

使用深度可分离卷积构建轻量级神经网络

两个全局超参数：

允许我们依据约束条件选择合适大小的模型，实现速度和精度的权衡

大幅降低参数量和计算量

MobileNet描述了一个高效的网络架构，允许通过两个超参数直接构建非常小、低延迟、易满足嵌入式设备要求的模型

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

Convolutional neural networks have become ubiquitous in computer vision ever since AlexNet [19] popularized deep convolutional neural networks by winning the ImageNet Challenge: ILSVRC 2012 [24]. The general trend has been to make deeper and more complicated networks in order to achieve higher accuracy [27, 31, 29, 8]. However, these advances to improve accuracy are not necessarily making networks more efficient with respect to size and speed. In many real world applications such as robotics, self-driving car and augmented reality, the recognition tasks need to be carried out in a timely fashion on a computationally limited platform.

This paper describes an efficient network architecture and a set of *two hyper-parameters* in order to build very small, low latency models that can be easily matched to the design requirements for mobile and embedded vision applications. Section 2 reviews prior work in building small

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 with a summary and conclusion.

2. Prior Work

There has been rising interest in building small and efficient neural networks in the recent literature, e.g. [16, 34, 12, 36, 22]. *Many different approaches can be generally categorized into either compressing pretrained networks or training small networks directly*. This paper proposes a class of network architectures that allows a model developer to specifically choose a small network that matches the resource restrictions (latency, size) for their application. MobileNets primarily focus on optimizing for latency but also yield small networks. Many papers on small networks focus only on size but do not consider speed.

MobileNets are built primarily from depthwise separable convolutions initially introduced in [26] and subsequently used in Inception models [13] to reduce the computation in the first few layers. Flattened networks [16] build a network out of fully factorized convolutions and showed the potential of extremely factorized networks. Independent of this current paper, Factorized Networks[34] introduces a similar factorized convolution as well as the use of topological connections. Subsequently, the Xception network [3] demonstrated how to scale up depthwise separable filters to outperform Inception V3 networks. Another small network is Squeezenet [12] which uses a bottleneck approach to design a very small network. Other reduced computation networks include structured transform networks [28] and deep fried convnets [37].

A different approach for obtaining small networks is shrinking, factorizing or compressing pretrained networks. Compression based on product quantization [36], hashing

轻量化卷积神经网络：边缘计算（终端实时计算）

轻量化网络 移动端、终端边缘计算

压缩已训练好的模型 知识蒸馏 权值量化 剪枝 {权重剪枝 注意力迁移
通道剪枝}

直接训练轻量化网络 SqueezeNet MobileNet v1, v2, v3 ShuffleNet Xception EfficientNet NasNet DARTS

加速卷积运算 im2col + GEMM Winograd 低秩分解

硬件部署 TensorRT Jetson Tensorflow-slim Tensorflow-lite Openvino

参数量 计算量 内存访问量 耗时 能耗 碳排放 CUDA加速 对抗学习

现阶段，在建立小型高效的神经网络工作中，通常可分为两类工作：

压缩预训练模型：

获得小型网络的一个办法是减小、分解或压缩预训练网络，例如量化压缩 (product quantization)、哈希(hashing)、剪枝(pruning)、矢量编码 (vector quantization)和霍夫曼编码(Huffman coding)等；此外还有各种分解因子(various factorizations)用来加速预训练网络；还有一种训练小型网络的方法叫蒸馏(distillation)，使用大型网络指导小型网络，这是对论文的方法做了一个补充，后续有介绍补充。

直接训练小模型：MobileNet就是这种

Flattened networks利用完全的因式分解的卷积网络构建模型，显示出完全分解网络的潜力；Factorized Networks引入了类似的分解卷积以及拓扑连接的使用；Xception network显示了如何扩展深度可分离卷积到Inception V3 networks；Squeezenet 使用一个bottleneck用于构建小型网络。

本文提出的MobileNet网络架构，允许开发人员专门选择与其资源限制(延迟、大小)匹配的小型模型，MobileNets主要注重于优化延迟同时考虑小型网络，从深度可分离卷积的角度重新构建模型。

