Famous CNN Architectures and CNN Visualization

Giacomo Boracchi

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31/10/2024

A few popular architectures

AlexNet

VGG

Networks In Networks (and GAP)

Inception

Resnet

The First CNN

Gradient-Based Learning Applied to Document Recognition

Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner

Abstract—
Multilayer Neural Networks trained with the backpropagation algorithm constitute the best example of a successful Gradient-Based Learning technique. Given an appropriate network architecture, Gradient-Based Learning algorithms can be used to synthesize a complex decision surface that can classify high-dimensional patterns such as handwritten characters, with minimal preprocessing. This paper reviews various methods applied to handwritten character recognition and compares them on a standard handwritten digit recognition task. Convolutional Neural Networks, that are specifically designed to deal with the variability of 2D shapes, are shown to outperform all other techniques.

I. Introduction

Over the last several years, machine learning techniques, particularly when applied to neural networks, have played an increasingly important role in the design of pattern recognition systems. In fact, it could be argued that the availability of learning techniques has been a crucial factor in the recent success of pattern recognition applications such as continuous speech recognition and handwriting recognition.

LeCun, Yann, et al. "Gradient-based learning applied to document recognition." *Proceedings of the IEEE* 86.11 (1998)

Gradient-Based Learning Applied to Document Recognition

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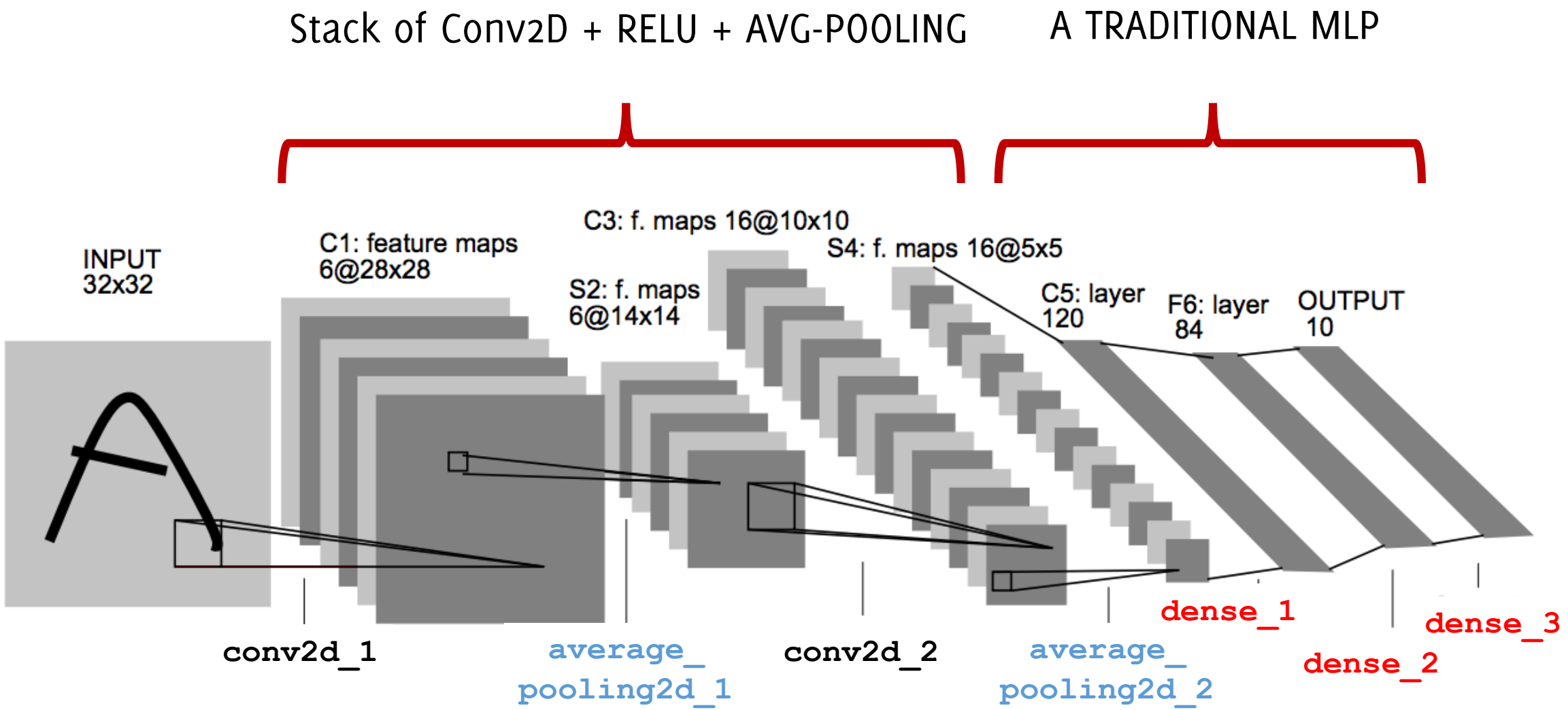
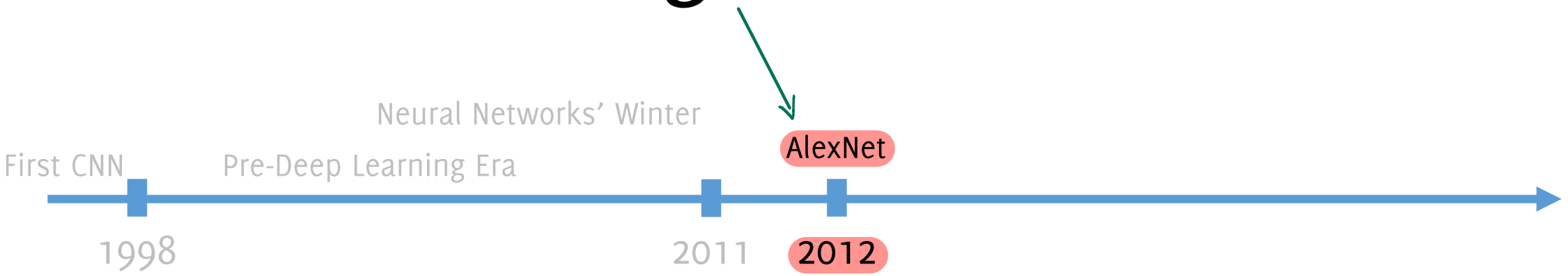
LeNet-5 (1998)



LeCun, Yann, et al. "Gradient-based learning applied to document recognition." *Proceedings of the IEEE* 86.11 (1998)

:hi

Award Winning CNNs



ImageNet Classification with Deep Convolutional Neural Networks

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Geoffrey E. Hinton
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Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "Imagenet classification with deep convolutional neural networks." NIPS 2012.

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Fathers of the Deep Learning Revolution Receive ACM A.M. Turing Award

Bengio, Hinton and LeCun Ushered in Major Breakthroughs in Artificial Intelligence

https://awards.acm.org/about/2018-turing

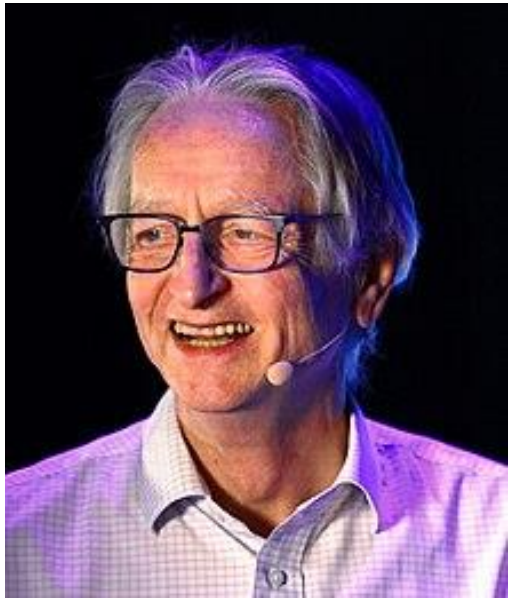
2018 Turing Award

20 years after LeNet ...

Yoshua Bengio

Professor at the Université de Montréal and scientific director of the Montreal Institute for Learning Algorithms (MILA)

Geoffrey Hinton



From 2013 to 2023, he divided his time working for Google (Google Brain) and the University of Toronto,

Yann LeCun

Silver Professor of the Courant Institute of Mathematical Sciences at New York University and Vice-President, Chief AI Scientist at Meta.

The Nobel Prize in Physics 2024

Summary

Laureates

John J. Hopfield

Geoffrey E. Hinton

Prize announcement

Press release

Popular information

Advanced information

Press release

English
English (pdf)
Swedish
Swedish (pdf)

KUNGL. VETENSKAPS-AKADEMIEN
THE ROYAL SWEDISH ACADEMY OF SCIENCES

Nobel 2024, physics.

8 October 2024

The Royal Swedish Academy of Sciences has decided to award the Nobel Prize in Physics 2024 to

John J. Hopfield
Princeton University, NJ, USA

Geoffrey E. Hinton
University of Toronto, Canada

The same !

"for foundational discoveries and inventions that enable machine learning with artificial neural networks"

AlexNet (2012)

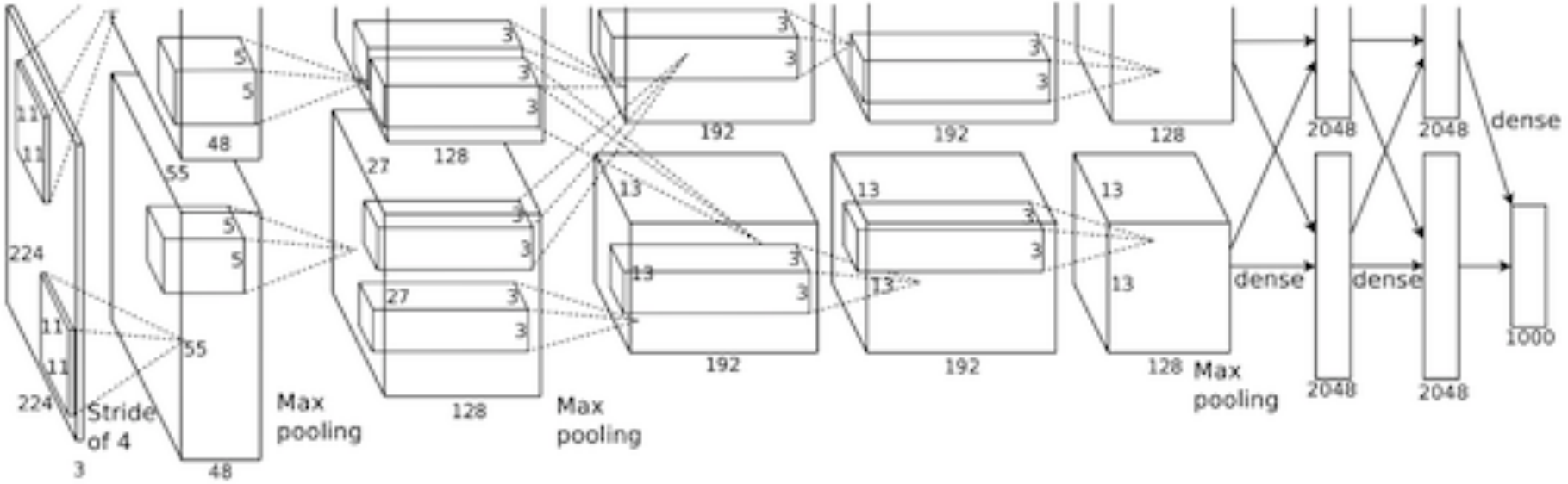
Developed by Alex Krizhevsky et al. in 2012 and won Imagenet competition

Architecture is quite similar to LeNet-5:

- 5 convolutional layers (rather large filters, 11x11, 5x5),
- 3 MLP

Input size 224 × 224 x 3 (the paper says 227 x 227 x 3) } way bigger than 32x32x3.

⚠ **Parameters**: 60 million [**Conv**: 3.7million (6%), **FC**: 58.6 million (94%)] Vast majority in FC.



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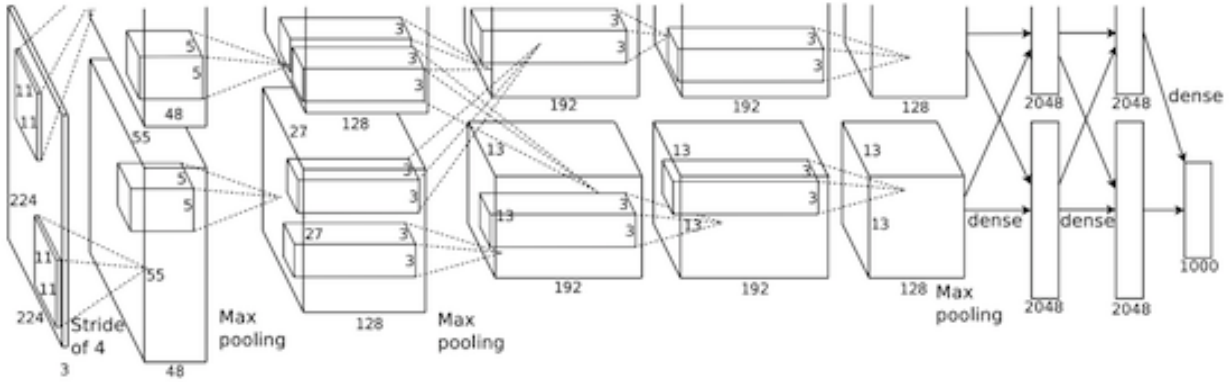
AlexNet (2012)



To counteract overfitting, they introduce:

- RELU (also faster than tanh)
- Dropout (0.5), weight decay and norm layers (not used anymore)
- Maxpooling

Terribly smaller than today.

The first conv layer has 96 **11x 11 filters, with stride 4.**

The output are **two volumes of 55 x 55 x 48 separated over two GTX 580 GPUs** (1.5GB each GPU, 90 epochs, 5/6 days to train).

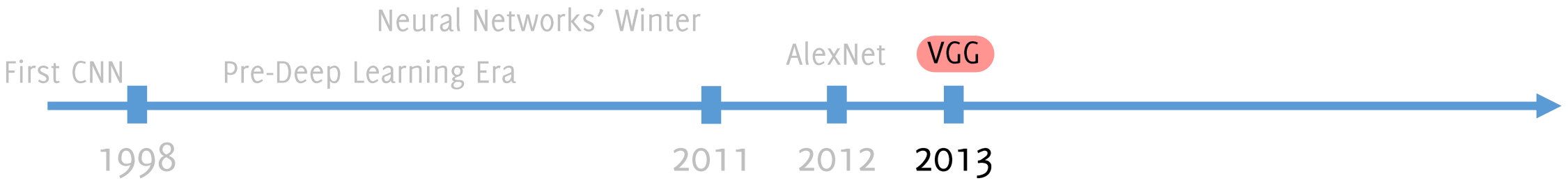
Most **connections are among** feature maps **of the same GPU**, which will be mixed at the last layer.

Won the ImageNet challenge in 2012

→ At the end they also trained an **ensemble of 7 models** to drop error: 18.2%->15.4%

Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "Imagenet classification with deep convolutional neural networks." NIPS 2012.

VGG: going deeper!



VERY DEEP CONVOLUTIONAL NETWORKS FOR LARGE-SCALE IMAGE RECOGNITION

Karen Simonyan* **& Andrew Zisserman+**
Visual Geometry Group, Department of Engineering Science, University of Oxford
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ABSTRACT

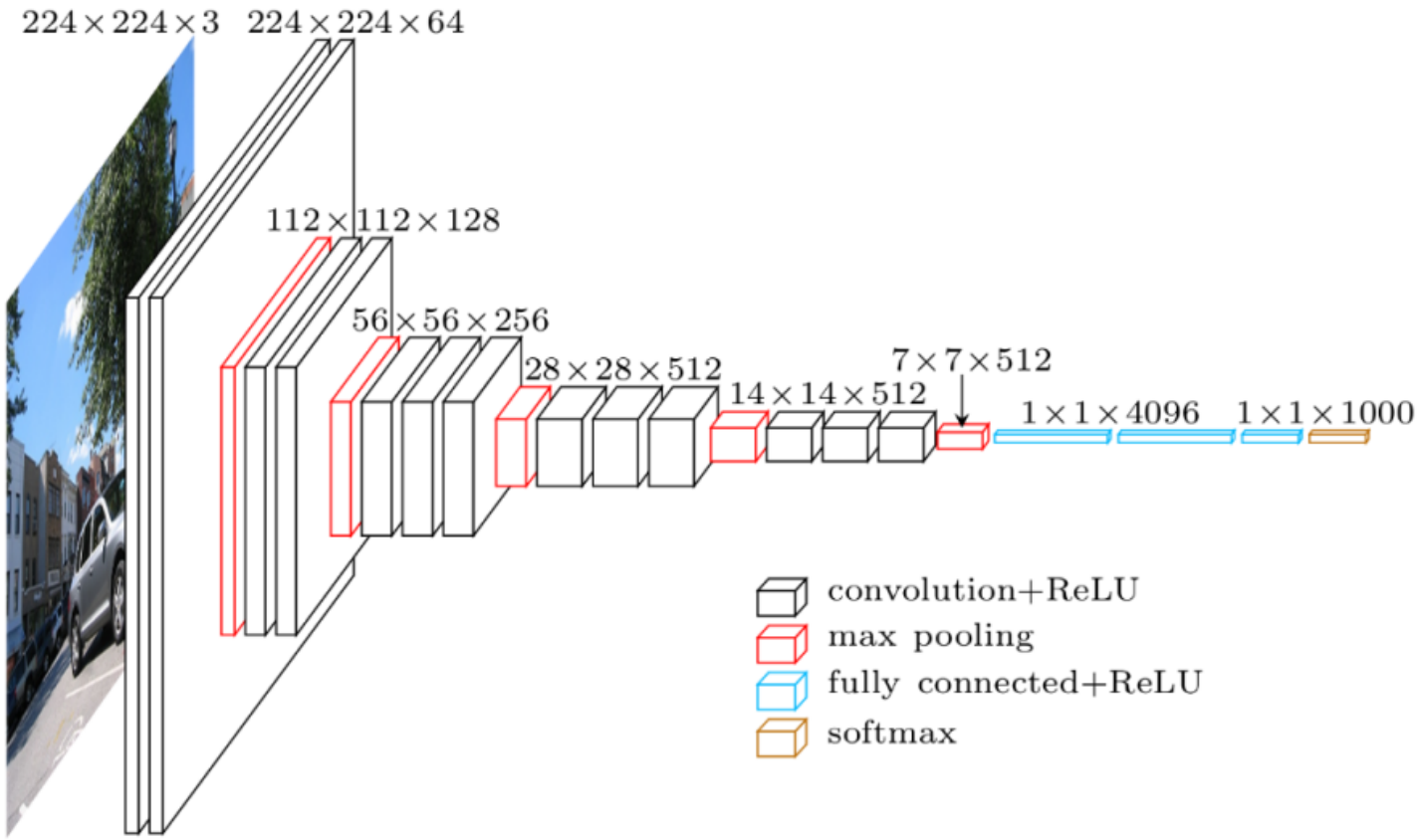
In this work we investigate the effect of the convolutional network depth on its accuracy in the large-scale image recognition setting. Our main contribution is a thorough evaluation of networks of increasing depth using an architecture with very small (3×3) convolution filters, which shows that a significant improvement on the prior-art configurations can be achieved by pushing the depth to 16–19 weight layers. These findings were the basis of our ImageNet Challenge 2014 submission, where our team secured the first and the second places in the localisation and classification tracks respectively. We also show that our representations generalise well to other datasets, where they achieve state-of-the-art results. We have made our two best-performing ConvNet models publicly available to facilitate further research on the use of deep visual representations in computer vision.

Simonyan, Karen, and Andrew Zisserman. "Very deep convolutional networks for large-scale image recognition." ICLR (2015)

VGG16 (2014)

The VGG16, introduced in 2014 is a deeper variant of the AlexNet convolutional structure. Smaller filters are used and the network is deeper

Parameters: 138 million [Conv: 11%, FC: 89%]



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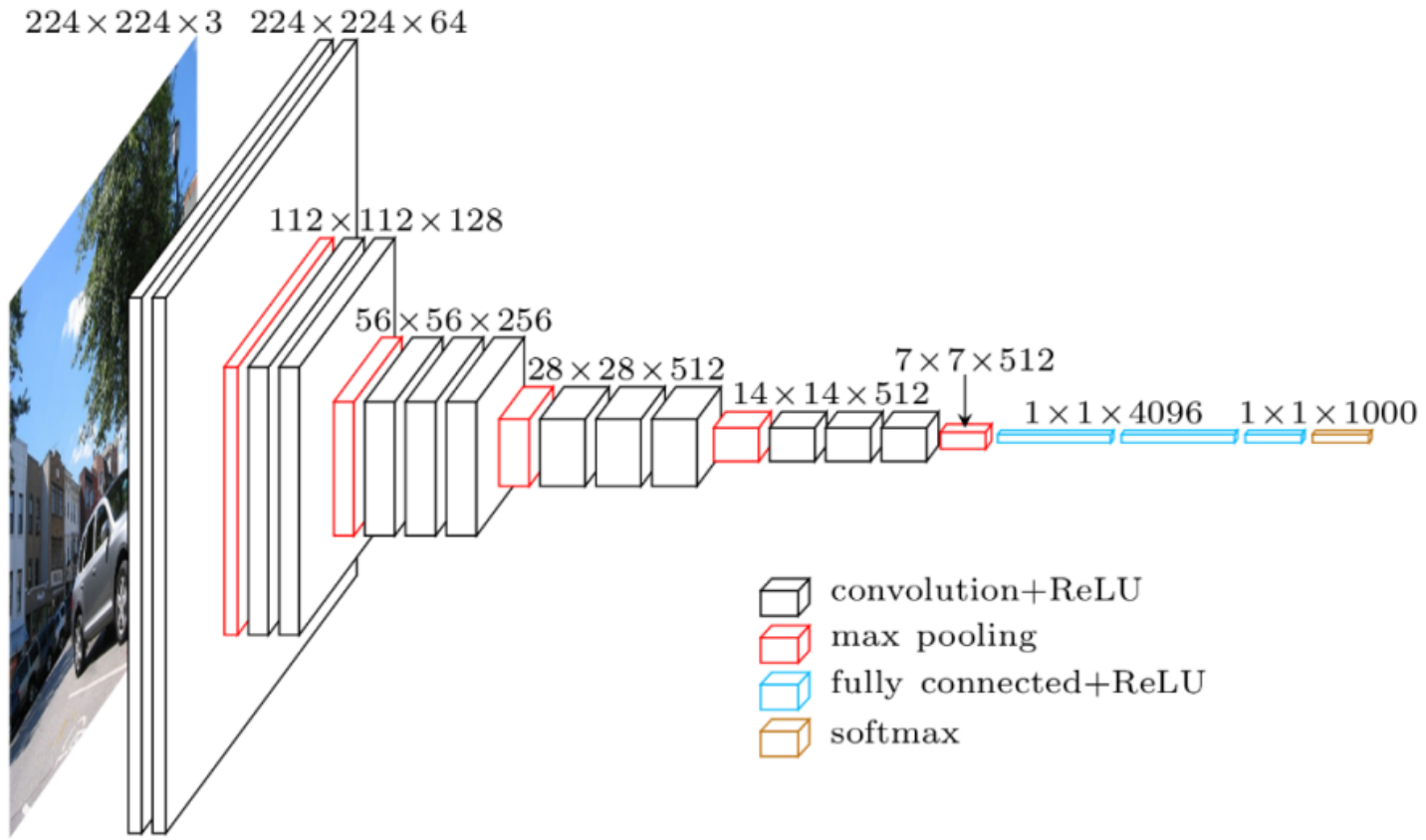
Parameters: 138 million [Conv: 11%, FC: 89%]

These architecture **won the first place places (localization) and the second place (classification) tracks in ImageNet Challenge 2014**

Input size 224 × 224 X 3



Simonyan, Karen, and Andrew Zisserman. "Very deep convolutional networks for large-scale image recognition." ICLR (2015)

VGG16 (2014): Smaller Filter, Deeper Network

The paper actually present a thorough **study on the role of network depth**.

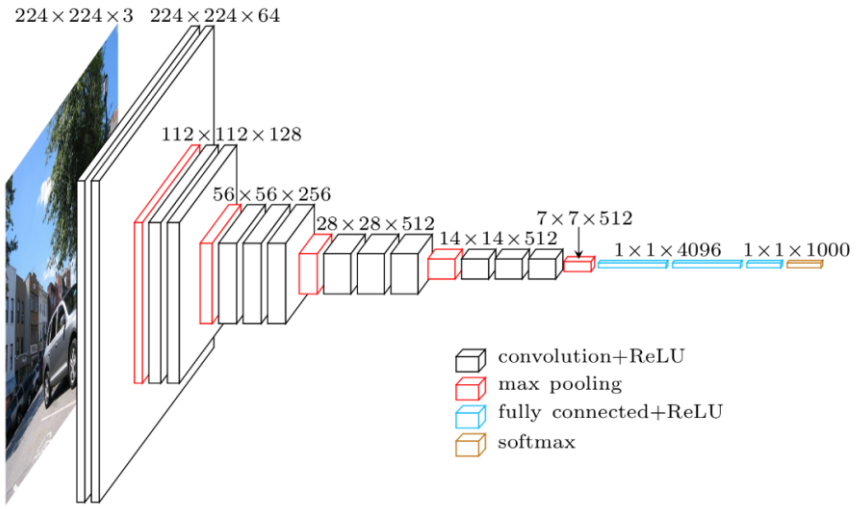
[…]Fix other parameters of the architecture, and steadily increase the depth of the network by adding more convolutional layers, which is feasible due ***to the use of very small (3. × 3) convolution filters in all layers.***

Idea: Multiple 3×3 convolution in a sequence achieve large receptive fields with:

- less parameters
- more nonlinearities

than larger filters in a single layer

	3 layers 3x3		1 layer 7x7
Receptive field	7x7	=	7x7
Nr of filter weights	3 x 3 x 3 = 27	<	49
Nr of nonlinearities	3	>	1



Simonyan, Karen, and Andrew Zisserman. "Very deep convolutional networks for large-scale image recognition." ICLR (2015)

VGG16

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 224, 224, 3)	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
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block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
flatten (Flatten)	(None, 25088)	0
fc1 (Dense)	(None, 4096)	102764544
fc2 (Dense)	(None, 4096)	16781312
predictions (Dense)	(None, 1000)	4097000

Total params: 138,357,544
Trainable params: 138,357,544
Non-trainable params: 0

VGG16

in red: blocks of convolution where the size is preserved.

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Many convolutional blocks without maxpooling

G. Boracchi

VGG16

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Huge nb of params

Most parameters in FC layers : **123,642,856**

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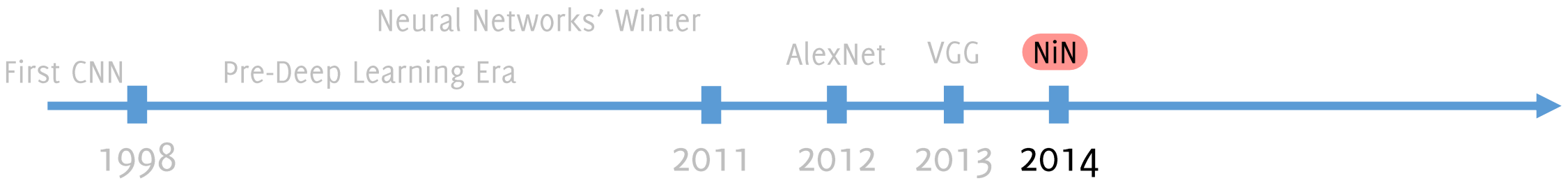
High memory request, about 100MB per image ($224 \times 224 \times 3$) to be stored in all the activation maps, only for the forward pass. During training, with the backward pass it's about twice

Networks in Networks



Network In Network

Min Lin[1,2], Qiang Chen[2], Shuicheng Yan[2]
[1]Graduate School for Integrative Sciences and Engineering
[2]Department of Electronic & Computer Engineering
National University of Singapore, Singapore
{linmin,chenqiang,eleyans}@nus.edu.sg

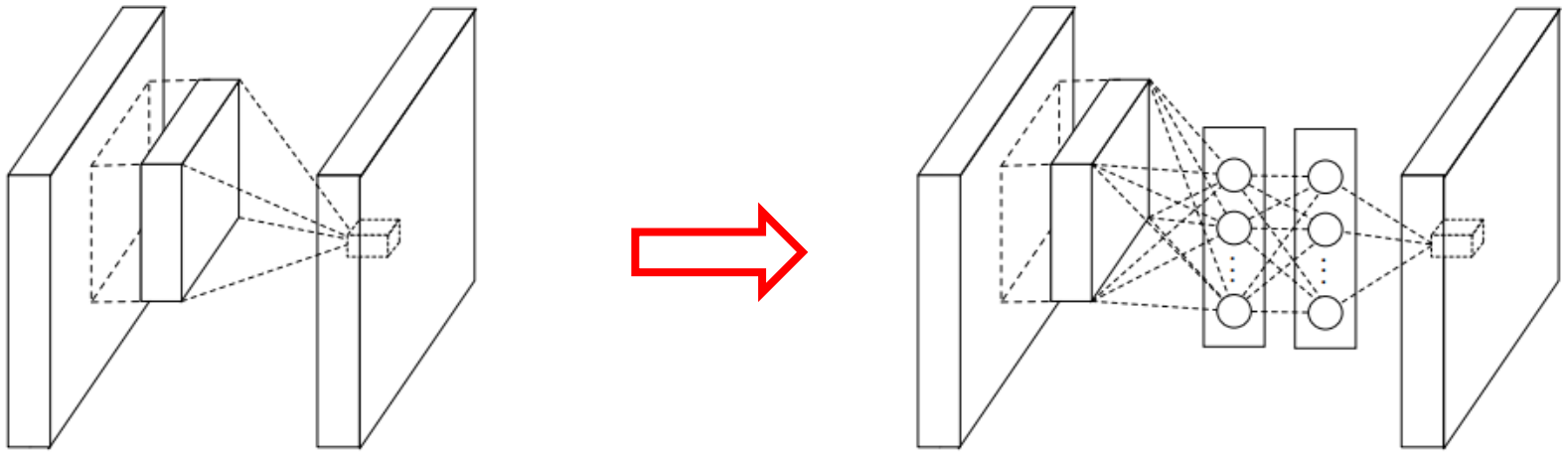
Lin, Min, Qiang Chen, and Shuicheng Yan. "Network in network." *ICLR 2014*

Network in Network

Multilayer perceptron Conv layers.

