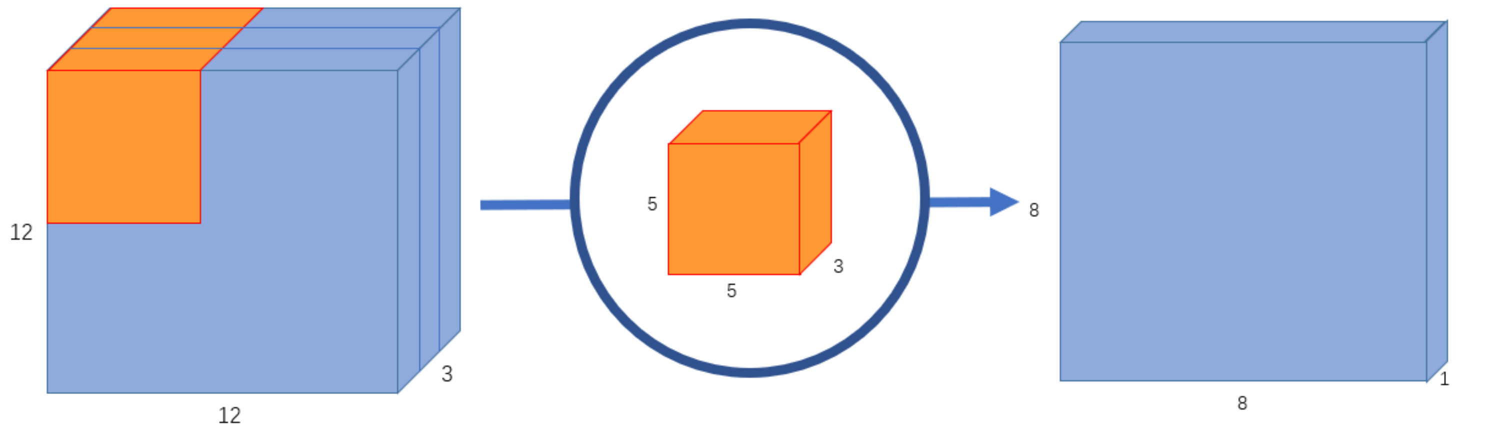
(a) Standard Convolution Filters



(b) Depthwise Convolutional Filters



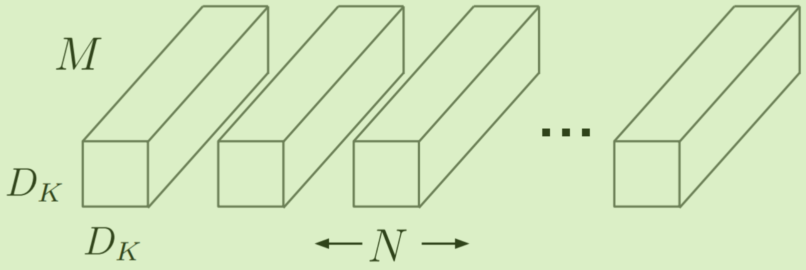
(c) 1×1 Convolutional Filters called Pointwise Convolution in the context of Depthwise Separable Convolution



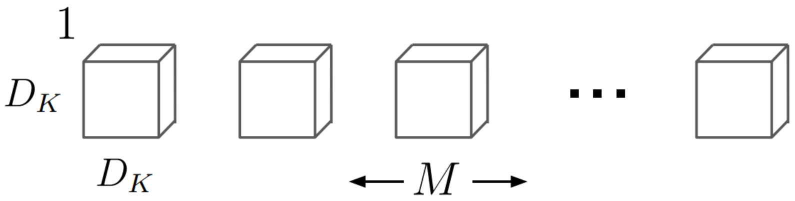
5x5x3=75 multiplications every time the kernel moves

https://arxiv.org/pdf/1704.04861v1
https://towardsdatascience.com/a-basic-introduction-to-separable-convolutions-b99ec3102728

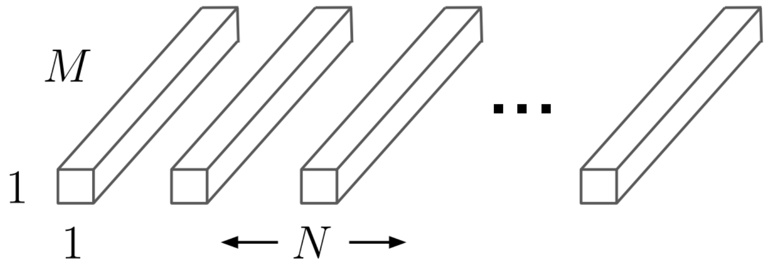
MobileNet



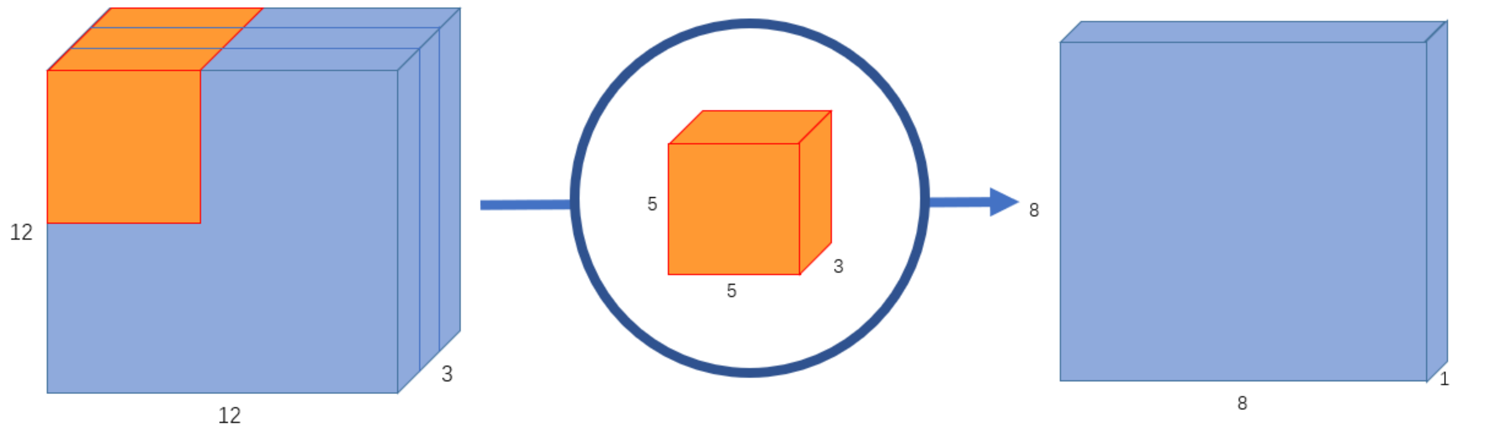
(a) Standard Convolution Filters



(b) Depthwise Convolutional Filters

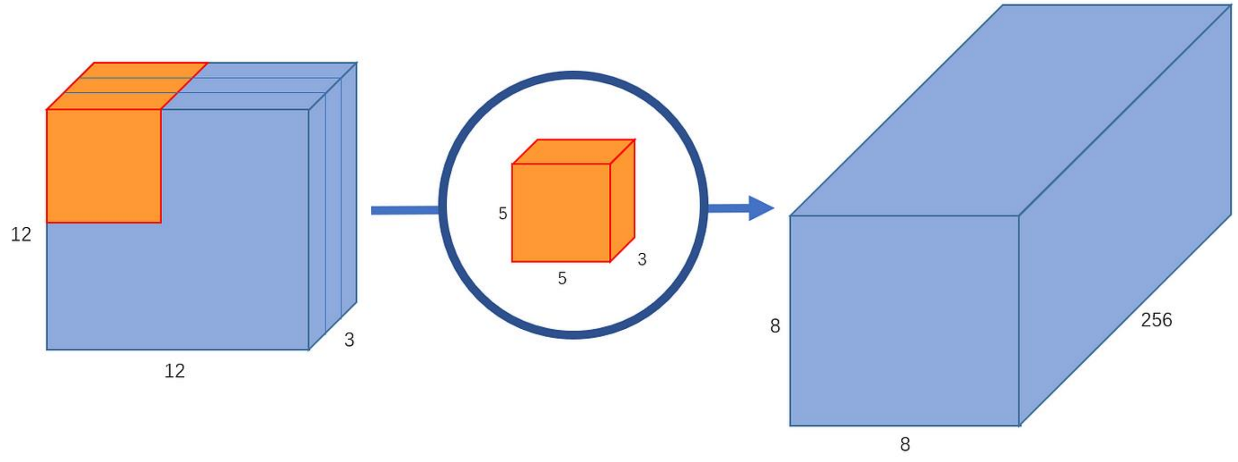


(c) 1×1 Convolutional Filters called Pointwise Convolution in the context of Depthwise Separable Convolution