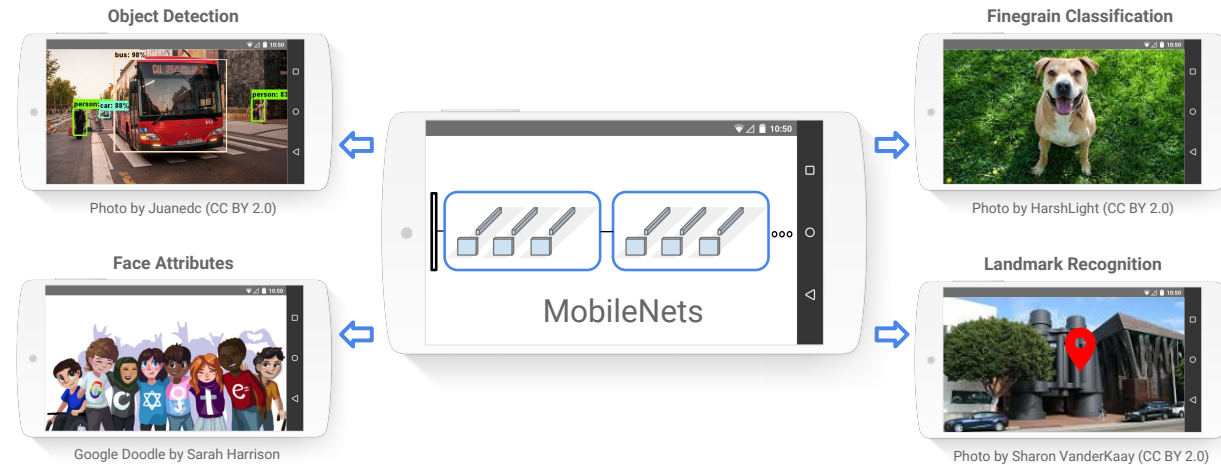


Figure 1. MobileNet models can be applied to various recognition tasks for efficient on device intelligence.

[2], and pruning, vector quantization and Huffman coding [5] have been proposed in the literature. Additionally various factorizations have been proposed to speed up pre-trained networks [14, 20]. Another method for training small networks is distillation [9] which uses a larger network to teach a smaller network. It is complementary to our approach and is covered in some of our use cases in section 4. Another emerging approach is low bit networks [4, 22, 11].

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 convolutional layer takes as input a $D_F \times$

$D_F \times M$ feature map \mathbf{F} and produces a $D_F \times D_F \times N$ feature map \mathbf{G} where D_F is the spatial width and height of a square input feature map¹, M is the number of input channels (input depth), D_F is the spatial width and height of a square output feature map and N is the number of output channel (output depth).

The standard convolutional layer is parameterized by convolution kernel \mathbf{K} of size $D_K \times D_K \times M \times N$ where D_K is the spatial dimension of the kernel assumed to be square and M is number of input channels and N is the number of output channels as defined previously.

The output feature map for standard convolution assuming stride one and padding is computed as:

$$\mathbf{G}_{k,l,n} = \sum_{i,j,m} \mathbf{K}_{i,j,m,n} \cdot \mathbf{F}_{k+i-1,l+j-1,m} \quad (1)$$

Standard convolutions have the computational cost of:

$$\text{标准卷积的乘法计算量} = \text{一次卷积的乘法运算次数} \cdot \text{输出feature map的特征点个数} = D_K \cdot D_K \cdot M \cdot N \cdot D_F \cdot D_F \quad (2)$$

where the computational cost depends multiplicatively on the number of input channels M , the number of output channels N the kernel size $D_k \times D_k$ and the feature map size $D_F \times D_F$. MobileNet models address each of these terms and their interactions. First it uses depthwise separable convolutions to break the interaction between the number of output channels and the size of the kernel.

The standard convolution operation has the effect of filtering features based on the convolutional kernels and combining features in order to produce a new representation. The filtering and combination steps can be split into two steps via the use of factorized convolutions called depthwise

¹We assume that the output feature map has the same spatial dimensions as the input and both feature maps are square. Our model shrinking results generalize to feature maps with arbitrary sizes and aspect ratios.



深度可分离卷积是分组卷积的特例
分组卷积提取私有特征

深度可分离卷积由两层组成：深度卷积和逐点卷积。我们使用深度卷积在每个输入通道（输入深度）上应用单个滤波器。逐点卷积，一个简单的 1×1 卷积，然后被用来创建一个深度层输出的线性组合。MobileNets对这两层都使用了batchnorm和ReLU非线性激活。

separable convolutions for substantial reduction in computational cost.

