“Fica, vai ter bolo”.

Inicialização de Pesos e Transfer Learning

Paulo Ricardo Lisboa de Almeida

DSBD

UFPR

O Elefante na Sala

Considere a seguinte CNN:

```
class custom_3_layer(nn.Module):
   def __init__(self):
       super(custom_3_layer, self).__init__()

       self.conv1 = nn.Conv2d(in_channels=INPUT_SHAPE[0], out_channels=32, kernel_size=3, stride=1, padding=1)
       self.pool1 = nn.MaxPool2d(kernel_size=2, stride=2, padding=0)

       self.conv2 = nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, stride=1, padding=0)
       self.pool2 = nn.MaxPool2d(kernel_size=2, stride=2, padding=0)

       self.conv3 = nn.Conv2d(in_channels=64, out_channels=64, kernel_size=3, stride=1, padding=0)
       …
```

O Elefante na Sala

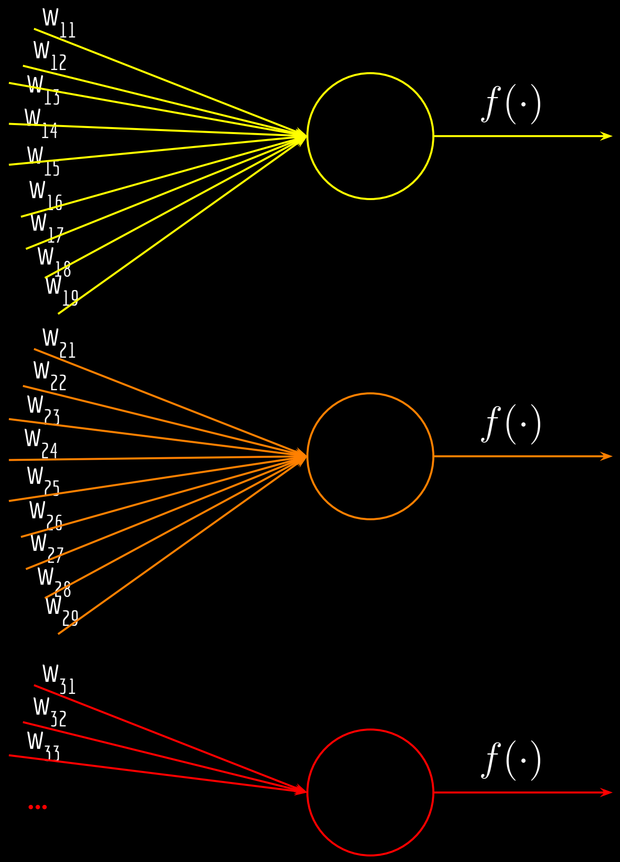
Considere a seguinte CNN:

```
class custom_3_layer(nn.Module):
   def __init__(self):
       super(custom_3_layer, self).__init__()

       self.conv1 = nn.Conv2d(in_channels=INPUT_SHAPE[0], out_channels=32, kernel_size=3, stride=1, padding=1)
       self.pool1 = nn.MaxPool2d(kernel_size=2, stride=2, padding=0)

       self.conv2 = nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3, stride=1, padding=0)
       self.pool2 = nn.MaxPool2d(kernel_size=2, stride=2, padding=0)

       self.conv3 = nn.Conv2d(in_channels=64, out_channels=64, kernel_size=3, stride=1, padding=0)
       …
```

Quantos filtros de convolução existem na primeira camada, e qual o tamanho dos filtros?

O Elefante na Sala

São 32 filtros de 3 x 3, com 9 parâmetros cada (mais o bias).

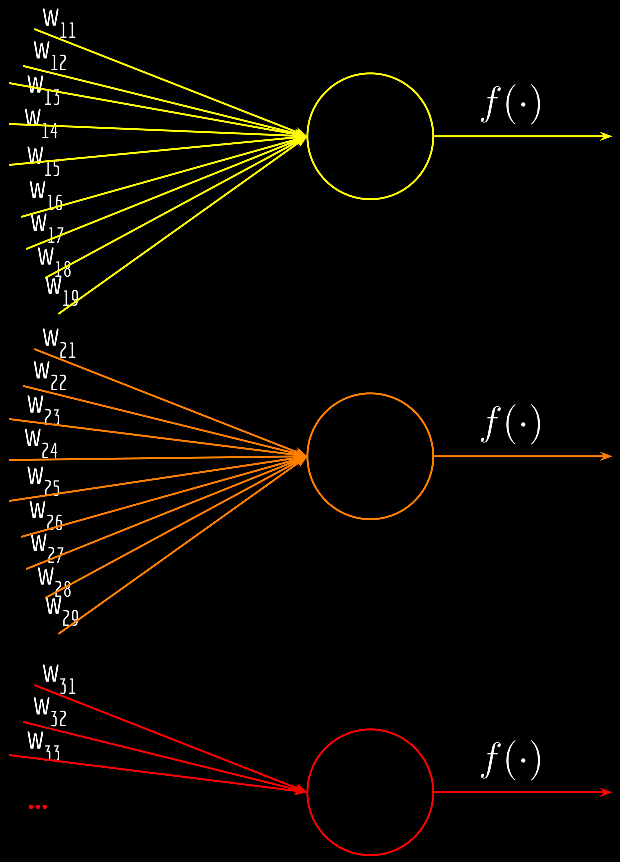


W_{11}	W_{12}	W_{13}
W_{14}	W_{15}	W_{16}
W_{17}	W_{18}	W_{19}

W_{21}	W_{22}	W_{23}
W_{24}	W_{25}	W_{26}
W_{27}	W_{28}	W_{29}

W_{31}	W_{32}	W_{33}
W_{34}	W_{35}	W_{36}
W_{37}	W_{38}	W_{39}

O Elefante na Sala



W_{11}	W_{12}	W_{13}
W_{14}	W_{15}	W_{16}
W_{17}	W_{18}	W_{19}

= ???