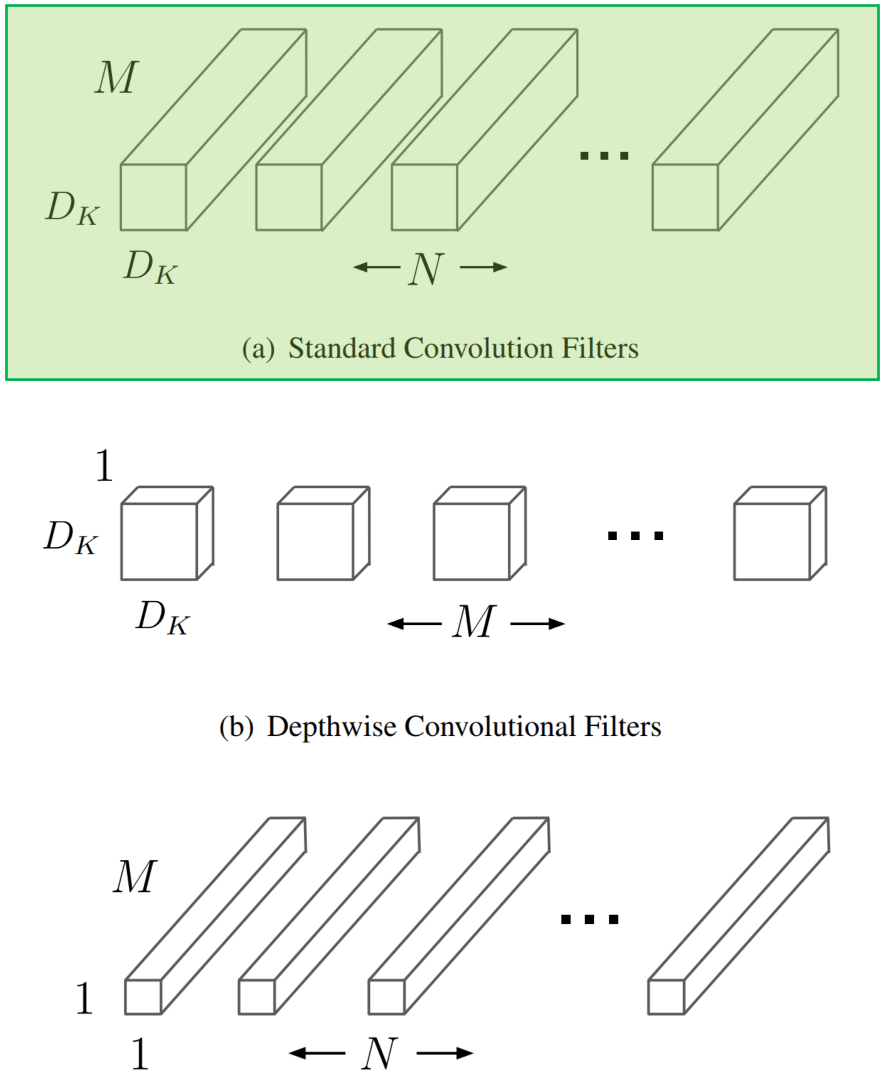
5x5x3=75 multiplications every time the kernel moves
as the output we obtain 8x8x1 image

In the case of output size 8x8x256, we use 256 kernels



https://arxiv.org/pdf/1704.04861v1
https://towardsdatascience.com/a-basic-introduction-to-separable-convolutions-b99ec3102728

MobileNet



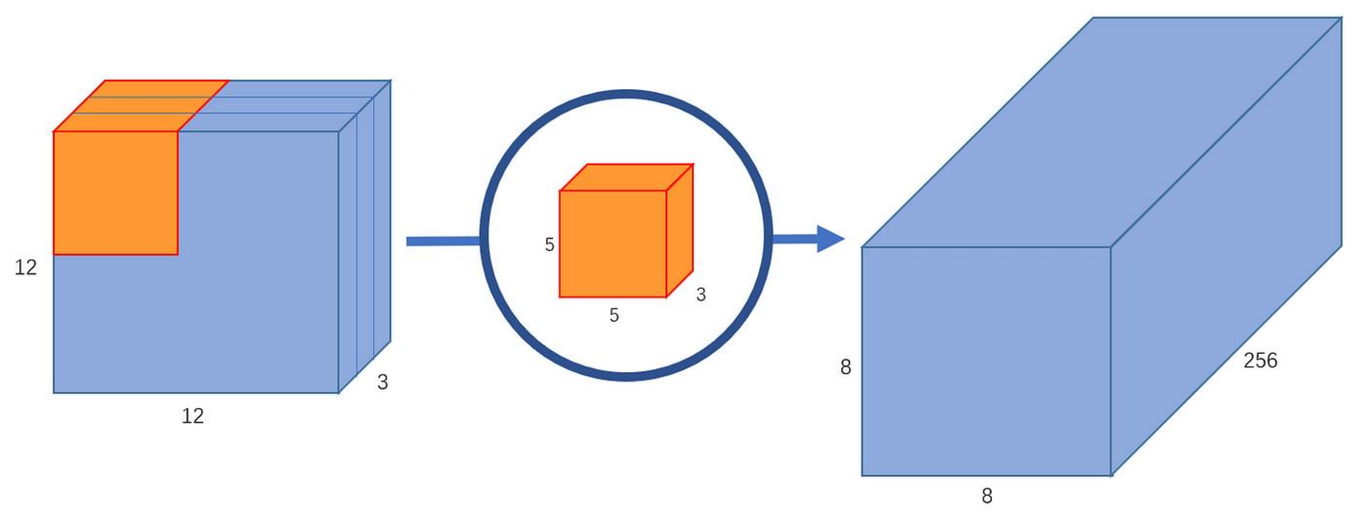
(a) Standard Convolution Filters

(b) Depthwise Convolutional Filters

(c) 1×1 Convolutional Filters called Pointwise Convolution in the context of Depthwise Separable Convolution

https://arxiv.org/pdf/1704.04861v1
https://towardsdatascience.com/a-basic-introduction-to-separable-convolutions-b99ec3102728

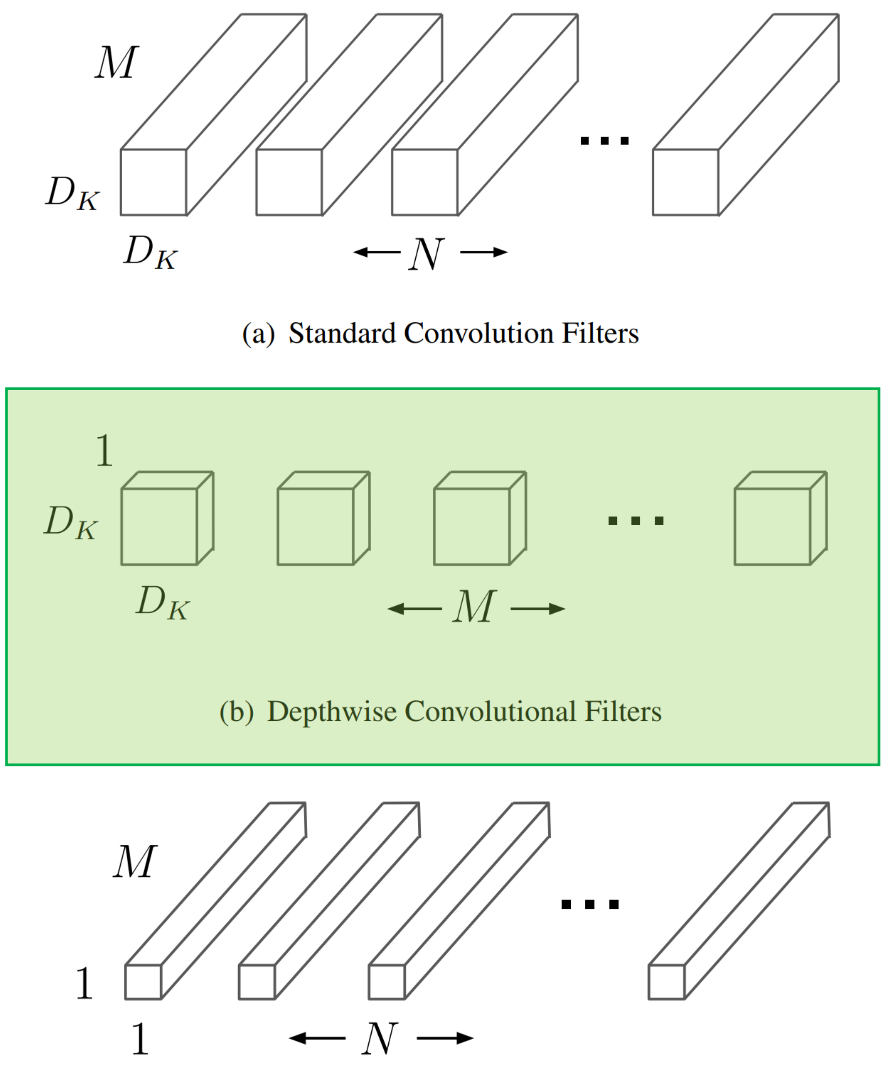
How many operations?