Mlpconv layers: instead of conv layers, use **a sequence of FC + RELU**

- Uses a stack of FC layers followed by RELU **in a sliding manner on the entire image. This corresponds to MLP networks used convolutionally** (still preserving sparsity and weight sharing).



(a) Linear convolution layer (b) Mlpconv layer

Lin, Min, Qiang Chen, and Shuicheng Yan. "Network in network." *ICLR 2014*

Network in Network

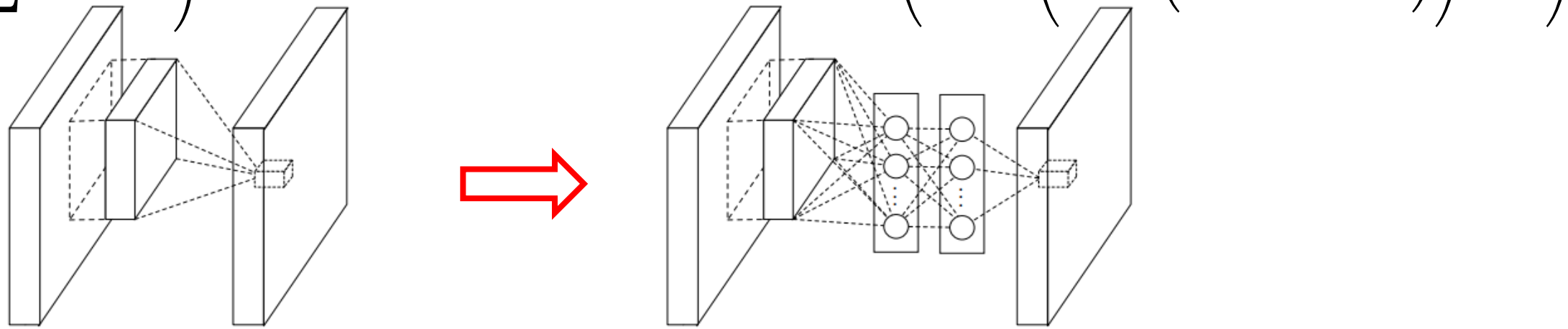
Mlpconv layers: instead of conv layers, use **a sequence of FC + RELU**

- Uses a stack of FC layers followed by RELU **in a sliding manner on the entire image. This corresponds to MLP networks used convolutionally**

Each layer features a **more powerful functional approximation** than a convolutional layer which is just linear + RELU

$$f = ReLU\left(\sum w_i\, x_i + b\right)$$

$$f = ReLU\left(\sum w_i^1 \left(ReLU\left(\sum w_i^2\, x_i + b^2\right)\right) + b^1\right)$$



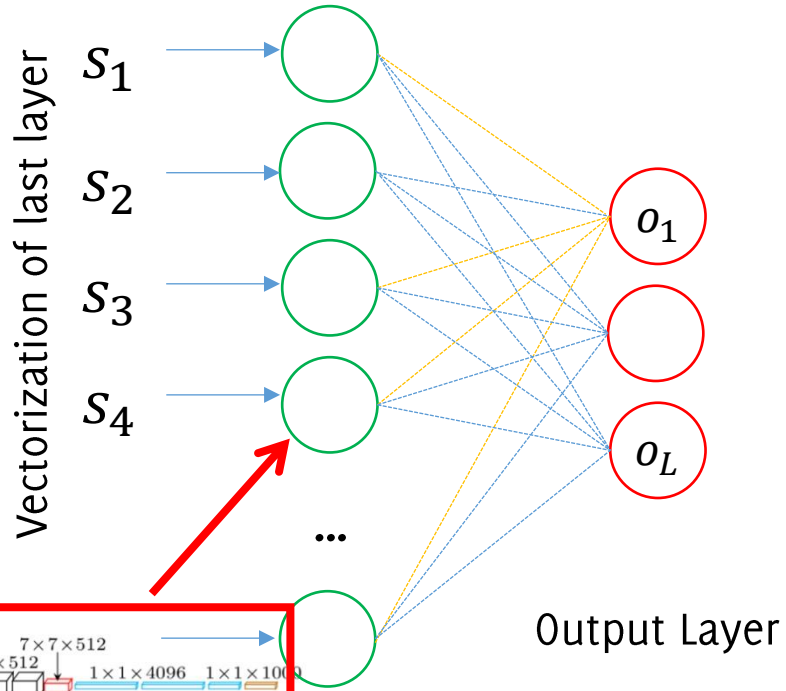
(a) Linear convolution layer (b) Mlpconv layer

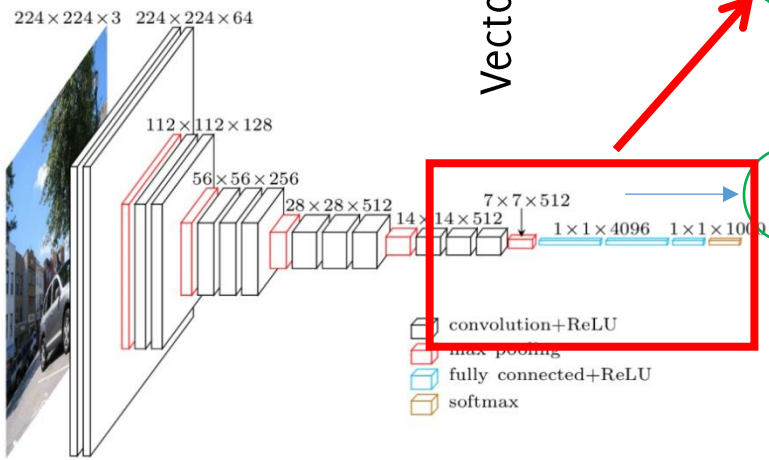
Lin, Min, Qiang Chen, and Shuicheng Yan. "Network in network." *ICLR 2014*

Network in Network

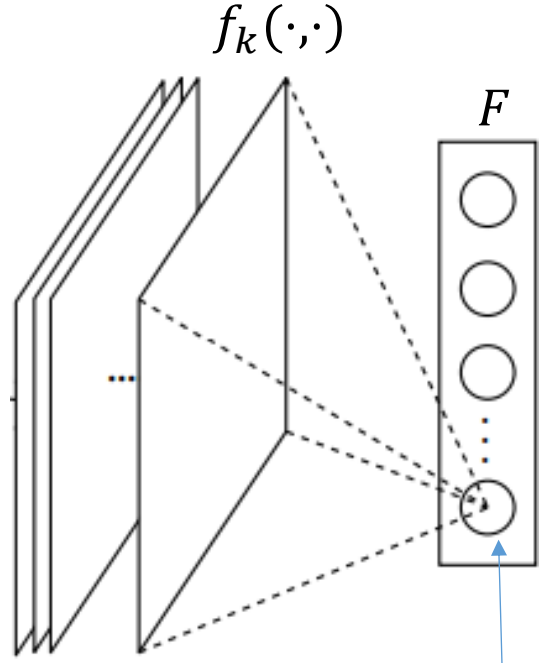
They also introduce Global Averaging Pooling Layers

Fully Connected Layer





Global Averaging Pooling Layer



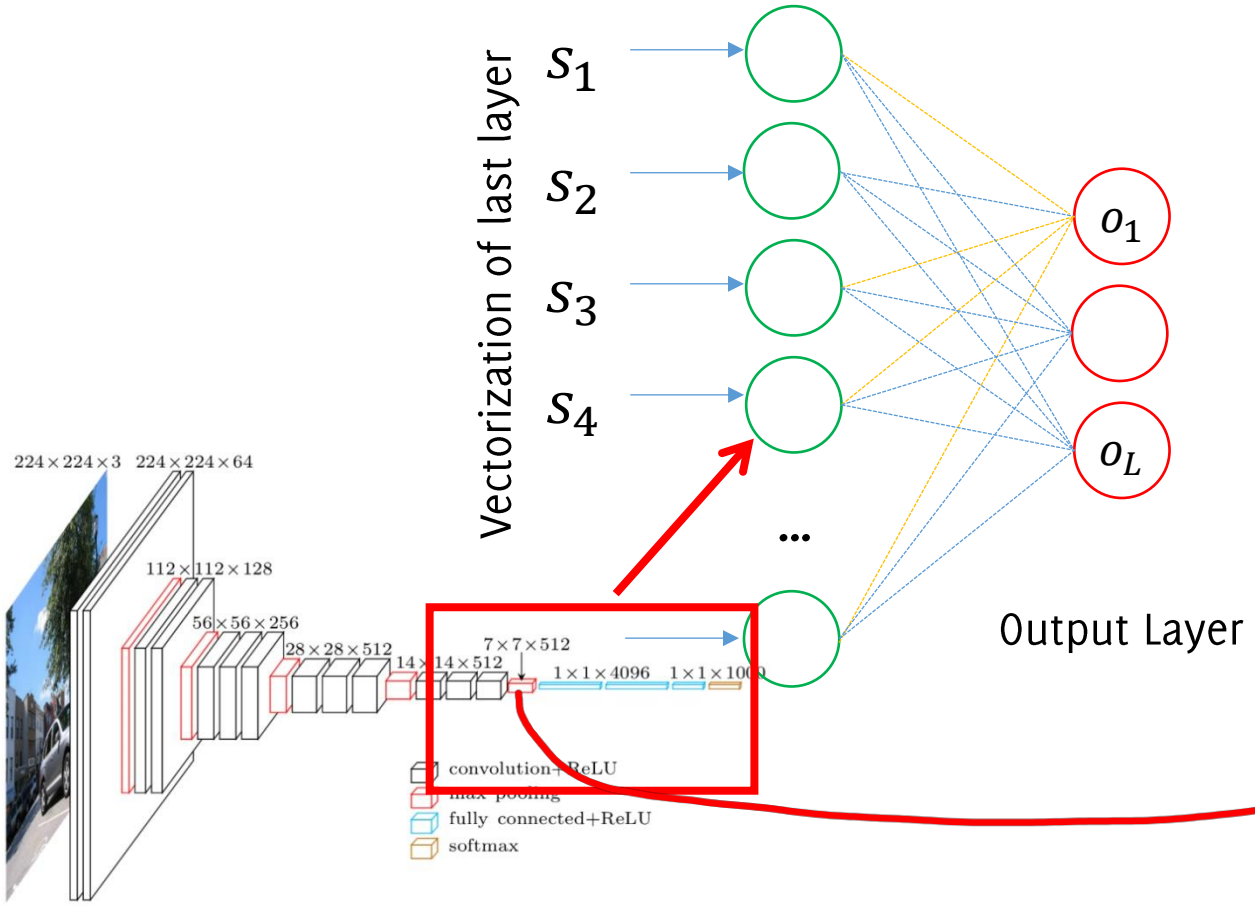
$$F_k = \frac{1}{N} \sum_{(x,y)} f_k(x,y)$$

Lin, Min, Qiang Chen, and Shuicheng Yan. "Network in network." *ICLR 2014*

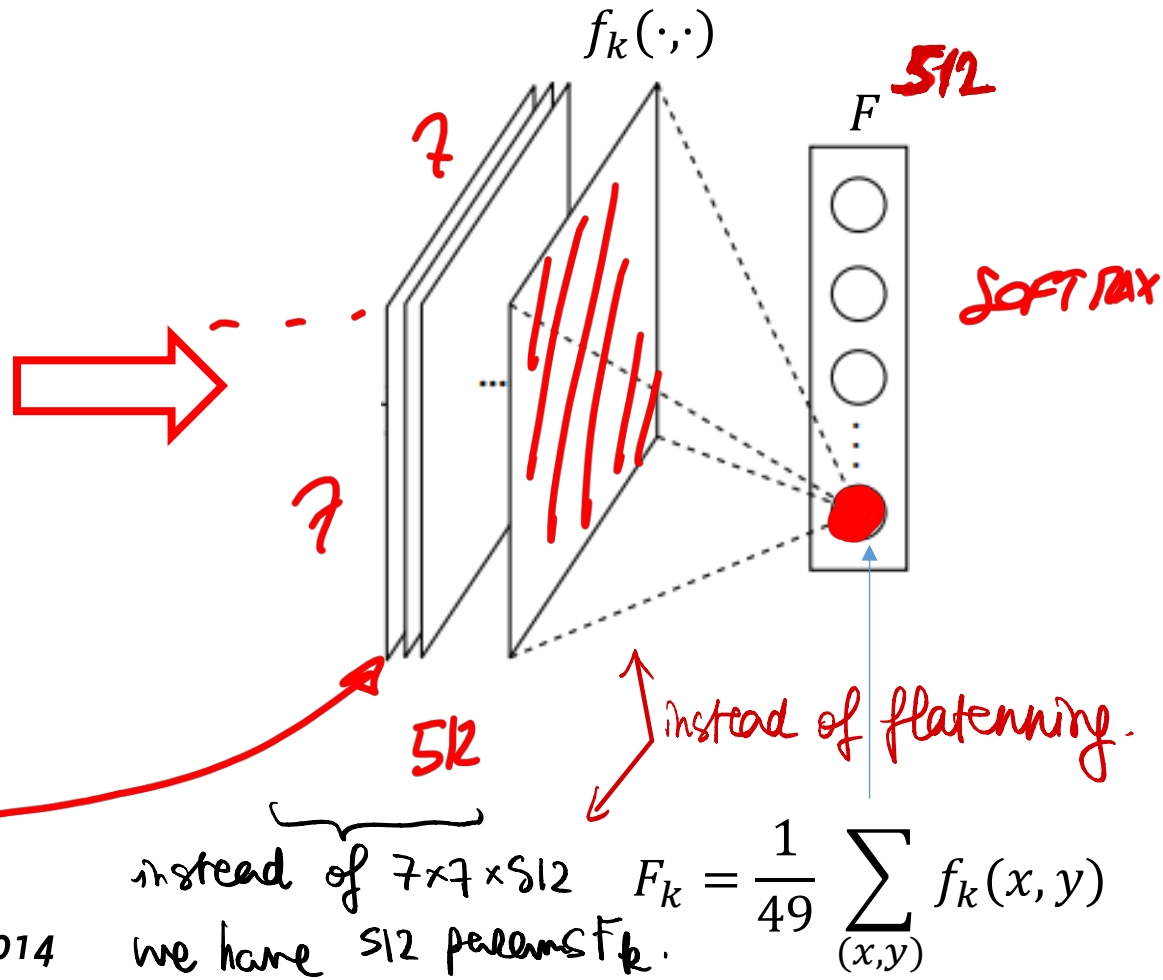
Network in Network

They also introduce Global Averaging Pooling Layers

Fully Connected Layer



GAP: Global Averaging Pooling Layer

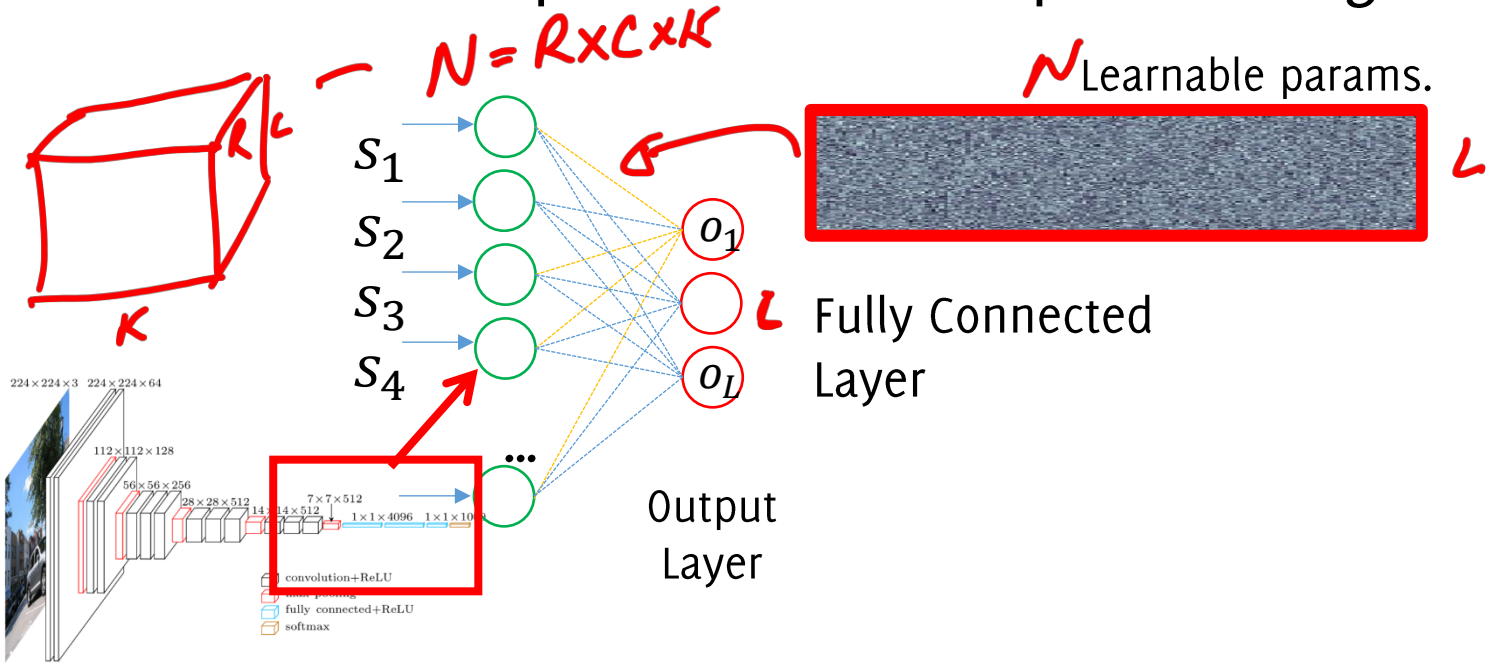


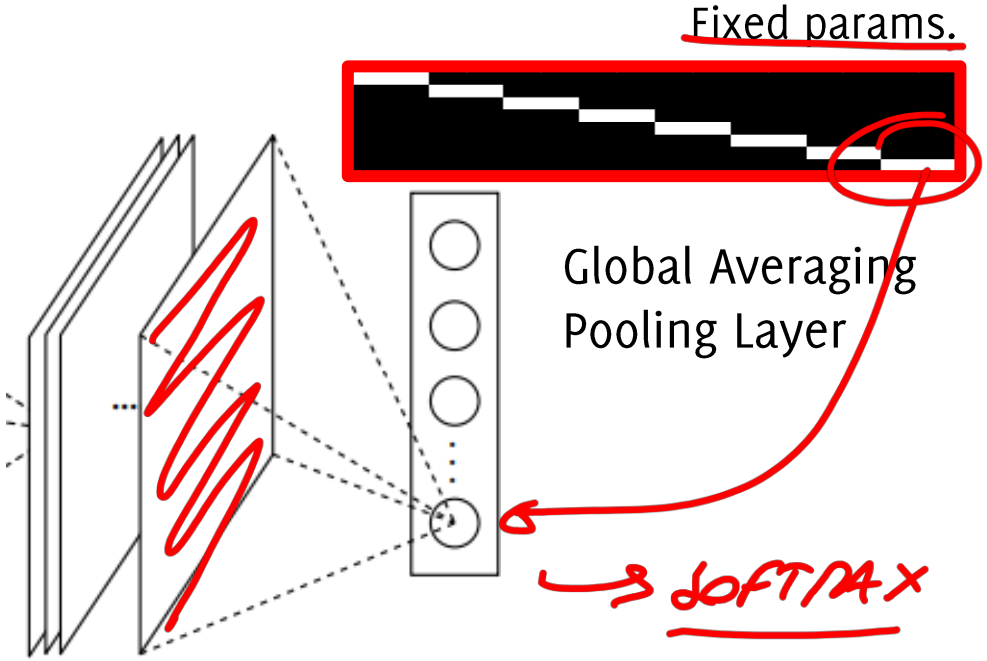
Lin, Min, Qiang Chen, and Shuicheng Yan. "Network in network." *ICLR 2014*

Network in Network: GAP "global averaging pooling"

Global Averaging Pooling Layers: instead of a FC layer at the end of the network, **compute the average of each feature map.**

- The **GAP** corresponds to a multiplication against **a block diagonal, non-trainable, constant matrix** (the input flattened layer-wise in a vector).
- A **MLP** corresponds to a multiplication against a trainable **dense matrix.**





Lin, Min, Qiang Chen, and Shuicheng Yan. "Network in network." *ICLR 2014*

Rationale behind GAP

Fully connected layers are prone to overfitting

- They have many parameters
- Dropout was proposed as a regularizer that randomly sets to zero a percentage of activations in the FC layers during training

The GAP was here used as follows:

1. **Remove the fully connected layer** at the end of the network!
2. **Introduce a GAP layer.**
3. **Predict by a simple soft-max after the GAP.**

The experiment they designed.

↳ they wanted to show that perf of NN was limited by the huge nb of params contained in dense layers. ↓ overfit!

Watch out: the number of feature maps has to correspond to the number of output classes!

In general, GAP can be used with more/fewer classes than channels **provided an hidden layer to adjust feature dimension**

The Advantages of GAP Layers:

- No parameters to optimize, lighter networks less prone to overfitting
- Classification is performed by a softMax layer at the end of the GAP
- More interpretability, creates a direct connection between layers and classes output (we'll see in localization)
- This makes GAP a **structural regularizer**
- **Increases robustness to spatial transformation** of the input images
- **The network can be used to classify images of different sizes**

Lin, Min, Qiang Chen, and Shuicheng Yan. "Network in network." ICLR 2014

Network in Network

The whole NiN stacks

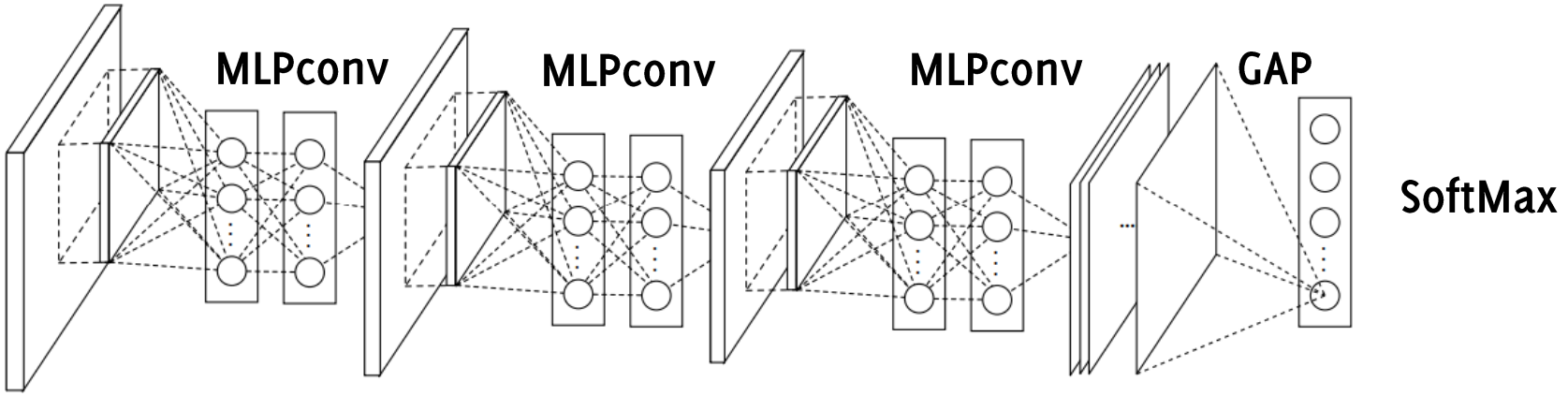
- mlpconv layers (RELU) + dropout
- Maxpooling

} A few layers of these

- Global Averaging Pooling (GAP) layer
- Softmax

} At the end of the network

simple NiNs achieve state-of-the-art performance on «small» datasets (CIFAR10, CIFAR100, SVHN, MNIST) and that **GAP effectively reduces overfitting** w.r.t. FC

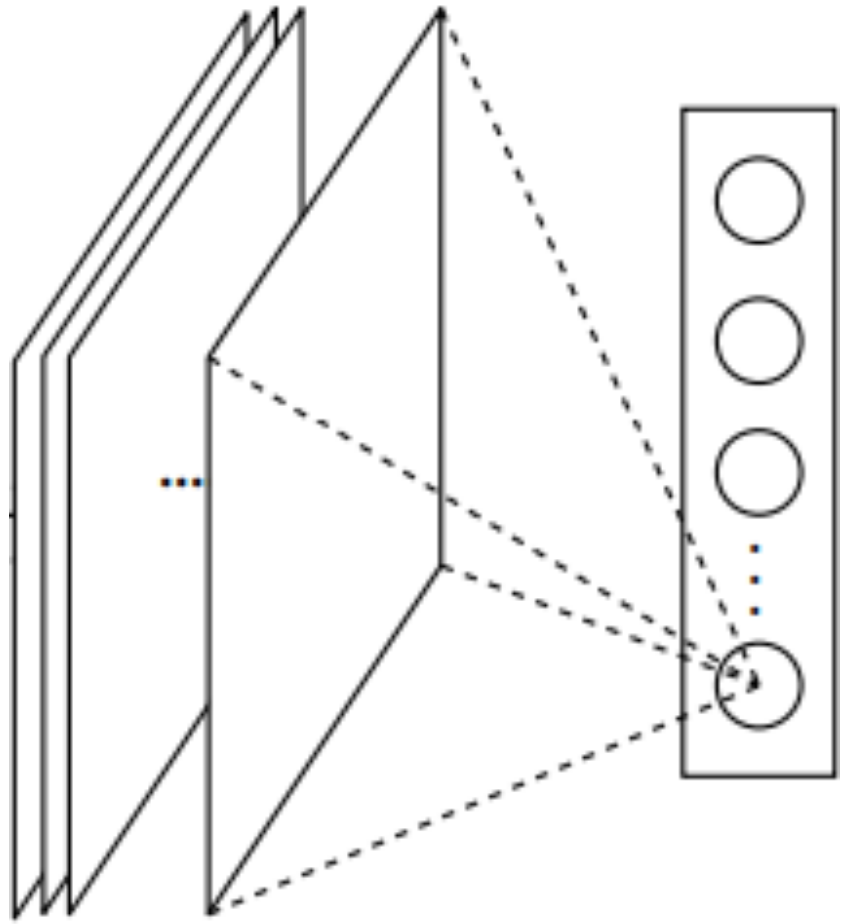


Lin, Min, Qiang Chen, and Shuicheng Yan. "Network in network." *ICLR 2014*

The Global Averaging Pooling (GAP) Layer

We indeed see that GAP is acting as a (structural) regularizer

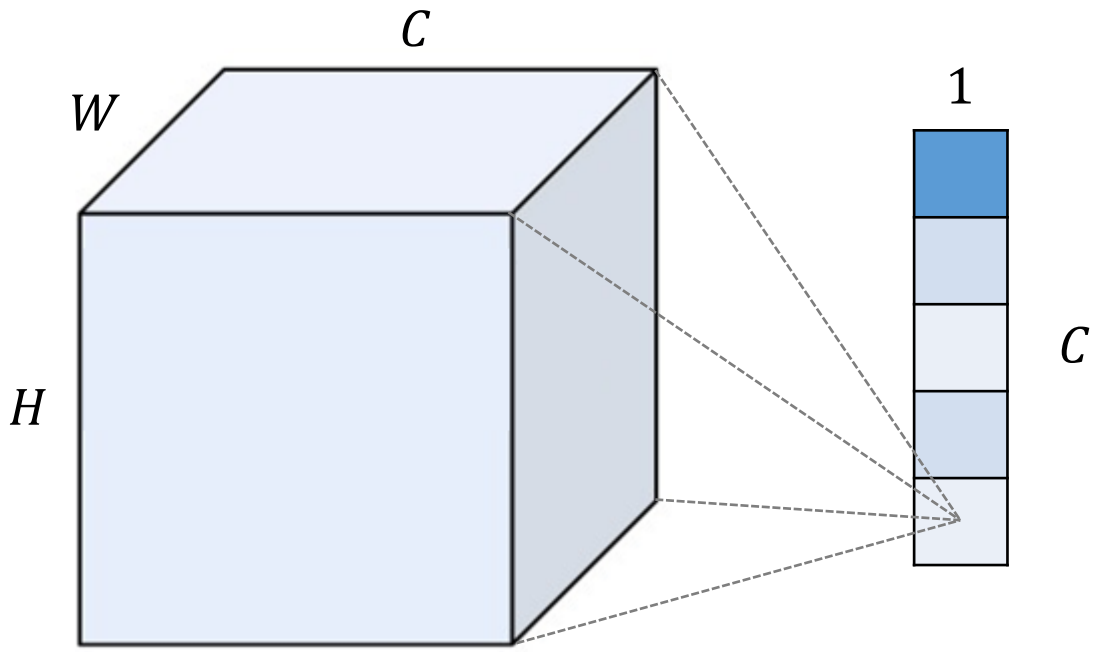
Method	Testing Error
mlpconv + Fully Connected	11.59%
mlpconv + Fully Connected + Dropout	10.88%
mlpconv + Global Average Pooling	10.41%



Lin, Min, Qiang Chen, and Shuicheng Yan. "Network in network." *arXiv preprint arXiv:1312.4400v3* (2014).