W_{21}	W_{22}	W_{23}
W_{24}	W_{25}	W_{26}
W_{27}	W_{28}	W_{29}

= ???

W_{31}	W_{32}	W_{33}
W_{34}	W_{35}	W_{36}
W_{37}	W_{38}	W_{39}

Durante o treinamento, era para todos os filtros convergirem para os mesmos pesos, não? Como que filtros diferentes aprendem coisas diferentes?

Faça você mesmo

Execute o exemplo disponibilizado no Google Colab.

É a mesma rede de aulas passadas, mas agora todos os filtros de convolução 3x3 são inicializados com os mesmos valores.

Todos biases inicializados com 1.

Faça você mesmo

É muito provável que todos os kernels de convolução tenham convergido para os mesmos valores.

Ter múltiplos kernels se tornou inútil.

```
... [[[-0.0698,  0.0933, -0.3015],
          [-0.1609, -0.0964, -0.3220],
          [-0.2577, -0.3699, -0.2675]]],


        [[[-0.0698,  0.0933, -0.3015],
          [-0.1609, -0.0964, -0.3220],
          [-0.2577, -0.3699, -0.2675]]],


        [[[-0.0698,  0.0933, -0.3015],
          [-0.1609, -0.0964, -0.3220],
          [-0.2577, -0.3699, -0.2675]]] ...
```

Quebra de simetria

Devemos considerar a quebra de simetria durante a inicialização dos pesos.

Se todos os pesos possuem os mesmos valores inicialmente, a rede é simétrica, eles contribuirão igualmente para o erro, e serão atualizados com os mesmos valores.

Quebra de simetria

É necessário inicializar os pesos aleatoriamente.

Mas qualquer aleatório também não serve.

Dependendo da complexidade da rede, ou da disponibilidade de recursos, podemos ter múltiplas inicializações, e escolher a que converge melhor no dataset de validação.

Inicialização

Geralmente os pesos são inicializados através de:

Distribuição Normal no intervalo $[-\epsilon, \epsilon]$.

Gaussiana de média zero $\mathcal{N}(0, \epsilon^2)$.

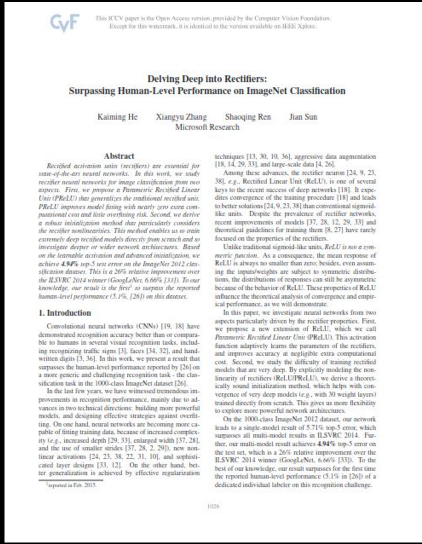
A escolha de ϵ varia de acordo com o método.

Exemplo - Inicialização de He

Em uma rede que utiliza a função de ativação ReLU e similares desejamos que a variância dos dados que entram nos neurônios:

- Não caiam para zero.
- Não subam muito.

He, K., Zhang, X., Ren, S., & Sun, J. Delving deep into rectifiers: Surpassing human-level performance on imagenet classification. *IEEE international conference on computer vision* , 2015.



**Delving Deep into Rectifiers:
Surpassing Human-Level Performance on ImageNet Classification**

Kaiming He Xiangyu Zhang Shaoqing Ren Jian Sun
Microsoft Research

Abstract

Rectified activation units (rectifiers) are essential for state-of-the-art neural networks. In this work, we study rectifier neural networks for image classification from two aspects. First, we propose a Parametric Rectified Linear Unit (PReLU) that generalizes the traditional rectified unit. PReLU improves model fitting with nearly zero extra computational cost and little overfitting risk. Second, we derive a robust initialization method that particularly considers the rectifier nonlinearities. This method enables us to train extremely deep rectified models directly from scratch and to investigate deeper or wider network architectures. Based on the learnable activation and advanced initialization, we achieve **4.94%** *top-5 test error on the ImageNet 2012 classification dataset. This is a 26% relative improvement over the ILSVRC 2014 winner (GoogLeNet, 6.66% [33]). To our knowledge, our result is the first[1] to surpass the reported human-level performance (5.1%, [26]) on this dataset.*

1. Introduction

Convolutional neural networks (CNNs) [19, 18] have demonstrated recognition accuracy better than or comparable to humans in several visual recognition tasks, including recognizing traffic signs [3], faces [34, 32], and handwritten digits [3, 36]. In this work, we present a result that surpasses the human-level performance reported by [26] on a more generic and challenging recognition task - the classification task in the 1000-class ImageNet dataset [26].