256 5x5x3 kernels that move 8x8 times

256x3x5x5x8x8=1,228,800 multiplications

MobileNet

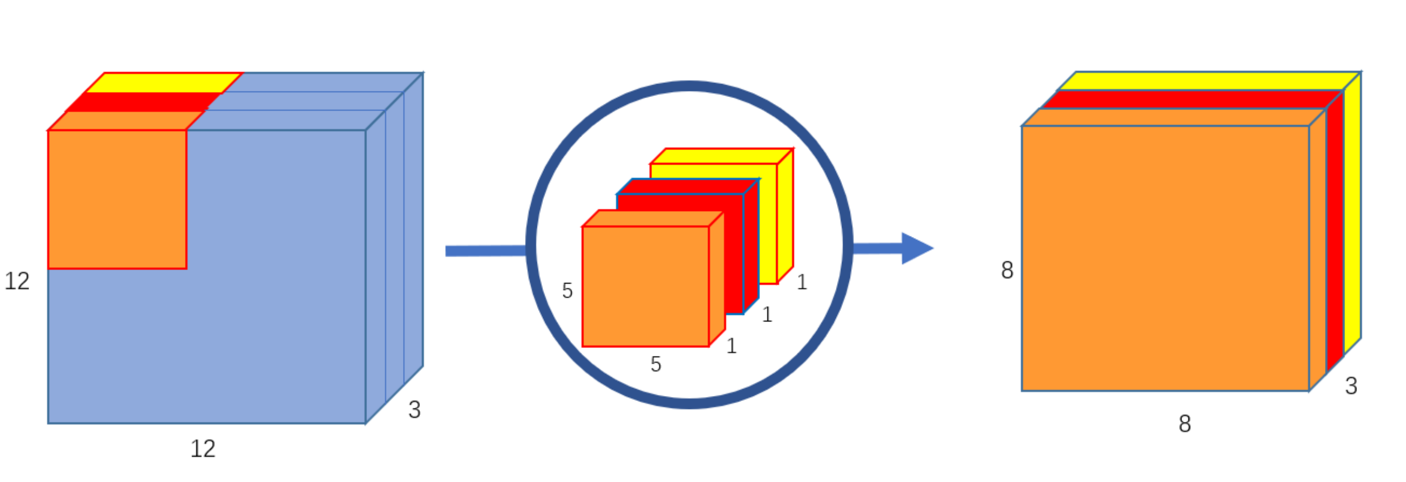


(a) Standard Convolution Filters

(b) Depthwise Convolutional Filters

(c) 1 × 1 Convolutional Filters called Pointwise Convolution in the context of Depthwise Separable Convolution

In the MobileNet approach (in the first step), **Depthwise convolution**: uses 3 kernels (each 5x5x1) to transform 12x12x3 image to 8x8x3 image



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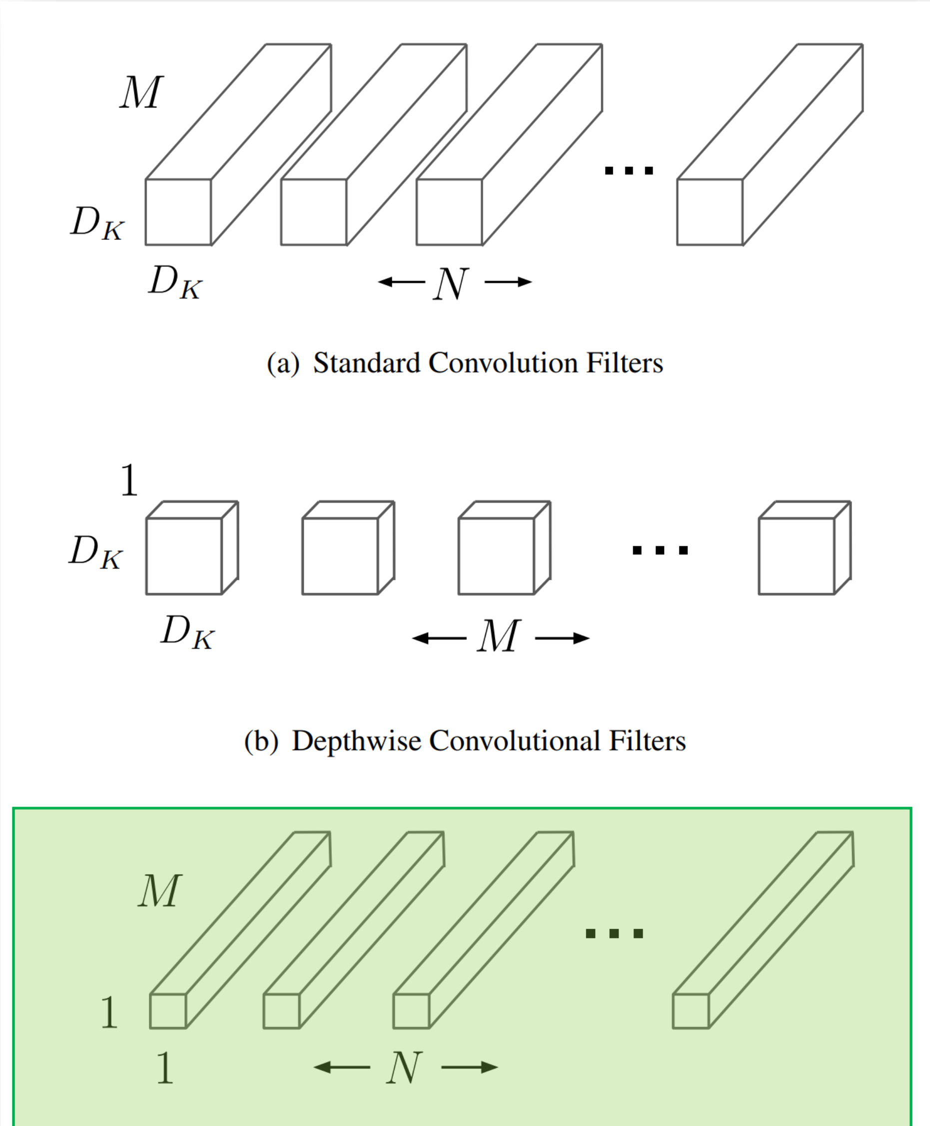
MobileNet