Depthwise separable convolution are made up of two layers: depthwise convolutions and pointwise convolutions. We use depthwise convolutions to apply a single filter per each input channel (input depth). Pointwise convolution, a simple 1×1 convolution, is then used to create a linear combination of the output of the depthwise layer. MobileNets use both batchnorm and ReLU nonlinearities for both layers.

Depthwise convolution with one filter per input channel (input depth) can be written as:

$$\hat{G}_{k,l,m} = \sum_{i,j} \hat{K}_{i,j,m} \cdot F_{k+i-1,l+j-1,m} \quad (3)$$

where \hat{K} is the depthwise convolutional kernel of size $D_K \times D_K \times M$ where the m_{th} filter in \hat{K} is applied to the m_{th} channel in F to produce the m_{th} channel of the filtered output feature map \hat{G} .

Depthwise convolution has a computational cost of:

$$D_K \cdot D_K \cdot M \cdot D_F \cdot D_F \quad (4)$$

Depthwise convolution is extremely efficient relative to standard convolution. However it only filters input channels, it does not combine them to create new features. So an additional layer that computes a linear combination of the output of depthwise convolution via 1×1 convolution is needed in order to generate these new features.

The combination of depthwise convolution and 1×1 (pointwise) convolution is called depthwise separable convolution which was originally introduced in [26].

Depthwise separable convolutions cost:

一次卷积的乘法运算次数 输出feature map的特征点个数

$$D_K \cdot D_K \cdot M \cdot D_F \cdot D_F + M \cdot N \cdot D_F \cdot D_F \quad (5)$$

Depthwise卷积 Pointwise卷积

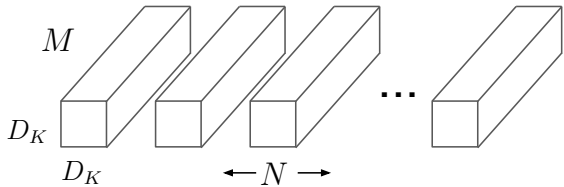
which is the sum of the depthwise and 1×1 pointwise convolutions.

By expressing convolution as a two step process of filtering and combining we get a reduction in computation of:

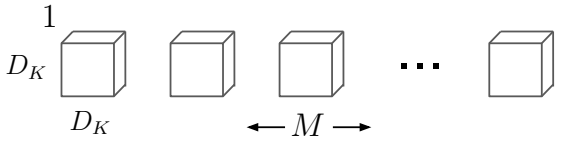
$$\frac{D_K \cdot D_K \cdot M \cdot D_F \cdot D_F + M \cdot N \cdot D_F \cdot D_F}{D_K \cdot D_K \cdot M \cdot N \cdot D_F \cdot D_F} = \frac{1}{N} + \frac{1}{D_K^2}$$

MobileNet uses 3×3 depthwise separable convolutions which uses between 8 to 9 times less computation than standard convolutions at only a small reduction in accuracy as seen in Section 4.

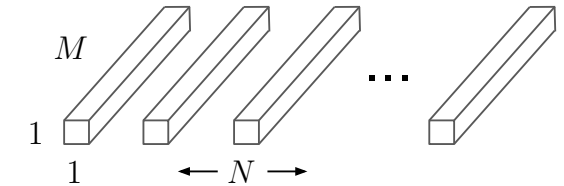
Additional factorization in spatial dimension such as in [16, 31] does not save much additional computation as very little computation is spent in depthwise convolutions.



(a) Standard Convolution Filters



(b) Depthwise Convolutional Filters



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

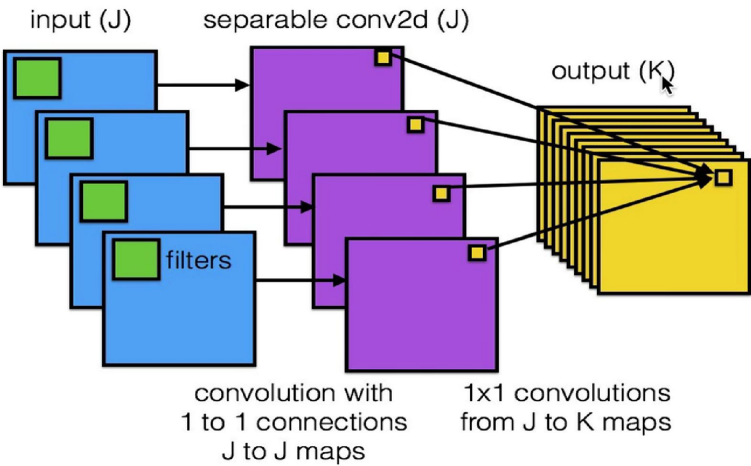
Figure 2. The standard convolutional filters in (a) are replaced by two layers: depthwise convolution in (b) and pointwise convolution in (c) to build a depthwise separable filter.