In the last few years, we have witnessed tremendous improvements in recognition performance, mainly due to advances in two technical directions: building more powerful models, and designing effective strategies against overfitting. On one hand, neural networks are becoming more capable of fitting training data, because of increased complexity (*e.g.*, increased depth [29, 33], enlarged width [37, 28], and the use of smaller strides [37, 28, 2, 29]), new nonlinear activations [24, 23, 38, 22, 31, 10], and sophisticated layer designs [33, 12]. On the other hand, better generalization is achieved by effective regularization techniques [13, 30, 10, 36], aggressive data augmentation [18, 14, 29, 33], and large-scale data [4, 26].

Among these advances, the rectifier neuron [24, 9, 23, 38], *e.g.*, Rectified Linear Unit (ReLU), is one of several keys to the recent success of deep networks [18]. It expedites convergence of the training procedure [18] and leads to better solutions [24, 9, 23, 38] than conventional sigmoid-like units. Despite the prevalence of rectifier networks, recent improvements of models [37, 28, 12, 29, 33] and theoretical guidelines for training them [8, 27] have rarely focused on the properties of the rectifiers.

Unlike traditional sigmoid-like units, *ReLU is not a symmetric function*. As a consequence, the mean response of ReLU is always no smaller than zero; besides, even assuming the inputs/weights are subject to symmetric distributions, the distributions of responses can still be asymmetric because of the behavior of ReLU. These properties of ReLU influence the theoretical analysis of convergence and empirical performance, as we will demonstrate.

In this paper, we investigate neural networks from two aspects particularly driven by the rectifier properties. First, we propose a new extension of ReLU, which we call *Parametric Rectified Linear Unit* (PReLU). This activation function adaptively learns the parameters of the rectifiers, and improves accuracy at negligible extra computational cost. Second, we study the difficulty of training rectified models that are very deep. By explicitly modeling the nonlinearity of rectifiers (ReLU/PReLU), we derive a theoretically sound initialization method, which helps with convergence of very deep models (*e.g.*, with 30 weight layers) trained directly from scratch. This gives us more flexibility to explore more powerful network architectures.

On the 1000-class ImageNet 2012 dataset, our network leads to a single-model result of 5.71% top-5 error, which surpasses all multi-model results in ILSVRC 2014. Further, our multi-model result achieves **4.94%** top-5 error on the test set, which is a 26% relative improvement over the ILSVRC 2014 winner (GoogLeNet, 6.66% [33]). To the best of our knowledge, our result surpasses for the first time the reported human-level performance (5.1% in [26]) of a dedicated individual labeler on this recognition challenge.

[1] reported in Feb. 2015.

Exemplo - Inicialização de He

Considerando que temos M conexões com a camada anterior da camada atual, o valor ϵ é dado por:

$$\epsilon = \sqrt{\frac{2}{M}}$$

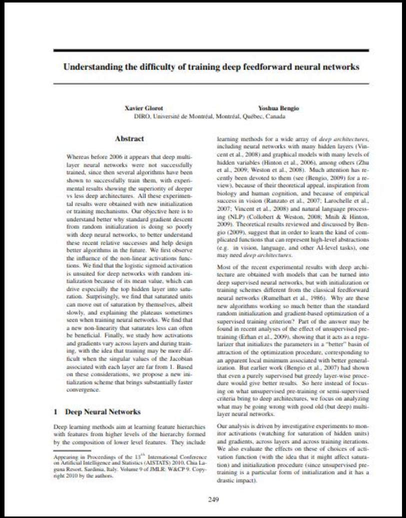
Outro exemplo

Inicialização de Xavier.

$$\epsilon = \sqrt{\frac{2}{M+N}}$$

Onde N é o número de conexões de saída.

Glorot, X., & Bengio, Y. Understanding the difficulty of training deep feedforward neural networks. In *Proceedings of the thirteenth international conference on artificial intelligence and statistics*. 2010.



Understanding the difficulty of training deep feedforward neural networks

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DIRO, Université de Montréal, Montréal, Québec, Canada

Abstract

Whereas before 2006 it appears that deep multi-layer neural networks were not successfully trained, since then several algorithms have been shown to successfully train them, with experimental results showing the superiority of deeper vs less deep architectures. All these experimental results were obtained with new initialization or training mechanisms. Our objective here is to understand better why standard gradient descent from random initialization is doing so poorly with deep neural networks, to better understand these recent relative successes and help design better algorithms in the future. We first observe the influence of the non-linear activations functions. We find that the logistic sigmoid activation is unsuited for deep networks with random initialization because of its mean value, which can drive especially the top hidden layer into saturation. Surprisingly, we find that saturated units can move out of saturation by themselves, albeit slowly, and explaining the plateaus sometimes seen when training neural networks. We find that a new non-linearity that saturates less can often be beneficial. Finally, we study how activations and gradients vary across layers and during training, with the idea that training may be more difficult when the singular values of the Jacobian associated with each layer are far from 1. Based on these considerations, we propose a new initialization scheme that brings substantially faster convergence.