Global Pooling Layers

Global Pooling Layer: Perform a global operation on each channel, **along the spatial components.** Out of each channel, keep a single value. Pooling operations can be the average (GAP), or the maximum (GMP)



$$F_k = \frac{1}{H \cdot W} \sum_{(x,y)} f_k(x,y)\,, k = 1, \dots, C$$

GAP in Keras

```
gap = tfkl.GlobalAveragePooling2D(
        name='gap'
    )(x)
```

There are a couple of optional parameters but this are not relevant..

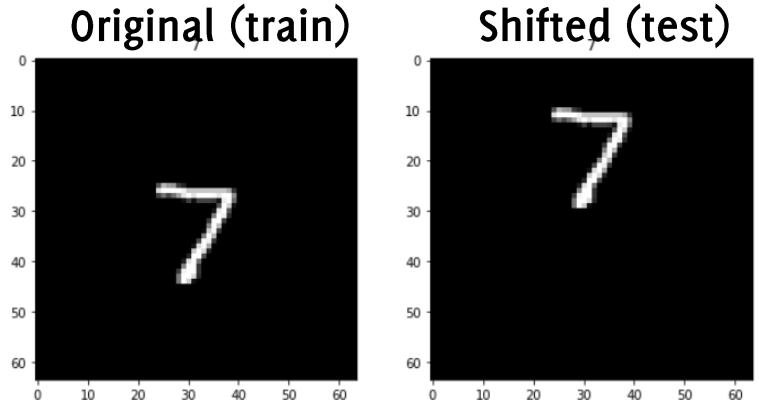
The output size of gap is (batch_size, channels)

GAP Increases Invariance to Shifts

Features extracted by the convolutional part of the network are invariant to shift of the input image

The MLP after the flattening is not invariant to shifts (different input neurons are connected by different weights)

Therefore, a CNN trained on centered images might not be able to correctly classify shifted ones



The GAP solves this problem, since there is no ~~GAP~~ MLP and the two images lead to the same or very similar features

Credits Eugenio Lomurno

G. Boracchi

GAP Increases Invariance to Shifts

Example:

Dataset: a 64x64 (zero padded) MNIST

CNN-flattening: a traditional CNN with flattening, trained

CNN-GAP: the same architecture CNN but with GAP instead of MLP

Train both CNNs over the **training set without shift**

Test both CNNs over both

- Original test set
- Sifted test set

CNN-flattening Architecture

Layer (type)	Output Shape	Param #
Input (InputLayer)	[(None, 64, 64)]	0
reshape_1 (Reshape)	(None, 64, 64, 1)	0
conv1 (Conv2D)	(None, 62, 62, 32)	320
pool1 (MaxPooling2D)	(None, 31, 31, 32)	0
conv2 (Conv2D)	(None, 29, 29, 64)	18496
pool2 (MaxPooling2D)	(None, 14, 14, 64)	0
conv3 (Conv2D)	(None, 12, 12, 128)	73856
pool3 (MaxPooling2D)	(None, 6, 6, 128)	0
flatten (Flatten)	(None, 4608)	0
dropout1 (Dropout)	(None, 4608)	0
classifier (Dense)	(None, 64)	294976
dropout2 (Dropout)	(None, 64)	0
Output (Dense)	(None, 10)	650

Total params: 388,298
Trainable params: 388,298
Non-trainable params: 0

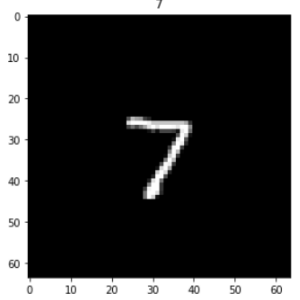
Credits Eugenio Lomurno

CNN-GAP Architecture

Layer (type)	Output Shape	Param #
Input (InputLayer)	[(None, 64, 64)]	0
reshape_3 (Reshape)	(None, 64, 64, 1)	0
conv1 (Conv2D)	(None, 62, 62, 32)	320
pool1 (MaxPooling2D)	(None, 31, 31, 32)	0
conv2 (Conv2D)	(None, 29, 29, 64)	18496
pool2 (MaxPooling2D)	(None, 14, 14, 64)	0
conv3 (Conv2D)	(None, 12, 12, 128)	73856
GAP gpooling (GlobalAveragePooli	(None, 128)	0
dropout1 (Dropout)	(None, 128)	0
classifier (Dense)	(None, 64)	8256
dropout2 (Dropout)	(None, 64)	0
Output (Dense)	(None, 10)	650

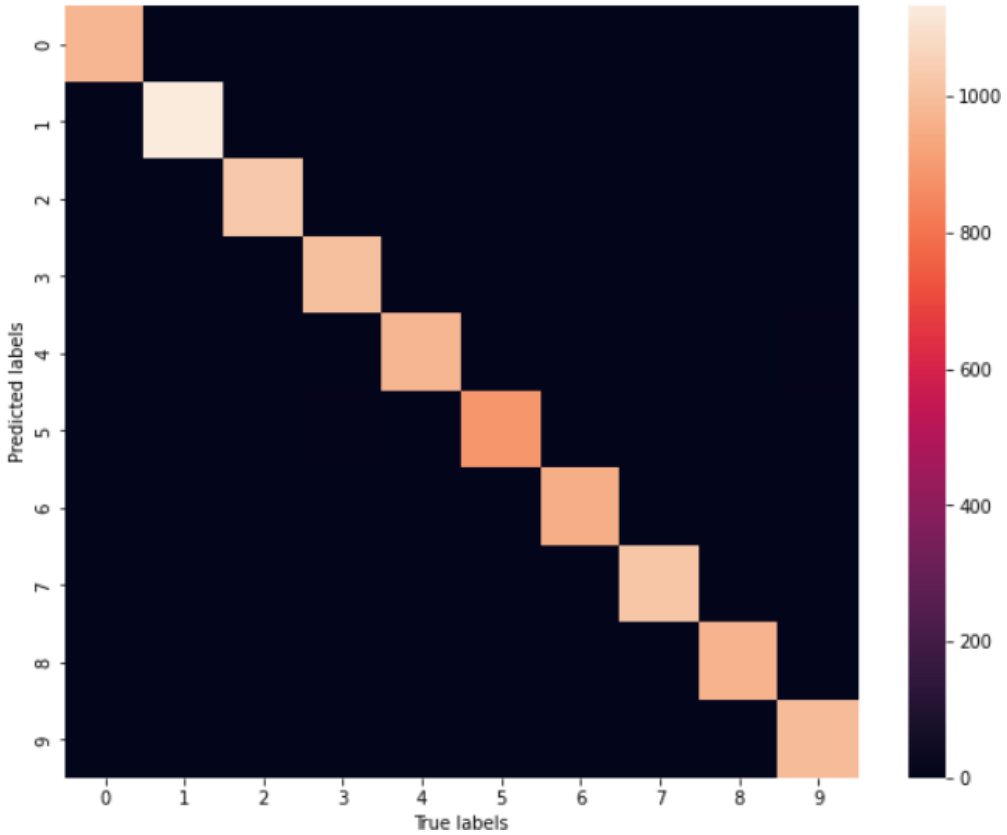
Total params: 101,578
Trainable params: 101,578
Non-trainable params: 0

Accuracy on (original) Non-Shifted Test Set



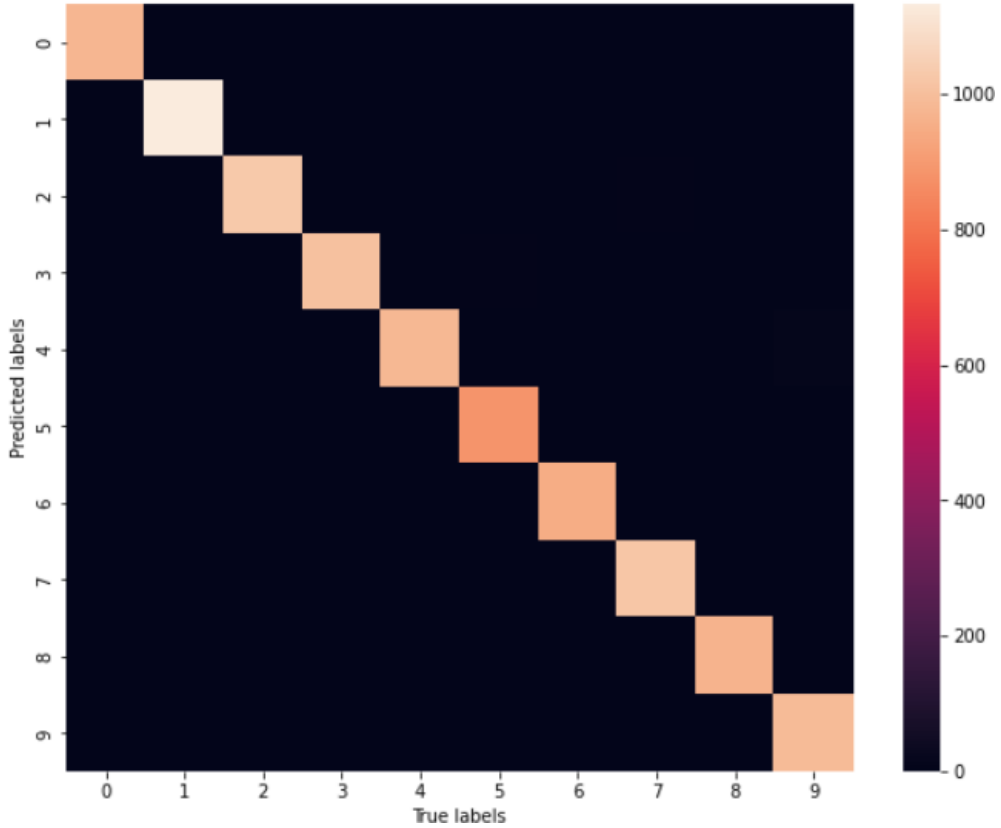
CNN-flattening:

Accuracy: 0.9936
Precision: 0.9935
Recall: 0.9936
F1: 0.9935



CNN-GAP

Accuracy: 0.9934
Precision: 0.9934
Recall: 0.9933
F1: 0.9933

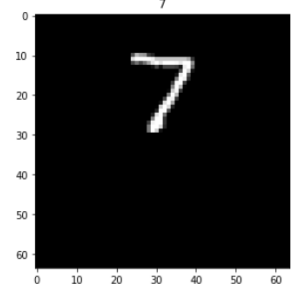


The two models are equally good !

Credits Eugenio Lomurno

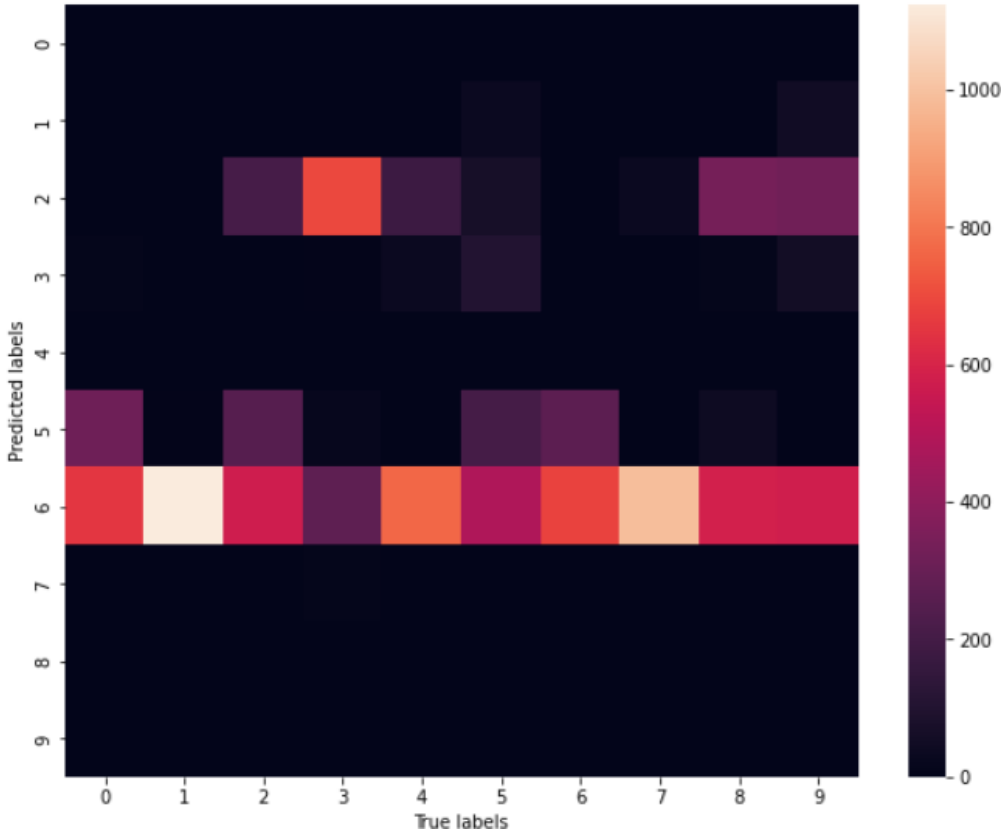
G. Boracchi

Accuracy on Shifted Test Set



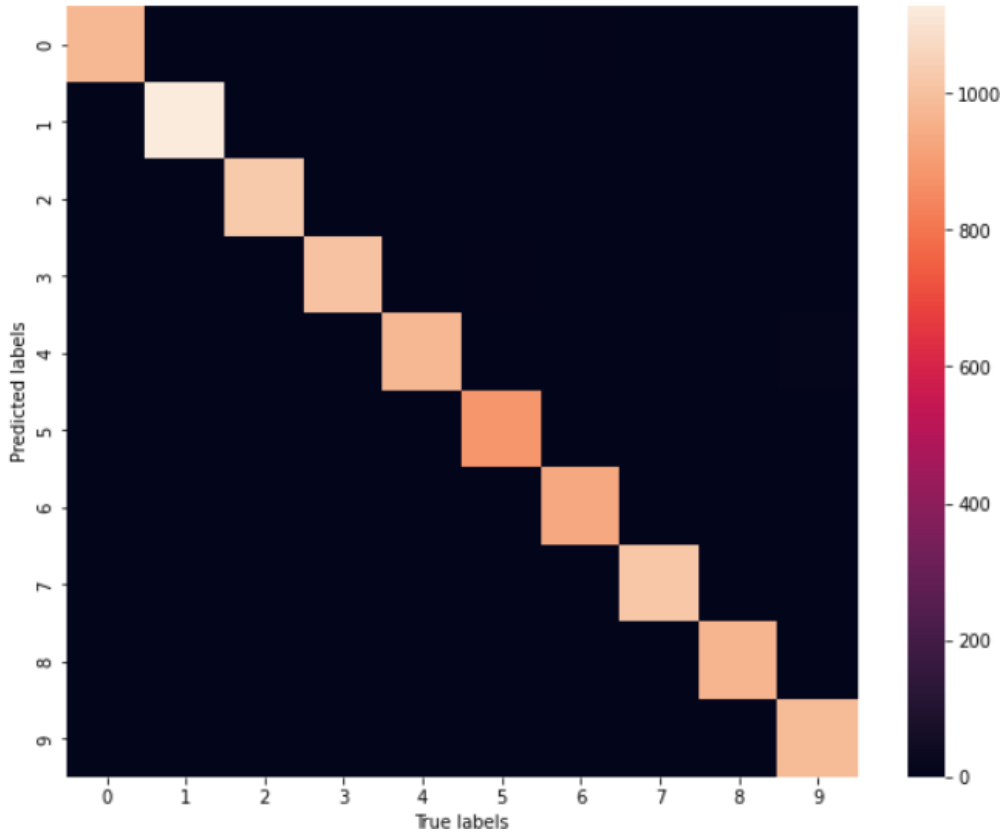
CNN-flattening:

Accuracy: 0.1103
Precision: 0.0435
Recall: 0.1151
F1: 0.0537



CNN-GAP

Accuracy: 0.9906
Precision: 0.9906
Recall: 0.9905
F1: 0.9905

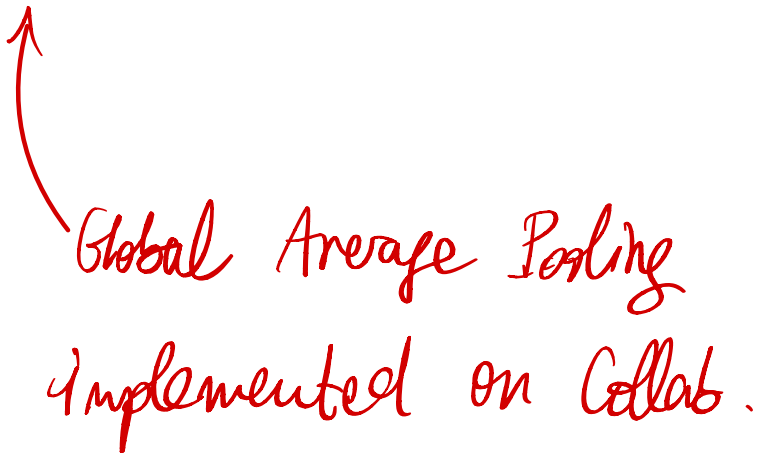


The GAP model is way better!

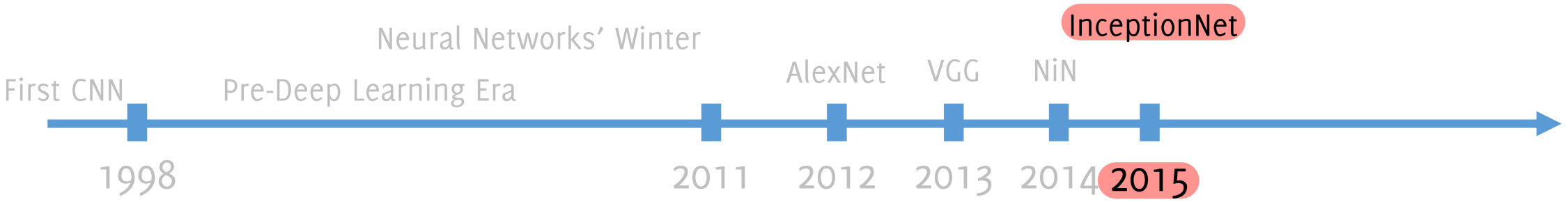
Credits Eugenio Lomurno

G. Boracchi

https://colab.research.google.com/drive/1dQoYzh4g-9aFGoTYMLlwN_0J653GArxP



InceptionNet: Multiple Branches



G. Boracchi

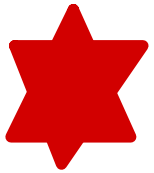
Going Deeper with Convolutions

Christian Szegedy[1], Wei Liu[2], Yangqing Jia[1], Pierre Sermanet[1], Scott Reed[3],
Dragomir Anguelov[1], Dumitru Erhan[1], Vincent Vanhoucke[1], Andrew Rabinovich[4]
[1]Google Inc. [2]University of North Carolina, Chapel Hill
[3]University of Michigan, Ann Arbor [4]Magic Leap Inc.

[1]{szegedy,jiayq,sermanet,dragomir,dumitru,vanhoucke}@google.com

[2]wliu@cs.unc.edu, [3]reedscott@umich.edu, [4]arabinovich@magicleap.com

Inception Module



The most straightforward way of improving the performance of deep neural networks is by increasing their size (either in depth or width)

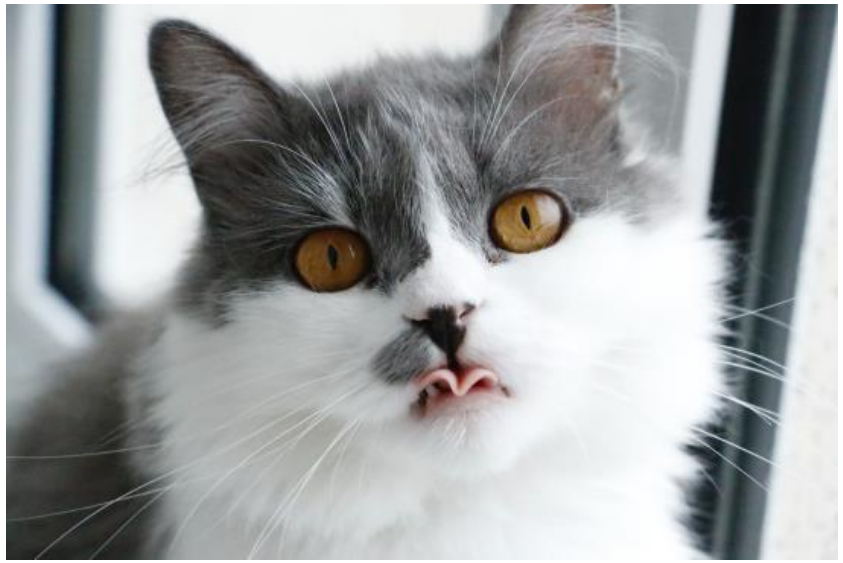
Bigger size typically means

- a larger number of parameters, which makes the enlarged network more prone to overfitting.
- dramatic increase in computational resources used.

Moreover **image features might appear at different scales**, and it is difficult to **define the right filter size.**

Features might appear at different scales

Difficult to set the right kernel size!



Photos from Unsplash

GoogLeNet and Inception v1 (2014)

Deep network, with **high computational efficiency**

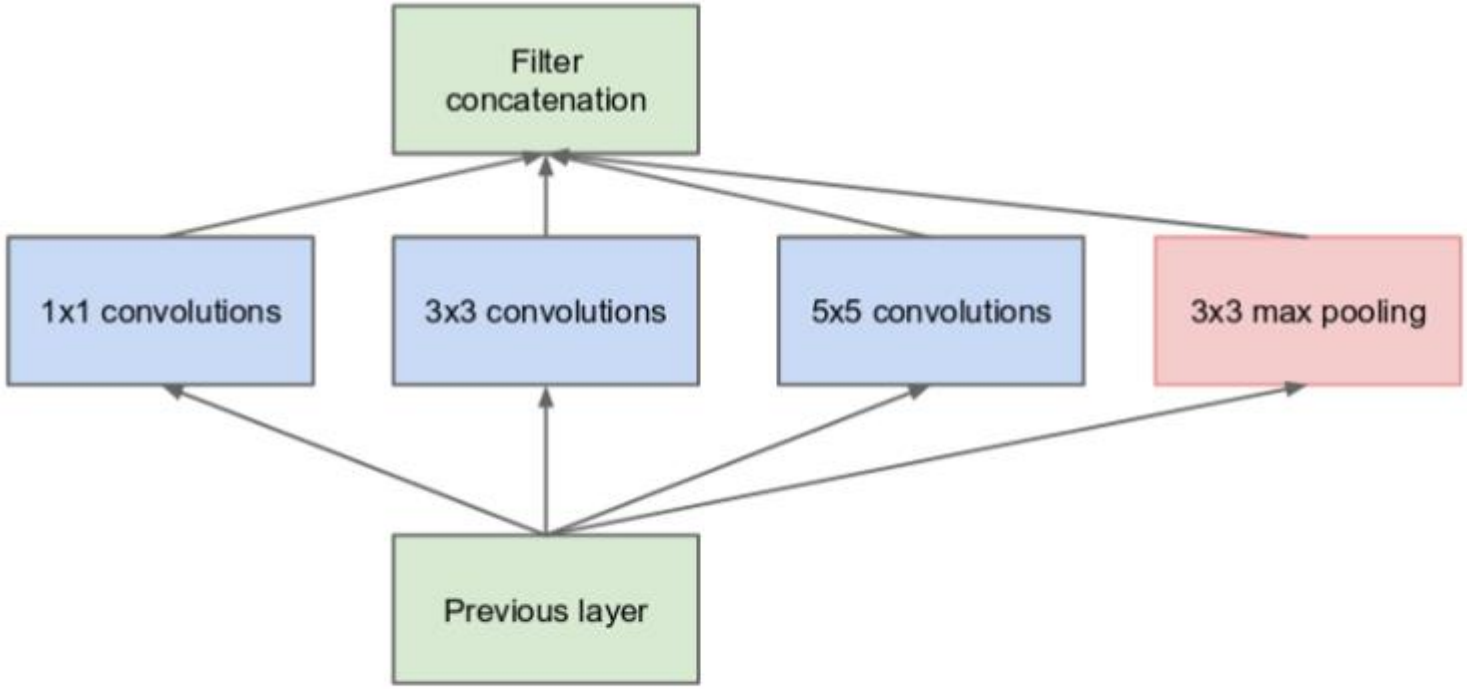
Only **5 million parameters**, **22 layers** of Inception modules

Won 2014 ILSVR-classification challenge (6,7% top 5 classification error)

Szegedy et al. "Going deeper with convolutions." *CVPR 2015*

GoogLeNet and Inception v1 (2014)

It is based on inception modules, which are sort of «local modules» where multiple convolutions are run in parallel.



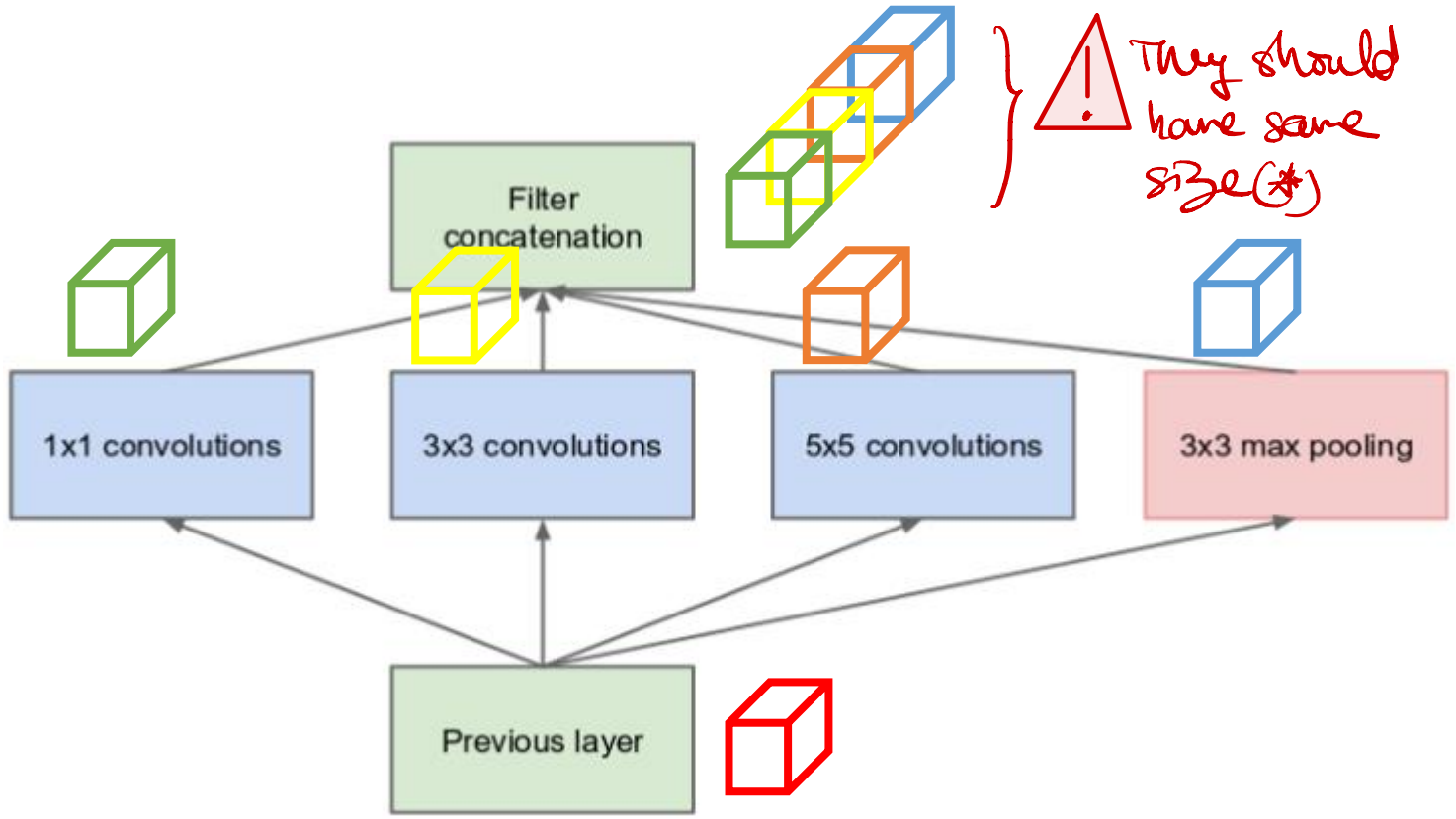
(a) Inception module, naïve version

Szegedy et al. "Going deeper with convolutions." *CVPR 2015*

Inception Module (2014)

The solution is to **exploit multiple filter size** at the same level (1x1, 3x3, 5x5) and then **merge by concatenation** the output activation maps together

(*) Convolution with padding, OR stride 1.



