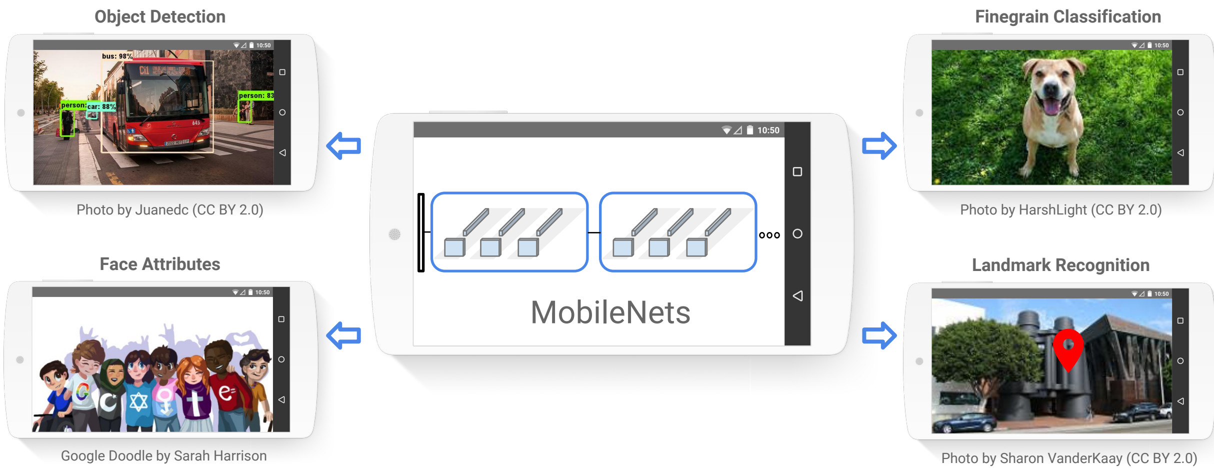


Figure 1. MobileNet models can be applied to various recognition tasks for efficient on device intelligence.

[2], and pruning, vector quantization and Huffman coding [5] have been proposed in the literature. Additionally various factorizations have been proposed to speed up pretrained 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 map[1], M is the number of input channels (input depth), D_G 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:

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

Standard convolutions have the computational cost of:

$$D_K \cdot D_K \cdot M \cdot N \cdot D_F \cdot D_F \qquad (2)$$

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

[1] We 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.

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:

$$\hat{\mathbf{G}}_{k,l,m} = \sum_{i,j} \hat{\mathbf{K}}_{i,j,m} \cdot \mathbf{F}_{k+i-1,l+j-1,m} \tag{3}$$

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

Depthwise convolution has a computational cost of:

$$D_K \cdot D_K \cdot M \cdot D_F \cdot D_F \tag{4}$$

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:

$$D_K \cdot D_K \cdot M \cdot D_F \cdot D_F + M \cdot N \cdot D_F \cdot D_F \tag{5}$$

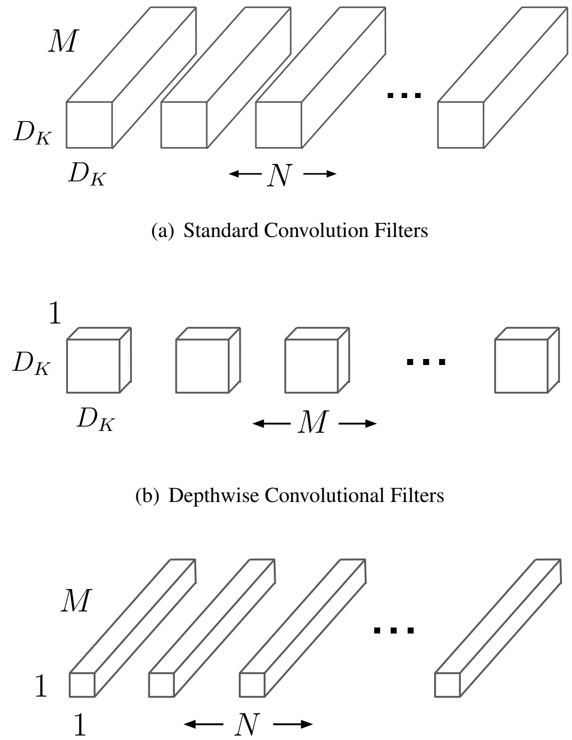
which is the sum of the depthwise and 1×1 pointwise convolutions.

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

$$\begin{aligned} & \frac{D_K \cdot D_K \cdot M \cdot D_F \cdot D_F + M \cdot N \cdot D_F \cdot D_F}{D_K \cdot D_K \cdot M \cdot N \cdot D_F \cdot D_F} \\ = \; & \frac{1}{N} + \frac{1}{D_K^2} \end{aligned}$$

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