(a) Standard Convolution Filters

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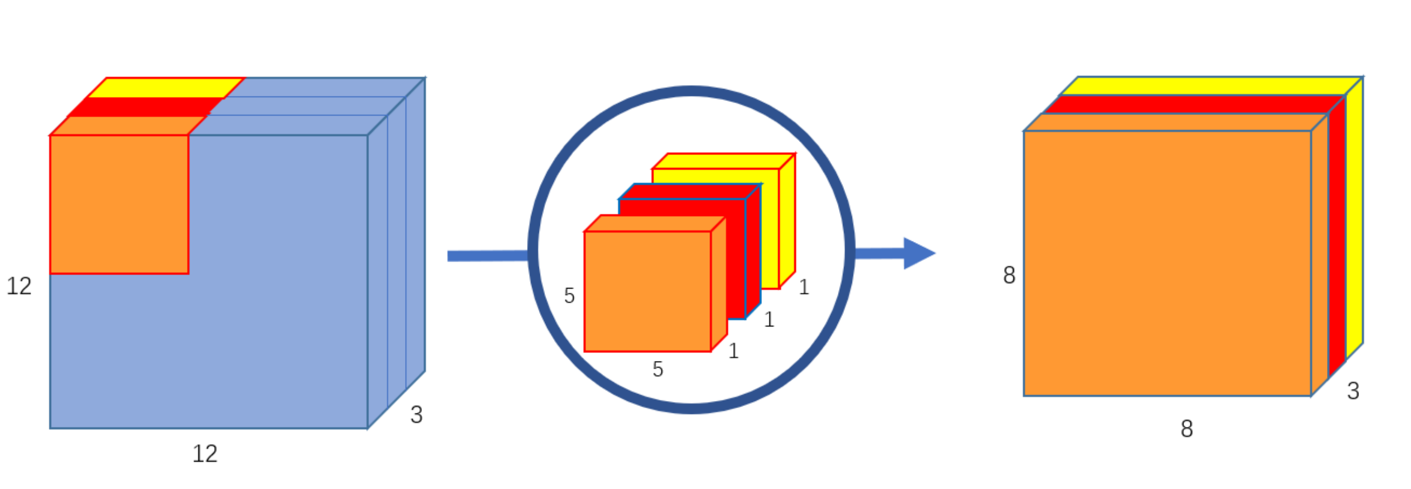
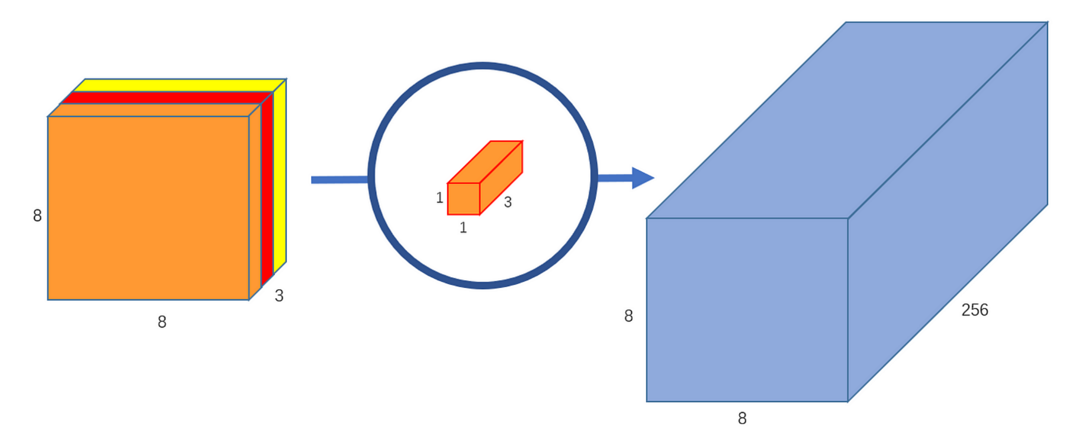
(c) 1×1 Convolutional Filters called Pointwise Convolution in the context of Depthwise Separable Convolution

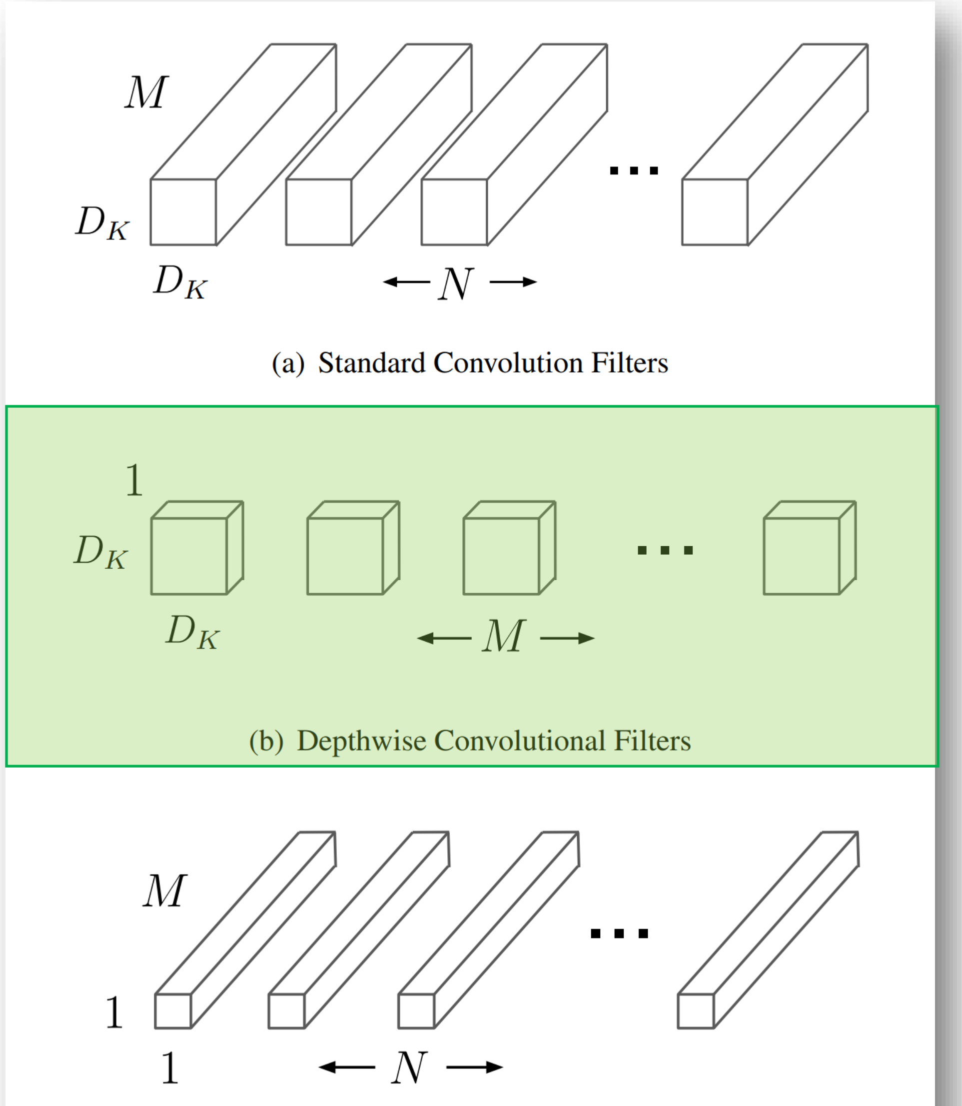
In the first step, **Depthwise convolution**:
uses 3 kernels (each 5x5x1) to transform a 12x12x3 image to 8x8x3 image



In the second step, **Pointwise convolution**:
uses 256 kernels - each 1x1x3 to create final 8x8x256 image (same shape as in the classical conv.)



MobileNet



(a) Standard Convolution Filters

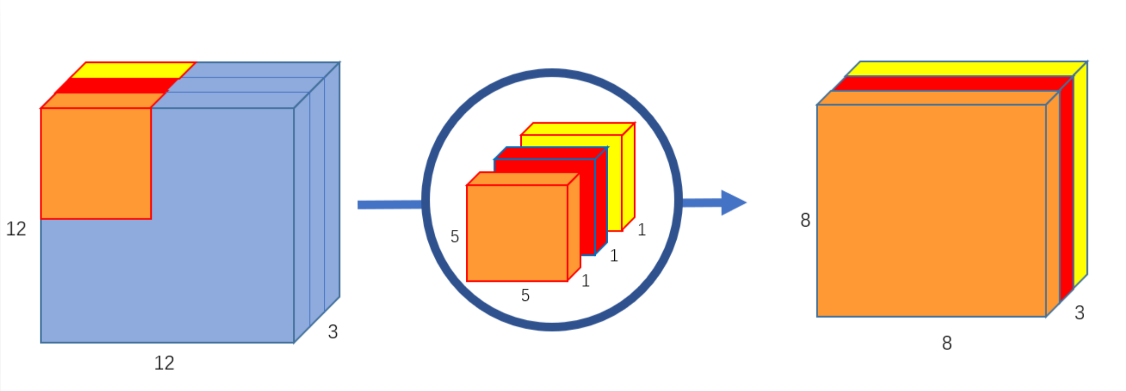
(b) Depthwise Convolutional Filters

(c) 1×1 Convolutional Filters called Pointwise Convolution in the context of Depthwise Separable Convolution

How many operations?