3.2. Network Structure and Training

The MobileNet structure is built on depthwise separable convolutions as mentioned in the previous section except for the first layer which is a full convolution. By defining the network in such simple terms we are able to easily explore network topologies to find a good network. The MobileNet architecture is defined in Table 1. All layers are followed by a batchnorm [13] and ReLU nonlinearity with the exception of the final fully connected layer which has no nonlinearity and feeds into a softmax layer for classification. Figure 3 contrasts a layer with regular convolutions, batchnorm and ReLU nonlinearity to the factorized layer with depthwise convolution, 1×1 pointwise convolution as well as batchnorm and ReLU after each convolutional layer. Down sampling is handled with strided convolution in the depthwise convolutions as well as in the first layer. A final average pooling reduces the spatial resolution to 1 before the fully connected layer. Counting depthwise and pointwise convolutions as separate layers, MobileNet has 28 layers.

It is not enough to simply define networks in terms of a small number of Mult-Adds. It is also important to make sure these operations can be efficiently implementable. For

深度可分离卷积：
depthwise卷积：
关注HW方向的信息
 1×1 卷积：
跨通道信息融合
实现了CHW方向的解耦



深度可分离卷积的参数量： $D_K \cdot D_K \cdot M + 1 \cdot 1 \cdot M \cdot N$
标准卷积参数量： $D_K \cdot D_K \cdot M \cdot N$

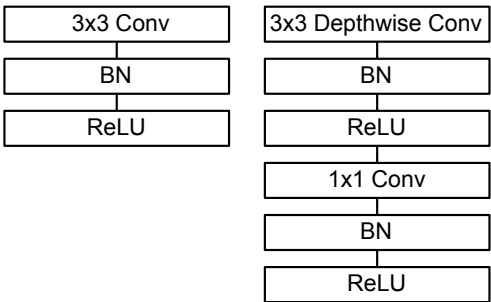


Figure 3. Left: Standard convolutional layer with batchnorm and ReLU. Right: Depthwise Separable convolutions with Depthwise and Pointwise layers followed by batchnorm and ReLU.

instance unstructured sparse matrix operations are not typically faster than dense matrix operations until a very high level of sparsity. Our model structure puts nearly all of the computation into dense 1×1 convolutions. This can be implemented with highly optimized general matrix multiply (GEMM) functions. Often convolutions are implemented by a GEMM but require an initial reordering in memory called im2col in order to map it to a GEMM. For instance, this approach is used in the popular Caffe package [15]. 1×1 convolutions do not require this reordering in memory and can be implemented directly with GEMM which is one of the most optimized numerical linear algebra algorithms. MobileNet spends 95% of its computation time in 1×1 convolutions which also has 75% of the parameters as can be seen in Table 2. Nearly all of the additional parameters are in the fully connected layer.

MobileNet models were trained in TensorFlow [1] using RMSprop [33] with asynchronous gradient descent similar to Inception V3 [31]. However, contrary to training large models we use less regularization and data augmentation techniques because small models have less trouble with overfitting. When training MobileNets we do not use side heads or label smoothing and additionally reduce the amount image of distortions by limiting the size of small crops that are used in large Inception training [31]. Additionally, we found that it was important to put very little or no weight decay (l2 regularization) on the depthwise filters since their are so few parameters in them. For the ImageNet benchmarks in the next section all models were trained with same training parameters regardless of the size of the model.

3.3. Width Multiplier: Thinner Models

Although the base MobileNet architecture is already small and low latency, many times a specific use case or application may require the model to be smaller and faster. In order to construct these smaller and less computationally expensive models we introduce a very simple parameter α called width multiplier. The role of the width multiplier α is to thin a network uniformly at each layer. For a given layer