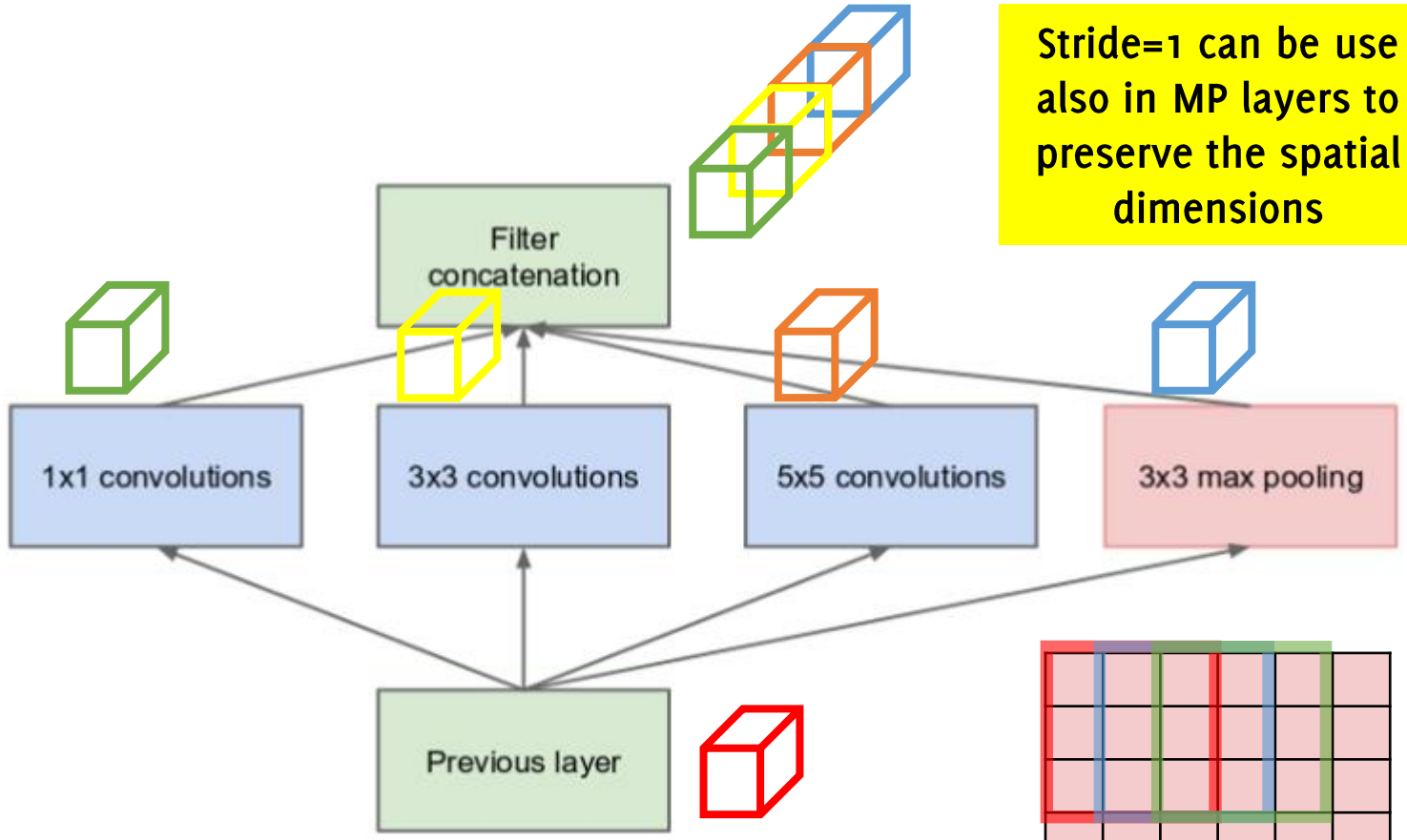
Szegedy et al. "Going deeper with convolutions." *CVPR 2015*

GoogLeNet and Inception v1 (2014)

Activation volumes are **concatenated along the channel-dimension.**

All the blocks preserve the spatial dimension by zero padding (convolutional filters) or by fractional stride (for Maxpooling)

Thus, outputs can be concatenated depth-wise



Stride=1 can be use also in MP layers to preserve the spatial dimensions

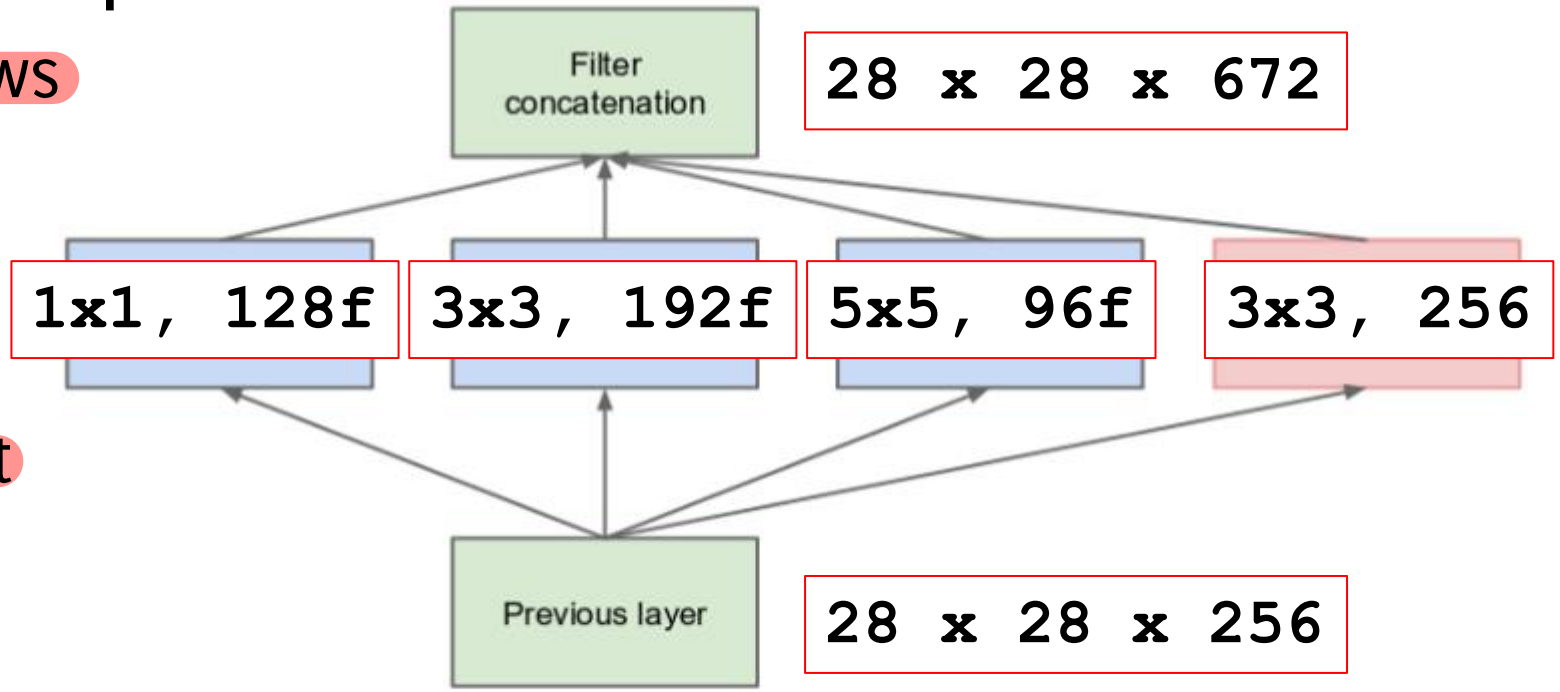
Szegedy et al. "Going deeper with convolutions." *CVPR 2015*

Inception Module (2014)

The solution is to exploit multiple filter size at the same level (1x1, 3x3, 5x5) and then **merge by concatenation** the output activation maps together

- **Zero padding to preserve spatial size**
- The activation map grows much in depth
- A large number of operations to be performed due to the large depth of the input of each convolutional block: **854M operations** in this example

How to decrease the depth?



(a) Inception module, naïve version

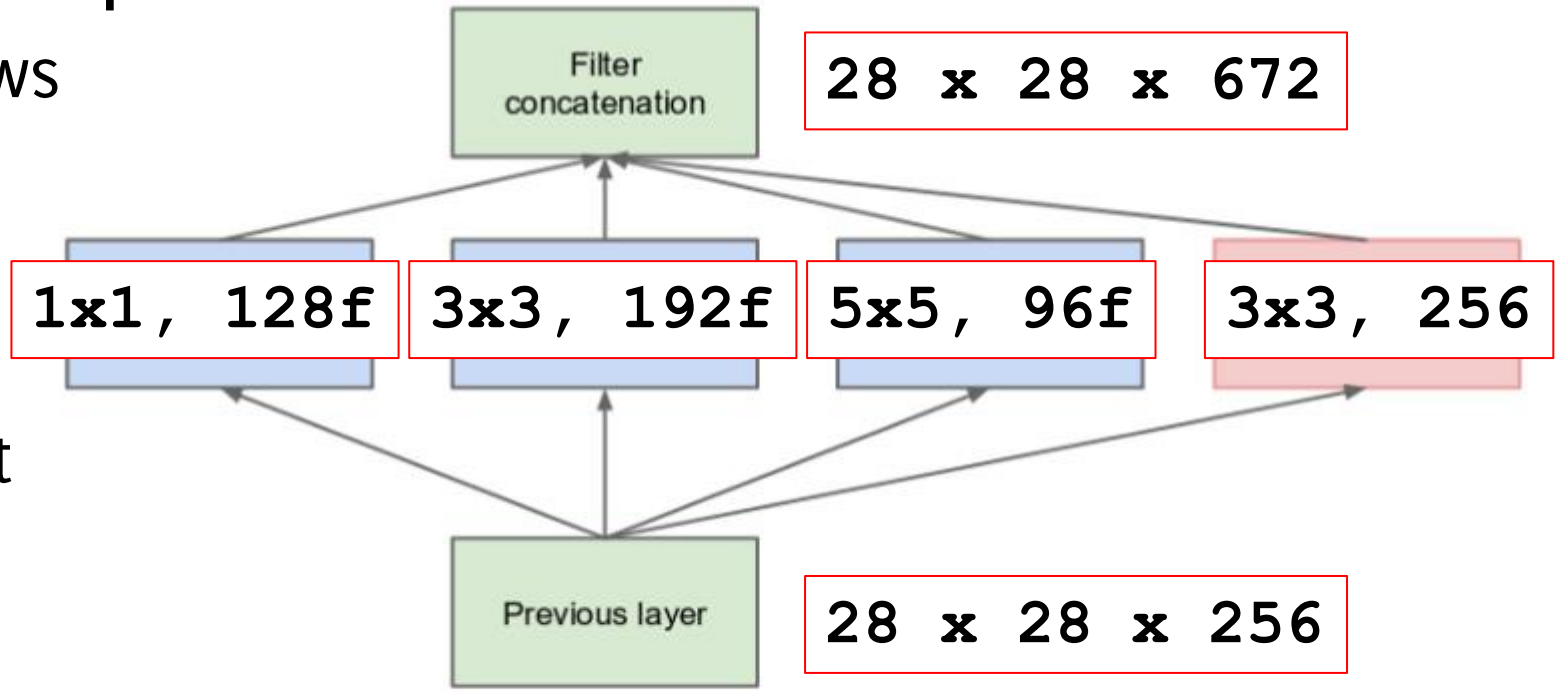
Szegedy et al. "Going deeper with convolutions." *CVPR 2015*

Inception Module (2014)

The sol… 3x3, 5x5) an… togethe…

The spatial extent is preserved, but the depth of the activation map is much expanded. This is very expensive to compute

- **Zero padding to preserve spatial size**
- The activation map grows much in depth
- A large number of operations to be performed due to the large depth of the input of each convolutional block: **854M operations** in this example



(a) Inception module, naïve version

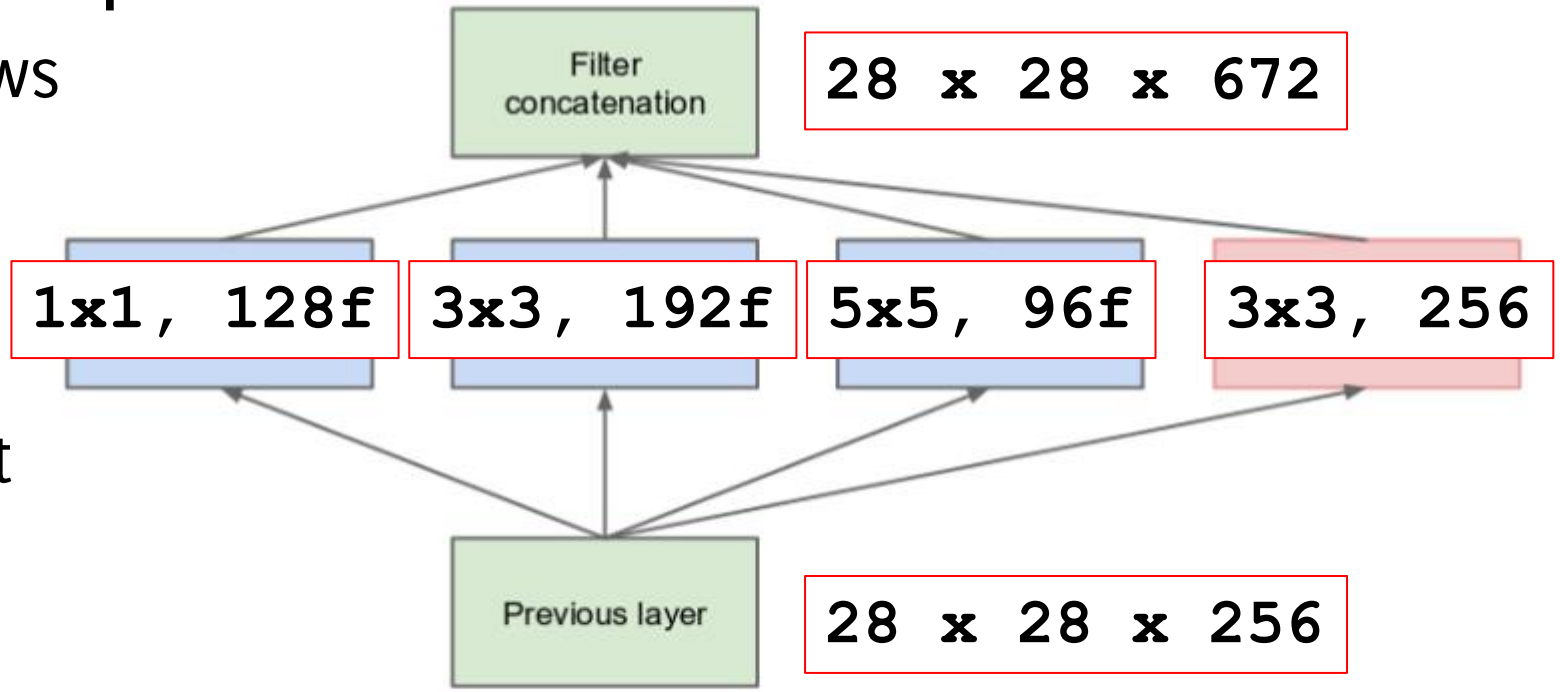
Szegedy et al. "Going deeper with convolutions." *CVPR 2015*

Inception Module (2014)

The sol… 3x3, 5x5) an… togethe…

Computational problems will get significantly worst when stacking multiple layers…

- **Zero padding to preserve spatial size**
- The activation map grows much in depth
- A large number of operations to be performed due to the large depth of the input of each convolutional block: **854M operations** in this example

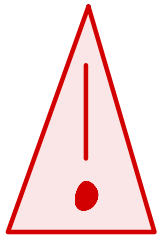


(a) Inception module, naïve version

Szegedy et al. "Going deeper with convolutions." *CVPR 2015*

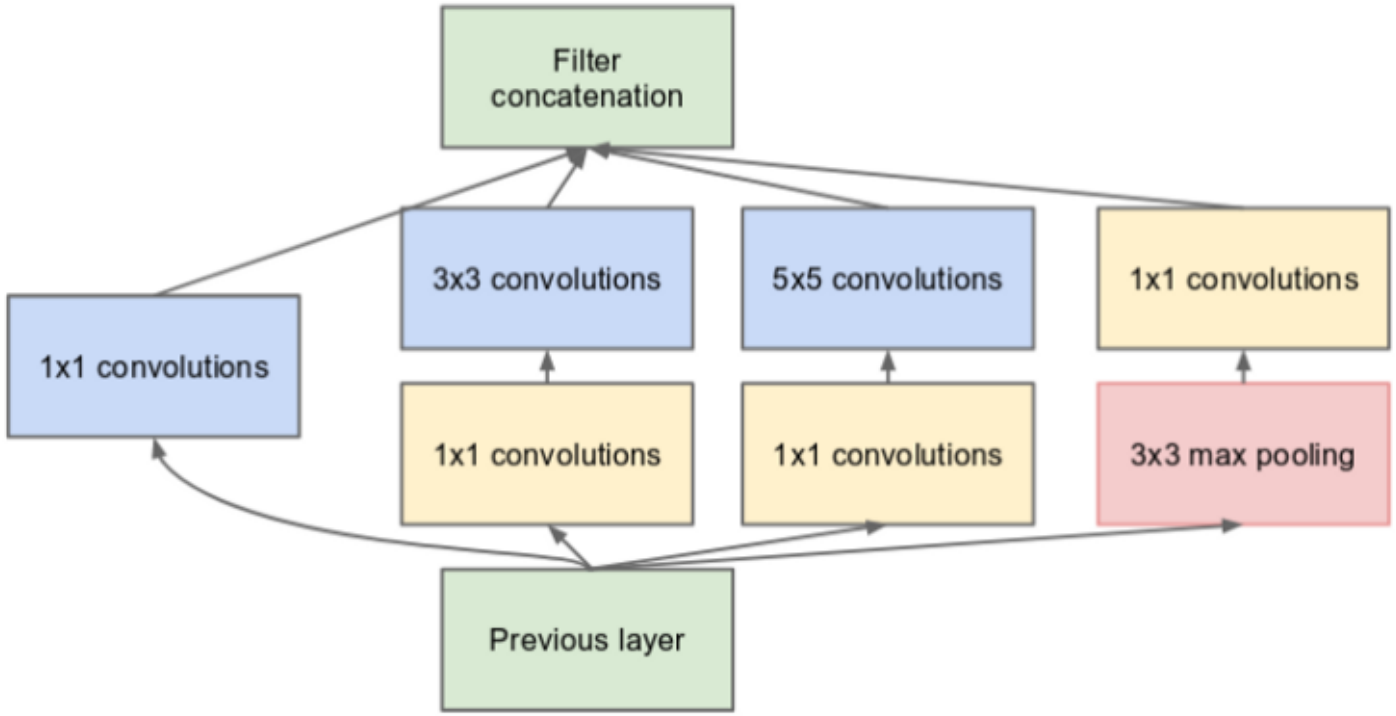
Inception Module (2014)

→ To reduce the complexity.



Idea: To reduce the computational load of the network, the number of **input channels** of each conv layer is reduced thanks to **1x1 convolution** layers before the 3x3 and 5x5 convolutions

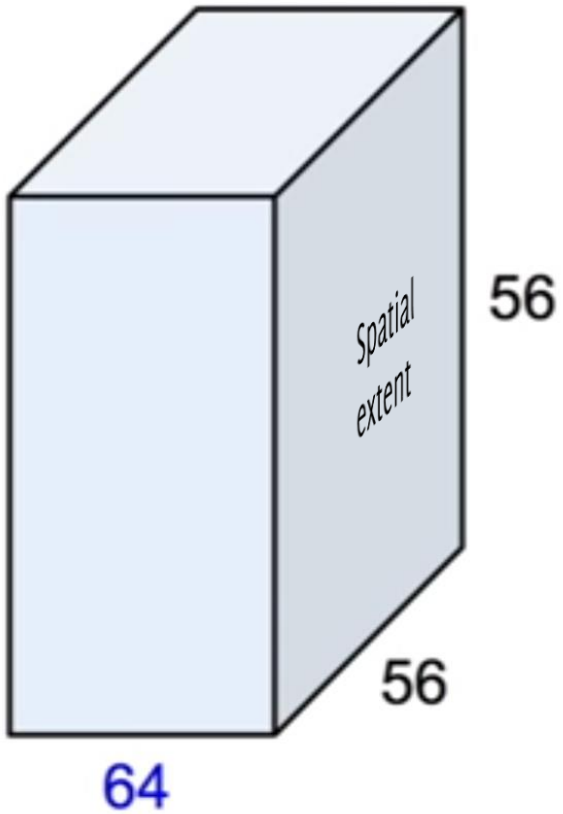
Using these 1x1 conv is referred to as **"bottleneck" layer**

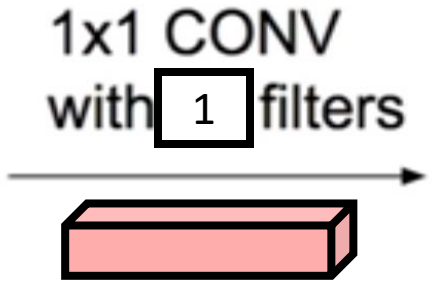


(b) Inception module with dimension reductions

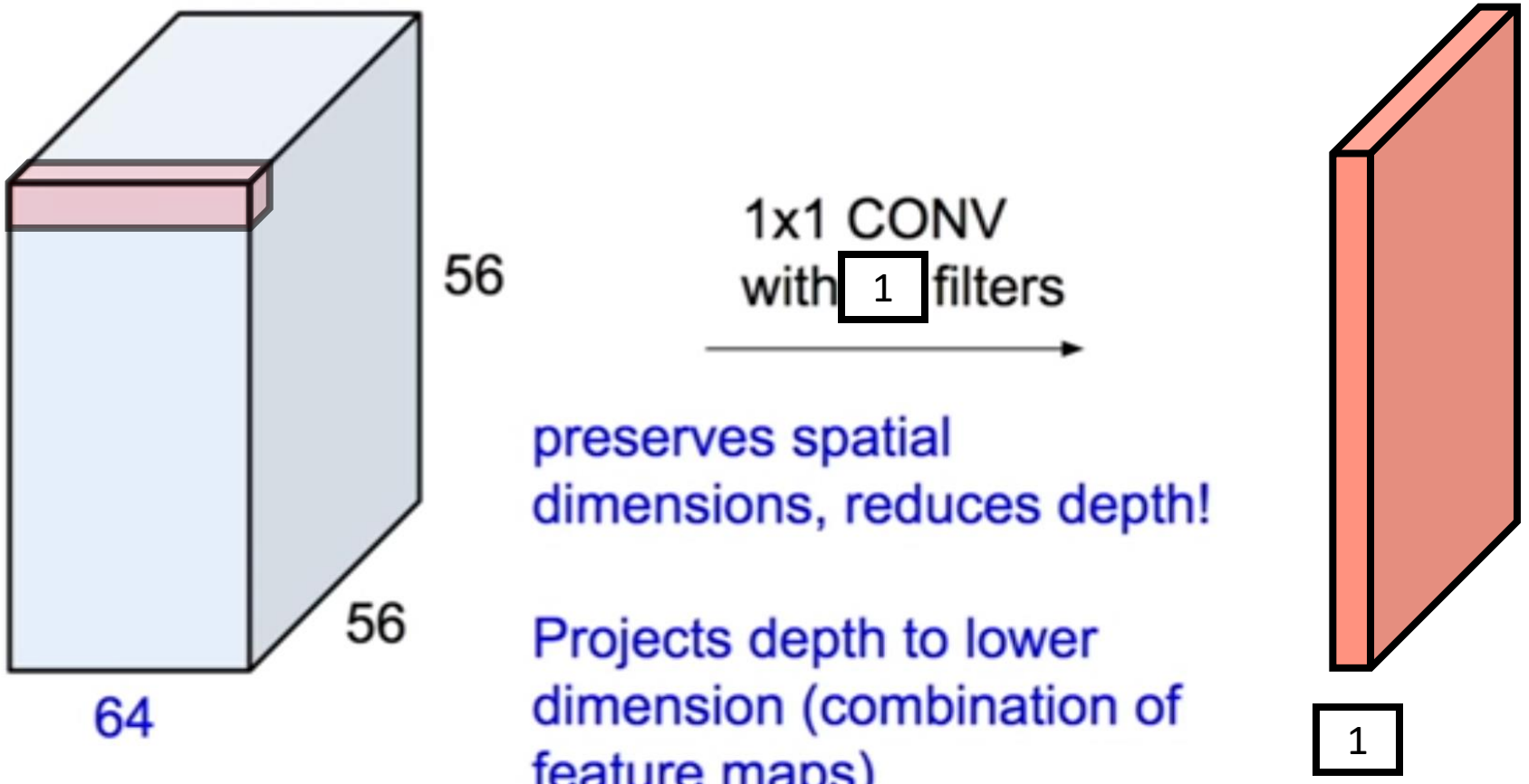
Szegedy et al. "Going deeper with convolutions." *CVPR 2015*

1x1 convolution layers as bottleneck

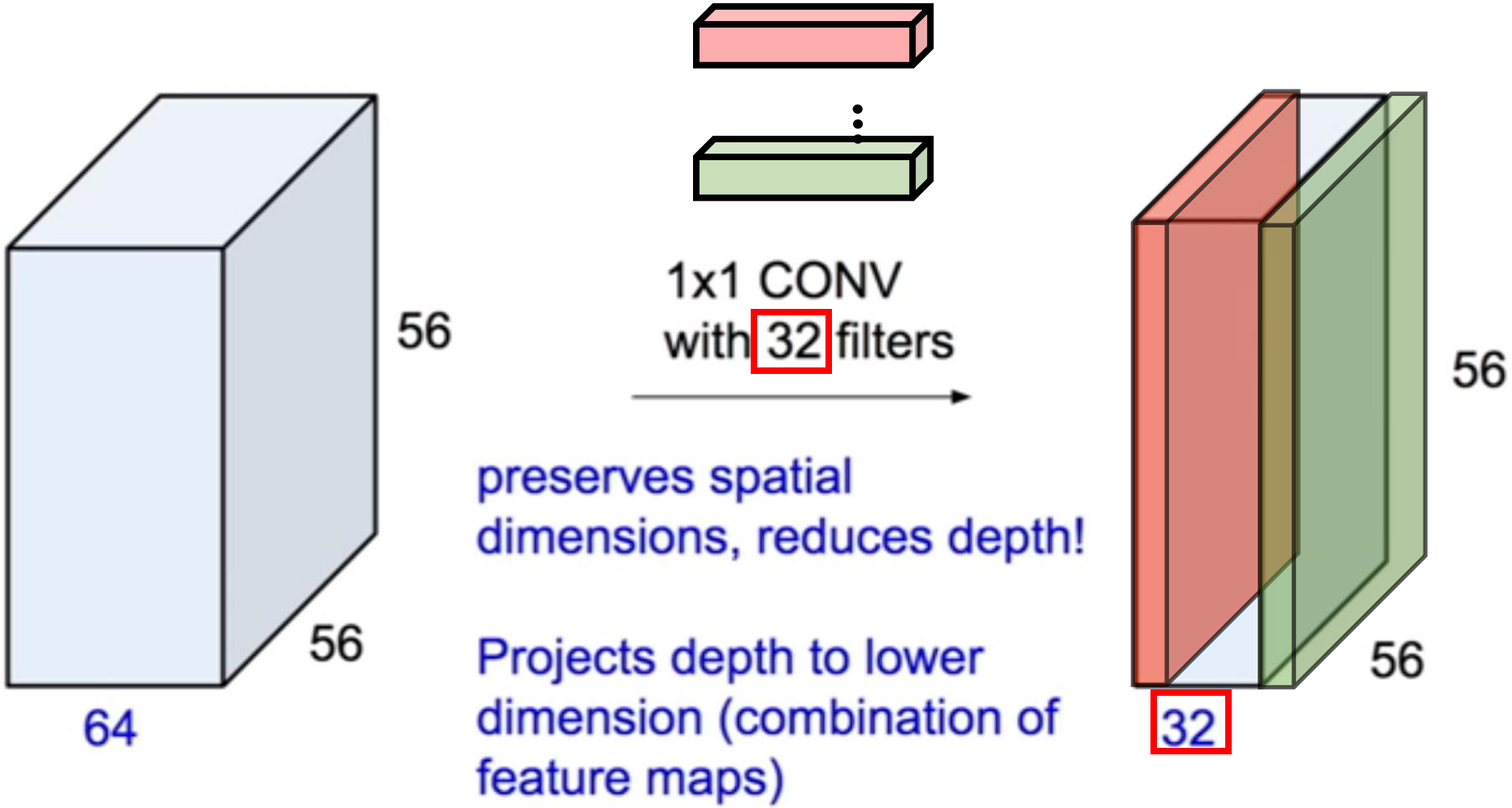




1x1 convolution layers as bottleneck



1x1 convolution layers as bottleneck

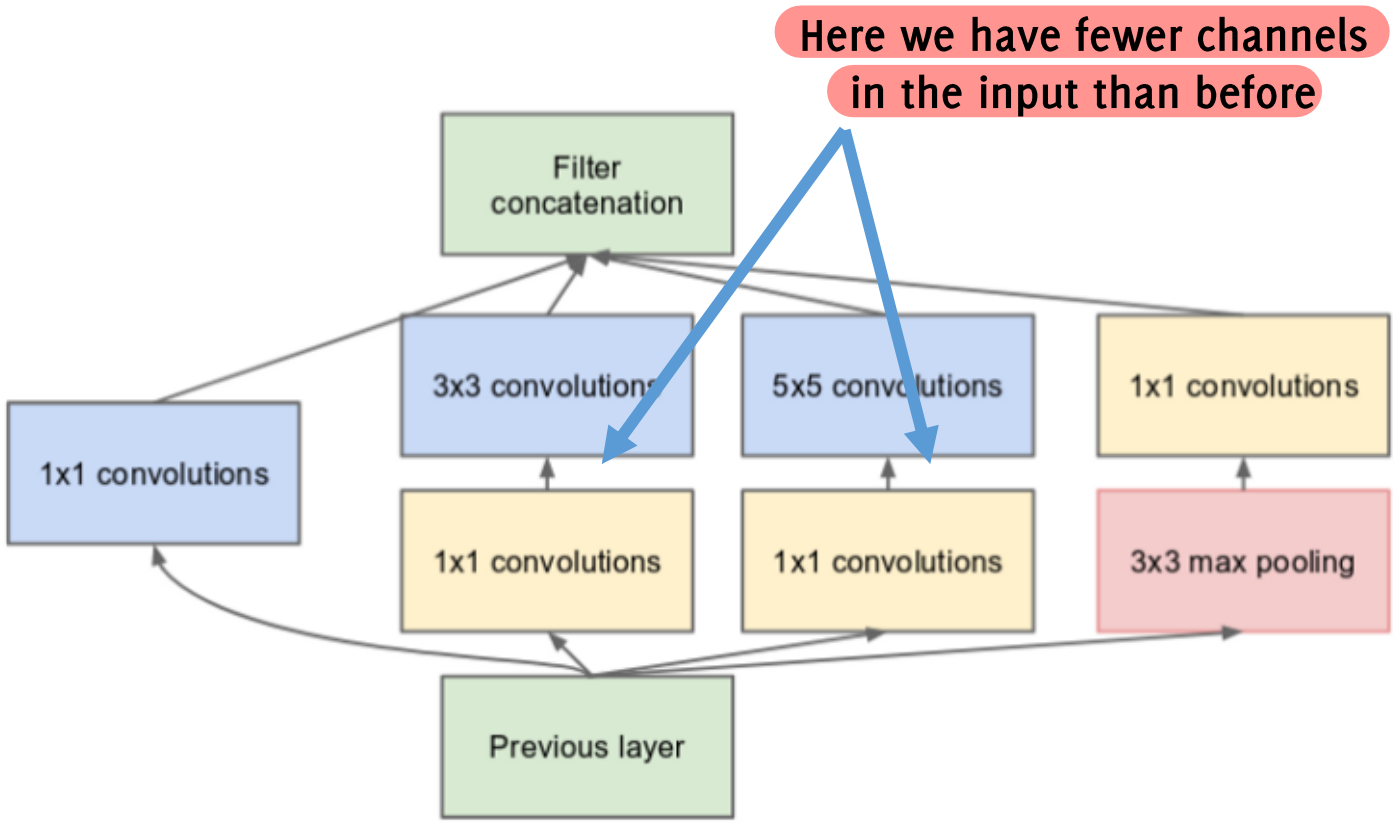


Inception Module (2014)