Depthwise convolution:

we have 3 5x5x1 kernels that move 8x8 times. That is 3x5x5x8x8 = **4,800**



https://arxiv.org/pdf/1704.04861v1
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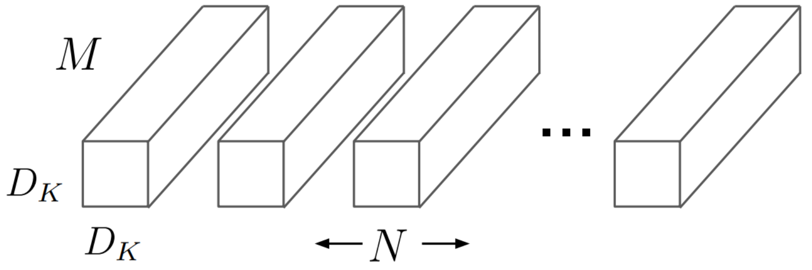
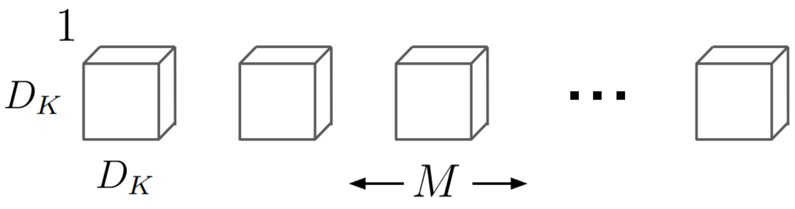
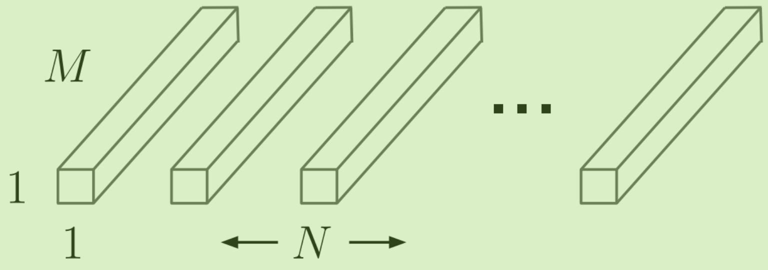
MobileNet



(a) Standard Convolution Filters



(b) Depthwise Convolutional Filters



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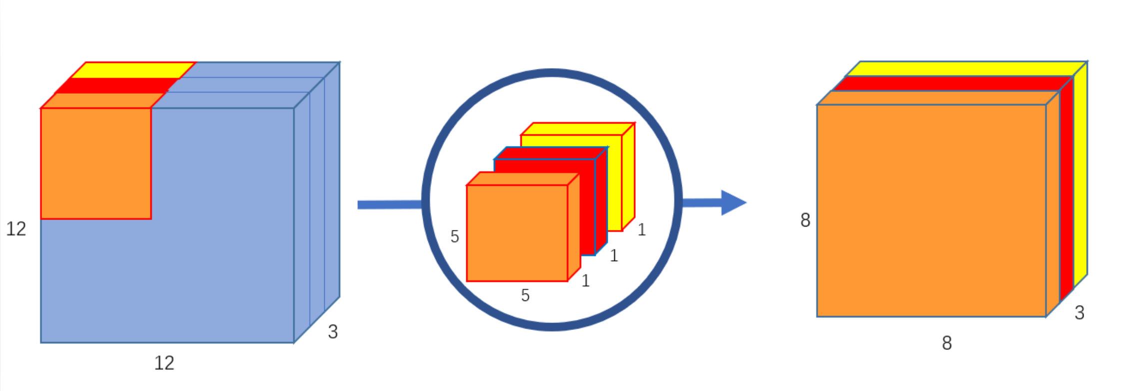
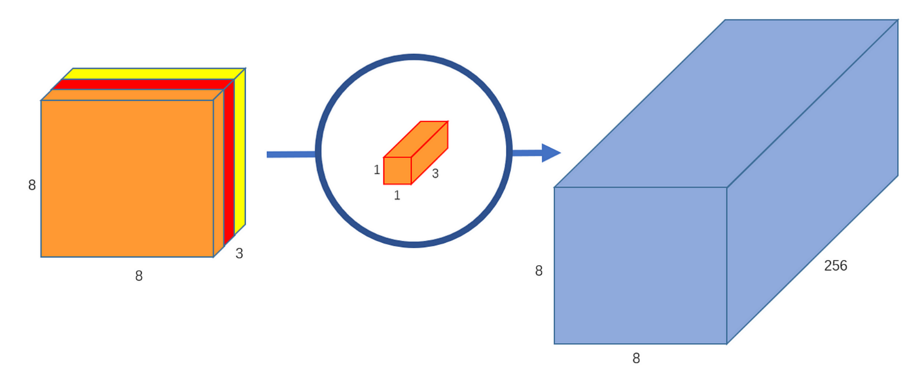
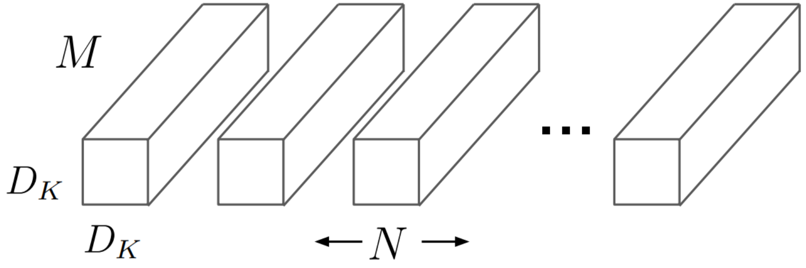


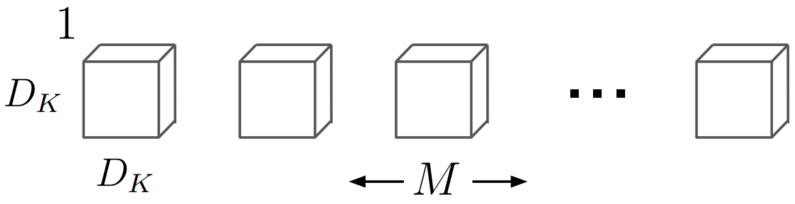
Pointwise convolution:
we have 256 1x1x3 kernels that move 8x8 times
That is 256x1x1x3x8x8 = **49,152** multiplications



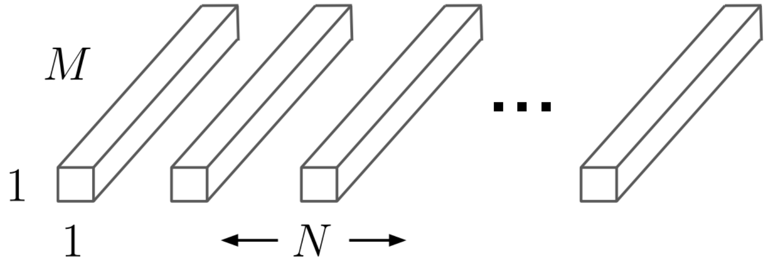
MobileNet



(a) Standard Convolution Filters



(b) Depthwise Convolutional Filters



(c) 1×1 Convolutional Filters called Pointwise Convolution in the context of Depthwise Separable Convolution

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How many operations?

Depthwise convolution:
we have 3 5x5x1 kernels that move 8x8 times. That's 3x5x5x8x8 = **4,800**

Pointwise convolution:
we have 256 1x1x3 kernels that move 8x8 times
That is 256x1x1x3x8x8 = **49,152**