1 Deep Neural Networks

Deep learning methods aim at learning feature hierarchies with features from higher levels of the hierarchy formed by the composition of lower level features. They include learning methods for a wide array of *deep architectures*, including neural networks with many hidden layers (Vincent et al., 2008) and graphical models with many levels of hidden variables (Hinton et al., 2006), among others (Zhu et al., 2009; Weston et al., 2008). Much attention has recently been devoted to them (see (Bengio, 2009) for a review), because of their theoretical appeal, inspiration from biology and human cognition, and because of empirical success in vision (Ranzato et al., 2007; Larochelle et al., 2007; Vincent et al., 2008) and natural language processing (NLP) (Collobert & Weston, 2008; Mnih & Hinton, 2009). Theoretical results reviewed and discussed by Bengio (2009), suggest that in order to learn the kind of complicated functions that can represent high-level abstractions (e.g. in vision, language, and other AI-level tasks), one may need *deep architectures*.

Most of the recent experimental results with deep architecture are obtained with models that can be turned into deep supervised neural networks, but with initialization or training schemes different from the classical feedforward neural networks (Rumelhart et al., 1986). Why are these new algorithms working so much better than the standard random initialization and gradient-based optimization of a supervised training criterion? Part of the answer may be found in recent analyses of the effect of unsupervised pre-training (Erhan et al., 2009), showing that it acts as a regularizer that initializes the parameters in a "better" basin of attraction of the optimization procedure, corresponding to an apparent local minimum associated with better generalization. But earlier work (Bengio et al., 2007) had shown that even a purely supervised but greedy layer-wise procedure would give better results. So here instead of focusing on what unsupervised pre-training or semi-supervised criteria bring to deep architectures, we focus on analyzing what may be going wrong with good old (but deep) multi-layer neural networks.

Our analysis is driven by investigative experiments to monitor activations (watching for saturation of hidden units) and gradients, across layers and across training iterations. We also evaluate the effects on these of choices of activation function (with the idea that it might affect saturation) and initialization procedure (since unsupervised pre-training is a particular form of initialization and it has a drastic impact).

Appearing in Proceedings of the 13th International Conference on Artificial Intelligence and Statistics (AISTATS) 2010, Chia Laguna Resort, Sardinia, Italy. Volume 9 of JMLR: W&CP 9. Copyright 2010 by the authors.

Transfer Learning

Ideia: usar algum dataset grande para treinar os filtros de convolução da rede.

- O dataset não precisa conter os mesmos dados da tarefa alvo.
  - Exemplo: treinamos uma rede para reconhecer cães, e depois a ajustamos para reconhecer gatos.

Transfer Learning

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Assume-se que os filtros de convolução podem ser usados para outras tarefas.

- Retreinamos a camada de classificação da rede, que usa como entrada os filtros de convolução já treinados.

Transfer Learning

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- Retreinamos a camada de classificação da rede, que usa como entrada os filtros de convolução já treinados.

Pode ser visto como uma técnica de **regularização**.

- Estamos usando dados de outras tarefas para treinar um modelo para a tarefa alvo.

Exemplo

No exemplo, vamos usar a MobileNetV3 small.

Veja como a rede funciona nos artigos.

Especial atenção para as camadas de *botleneck*.

Misturam convoluções com expansões sem uso de não linearidades para dimensões maiores.

Sandler, M., et al. Mobilenetv2: Inverted residuals and linear bottlenecks. *IEEE conference on computer vision and pattern recognition*. 2018.

arXiv:1801.04381v4 [cs.CV] 21 Mar 2019

MobileNetV2: Inverted Residuals and Linear Bottlenecks

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{sandler, howarda, menglong, azhmogin, lcchen}@google.com

Abstract

In this paper we describe a new mobile architecture, MobileNetV2, that improves the state of the art performance of mobile models on multiple tasks and benchmarks as well as across a spectrum of different model sizes. We also describe efficient ways of applying these mobile models to object detection in a novel framework we call SSDLite. Additionally, we demonstrate how to build mobile semantic segmentation models through a reduced form of DeepLabv3 which we call Mobile DeepLabv3.

is based on an inverted residual structure where the shortcut connections are between the thin bottleneck layers. The intermediate expansion layer uses lightweight depthwise convolutions to filter features as a source of non-linearity. Additionally, we find that it is important to remove non-linearities in the narrow layers in order to maintain representational power. We demonstrate that this improves performance and provide an intuition that led to this design.

Finally, our approach allows decoupling of the input/output domains from the expressiveness of the transformation, which provides a convenient framework for further analysis. We measure our performance on ImageNet [1] classification, COCO object detection [2], VOC image segmentation [3]. We evaluate the trade-offs between accuracy, and number of operations measured by multiply-adds (MAdd), as well as actual latency, and the number of parameters.

1. Introduction

Neural networks have revolutionized many areas of machine intelligence, enabling superhuman accuracy for challenging image recognition tasks. However, the drive to improve accuracy often comes at a cost: modern state of the art networks require high computational resources beyond the capabilities of many mobile and embedded applications.

This paper introduces a new neural network architecture that is specifically tailored for mobile and resource constrained environments. Our network pushes the state of the art for mobile tailored computer vision models, by significantly decreasing the number of operations and memory needed while retaining the same accuracy.