To reduce the computational load of the network, the number of **input channels** is reduced by adding an **1x1 convolution** layers before the 3x3 and 5x5 convolutions

The output volume has similar size, but the number of operation required is significantly reduced due to the 1x1 conv:
358M operations now

Adding 1x1 convolution layers increases the number of nonlinearities



(b) Inception module with dimension reductions

Szegedy et al. "Going deeper with convolutions." *CVPR 2015*

Inception Module (2014)

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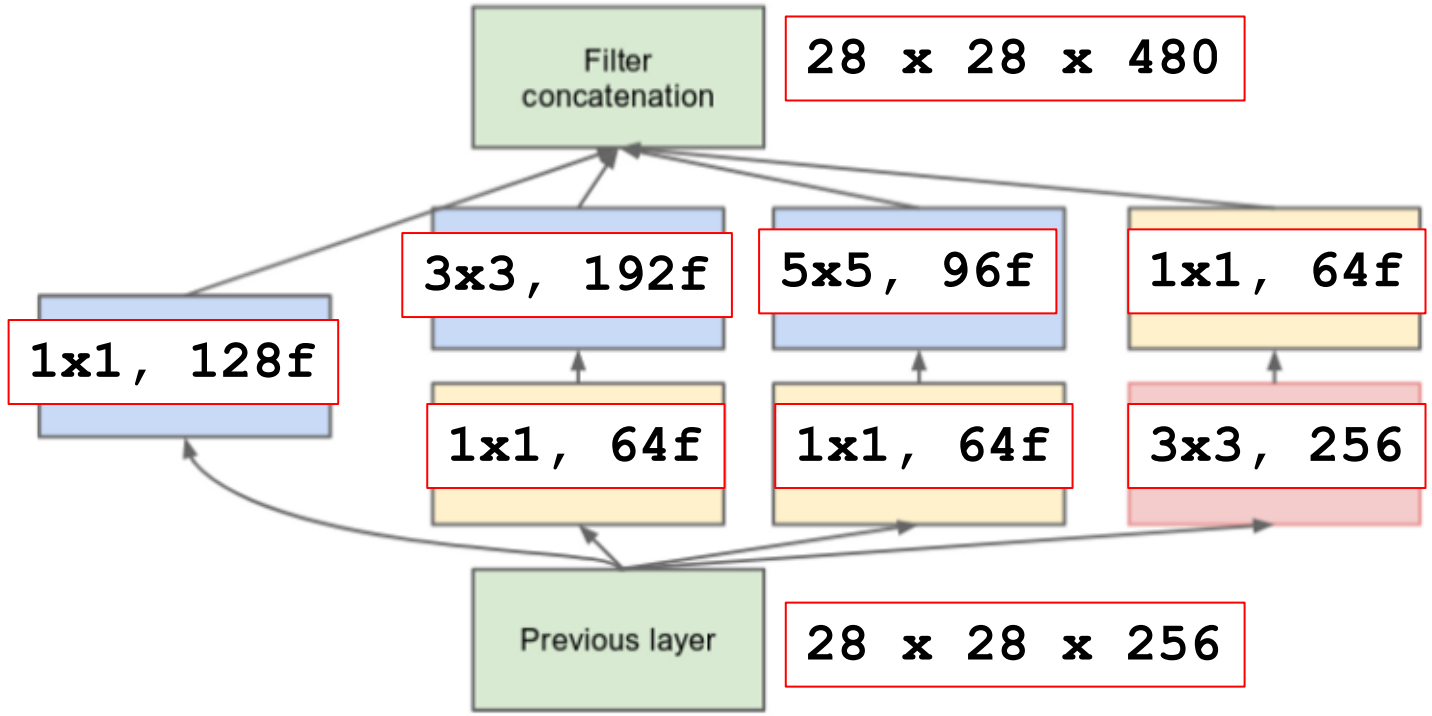
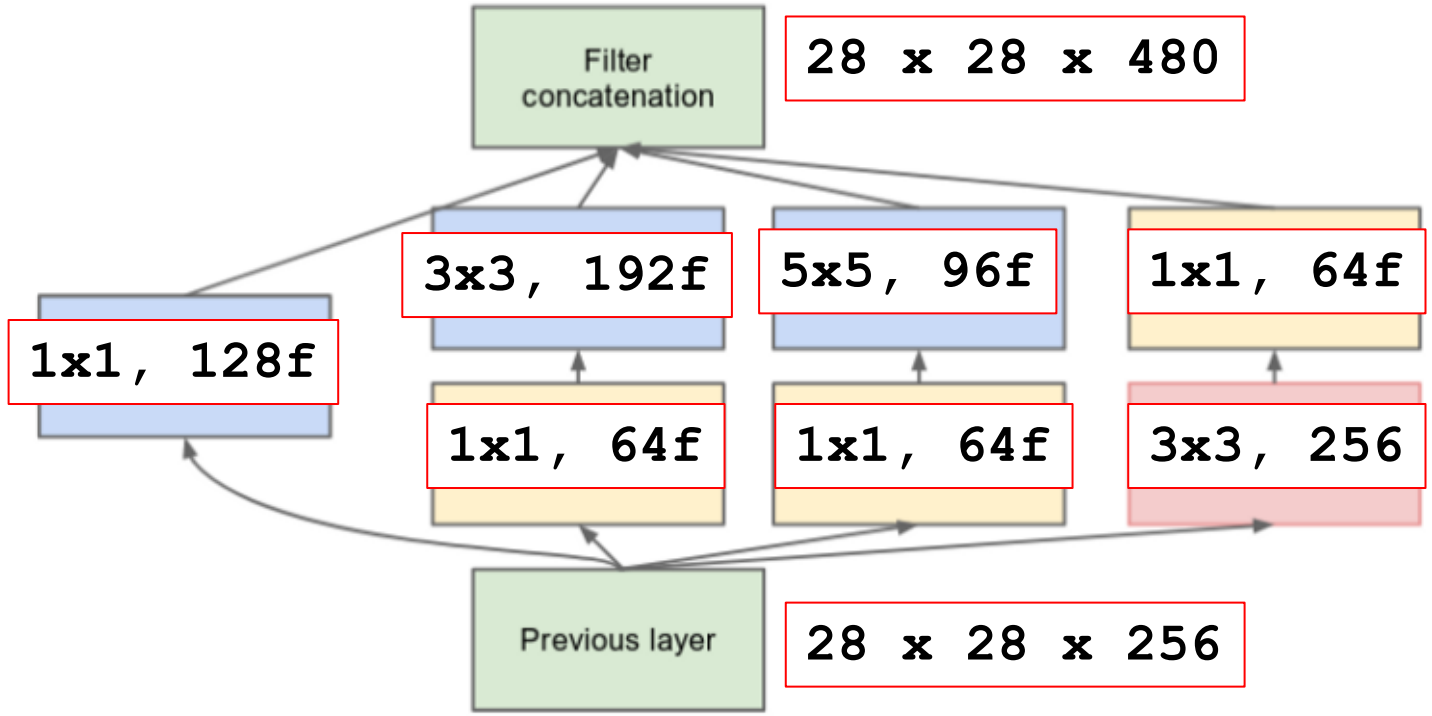


(b) Inception module with dimension reductions

Szegedy et al. "Going deeper with convolutions." *CVPR 2015*

Inception Module (2014)

Network are no longer sequential.
There are parallel processing



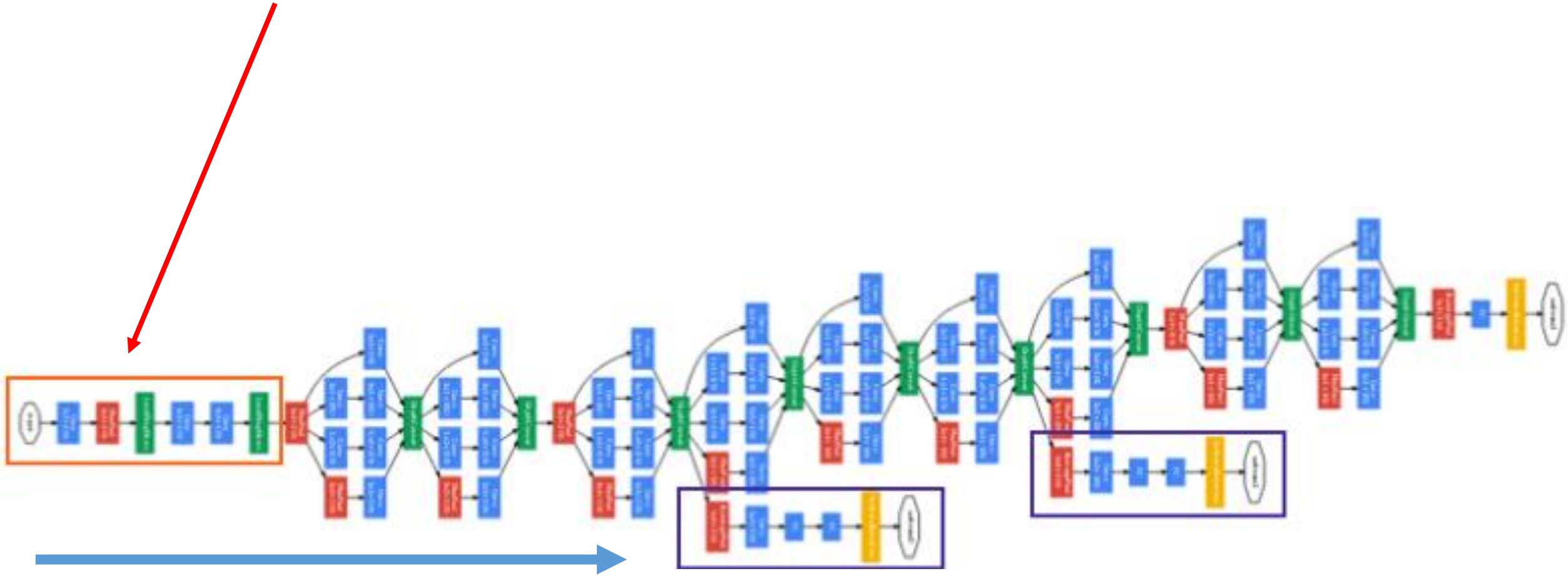
(b) Inception module with dimension reductions

Szegedy et al. "Going deeper with convolutions." *CVPR 2015*

GoogLeNet (2014)

GoogleNet stacks 27 layers considering pooling ones.

At the beginning there are two blocks of conv + pool layers

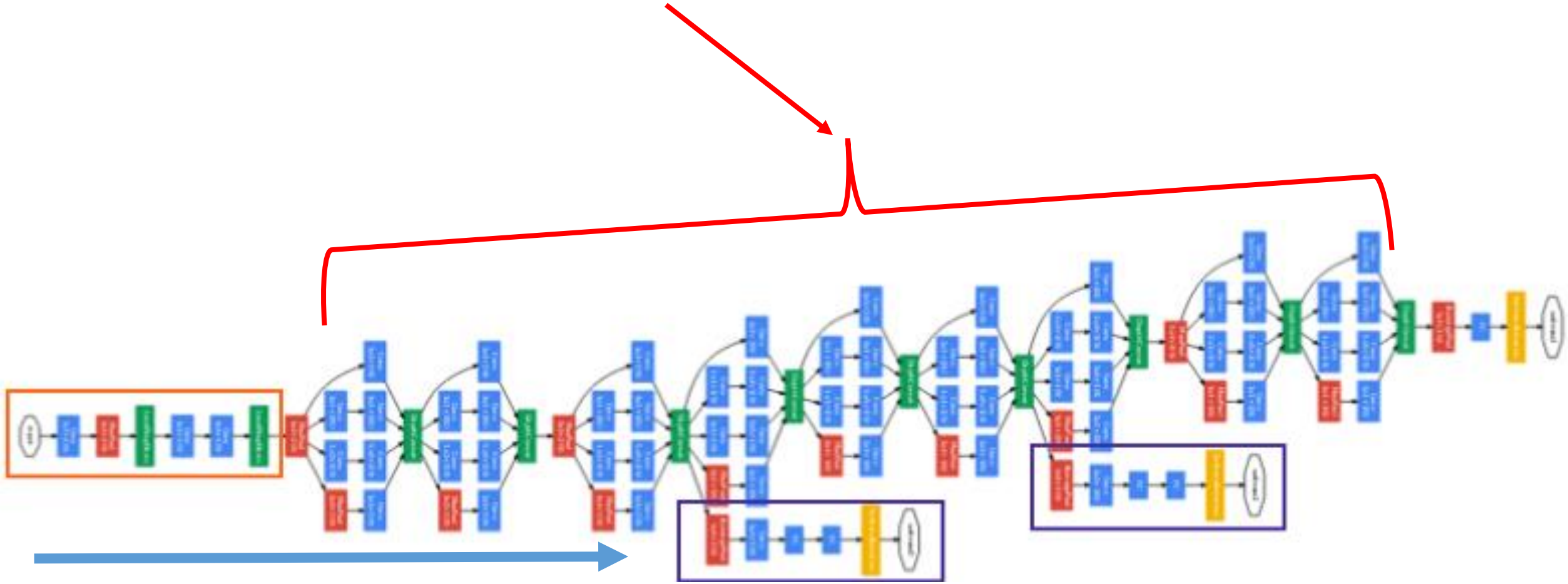


Szegedy et al. "Going deeper with convolutions." *CVPR 2015*

GoogLeNet (2014)

GoogleNet stacks 27 layers considering pooling ones.

Then, there are a stack of 9 of inception modules



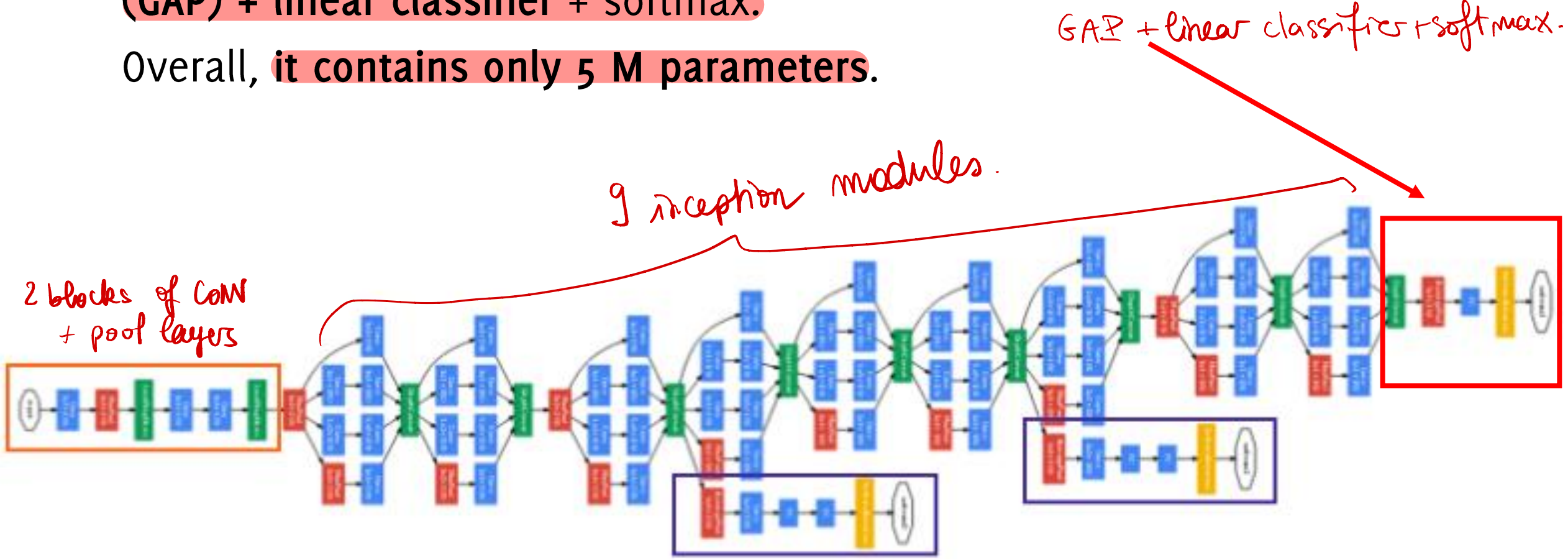
Szegedy et al. "Going deeper with convolutions." *CVPR 2015*

GoogLeNet (2014)

GoogleNet stacks 27 layers considering pooling ones.

No Fully connected layer at the end, **simple global averaging pooling (GAP) + linear classifier** + softmax.

Overall, **it contains only 5 M parameters**.

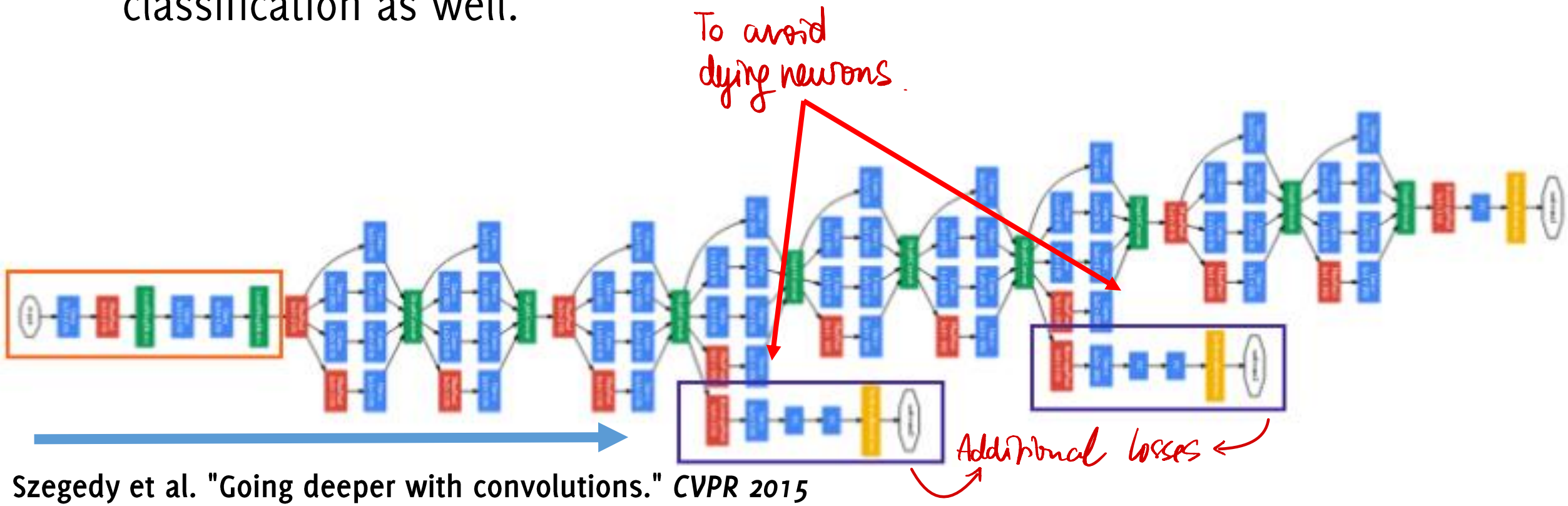


Szegedy et al. "Going deeper with convolutions." *CVPR 2015*

GoogLeNet (2014)

It also suffers of the **dying neuron problem**, therefore the authors **add two extra auxiliary classifiers** on the intermediate representation **to compute an intermediate loss that is used during training.**

You expect intermediate layers to provide meaningful features for classification as well.



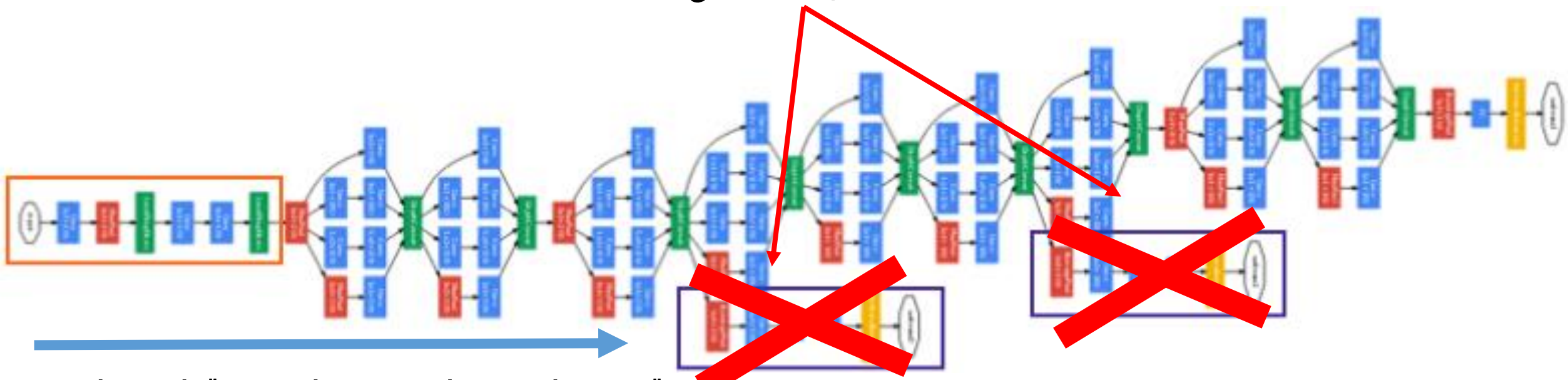
Szegedy et al. "Going deeper with convolutions." *CVPR 2015*

GoogLeNet (2014)

It also suffers of the **dying neuron problem**, therefore the authors **add two extra auxiliary classifiers** on the intermediate representation **to compute an intermediate loss that is used during training.**

You expect intermediate layers to provide meaningful features for classification as well.

Classification heads are then ignored / removed at inference time



Szegedy et al. "Going deeper with convolutions." *CVPR 2015*

3 Take home messages

1. Blocks made of multiple connections instead of having a single tread.
2. 1x1 convolutions: a (general) practical tool to introduce bottlenecks to reduce the number of operations and parameters of the network.
3. Additional losses: you might want to train your network on additional tasks just for improving training convergence.

(in parallel)

To prevent dying neuron problem.

Inception Block in Keras:

```
# input x

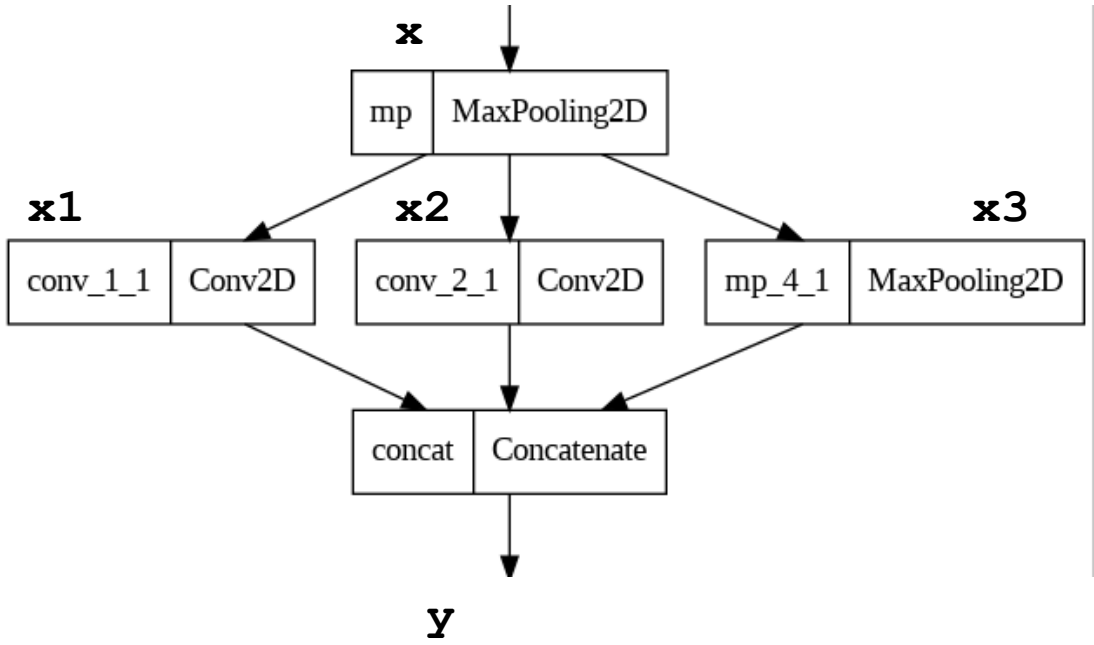
x = tfkl.MaxPooling2D(name='mp')(x)

x1 = tfkl.Conv2D(32,
   kernel_size=1,
   padding='same',
   activation='relu',
   name='conv_1_1')(x)

x2 = tfkl.Conv2D(64,
   kernel_size=1,
   padding='same',
   activation='relu',
   name='conv_2_1')(x)

x4 = tfkl.MaxPooling2D((3,3),
   strides=(1,1),
   padding='same',
   name='mp_4_1',)(x)

y = tfkl.Concatenate(
   axis=-1,
   name='concat')([x1, x2, x4])
```



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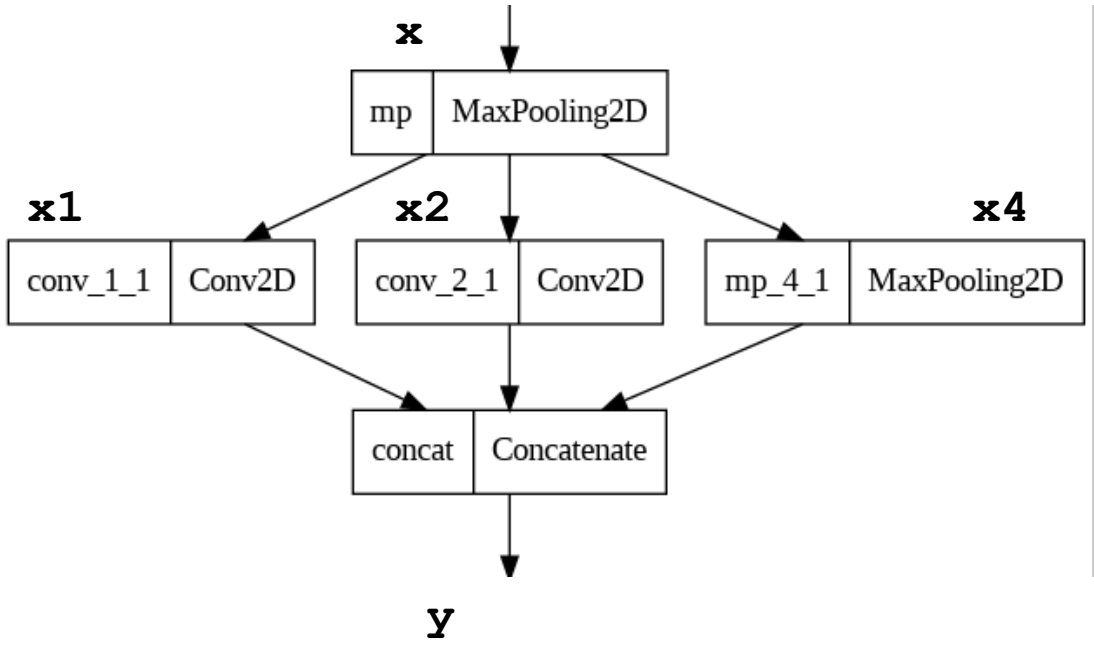
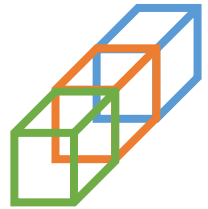


Concatenate layer to stack multiple activations along the last axis (**`axis=-1`**)