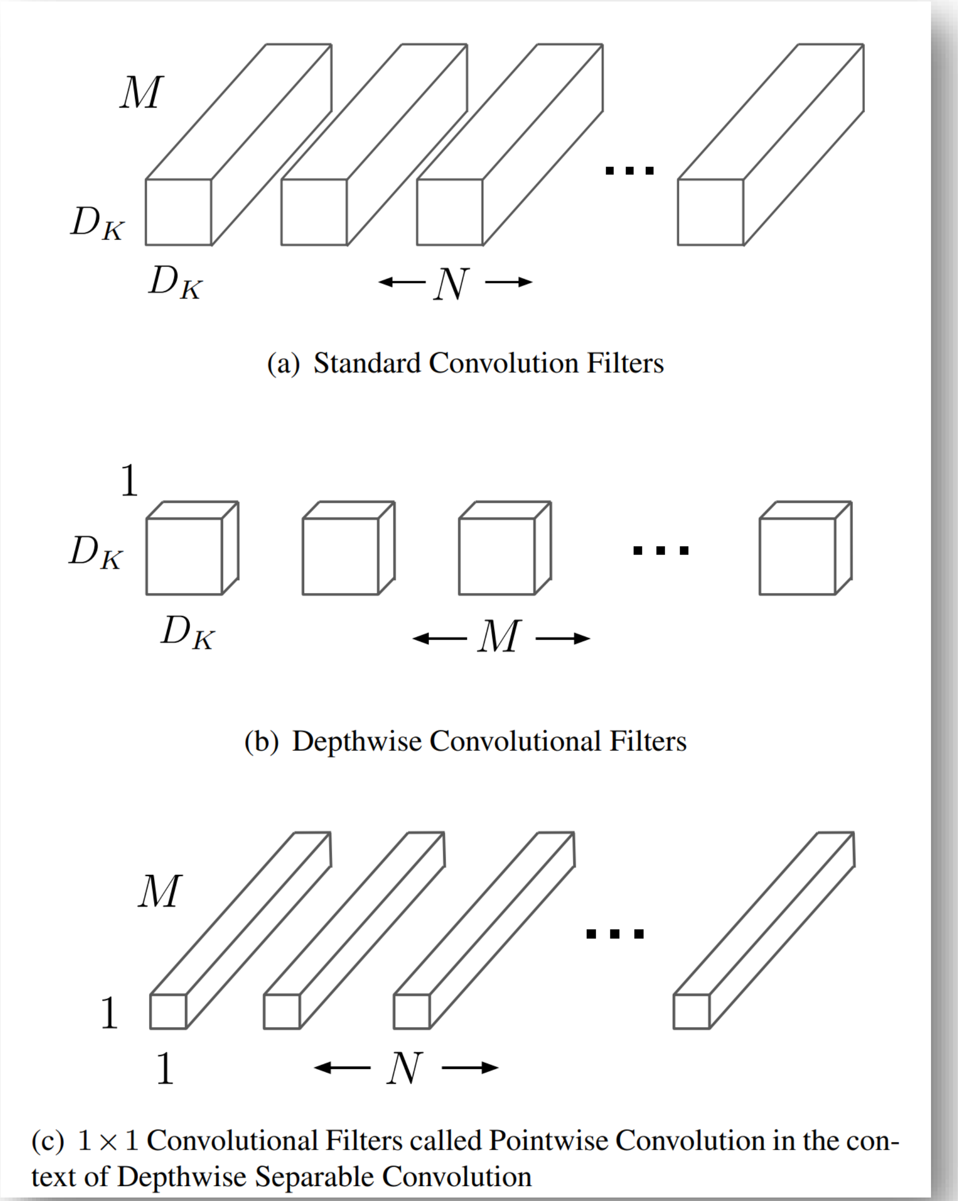
Adding them up together, that is 53,952 multiplications.

53,952 (Depthwise + Pointwise)

Vs.

1,228,800 (Standard way)

MobileNet



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53,952 (Depthwise + Pointwise)

Vs.

1,228,800 (Standard way)

SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and <0.5MB model size

Forrest N. Iandola[1], **Song Han**[2], **Matthew W. Moskewicz**[1], **Khalid Ashraf**[1], **William J. Dally**[2], **Kurt Keutzer**[1]
[1]DeepScale* & UC Berkeley [2]Stanford University

- **More efficient distributed training.** Communication among servers is the limiting factor to the scalability of distributed CNN training. For distributed data-parallel training, communication overhead is directly proportional to the number of parameters in the model (Iandola et al., 2016). In short, small models train faster due to requiring less communication.
- **Less overhead when exporting new models to clients.** For autonomous driving, companies such as Tesla periodically copy new models from their servers to customers' cars. This practice is often referred to as an *over-the-air* update. Consumer Reports has found that the safety of Tesla's *Autopilot* semi-autonomous driving functionality has incrementally improved with recent over-the-air updates (Consumer Reports, 2016). However, over-the-air updates of today's typical CNN/DNN models can require large data transfers. With AlexNet, this would require 240MB of communication from the server to the car. Smaller models require less communication, making frequent updates more feasible.
- **Feasible FPGA and embedded deployment.** FPGAs often have less than 10MB[1] of on-chip memory and no off-chip memory or storage. For inference, a sufficiently small model could be stored directly on the FPGA instead of being bottlenecked by memory bandwidth (Qiu et al., 2016), while video frames stream through the FPGA in real time. Further, when deploying CNNs on Application-Specific Integrated Circuits (ASICs), a sufficiently small model could be stored directly on-chip, and smaller models may enable the ASIC to fit on a smaller die.

https://arxiv.org/abs/1602.07360

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3.1 Architectural Design Strategies

Our overarching objective in this paper is to identify CNN architectures that have few parameters while maintaining competitive accuracy. To achieve this, we employ three main strategies when designing CNN architectures:

Strategy 1. **Replace 3x3 filters with 1x1 filters.** Given a budget of a certain number of convolution filters, we will choose to make the majority of these filters 1x1, since a 1x1 filter has 9X fewer parameters than a 3x3 filter.

Strategy 2. **Decrease the number of input channels to 3x3 filters.** Consider a convolution layer that is comprised entirely of 3x3 filters. The total quantity of parameters in this layer is (number of input channels) * (number of filters) * (3*3). So, to maintain a small total number of parameters in a CNN, it is important not only to decrease the number of 3x3 filters (see Strategy 1 above), but also to decrease the number of *input channels* to the 3x3 filters. We decrease the number of input channels to 3x3 filters using *squeeze layers*, which we describe in the next section.

Strategy 3. **Downsample late in the network so that convolution layers have large activation maps.** In a convolutional network, each convolution layer produces an output activation map with a spatial resolution that is at least 1x1 and often much larger than 1x1. The height and width of these activation maps are controlled by: (1) the size of the input data (e.g. 256x256 images) and (2)

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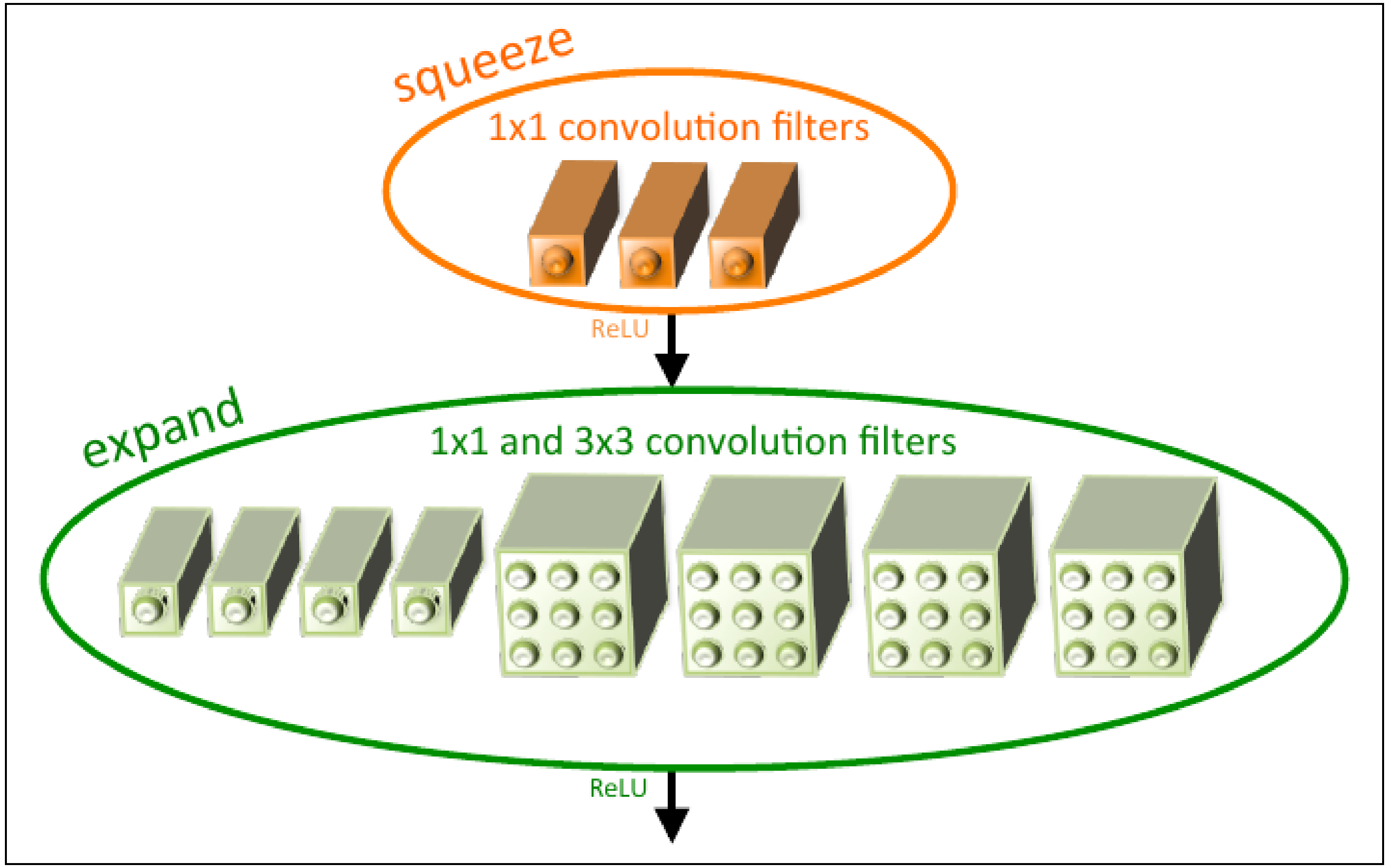