Table 1. MobileNet Body Architecture		
Type / Stride	Filter Shape	Input Size
Conv / s2	$3 \times 3 \times 3 \times 32$	$224 \times 224 \times 3$
Conv dw / s1	$3 \times 3 \times 32 \text{ dw}$	$112 \times 112 \times 32$
Conv / s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$
Conv dw / s2	$3 \times 3 \times 64 \text{ dw}$	$112 \times 112 \times 64$
Conv / s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$
Conv dw / s1	$3 \times 3 \times 128 \text{ dw}$	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$
Conv dw / s2	$3 \times 3 \times 128 \text{ dw}$	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 256$	$28 \times 28 \times 128$
Conv dw / s1	$3 \times 3 \times 256 \text{ dw}$	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 256$	$28 \times 28 \times 256$
Conv dw / s2	$3 \times 3 \times 256 \text{ dw}$	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$
5x	Conv dw / s1	$3 \times 3 \times 512 \text{ dw}$
	Conv / s1	$1 \times 1 \times 512 \times 512$
	Conv dw / s2	$3 \times 3 \times 512 \text{ dw}$
	Conv / s1	$1 \times 1 \times 512 \times 1024$
	Conv dw / s2	$3 \times 3 \times 1024 \text{ dw}$
	Conv / s1	$1 \times 1 \times 1024 \times 1024$
	Avg Pool / s1	Pool 7×7
	FC / s1	1024×1000
	Softmax / s1	Classifier

Table 2. Resource Per Layer Type		
Type	Mult-Adds	Parameters
Conv 1×1	94.86%	74.59%
Conv DW 3×3	3.06%	1.06%
Conv 3×3	1.19%	0.02%
Fully Connected	0.18%	24.33%

and width multiplier α , the number of input channels M becomes αM and the number of output channels N becomes αN .

The computational cost of a depthwise separable convolution with width multiplier α is:

$$D_K \cdot D_K \cdot \alpha M \cdot D_F \cdot D_F + \alpha M \cdot \alpha N \cdot D_F \cdot D_F \quad (6)$$

where $\alpha \in (0, 1]$ with typical settings of 1, 0.75, 0.5 and 0.25. $\alpha = 1$ is the baseline MobileNet and $\alpha < 1$ are reduced MobileNets. Width multiplier has the effect of reducing computational cost and the number of parameters quadratically by roughly α^2 . Width multiplier can be applied to any model structure to define a new smaller model with a reasonable accuracy, latency and size trade off. It is used to define a new reduced structure that needs to be trained from scratch.

3.4. Resolution Multiplier: Reduced Representation

The second hyper-parameter to reduce the computational cost of a neural network is a resolution multiplier ρ . We ap-

1个普通卷积+13组深度可分离卷积（26）+一个FC=共28层
注意：
1、如果是需要下采样，则在第一个深度卷积上取步长为2
2、除了最后的FC层没有非线性激活函数，其他层都有BN和ReLU

较少使用正则和数据增强技术，
因为小模型不易陷入过拟合

宽度因子：(控制特征维度的通道数)
控制模型大小的超参数：宽度因子
(Width multiplier)，用于控制输入和输出的通道数，即输入通道从M变为 αM ，
输出通道从N变为 αN 。

分辨率因子：(控制输入图像的分辨率)
引入的第二个控制模型大小的超参数是：分辨率因子
(resolution multiplier).用于控制输入和内部层表示。

Table 3. Resource usage for modifications to standard convolution. Note that each row is a cumulative effect adding on top of the previous row. This example is for an internal MobileNet layer with $D_K = 3$, $M = 512$, $N = 512$, $D_F = 14$.

Layer/Modification	Million Mult-Adds	Million Parameters
Convolution	462	2.36
Depthwise Separable Conv	52.3	0.27
$\alpha = 0.75$	29.6	0.15
$\rho = 0.714$	15.1	0.15

ply this to the input image and the internal representation of every layer is subsequently reduced by the same multiplier. In practice we **implicitly set ρ by setting the input resolution**.

We can now express the computational cost for the core layers of our network as depthwise separable convolutions with width multiplier α and resolution multiplier ρ :

$$D_K \cdot D_K \cdot \alpha M \cdot \rho D_F \cdot \rho D_F + \alpha M \cdot \alpha N \cdot \rho D_F \cdot \rho D_F \quad (7)$$

where $\rho \in (0, 1]$ which is typically set implicitly so that the input resolution of the network is 224, 192, 160 or 128. $\rho = 1$ is the baseline MobileNet and $\rho < 1$ are reduced computation MobileNets. Resolution multiplier has the effect of reducing computational cost by ρ^2 .