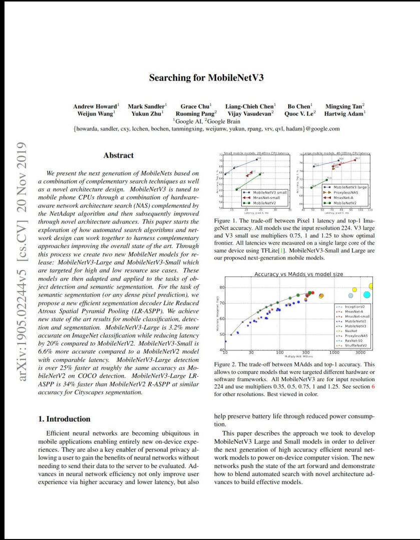
Our main contribution is a novel layer module: the inverted residual with linear bottleneck. This module takes as an input a low-dimensional compressed representation which is first expanded to high dimension and filtered with a lightweight depthwise convolution. Features are subsequently projected back to a low-dimensional representation with a *linear convolution*. The official implementation is available as part of TensorFlow-Slim model library in [4].

This module can be efficiently implemented using standard operations in any modern framework and allows our models to beat state of the art along multiple performance points using standard benchmarks. Furthermore, this convolutional module is particularly suitable for mobile designs, because it allows to significantly reduce the memory footprint needed during inference by never fully materializing large intermediate tensors. This reduces the need for main memory access in many embedded hardware designs, that provide small amounts of very fast software controlled cache memory.

2. Related Work

Tuning deep neural architectures to strike an optimal balance between accuracy and performance has been an area of active research for the last several years. Both manual architecture search and improvements in training algorithms, carried out by numerous teams has lead to dramatic improvements over early designs such as AlexNet [5], VGGNet [6], GoogLeNet [7]. , and ResNet [8]. Recently there has been lots of progress in algorithmic architecture exploration included hyperparameter optimization [9, 10, 11] as well as various

Howard, Andrew, et al. Searching for mobilenetv3. IEEE/CVF international conference on computer vision. 2019.



arXiv:1905.02244v5 [cs.CV] 20 Nov 2019

Searching for MobileNetV3

Andrew Howard[1] Mark Sandler[1] Grace Chu[1] Liang-Chieh Chen[1] Bo Chen[1] Mingxing Tan[2]
Weijun Wang[1] Yukun Zhu[1] Ruoming Pang[2] Vijay Vasudevan[2] Quoc V. Le[2] Hartwig Adam[1]
[1]Google AI, [2]Google Brain
{howarda, sandler, cxy, lcchen, bochen, tanmingxing, weijunw, yukun, rpang, vrv, qvl, hadam}@google.com

Abstract

We present the next generation of MobileNets based on a combination of complementary search techniques as well as a novel architecture design. MobileNetV3 is tuned to mobile phone CPUs through a combination of hardware-aware network architecture search (NAS) complemented by the NetAdapt algorithm and then subsequently improved through novel architecture advances. This paper starts the exploration of how automated search algorithms and network design can work together to harness complementary approaches improving the overall state of the art. Through this process we create two new MobileNet models for release: MobileNetV3-Large and MobileNetV3-Small which are targeted for high and low resource use cases. These models are then adapted and applied to the tasks of object detection and semantic segmentation. For the task of semantic segmentation (or any dense pixel prediction), we propose a new efficient segmentation decoder Lite Reduced Atrous Spatial Pyramid Pooling (LR-ASPP). We achieve new state of the art results for mobile classification, detection and segmentation. MobileNetV3-Large is 3.2% more accurate on ImageNet classification while reducing latency by 20% compared to MobileNetV2. MobileNetV3-Small is 6.6% more accurate compared to a MobileNetV2 model with comparable latency. MobileNetV3-Large detection is over 25% faster at roughly the same accuracy as MobileNetV2 on COCO detection. MobileNetV3-Large LR-ASPP is 34% faster than MobileNetV2 R-ASPP at similar accuracy for Cityscapes segmentation.

Figure 1. The trade-off between Pixel 1 latency and top-1 ImageNet accuracy. All models use the input resolution 224. V3 large and V3 small use multipliers 0.75, 1 and 1.25 to show optimal frontier. All latencies were measured on a single large core of the same device using TFLite[1]. MobileNetV3-Small and Large are our proposed next-generation mobile models.

Figure 2. The trade-off between MAdds and top-1 accuracy. This allows to compare models that were targeted different hardware or software frameworks. All MobileNetV3 are for input resolution 224 and use multipliers 0.35, 0.5, 0.75, 1 and 1.25. See section 6 for other resolutions. Best viewed in color.