Figure 1: Microarchitectural view: Organization of convolution filters in the **Fire module**. In this example, $s_{1x1} = 3$, $e_{1x1} = 4$, and $e_{3x3} = 4$. We illustrate the convolution filters but not the activations.

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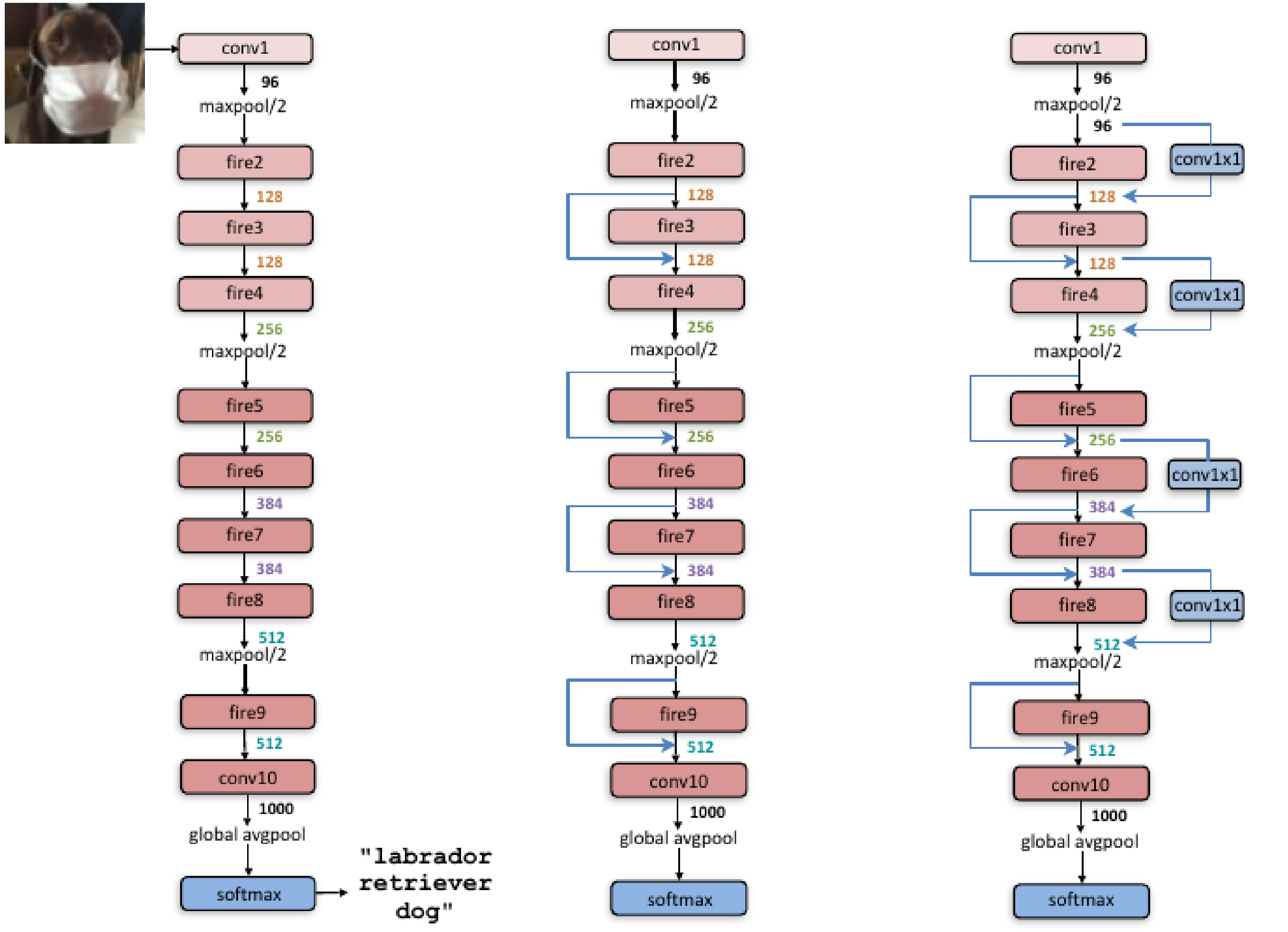

Figure 2: Macroarchitectural view of our SqueezeNet architecture. Left: SqueezeNet (Section 3.3); Middle: SqueezeNet with simple bypass (Section 6); Right: SqueezeNet with complex bypass (Section 6).

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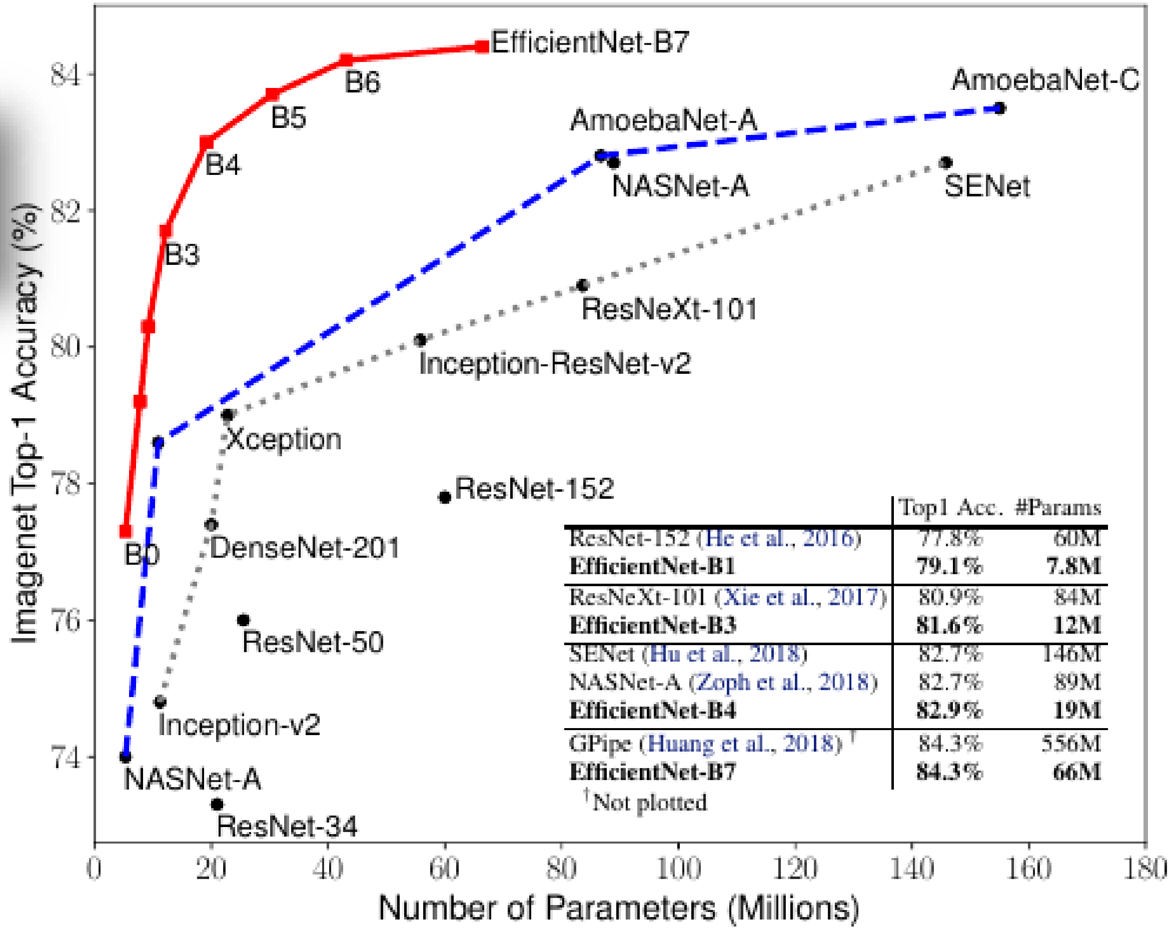
EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks

Mingxing Tan [1] Quoc V. Le [1]

To go even further, we use neural architecture search to design a new baseline network and scale it up to obtain a family of models, called *EfficientNets*, which achieve much better accuracy and efficiency than previous ConvNets. In particular, our EfficientNet-B7 achieves state-of-the-art 84.3% top-1 accuracy on ImageNet, while being **8.4x smaller** and **6.1x faster** on inference than the best existing ConvNet. Our EfficientNets also transfer well and achieve state-of-the-art accuracy on CIFAR-100 (91.7%), Flowers (98.8%), and 3 other transfer learning datasets, with an order of magnitude fewer parameters. Source code is at `https://github.com/tensorflow/tpu/tree/master/models/official/efficientnet`.

https://arxiv.org/abs/1905.11946



	Top1 Acc.	#Params
ResNet-152 (He et al., 2016)	77.8%	60M
EfficientNet-B1	**79.1%**	**7.8M**
ResNeXt-101 (Xie et al., 2017)	80.9%	84M
EfficientNet-B3	**81.6%**	**12M**
SENet (Hu et al., 2018)	82.7%	146M
NASNet-A (Zoph et al., 2018)	82.7%	89M
EfficientNet-B4	**82.9%**	**19M**
GPipe (Huang et al., 2018) [†]	84.3%	556M
EfficientNet-B7	**84.3%**	**66M**

[†] Not plotted

Figure 1. **Model Size vs. ImageNet Accuracy.** All numbers are for single-crop, single-model. Our EfficientNets significantly outperform other ConvNets. In particular, EfficientNet-B7 achieves new state-of-the-art 84.3% top-1 accuracy but being 8.4x smaller and 6.1x faster than GPipe. EfficientNet-B1 is 7.6x smaller and 5.7x faster than ResNet-152. Details are in Table 2 and 4.

EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks

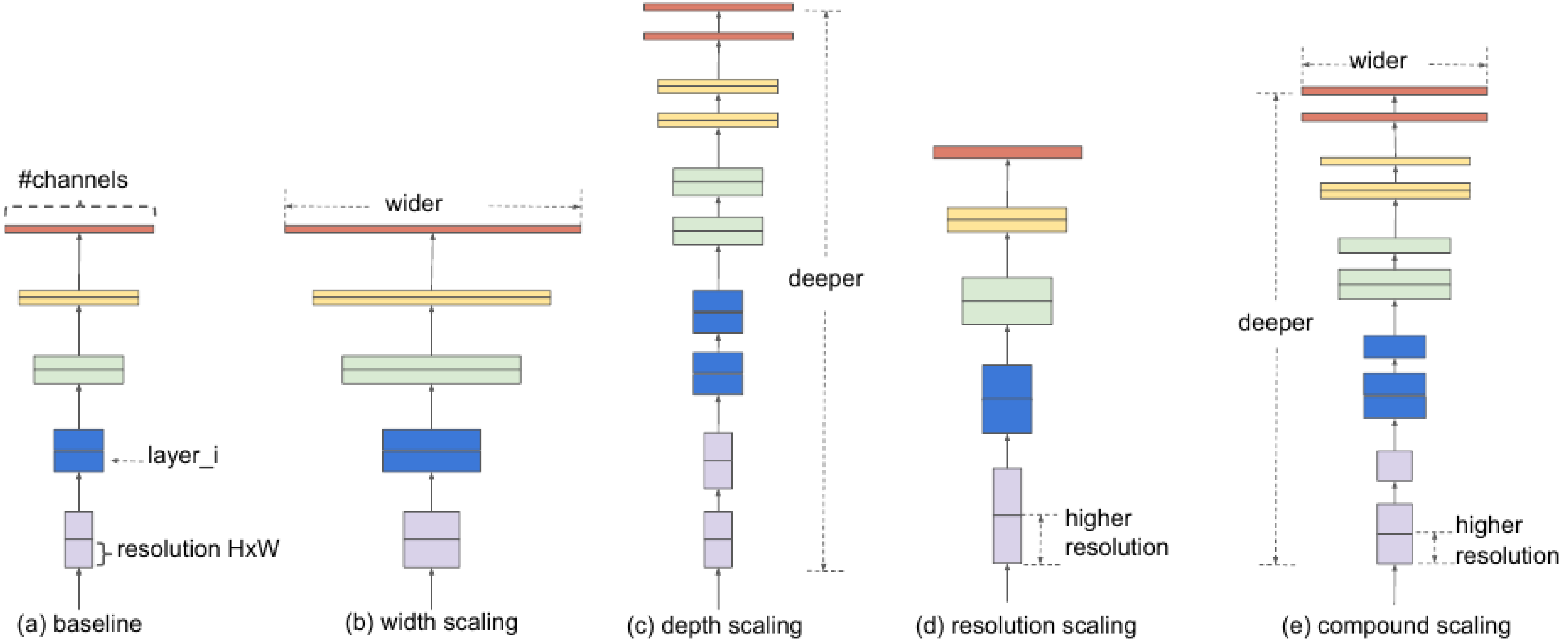


Figure 2. **Model Scaling.** (a) is a baseline network example; (b)-(d) are conventional scaling that only increases one dimension of network width, depth, or resolution. (e) is our proposed compound scaling method that uniformly scales all three dimensions with a fixed ratio.

https://arxiv.org/abs/1905.11946

In this paper, we propose a new **compound scaling method**, which use a compound coefficient ϕ to uniformly scales network width, depth, and resolution in a principled way:

$$\begin{aligned} \text{depth: } d &= \alpha^\phi \\ \text{width: } w &= \beta^\phi \\ \text{resolution: } r &= \gamma^\phi \\ \text{s.t. } \alpha \cdot \beta^2 \cdot \gamma^2 &\approx 2 \\ \alpha \geq 1, \beta \geq 1&, \gamma \geq 1 \end{aligned} \tag{3}$$

where α, β, γ are constants that can be determined by a small grid search. Intuitively, ϕ is a user-specified coefficient that controls how many more resources are available for model scaling, while α, β, γ specify how to assign these extra resources to network width, depth, and resolution re-

Starting from the baseline EfficientNet-B0, we apply our compound scaling method to scale it up with two steps:

- STEP 1: we first fix $\phi = 1$, assuming twice more resources available, and do a small grid search of α, β, γ based on Equation 2 and 3. In particular, we find the best values for EfficientNet-B0 are $\alpha = 1.2, \beta = 1.1, \gamma = 1.15$, under constraint of $\alpha \cdot \beta^2 \cdot \gamma^2 \approx 2$.
- STEP 2: we then fix α, β, γ as constants and scale up baseline network with different ϕ using Equation 3, to obtain EfficientNet-B1 to B7 (Details in Table 2).

Table 7. **Scaled Models Used in Figure 7.**

Model	FLOPS	Top-1 Acc.
Baseline model (EfficientNet-B0)	0.4B	77.3%
Scale model by depth (d=4)	1.8B	79.0%
Scale model by width (w=2)	1.8B	78.9%
Scale model by resolution (r=2)	1.9B	79.1%
Compound Scale (d=1.4, w=1.2, r=1.3)	**1.8B**	**81.1%**

https://arxiv.org/abs/1905.11946

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Shortcuts

The only exception to the above are the detection models included on `torchvision.models.detection`. These models require TorchVision to be installed because they depend on custom C++ operators.

Classification

The following classification models are available, with or without pre-trained weights:

- AlexNet
- ConvNeXt
- DenseNet
- EfficientNet
- EfficientNetV2
- GoogLeNet
- Inception V3
- MaxVit
- MNASNet
- MobileNet V2
- MobileNet V3
- RegNet
- ResNet
- ResNeXt
- ShuffleNet V2
- SqueezeNet
- SwinTransformer
- VGG
- VisionTransformer
- Wide ResNet

https://pytorch.org/vision/stable/models.html