As an example we can look at a typical layer in MobileNet and see how depthwise separable convolutions, width multiplier and resolution multiplier reduce the cost and parameters. Table 3 shows the computation and number of parameters for a layer as architecture shrinking methods are sequentially applied to the layer. The first row shows the Mult-Adds and parameters for a full convolutional layer with an input feature map of size $14 \times 14 \times 512$ with a kernel K of size $3 \times 3 \times 512 \times 512$. We will look in detail in the next section at the trade offs between resources and accuracy.

4. Experiments

In this section we first investigate the effects of depthwise convolutions as well as the choice of shrinking by reducing the width of the network rather than the number of layers. We then show the trade offs of reducing the network based on the two hyper-parameters: width multiplier and resolution multiplier and compare results to a number of popular models. We then investigate MobileNets applied to a number of different applications.

4.1. Model Choices

First we show results for MobileNet with depthwise separable convolutions compared to a model built with full convolutions. In Table 4 we see that using depthwise separable convolutions compared to full convolutions only reduces

Table 4. Depthwise Separable vs Full Convolution MobileNet

Model	ImageNet Accuracy	Million Mult-Adds	Million Parameters
Conv MobileNet	71.7%	4866	29.3
MobileNet	70.6%	569	4.2

Table 5. Narrow vs Shallow MobileNet

Model	ImageNet Accuracy	Million Mult-Adds	Million Parameters
0.75 MobileNet	68.4%	325	2.6
Shallow MobileNet	65.3%	307	2.9

Table 6. MobileNet Width Multiplier

Width Multiplier	ImageNet Accuracy	Million Mult-Adds	Million Parameters
1.0 MobileNet-224	70.6%	569	4.2
0.75 MobileNet-224	68.4%	325	2.6
0.5 MobileNet-224	63.7%	149	1.3
0.25 MobileNet-224	50.6%	41	0.5

Table 7. MobileNet Resolution

Resolution	ImageNet Accuracy	Million Mult-Adds	Million Parameters
1.0 MobileNet-224	70.6%	569	4.2
1.0 MobileNet-192	69.1%	418	4.2
1.0 MobileNet-160	67.2%	290	4.2
1.0 MobileNet-128	64.4%	186	4.2

accuracy by 1% on ImageNet was saving tremendously on mult-adds and parameters.

We next show results comparing thinner models with width multiplier to shallower models using less layers. To make MobileNet shallower, the 5 layers of separable filters with feature size $14 \times 14 \times 512$ in Table 1 are removed. Table 5 shows that at similar computation and number of parameters, that making MobileNets thinner is 3% better than making them shallower.

4.2. Model Shrinking Hyperparameters

Table 6 shows the accuracy, computation and size trade offs of shrinking the MobileNet architecture with the width multiplier α . Accuracy drops off smoothly until the architecture is made too small at $\alpha = 0.25$.

Table 7 shows the accuracy, computation and size trade offs for different resolution multipliers by training MobileNets with reduced input resolutions. Accuracy drops off smoothly across resolution.

Figure 4 shows the trade off between ImageNet Accuracy and computation for the 16 models made from the cross product of width multiplier $\alpha \in \{1, 0.75, 0.5, 0.25\}$ and resolutions $\{224, 192, 160, 128\}$. Results are log linear with a jump when models get very small at $\alpha = 0.25$.

使用深度可分离卷积与标准卷积，参数和计算量下降为后者九分之一到八分之一。但是准确率只有下降极小的1%。

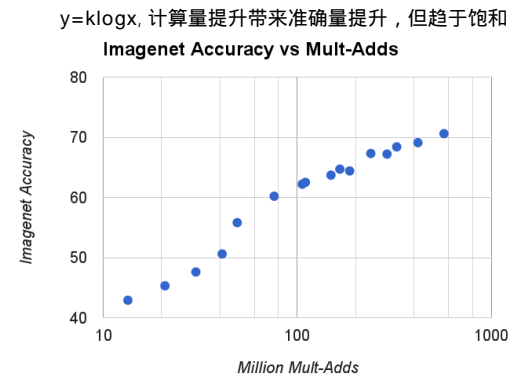


Figure 4. This figure shows the trade off between computation (Mult-Adds) and accuracy on the ImageNet benchmark. Note the log linear dependence between accuracy and computation.