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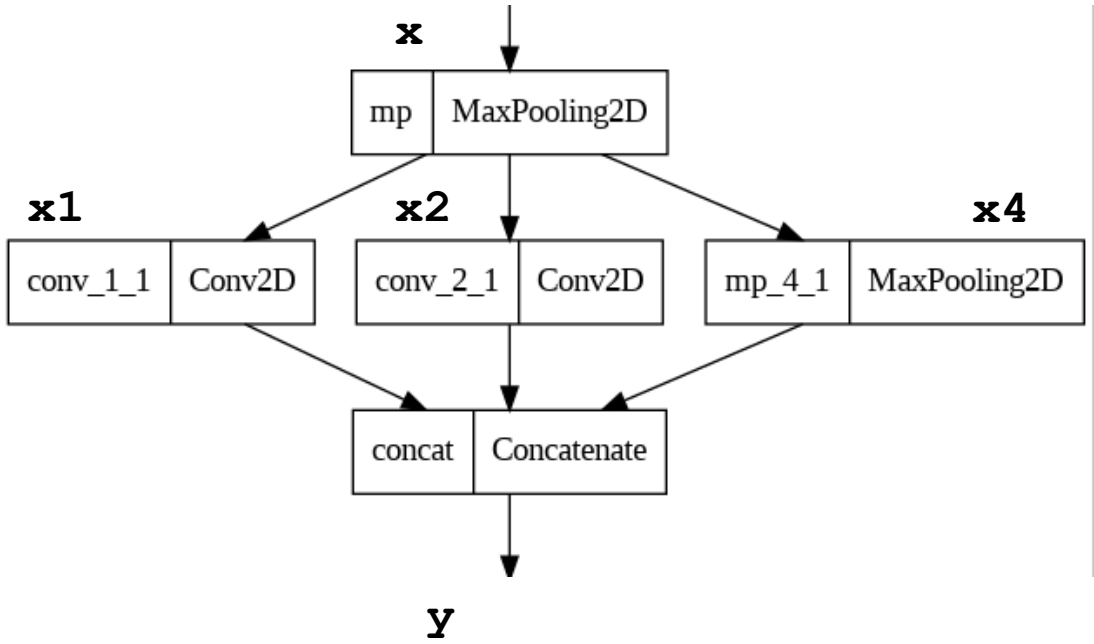
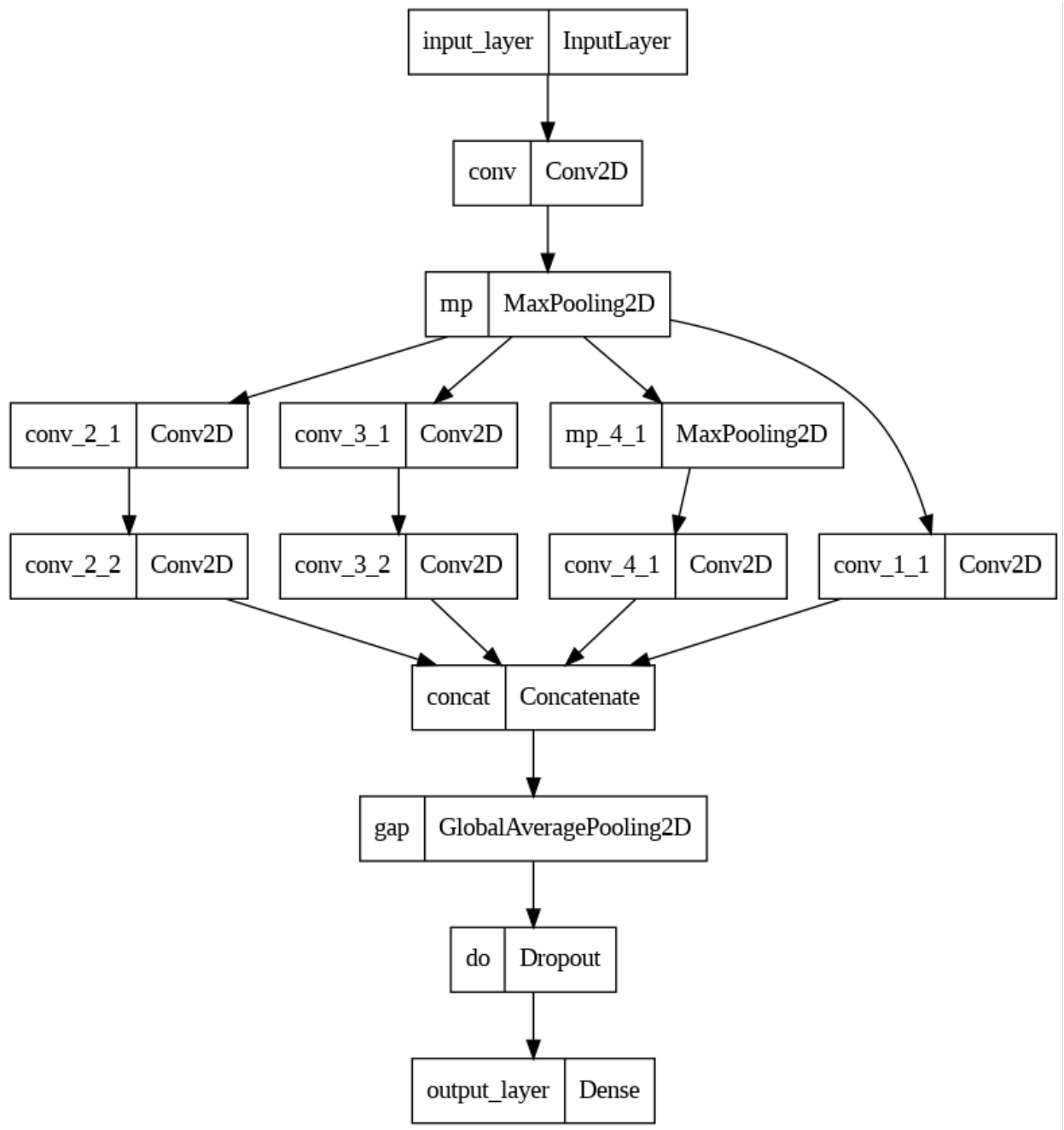
```



Spatial dimension should be preserved both by padding and stride in maxpooling

… and more



G. Boracchi

model.summary()

```
Model: "model"
__________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to
==================================================================================================
 input_layer (InputLayer)       [(None, 32, 32, 3)]  0           []

 conv (Conv2D)                  (None, 32, 32, 32)   896         ['input_layer[0][0]']

 mp (MaxPooling2D)              (None, 16, 16, 32)   0           ['conv[0][0]']

 conv_2_1 (Conv2D)              (None, 16, 16, 64)   2112        ['mp[0][0]']

 conv_3_1 (Conv2D)              (None, 16, 16, 64)   2112        ['mp[0][0]']

 mp_4_1 (MaxPooling2D)          (None, 16, 16, 32)   0           ['mp[0][0]']

 conv_1_1 (Conv2D)              (None, 16, 16, 32)   1056        ['mp[0][0]']

 conv_2_2 (Conv2D)              (None, 16, 16, 32)   18464       ['conv_2_1[0][0]']

 conv_3_2 (Conv2D)              (None, 16, 16, 32)   51232       ['conv_3_1[0][0]']

 conv_4_1 (Conv2D)              (None, 16, 16, 32)   1056        ['mp_4_1[0][0]']

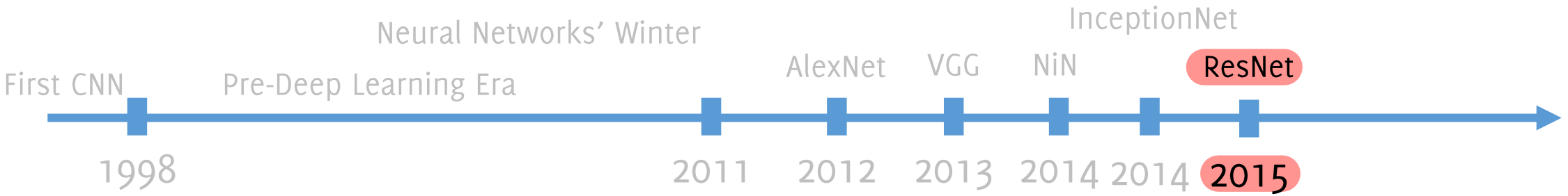
 concat (Concatenate)           (None, 16, 16, 128)  0           ['conv_1_1[0][0]',
                                                                  'conv_2_2[0][0]',
                                                                  'conv_3_2[0][0]',
                                                                  'conv_4_1[0][0]']

 gap (GlobalAveragePooling2D)   (None, 128)          0           ['concat[0][0]']

 do (Dropout)                   (None, 128)          0           ['gap[0][0]']