1. Introduction

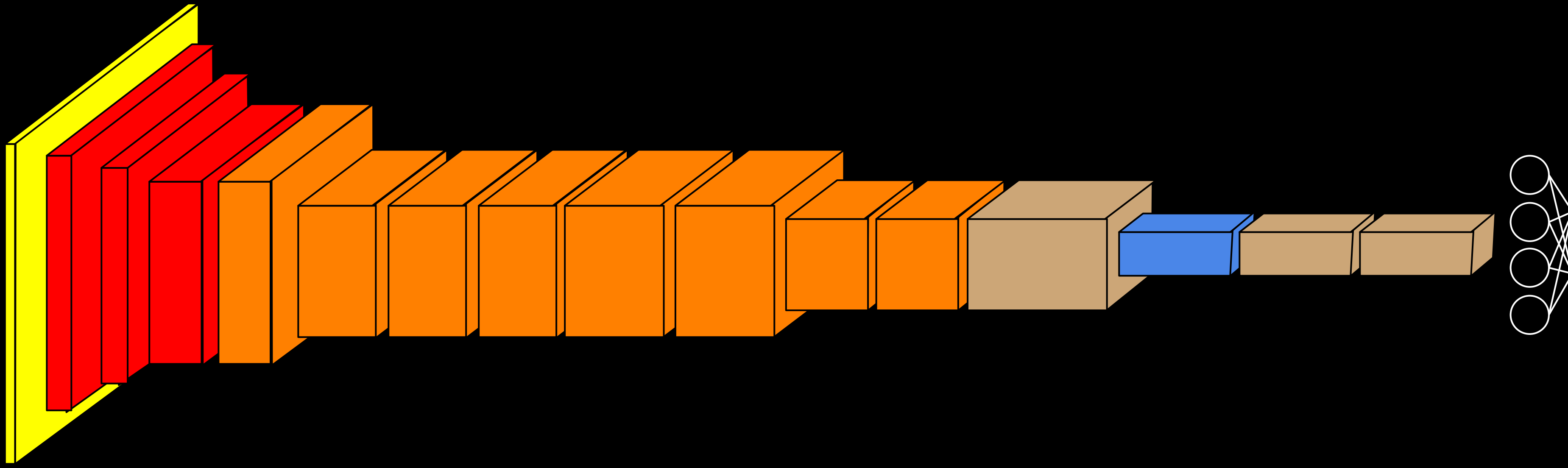
Efficient neural networks are becoming ubiquitous in mobile applications enabling entirely new on-device experiences. They are also a key enabler of personal privacy allowing a user to gain the benefits of neural networks without needing to send their data to the server to be evaluated. Advances in neural network efficiency not only improve user experience via higher accuracy and lower latency, but also help preserve battery life through reduced power consumption.

This paper describes the approach we took to develop MobileNetV3 Large and Small models in order to deliver the next generation of high accuracy efficient neural network models to power on-device computer vision. The new networks push the state of the art forward and demonstrate how to blend automated search with novel architecture advances to build effective models.

MobileNetV3 Small

Convolucional 3x3
Bottleneck 3x3
Bottleneck 5x5
Pooling
Convolucional 1x1

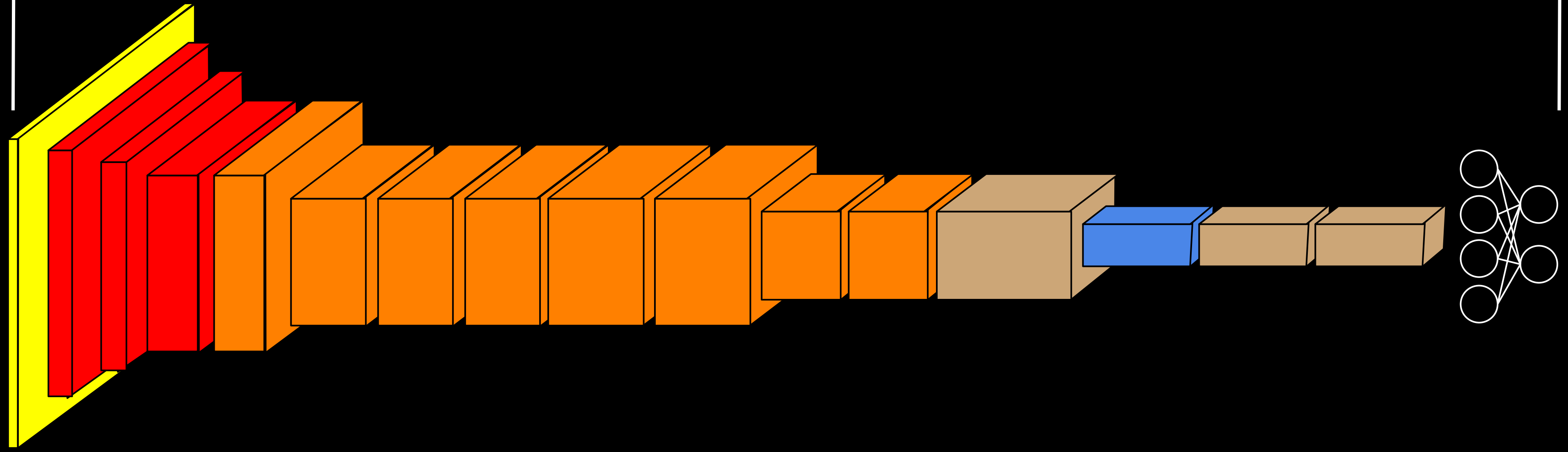
Tensores de entrada 224x224x3.



MobileNetV3 Small

Convolucional 3x3
Bottleneck 3x3
Bottleneck 5x5
Pooling
Convolucional 1x1

Treinar a rede completa na ImageNet – aprox. 14 milhões de imagens.