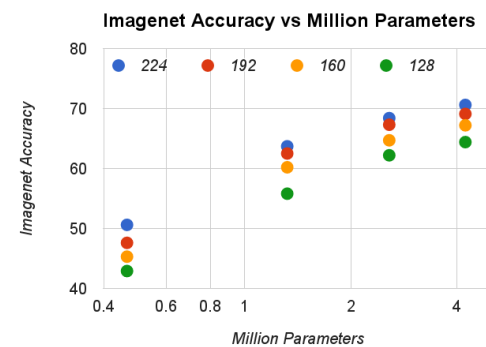


Figure 5. This figure shows the trade off between the number of parameters and accuracy on the ImageNet benchmark. The colors encode input resolutions. The number of parameters do not vary based on the input resolution.

Figure 5 shows the trade off between ImageNet Accuracy and number of parameters for the 16 models made from the cross product of width multiplier $\alpha \in \{1, 0.75, 0.5, 0.25\}$ and resolutions $\{224, 192, 160, 128\}$.

Table 8 compares full MobileNet to the original GoogleNet [30] and VGG16 [27]. MobileNet is nearly as accurate as VGG16 while being 32 times smaller and 27 times less compute intensive. It is more accurate than GoogleNet while being smaller and more than 2.5 times less computation.

Table 9 compares a reduced MobileNet with width multiplier $\alpha = 0.5$ and reduced resolution 160×160 . Reduced MobileNet is 4% better than AlexNet [19] while being $45 \times$ smaller and $9.4 \times$ less compute than AlexNet. It is also 4% better than Squeezenet [12] at about the same size and $22 \times$ less computation.

Table 8. MobileNet Comparison to Popular Models

Model	ImageNet Accuracy	Million Mult-Adds	Million Parameters
1.0 MobileNet-224	70.6%	569	4.2
GoogleNet	69.8%	1550	6.8
VGG 16	71.5%	15300	138

Table 9. Smaller MobileNet Comparison to Popular Models

Model	ImageNet Accuracy	Million Mult-Adds	Million Parameters
0.50 MobileNet-160	60.2%	76	1.32
Squeezenet	57.5%	1700	1.25
AlexNet	57.2%	720	60

Table 10. MobileNet for Stanford Dogs

Model	Top-1 Accuracy	Million Mult-Adds	Million Parameters
Inception V3 [18]	84%	5000	23.2
1.0 MobileNet-224	83.3%	569	3.3
0.75 MobileNet-224	81.9%	325	1.9
1.0 MobileNet-192	81.9%	418	3.3
0.75 MobileNet-192	80.5%	239	1.9

Table 11. Performance of PlaNet using the MobileNet architecture. Percentages are the fraction of the Im2GPS test dataset that were localized within a certain distance from the ground truth. The numbers for the original PlaNet model are based on an updated version that has an improved architecture and training dataset.

Scale	Im2GPS [7]	PlaNet [35]	PlaNet MobileNet
Continent (2500 km)	51.9%	77.6%	79.3%
Country (750 km)	35.4%	64.0%	60.3%
Region (200 km)	32.1%	51.1%	45.2%
City (25 km)	21.9%	31.7%	31.7%
Street (1 km)	2.5%	11.0%	11.4%

4.3. Fine Grained Recognition

We train MobileNet for fine grained recognition on the Stanford Dogs dataset [17]. We extend the approach of [18] and collect an even larger but noisy training set than [18] from the web. We use the noisy web data to pretrain a fine grained dog recognition model and then fine tune the model on the Stanford Dogs training set. Results on Stanford Dogs test set are in Table 10. MobileNet can almost achieve the state of the art results from [18] at greatly reduced computation and size.

4.4. Large Scale Geolocalization

PlaNet [35] casts the task of determining where on earth a photo was taken as a classification problem. The approach divides the earth into a grid of geographic cells that serve as the target classes and trains a convolutional neural network

on millions of geo-tagged photos. PlaNet has been shown to successfully localize a large variety of photos and to outperform Im2GPS [6, 7] that addresses the same task.

We re-train PlaNet using the MobileNet architecture on the same data. While the full PlaNet model based on the Inception V3 architecture [31] has 52 million parameters and 5.74 billion mult-adds. The MobileNet model has only 13 million parameters with the usual 3 million for the body and 10 million for the final layer and 0.58 Million mult-adds. As shown in Tab. 11, the MobileNet version delivers only slightly decreased performance compared to PlaNet despite being much more compact. Moreover, it still outperforms Im2GPS by a large margin.

4.5. Face Attributes

Another use-case for MobileNet is compressing large systems with unknown or esoteric training procedures. In a face attribute classification task, we demonstrate a synergistic relationship between MobileNet and distillation [9], a knowledge transfer technique for deep networks. We seek to reduce a large face attribute classifier with 75 million parameters and 1600 million Mult-Adds. The classifier is trained on a multi-attribute dataset similar to YFCC100M [32].

We distill a face attribute classifier using the MobileNet architecture. Distillation [9] works by training the classifier to emulate the outputs of a larger model² instead of the ground-truth labels, hence enabling training from large (and potentially infinite) unlabeled datasets. Marrying the scalability of distillation training and the parsimonious parameterization of MobileNet, the end system not only requires no regularization (e.g. weight-decay and early-stopping), but also demonstrates enhanced performances. It is evident from Tab. 12 that the MobileNet-based classifier is resilient to aggressive model shrinking: it achieves a similar mean average precision across attributes (mean AP) as the in-house while consuming only 1% the Multi-Adds.

4.6. Object Detection

MobileNet can also be deployed as an effective base network in modern object detection systems. We report results for MobileNet trained for object detection on COCO data based on the recent work that won the 2016 COCO challenge [10]. In table 13, MobileNet is compared to VGG and Inception V2 [13] under both Faster-RCNN [23] and SSD [21] framework. In our experiments, SSD is evaluated with 300 input resolution (SSD 300) and Faster-RCNN is compared with both 300 and 600 input resolution (Faster-RCNN 300, Faster-RCNN 600). The Faster-RCNN model evaluates 300 RPN proposal boxes per image. The models are trained on COCO train+val excluding 8k minival images

²The emulation quality is measured by averaging the per-attribute cross-entropy over all attributes.

Table 12. Face attribute classification using the MobileNet architecture. Each row corresponds to a different hyper-parameter setting (width multiplier α and image resolution).

Width Multiplier / Resolution	Mean AP	Million Mult-Adds	Million Parameters
1.0 MobileNet-224	88.7%	568	3.2
0.5 MobileNet-224	88.1%	149	0.8
0.25 MobileNet-224	87.2%	45	0.2
1.0 MobileNet-128	88.1%	185	3.2
0.5 MobileNet-128	87.7%	48	0.8
0.25 MobileNet-128	86.4%	15	0.2
Baseline	86.9%	1600	7.5

Table 13. COCO object detection results comparison using different frameworks and network architectures. mAP is reported with COCO primary challenge metric (AP at IoU=0.50:0.05:0.95)

Framework Resolution	Model	mAP	Billion Mult-Adds	Million Parameters
SSD 300	deeplab-VGG	21.1%	34.9	33.1
	Inception V2	22.0%	3.8	13.7
	MobileNet	19.3%	1.2	6.8
Faster-RCNN 300	VGG	22.9%	64.3	138.5
	Inception V2	15.4%	118.2	13.3
	MobileNet	16.4%	25.2	6.1
Faster-RCNN 600	VGG	25.7%	149.6	138.5
	Inception V2	21.9%	129.6	13.3
	Mobilenet	19.8%	30.5	6.1



Figure 6. Example objection detection results using MobileNet SSD.

and evaluated on minival. For both frameworks, MobileNet achieves comparable results to other networks with only a fraction of computational complexity and model size.

4.7. Face Embeddings

The FaceNet model is a state of the art face recognition model [25]. It builds face embeddings based on the triplet loss. To build a mobile FaceNet model we use distillation to train by minimizing the squared differences of the output

Table 14. MobileNet Distilled from FaceNet			
Model	1e-4	Million	Million
	Accuracy	Mult-Adds	Parameters
FaceNet [25]	83%	1600	7.5
1.0 MobileNet-160	79.4%	286	4.9
1.0 MobileNet-128	78.3%	185	5.5
0.75 MobileNet-128	75.2%	166	3.4
0.75 MobileNet-128	72.5%	108	3.8

of FaceNet and MobileNet on the training data. Results for very small MobileNet models can be found in table 14.

5. Conclusion

We proposed a new model architecture called MobileNets based on depthwise separable convolutions. We investigated some of the important design decisions leading to an efficient model. We then demonstrated how to build smaller and faster MobileNets using width multiplier and resolution multiplier by trading off a reasonable amount of accuracy to reduce size and latency. We then compared different MobileNets to popular models demonstrating superior size, speed and accuracy characteristics. We concluded by demonstrating MobileNet’s effectiveness when applied to a wide variety of tasks. As a next step to help adoption and exploration of MobileNets, we plan on releasing models in Tensor Flow.

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tensorflow

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