MobileNetV3 Small

Convolucional 3x3

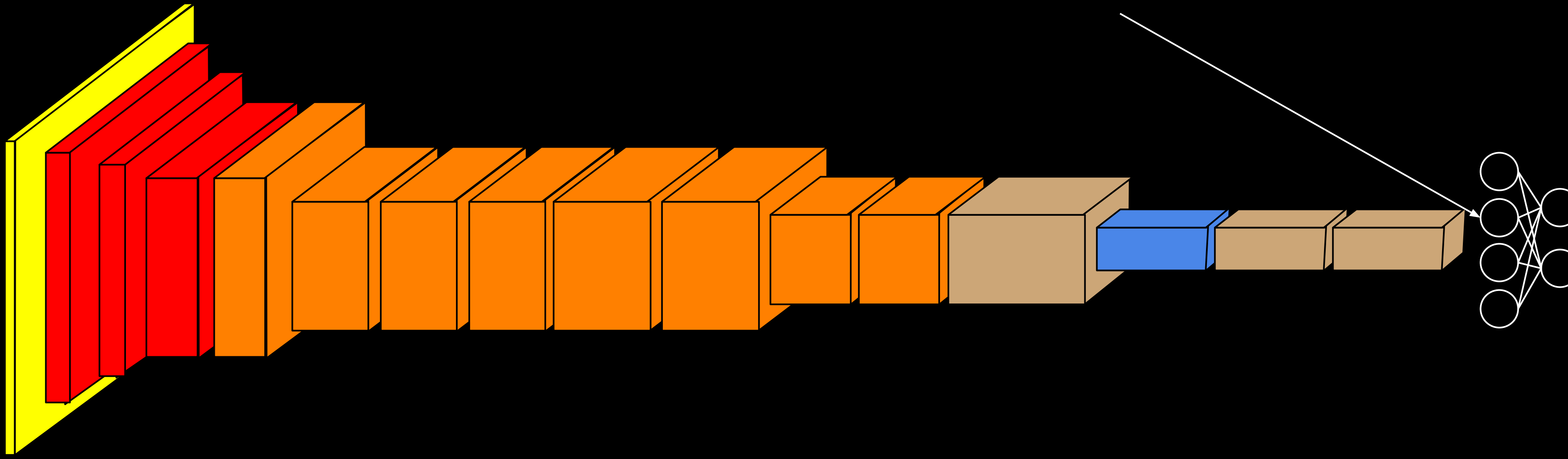
Bottleneck 3x3

Bottleneck 5x5

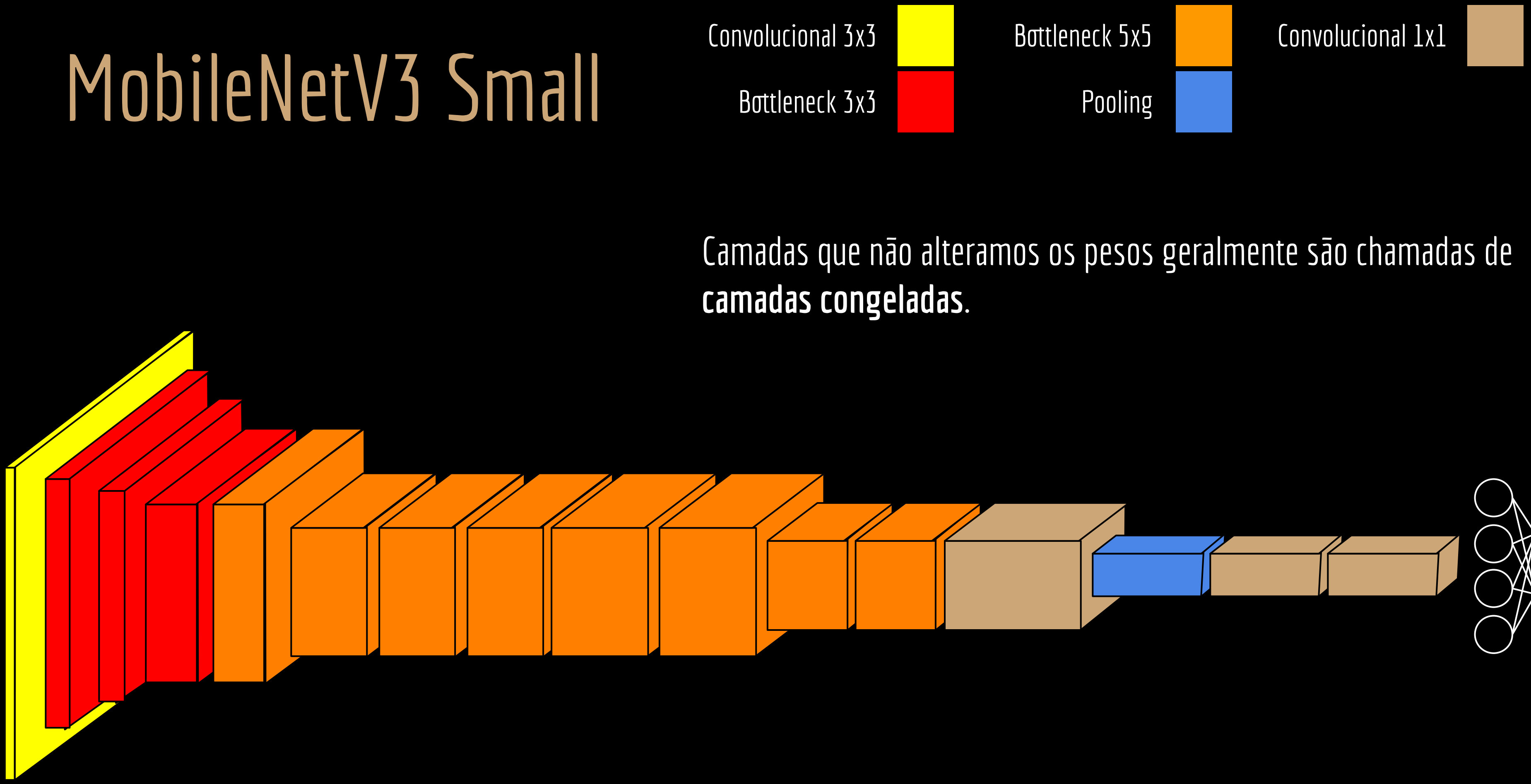
Pooling

Convolucional 1x1

Criar uma nova camada fully-connected, ou retreinar a camada existente nos dados alvo. Não alterar os pesos das demais camadas.



MobileNetV3 Small



Camadas que não alteramos os pesos geralmente são chamadas de **camadas congeladas**.

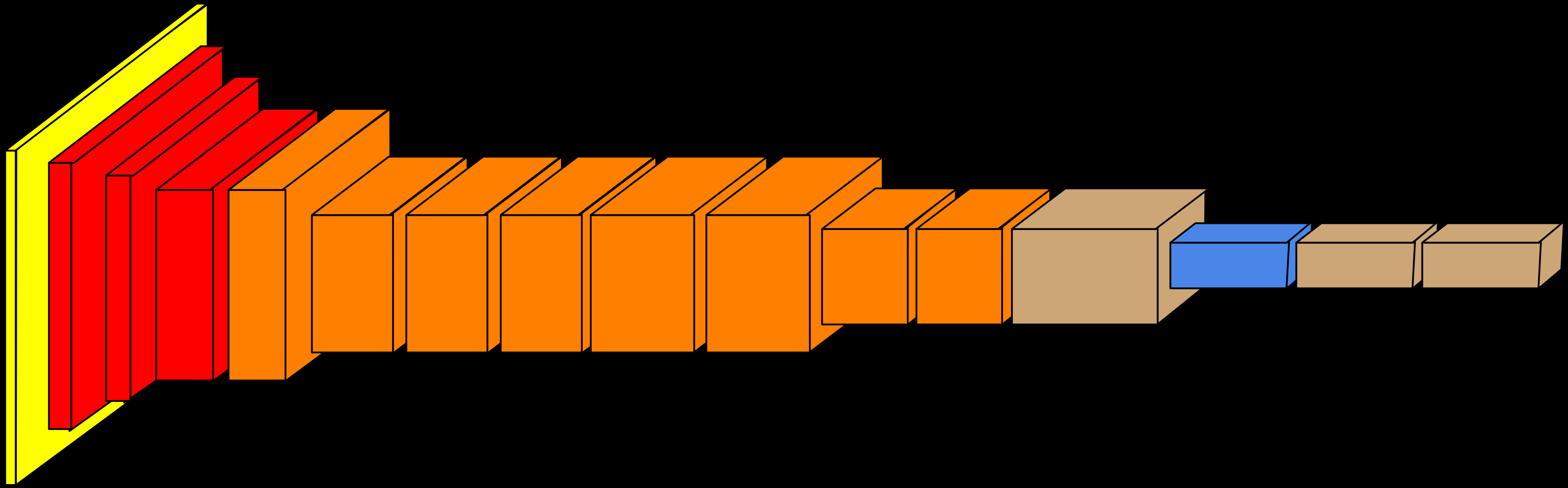
Faça você mesmo

Execute o exemplo de Transfer Learning no Google Colab disponibilizado.

Fine-tuning

Podemos descongelar mais camadas da rede (geralmente de trás para frente).

Nesse caso, comumente chamamos de Fine-tuning da rede.



Fine-tuning

Um fine-tuning de todas as camadas da rede pode ser considerado uma espécie de inicialização da rede.

A rede foi inicializada em uma região do espaço “boa para outro problema”.

Esperamos que essa região seja, pelo menos, próxima de uma boa região para o problema em questão.

Geralmente usamos fatores de aprendizagem baixos para realizar o fine-tuning.

Exercícios

1. Baseado no exemplo de transfer learning.
   a. Faça um Fine-tuning em todas as camadas da rede.
   b. Treine, e compare os resultados com os obtidos com o transfer learning.

Referências

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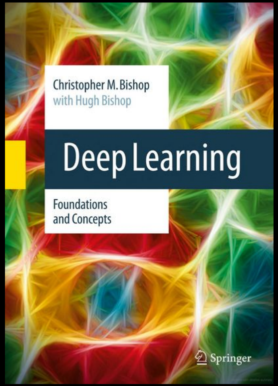

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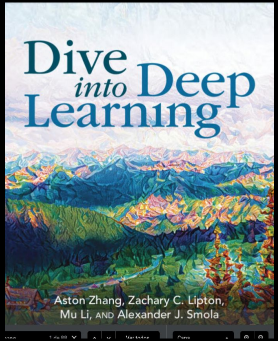

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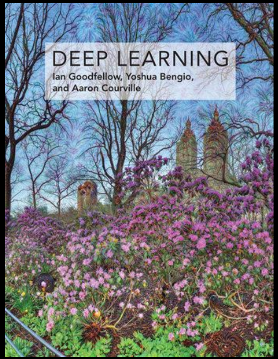

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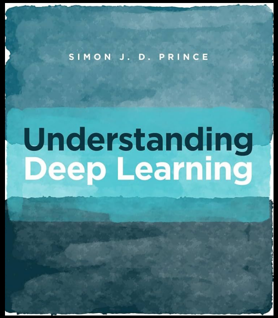

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