 output_layer (Dense)           (None, 10)           1290        ['do[0][0]']
```

ResNet: Residual Learning



Deep Residual Learning for Image Recognition

Kaiming He Xiangyu Zhang Shaoqing Ren Jian Sun

Microsoft Research

{kahe, v-xiangz, v-shren, jiansun}@microsoft.com

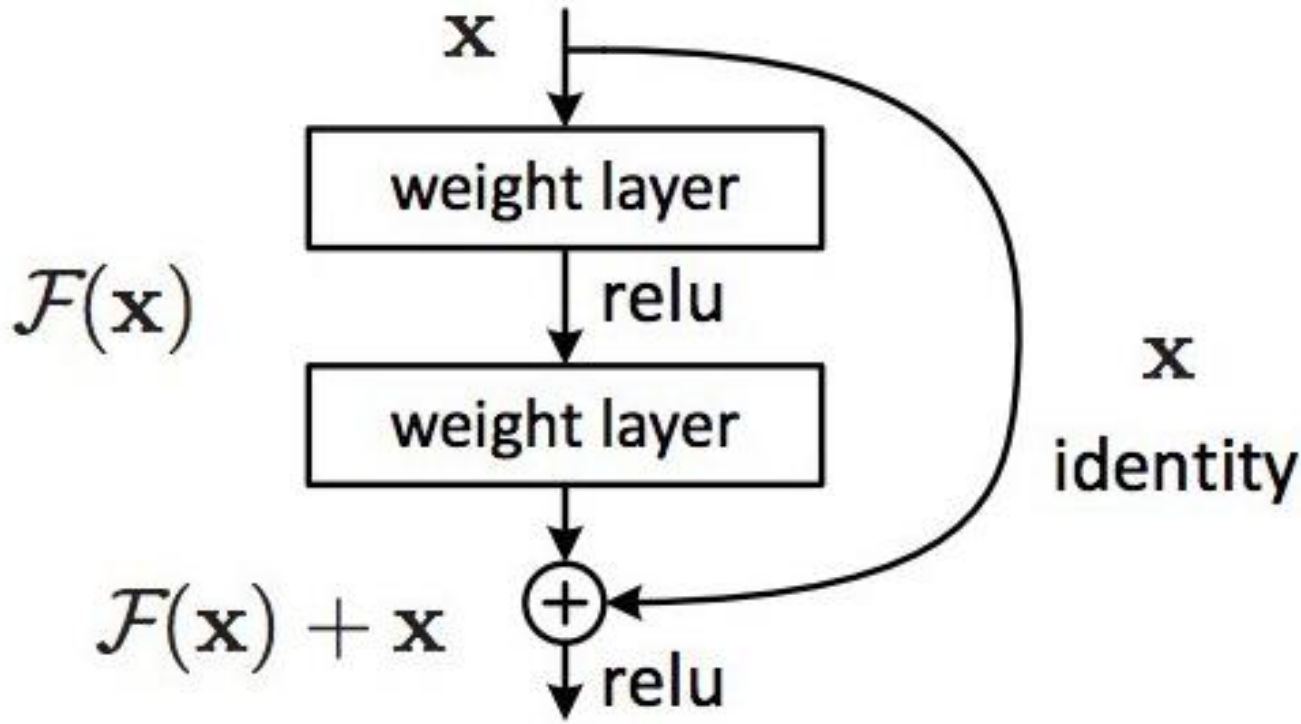
ResNet (2015)

Very Deep network: **152 layers** for a deep network trained on Imagenet!

1202 layers on CIFAR!

2015 ILSVR winner both localization and classification (3.57% top 5 classification error). **Better than *human performance***

The main investigation was:
is it possible to continuosly improve accuracy by stacking more and more layers



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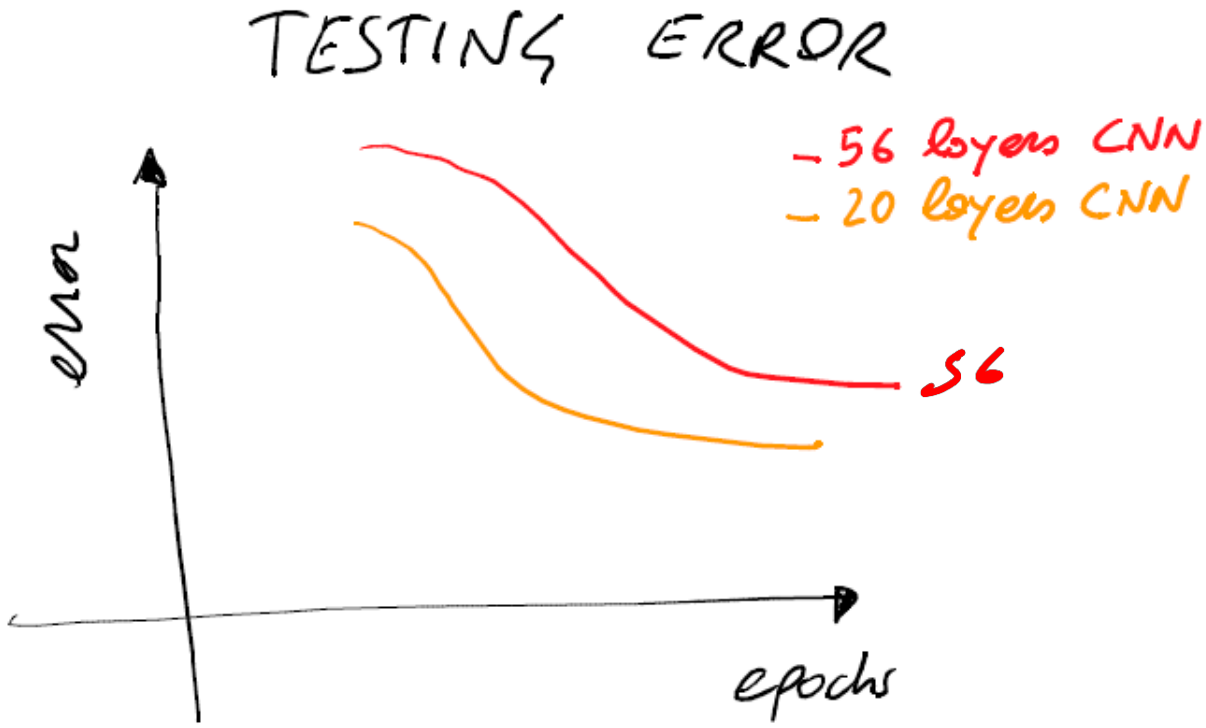
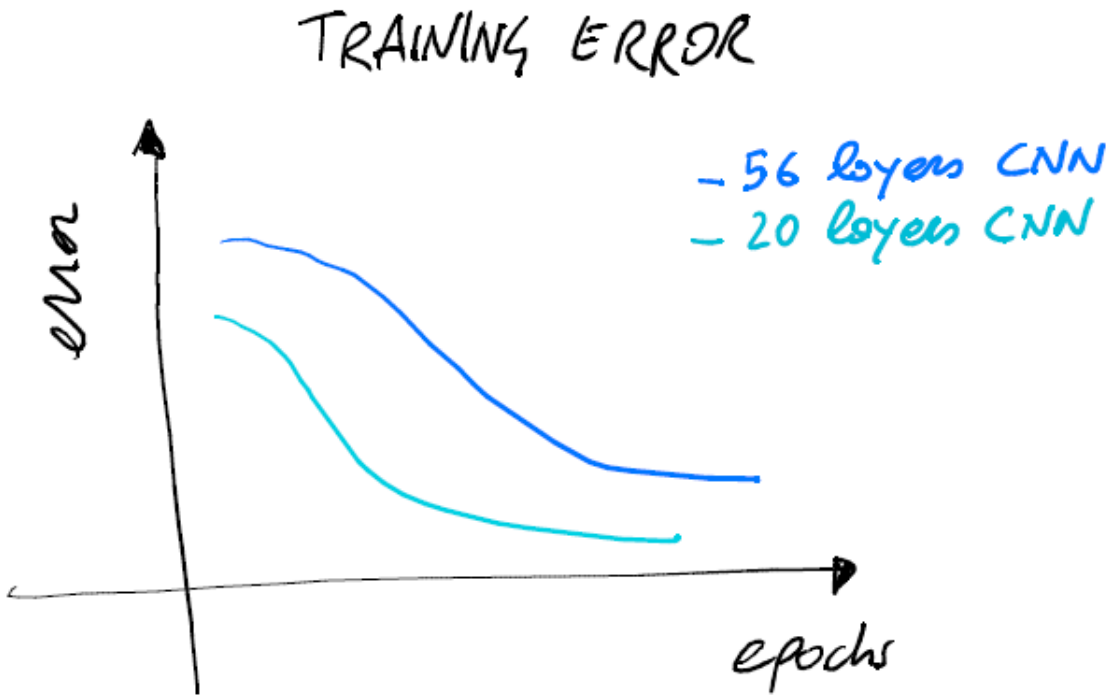
ResNet (2015): The rationale

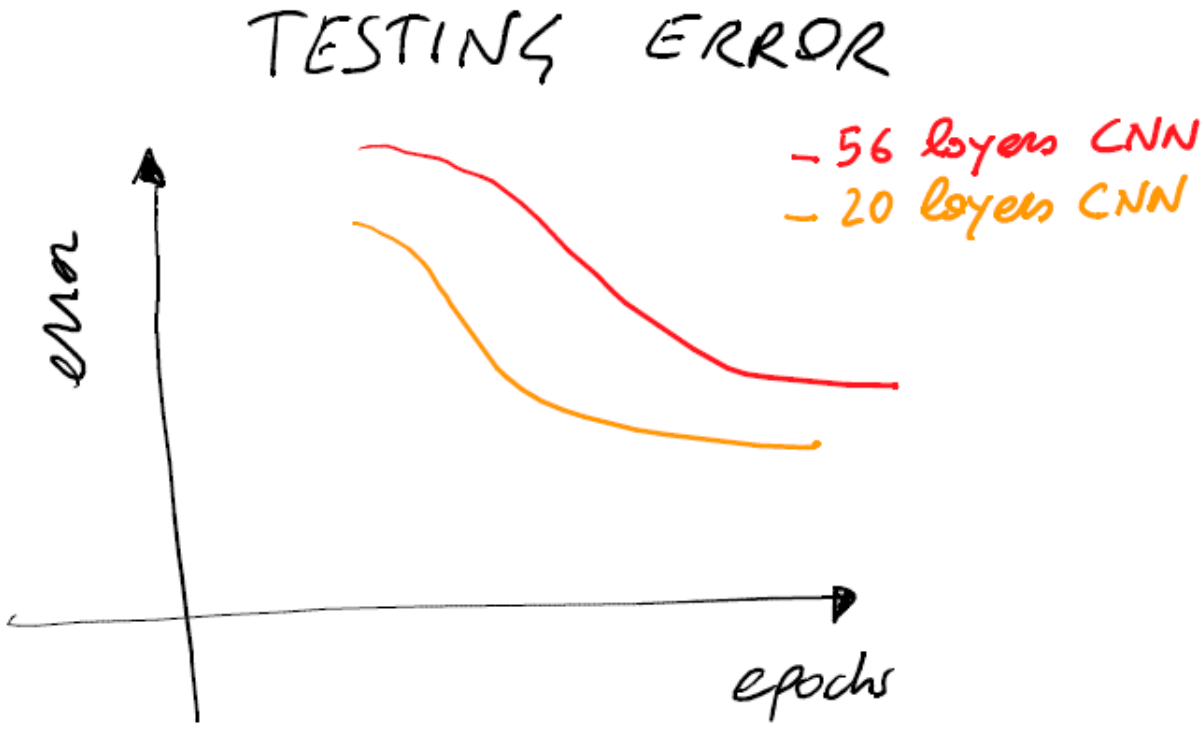
Empirical observation: **Increasing the network depth**, by stacking an increasingly number of layers, **does not always improve performance**



ResNet (2015): The rationale

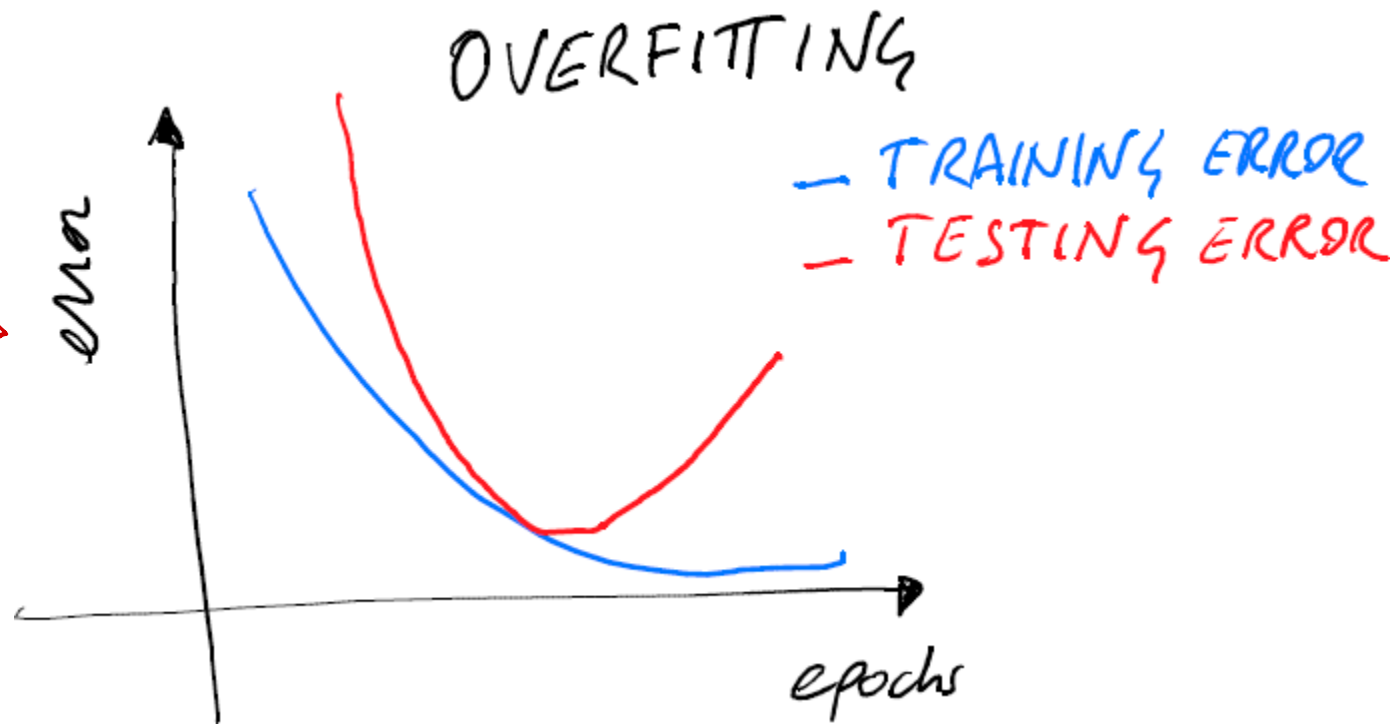
But **this is not due to overfitting,** since the same trend is shown in the training error





ResNet (2015): The rationale

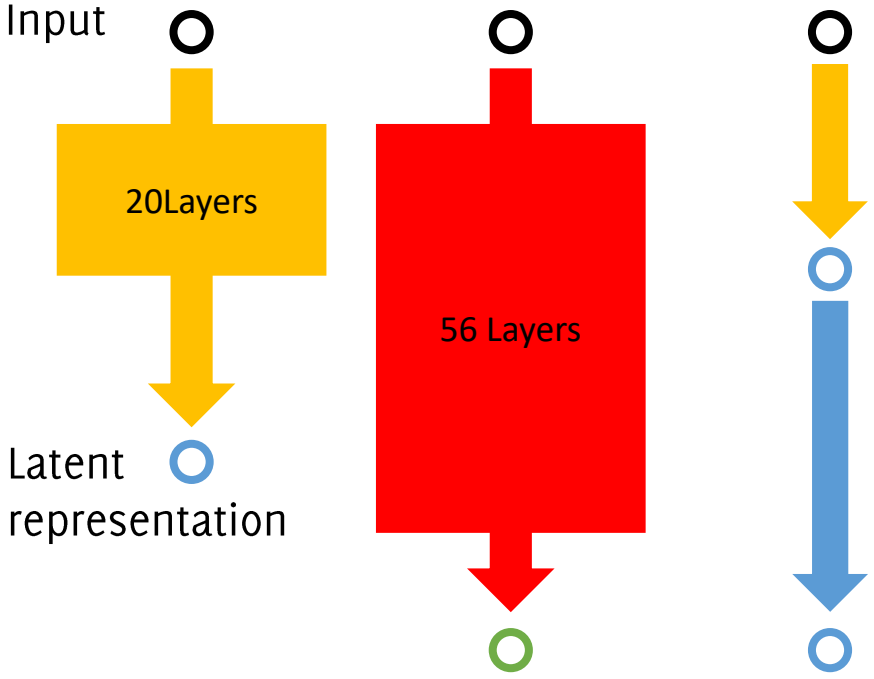
But **this is not due to overfitting**, since the same trend is shown in the training error, while for overfitting we have that training and test error diverge.

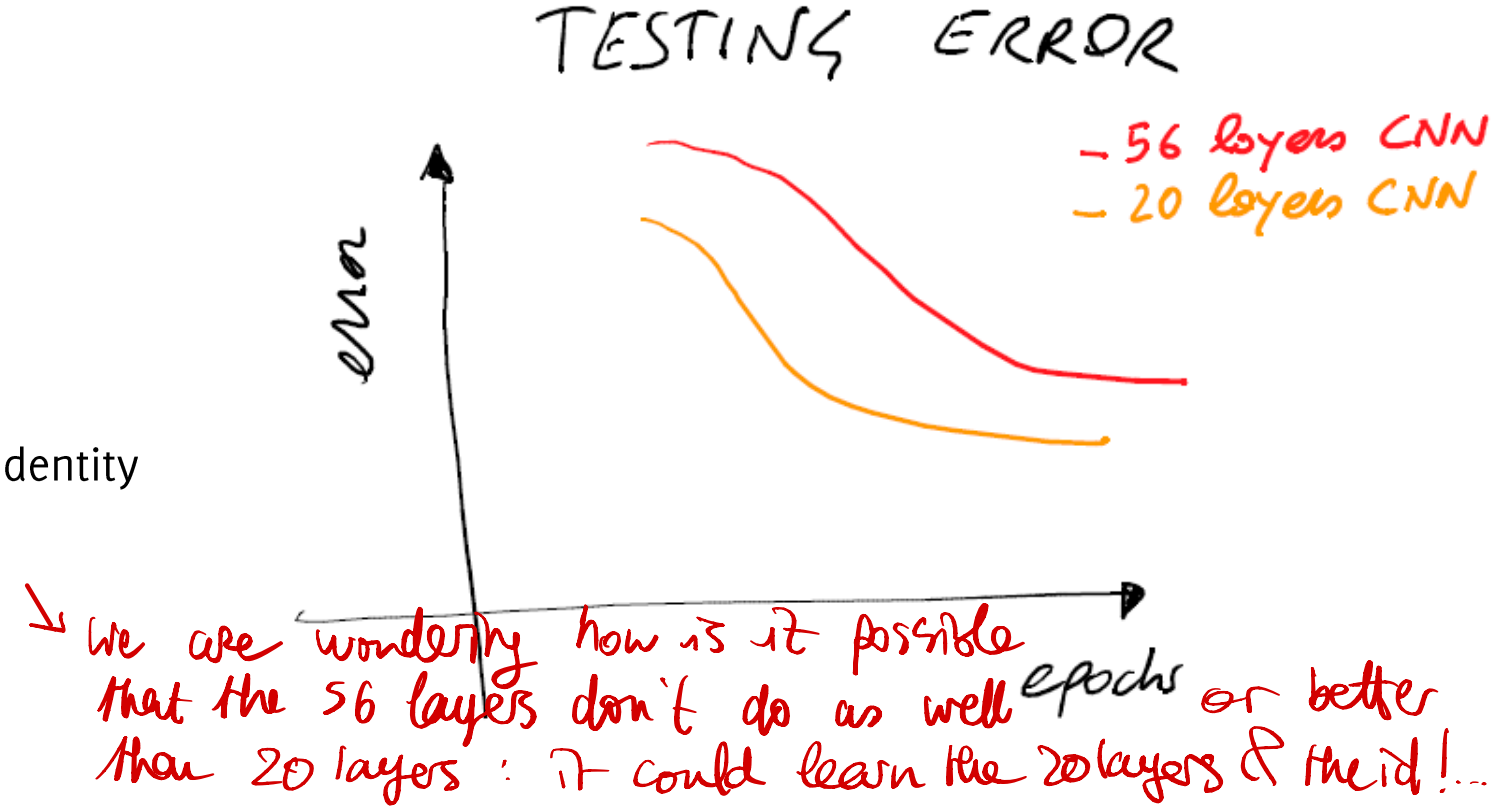


ResNet (2015): the intuition

Deeper model are harder to optimize than shallower models.

However, we might in principle **copy the parameters of the shallow** network **in the deeper one** and then **in the remaining part**, set the weights to **yield an identity mapping.**





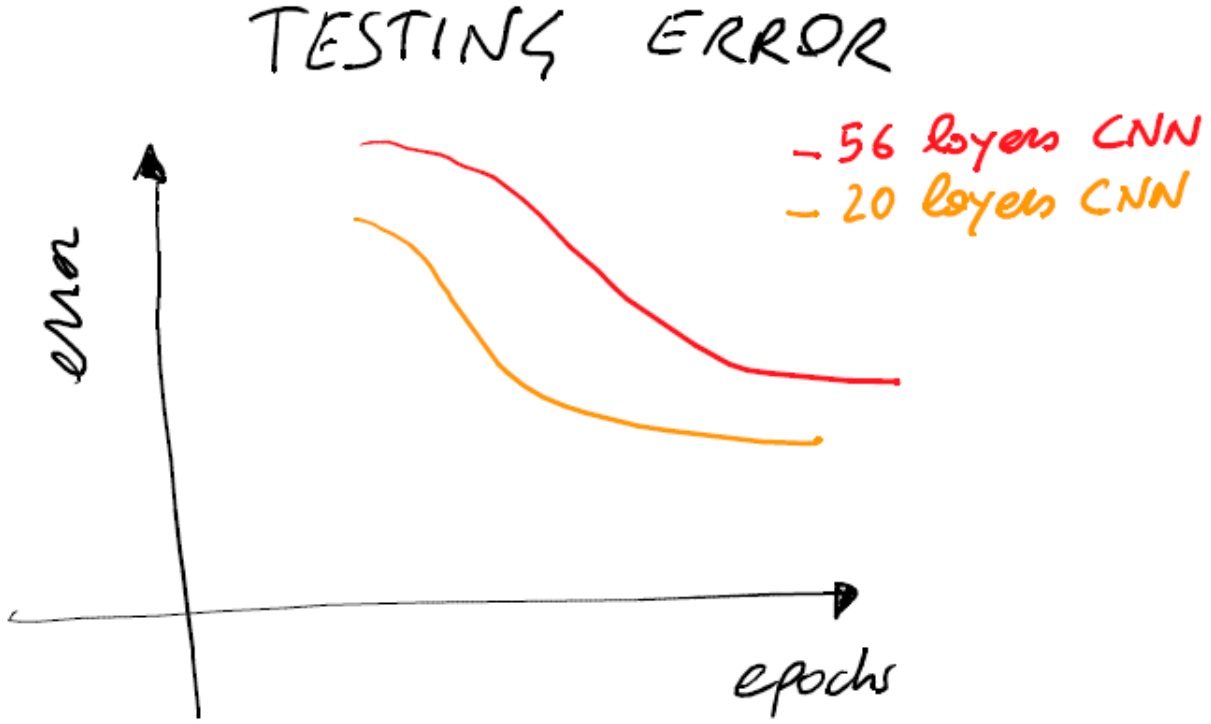
ResNet (2015): the intuition

Deeper model are harder to optimize than shallower models.

However, we might in principle **copy the parameters of the shallow** network **in the deeper one** and then in the remaining part, set the weights to **yield an identity mapping**.

Therefore, deeper networks should be in principle as good as the shallow ones

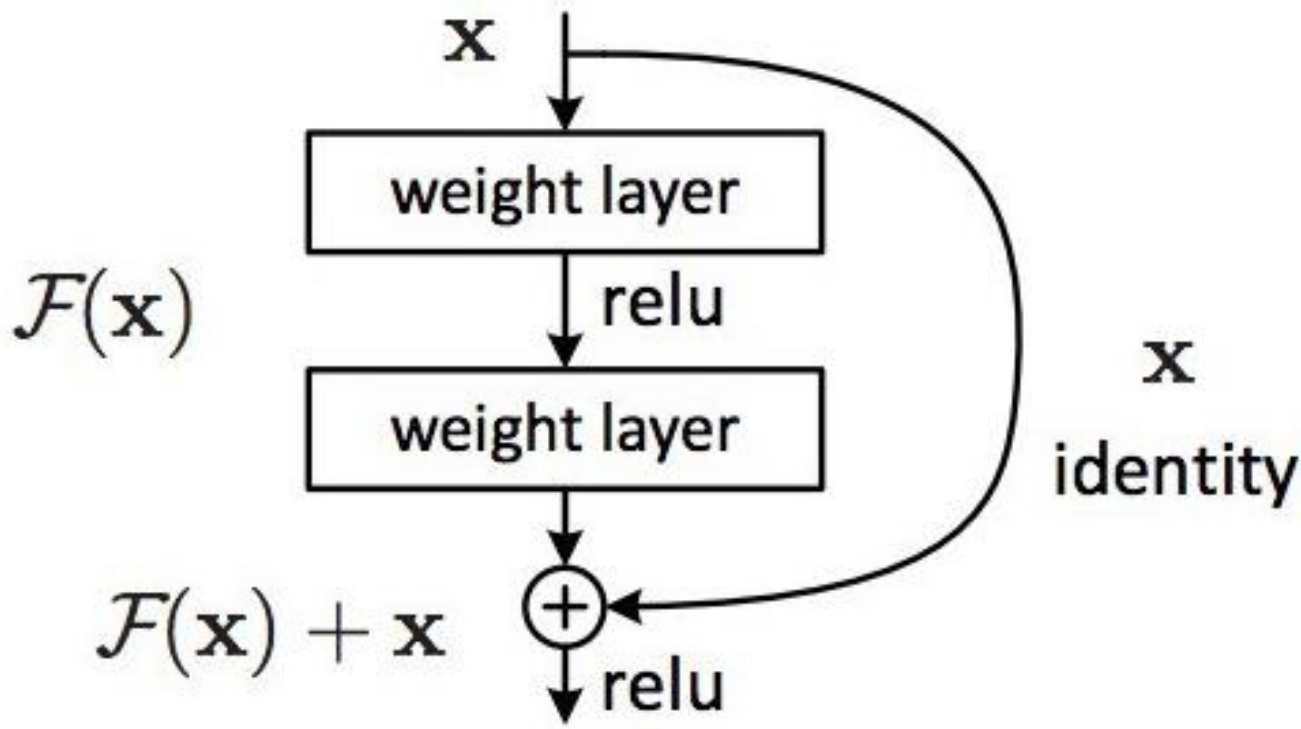
Given this experimental evidence:
the identity function is not easy to learn!



ResNet: Very deep by residual connections

Adding an "identity shortcut connection" :

- Helps in **mitigating the vanishing gradient problem** and enables deeper architectures.
- Does not add any parameter or significant computational overhead.
- In case the **network layers till the connection were optimal**, the **weights to be learned goes to zero** and information is propagated by the identity
- The network can still be trained through back-propagation



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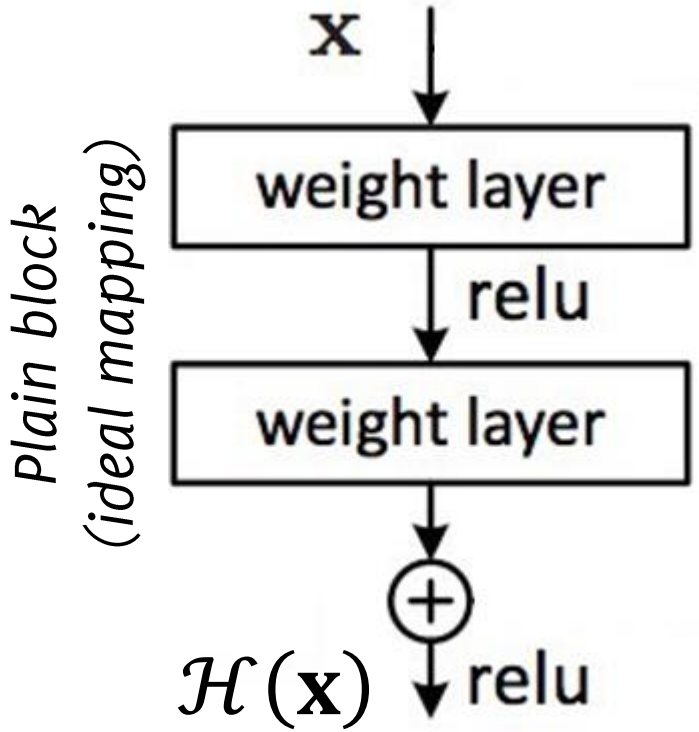
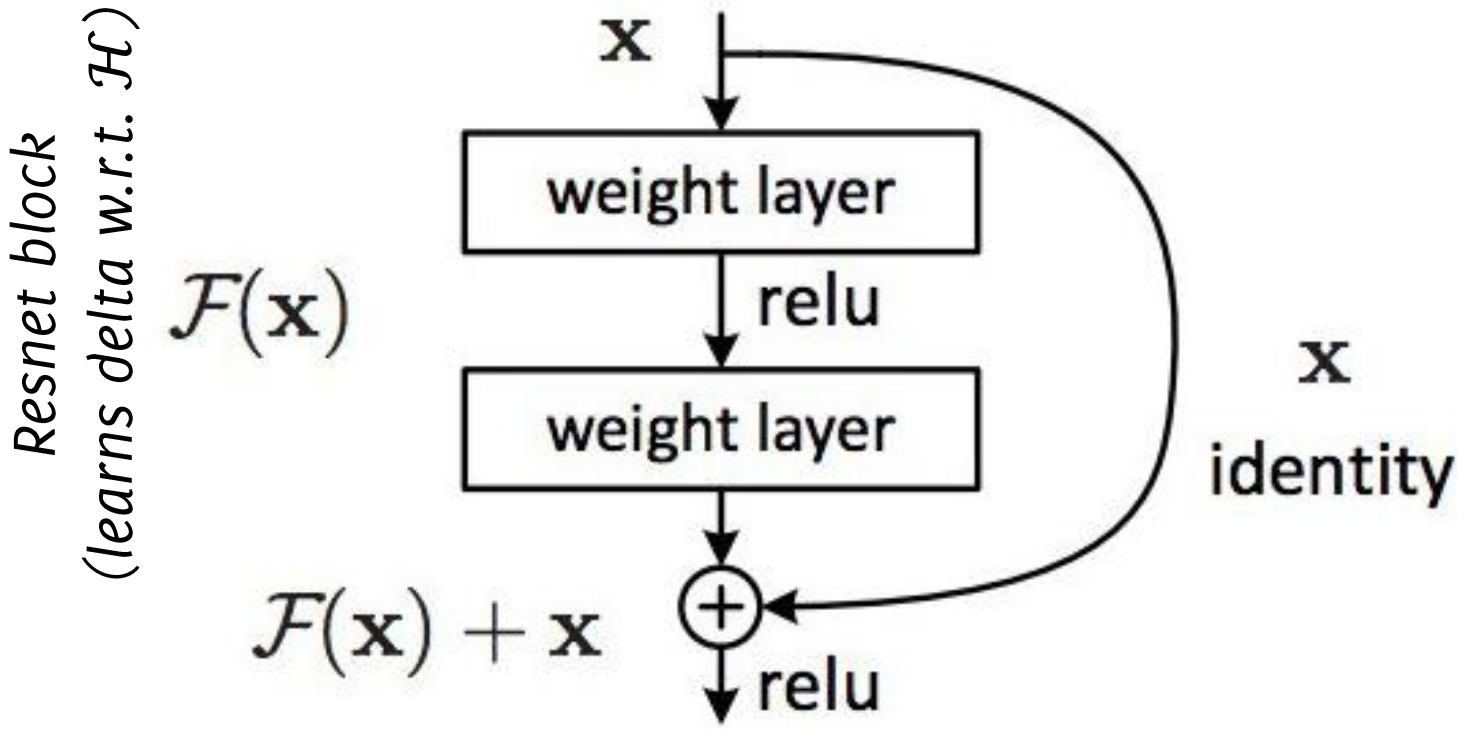
ResNet: Very deep by residual connections

Intuition: force the network to learn a different task in each block. If $\mathcal{H}(\mathbf{x})$ is the **ideal mapping** to be learned from a plain network, by skip connections **we force the network to learn** $\mathcal{F}(\mathbf{x}) = \mathcal{H}(\mathbf{x}) - \mathbf{x}$, here the term *residual*.





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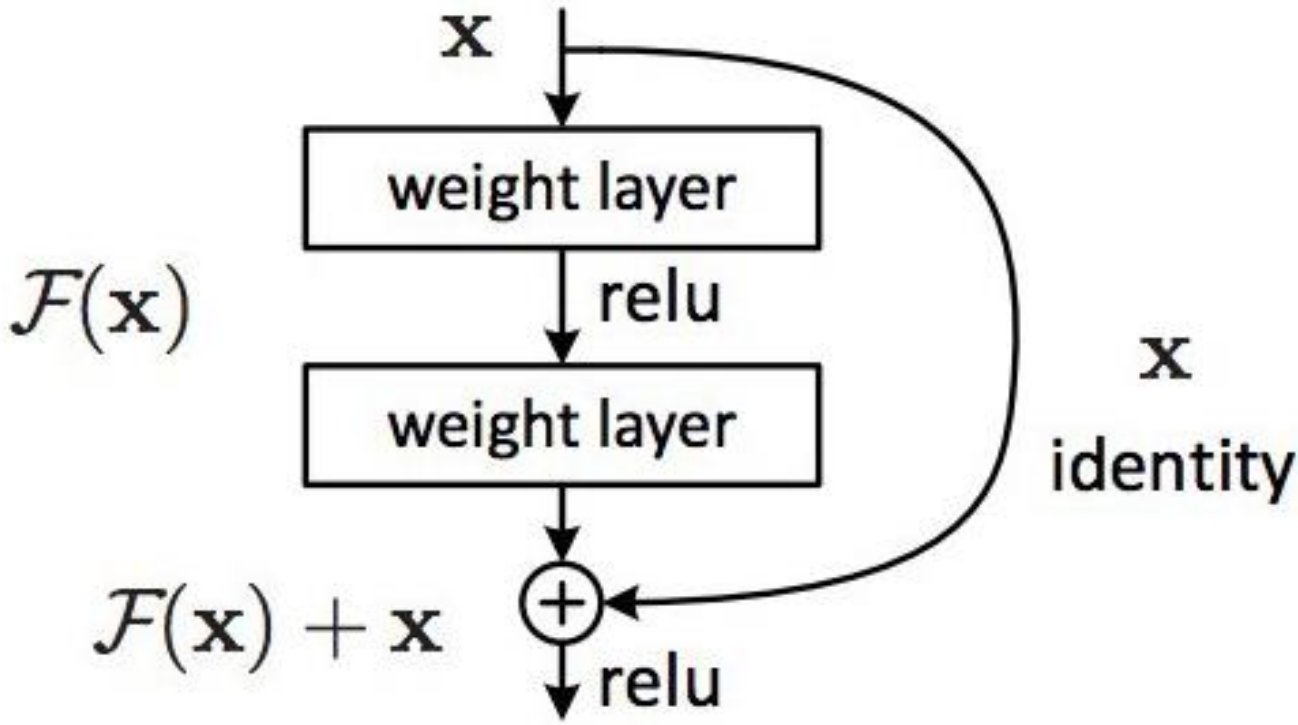
ResNet: Very deep by residual connections

- $\mathcal{F}(\mathbf{x})$ is called the **residual** (something to add on top of identity), which turns to be easier to train in deep networks.
- **Weights in between the skip connection can be used to learn a «delta», a residual i.e., $\mathcal{F}(\mathbf{x})$ to improve over the solution that can be achieved by a shallow network.**
- Since $\mathbf{x}$ and $\mathcal{F}(\mathbf{x})$ must have the same size, the convolutional layers in between are to **preserve dimension space-wise and depth-wise.**
- **1x1 convolutions** can be used to re-arrange the number of channels



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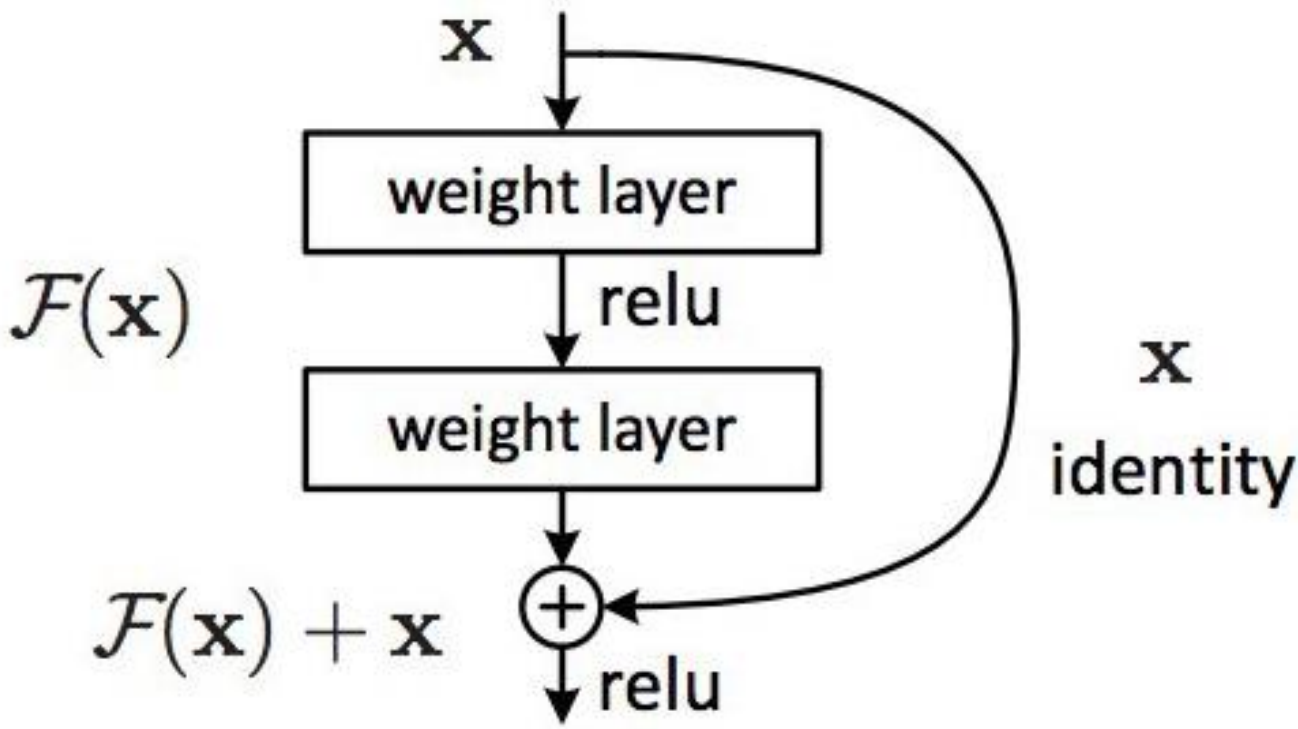
ResNet (2015)

The rationale behind adding this identity mapping is that:

- It is **easier** for the following layers **to learn features on top of the input value**
- In practice the layers between an identity mapping would otherwise fail at learning the identity function to transfer the input to the output
- The performance achieved by resNet suggests that **probably most of the deep layers have to be close to the identity!**



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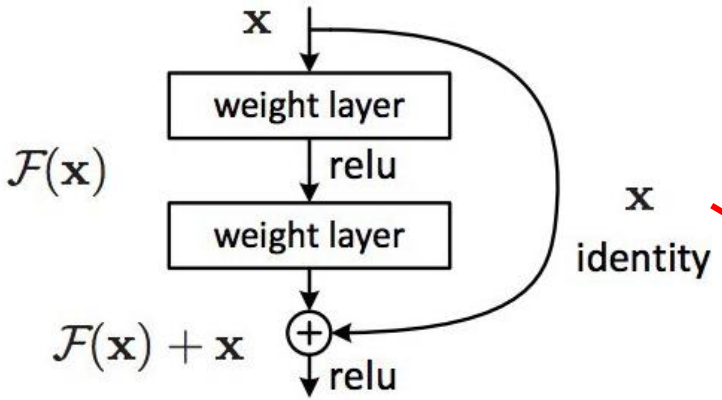
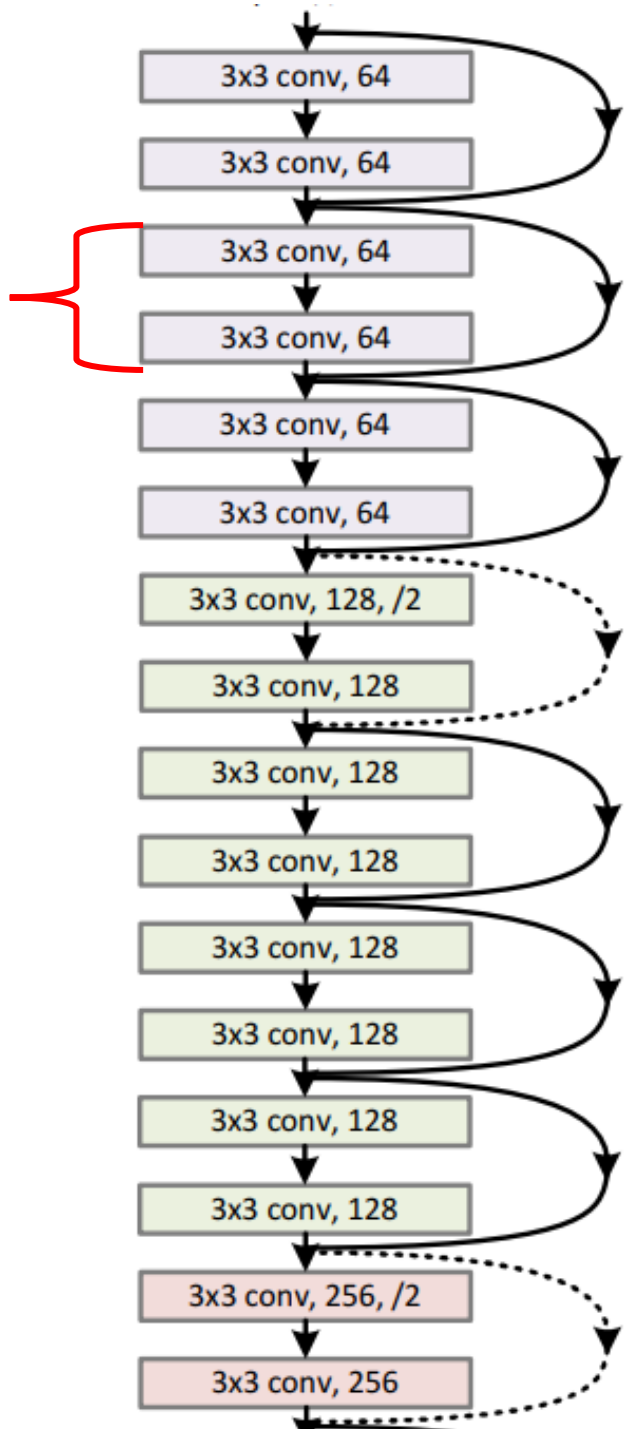
ResNet (2015)

The ResNet is a stack of
152 layers of this module





The network alternates

- some spatial **pooling by convolution with stride 2**
- **doubling the number of filters**

At the beginning there is a **convolutional layer**

At the end: no FC but just a **GAP to be fed in the final softmax**

Deeper networks are able to achieve lower errors as expected

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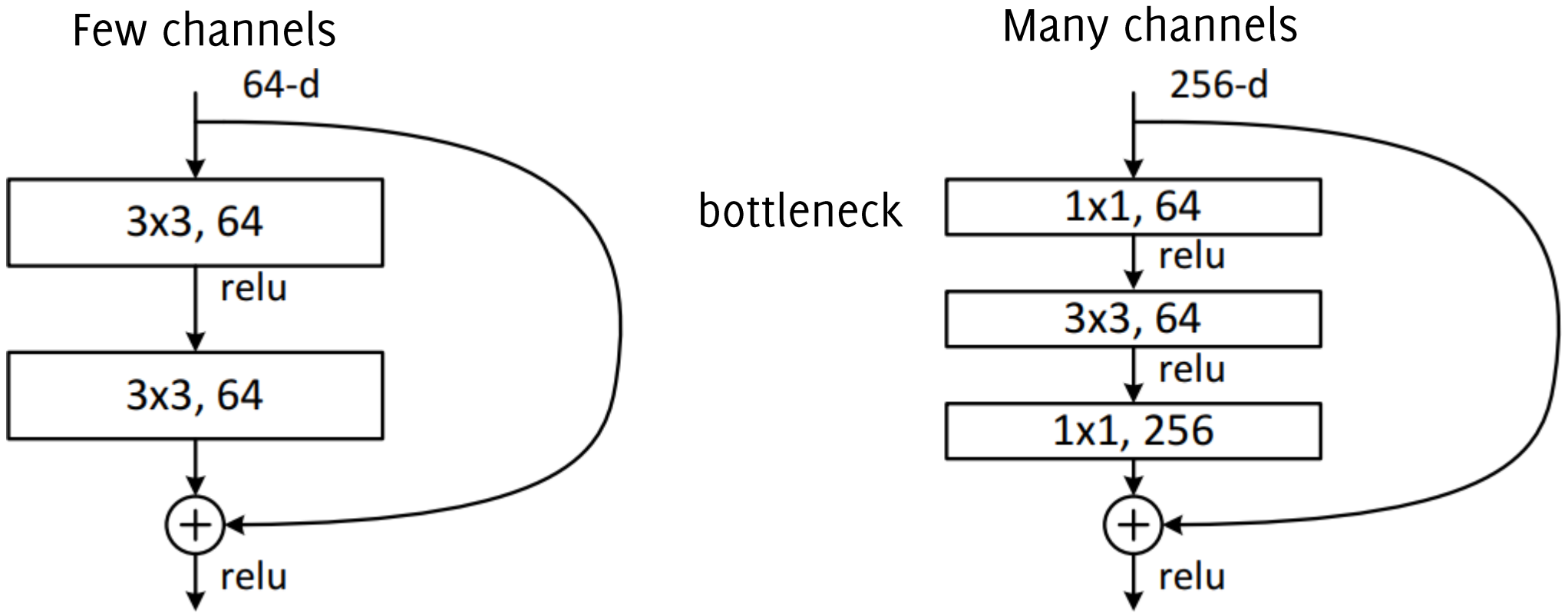
ResNet (2015)

Very deep architecture (say more than 50 layers) **adopt a bottleneck layer to reduce the depth within each block, thus the computational complexity** of the network (as in the inception module)



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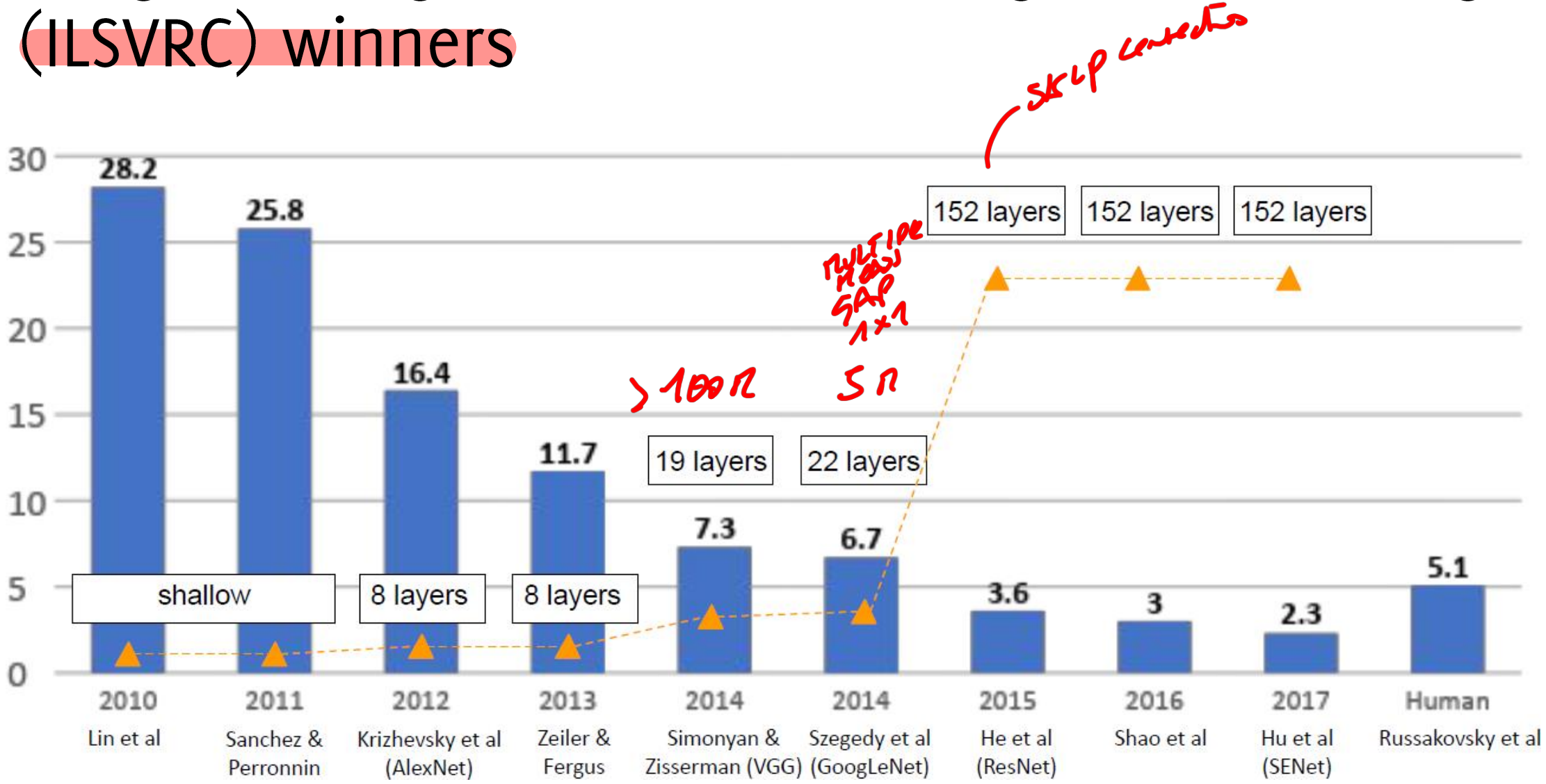
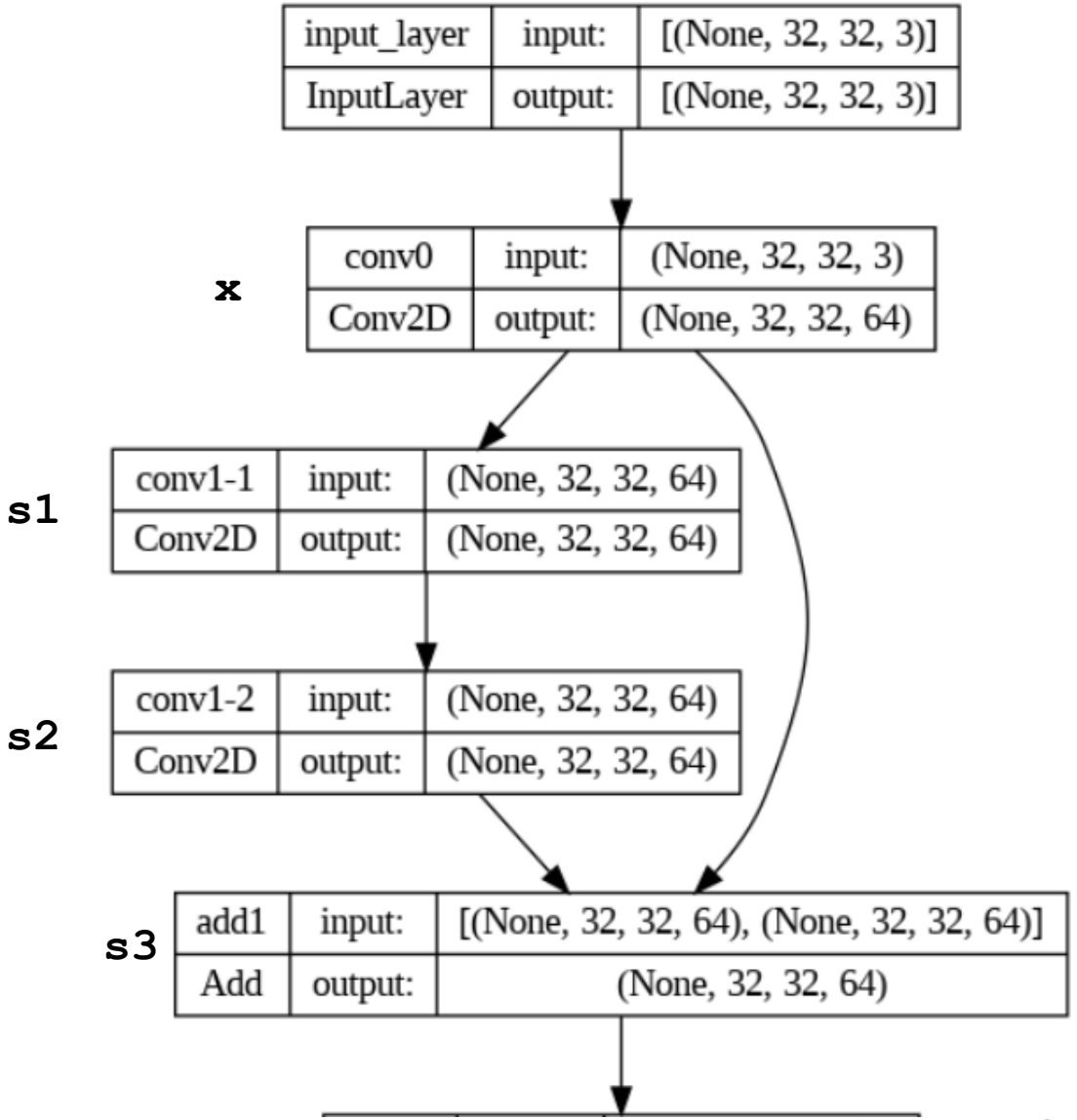
ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



Resnet Block in Keras:

```
# input x
s1 = tfkl.Conv2D(
        filters=filters,
        kernel_size=3,
        padding='same',
        activation='relu',
        name='conv'+name+'-'+str(1)
    )(x)
 s2 = tfkl.Conv2D(
        filters=filters,
        kernel_size=3,
        padding='same',
        activation='relu',
        name='conv'+name+'-'+str(c+2)
        )(s1)
s3 = tfkl.Add(name='add'+name)([x,s2])
s4 = tfkl.ReLU(name='relu'+name)(s3)
s5 = tfkl.MaxPooling2D(name='pooling'+name)(s4)
```



G. Boracchi

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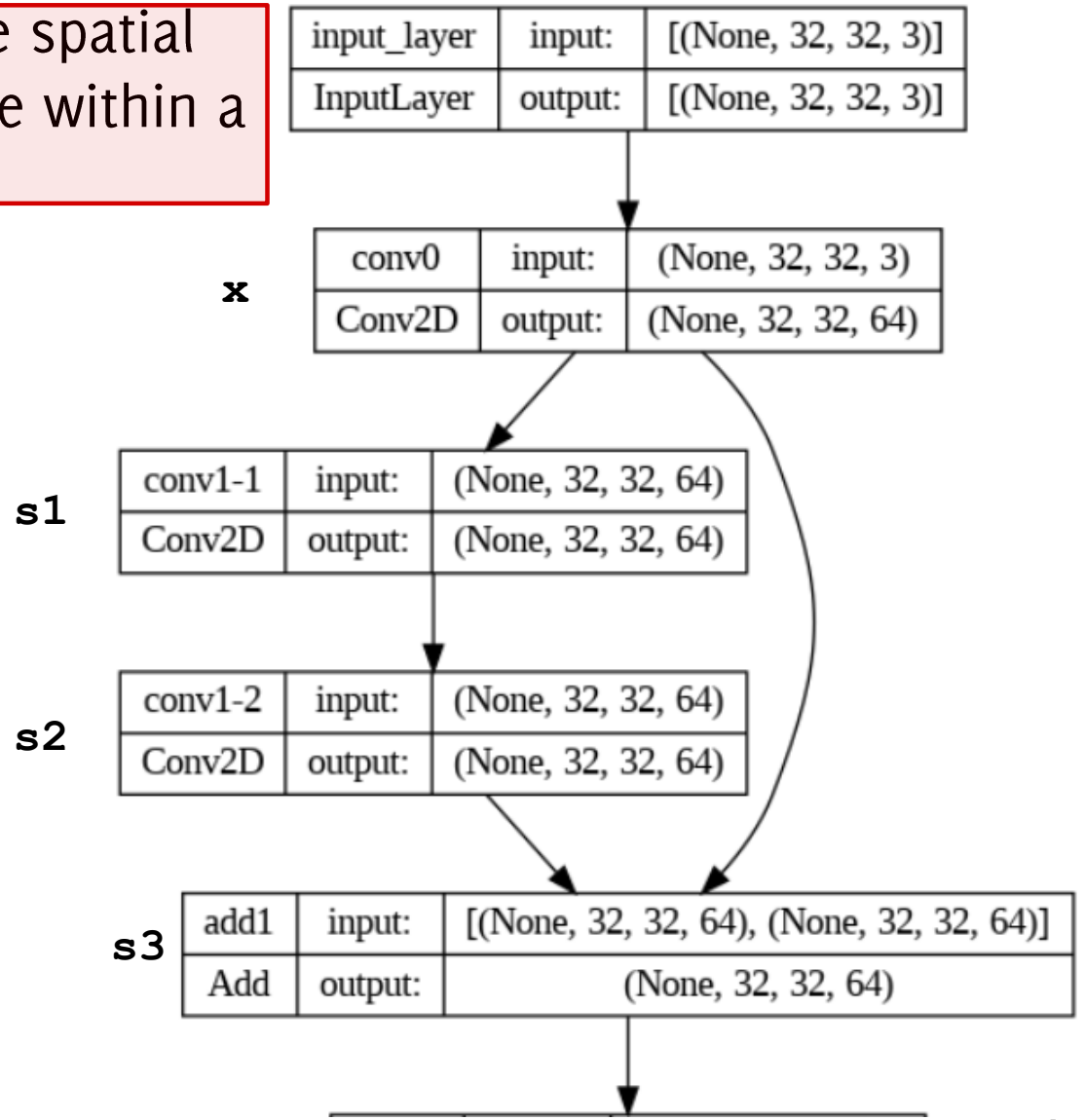
s4 = tfkl.ReLU(name='relu'+name)(s3)
s5 = tfkl.MaxPooling2D(name='pooling'+name)(s4)
```

It is important that the spatial extent does not change within a resnet block



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        name='conv'+name+'-'+str(c+2)
        )(s1)
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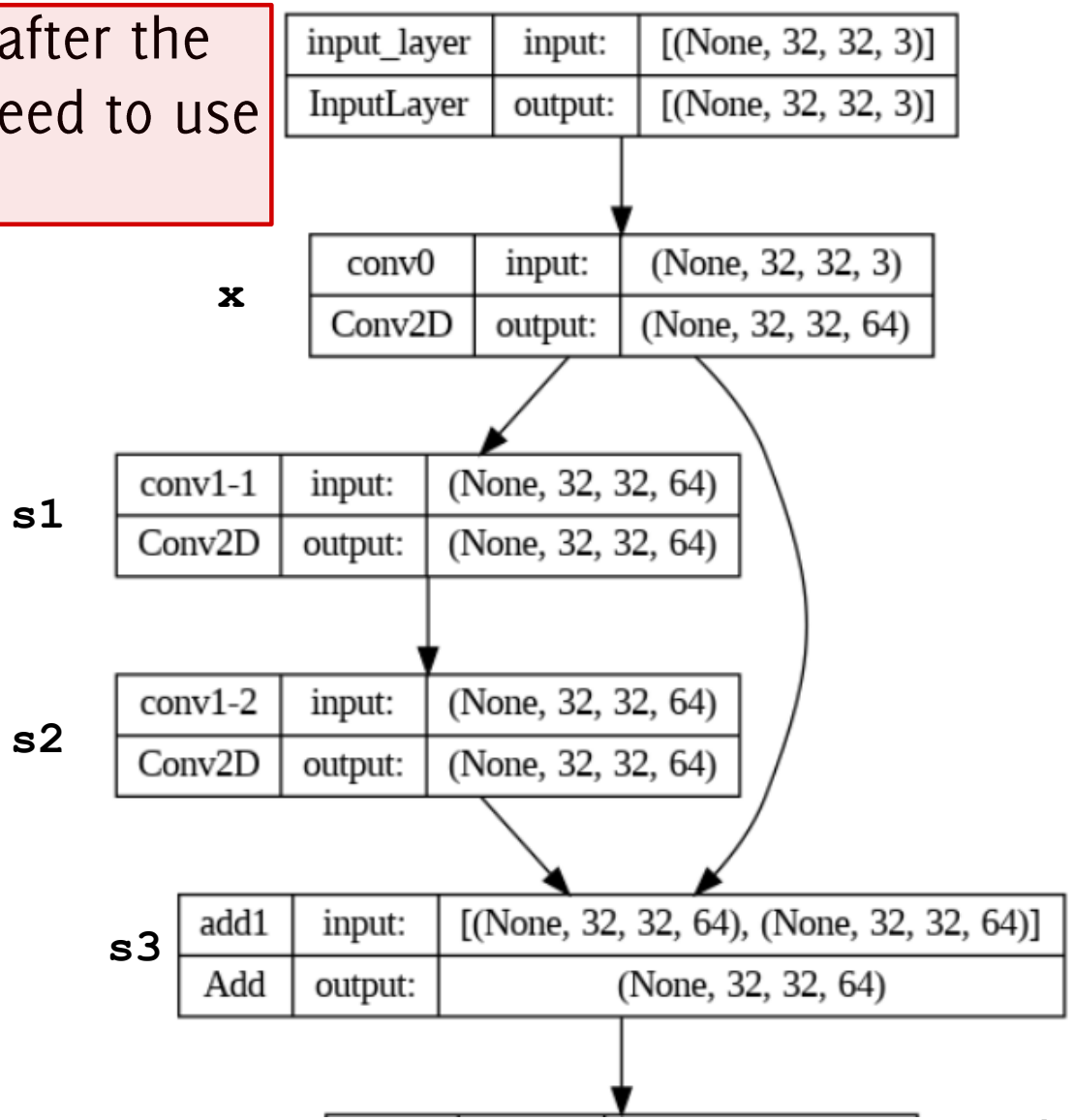
s4 = tfkl.ReLU(name='relu'+name)(s3)
s5 = tfkl.MaxPooling2D(name='pooling'+name)(s4)
```

Include a nonlinearity after the add layer. You might need to use a sepecific layer



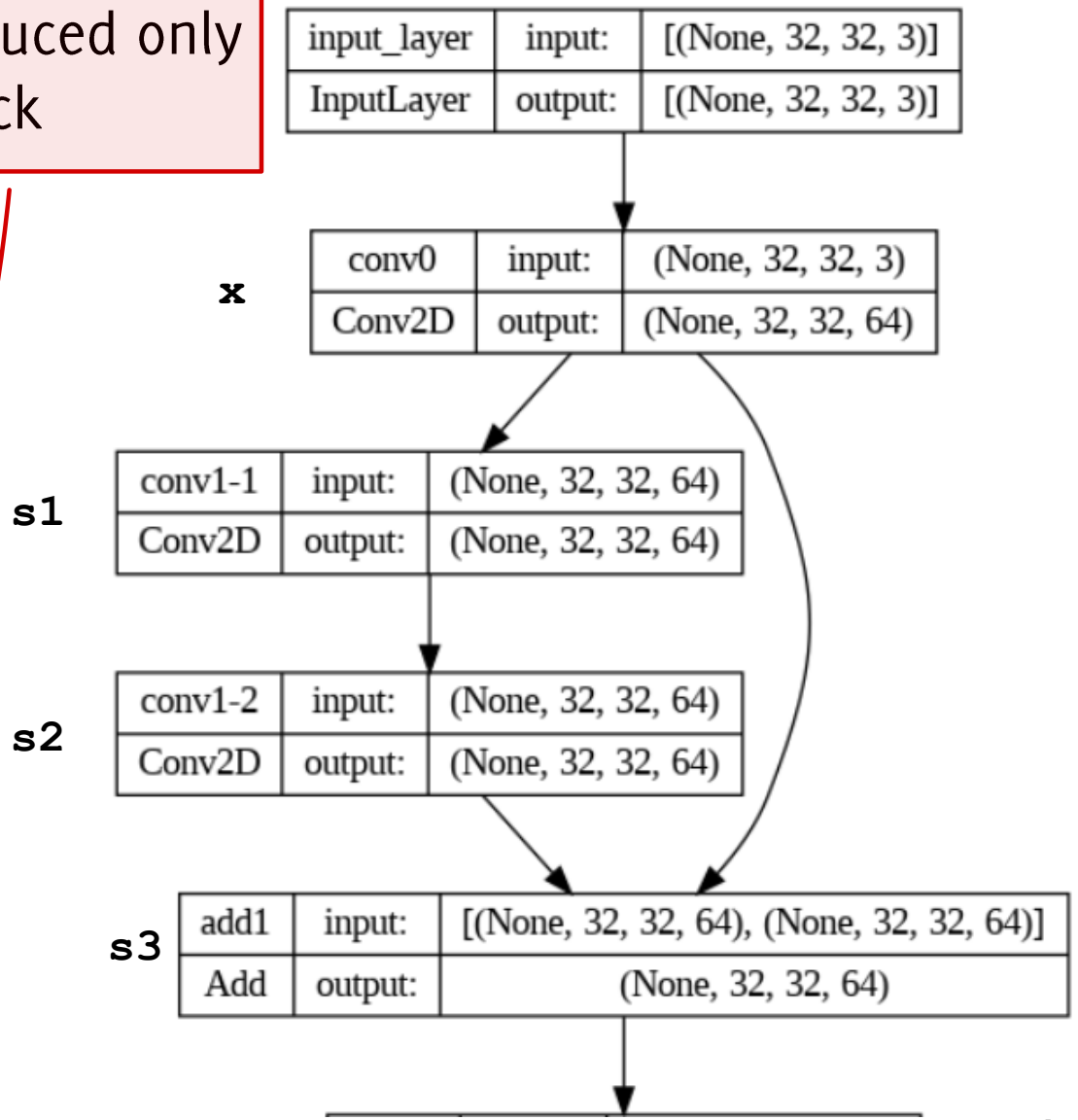
G. Boracchi

Resnet Block in Keras:

```
# input x
s1 = tfkl.Conv2D(
        filters=filters,
        kernel_size=3,
        padding='same',
        activation='relu',
        name='conv'+name+'-'+str(1)
    )(x)
 s2 = tfkl.Conv2D(
        filters=filters,
        kernel_size=3,
        padding='same',
        activation='relu',
        name='conv'+name+'-'+str(c+2)
        )(s1)
s3 = tfkl.Add(name='add'+name)([x,s2])
s4 = tfkl.ReLU(name='relu'+name)(s3)
s5 = tfkl.MaxPooling2D(name='pooling'+name)(s4)
```

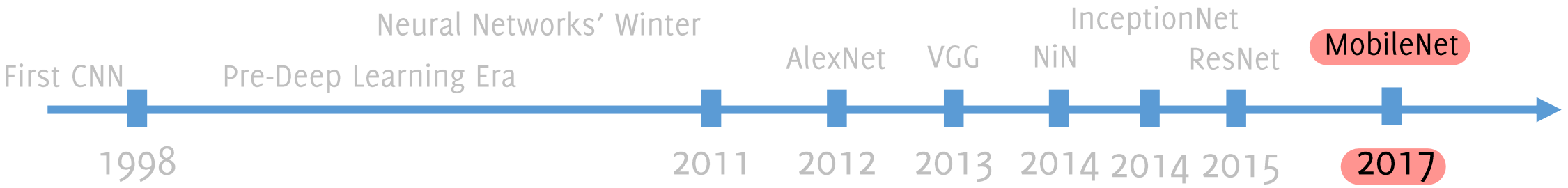
Spatial size can be reduced only outside the resnet block

what we just saw: $F(x) + x$ (identity)



G. Boracchi

MobileNet: Reducing Computational Costs



G. Boracchi

MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications

Andrew G. Howard Menglong Zhu Bo Chen Dmitry Kalenichenko
Weijun Wang Tobias Weyand Marco Andreetto Hartwig Adam

Google Inc.

{howarda,menglong,bochen,dkalenichenko,weijunw,weyand,anm,hadam}@google.com

Howard, A. G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., ... & Adam, H. (2017). Mobilenets: Efficient convolutional neural networks for mobile vision applications. arXiv preprint arXiv:1704.04861.

Mobilenets

TRANSFER LEARNING ON COLLAB : FEASIBLE.

Designed to reduce the number of parameters and of operations, to embed networks in mobile application.

Issues preventing use in mobile devices:

- conv2D layers have (still) quite a few parameters
- conv2D layers are quite computationally demending

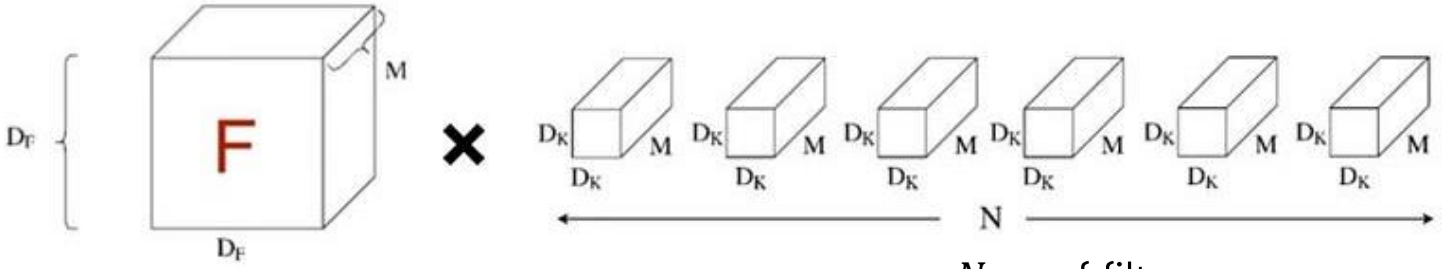
Howard, A. G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., ... & Adam, H. (2017). Mobilenets: Efficient convolutional neural networks for mobile vision applications. arXiv preprint arXiv:1704.04861.

Mobilenets

Nr of operations: $(D_K \times D_K \times M \times D_F \times D_F) \times N$

Traditional Conv2D

Each filter, mixes all the input channels

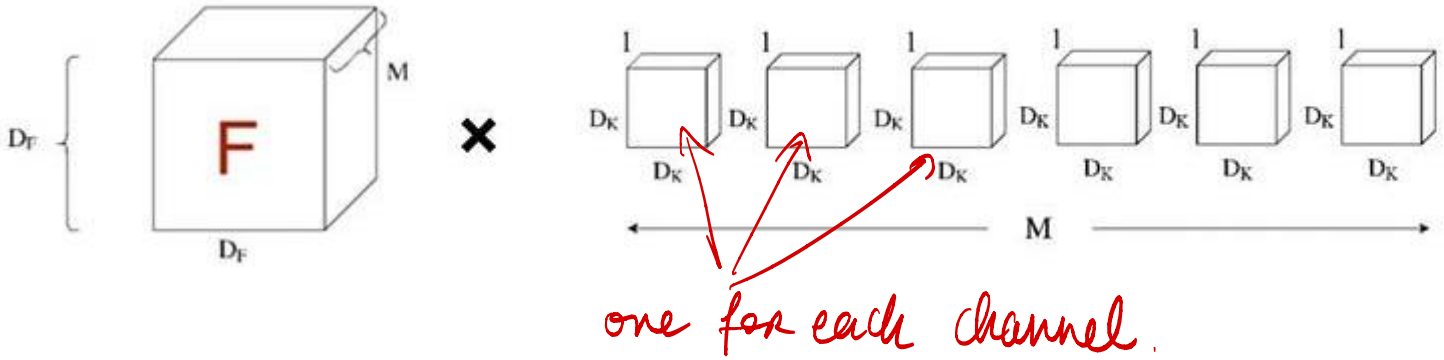


N=nr of filters

Separable Convolution, made of two steps

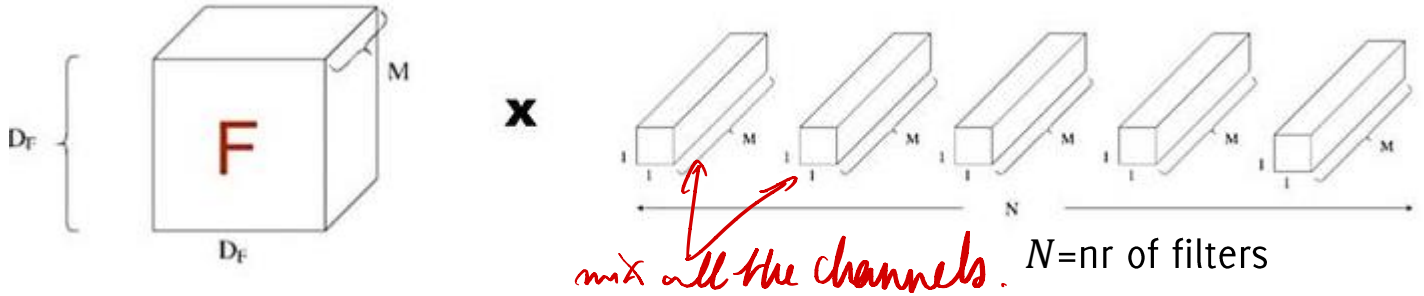
Nr of operations: $(D_K \times D_K \times M \times D_F \times D_F)$

1) **Depth-wise convolution**:
this does not mix channels, it is like 2D convolution on each channel of input activation F.



2) **Point-wise convolution:**
Combines the **output of dept-wise convolution** by N filters that are 1×1.
It does not perform spatial convolution anymore

Nr of operations: $(M \times D_F \times D_F \times N)$



N=nr of filters

Image Credits: https://medium.com/@godeep48/an-overview-on-mobilenet-an-efficient-mobile-vision-cnn-f301141db94d

Depth-wise Separable Convolutions

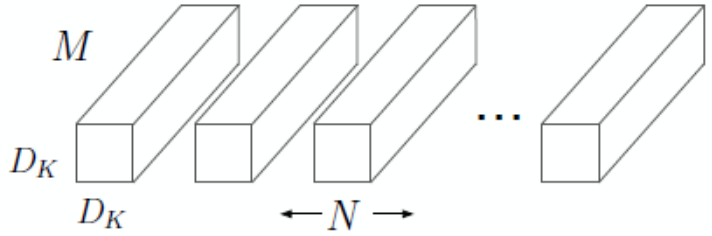
All in all, a layer of dept-wise separable convolution using N filters costs

$$(D_K^2 \times M \times D_F^2) + M \times D_F^2 \times N$$

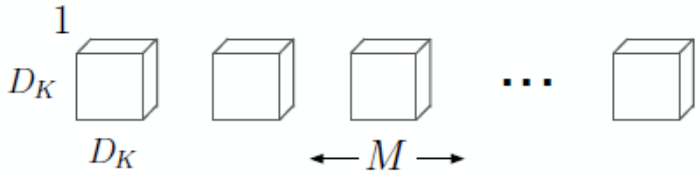
Which compared to conv2D layers

$$\frac{(D_K^2 \times M \times D_F^2) + M \times D_F^2 \times N}{D_K^2 \times M \times D_F^2 \times N} = \frac{1}{N} + \frac{1}{D_K^2}$$

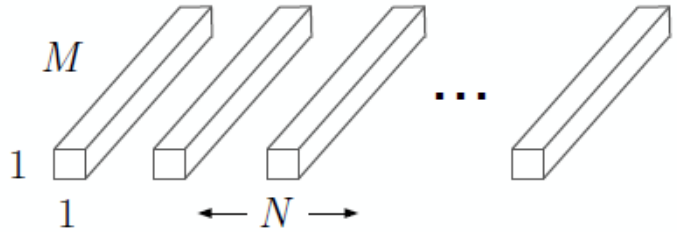
Which denotes a substantial savings when N and D_K are large



(a) Standard Convolution Filters



(b) Depthwise Convolutional Filters



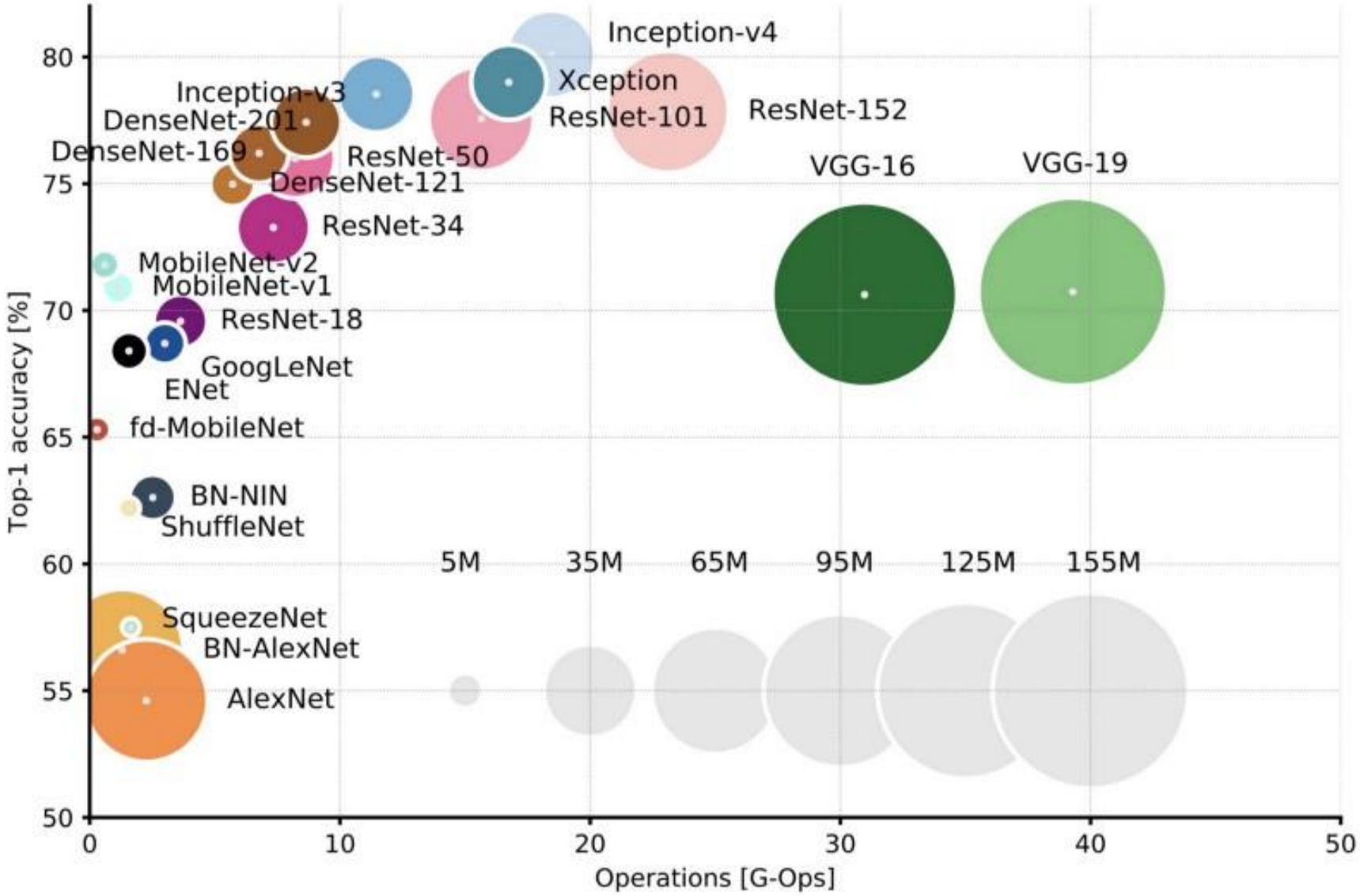
(c) 1×1 Convolutional Filters called Pointwise Convolution in the context of Depthwise Separable Convolution

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.

Howard, A. G., Zhu, M., Chen, B., Kalenichenko, D., Wang, W., Weyand, T., ... & Adam, H. (2017). Mobilenets: Efficient convolutional neural networks for mobile vision applications. arXiv preprint arXiv:1704.04861.

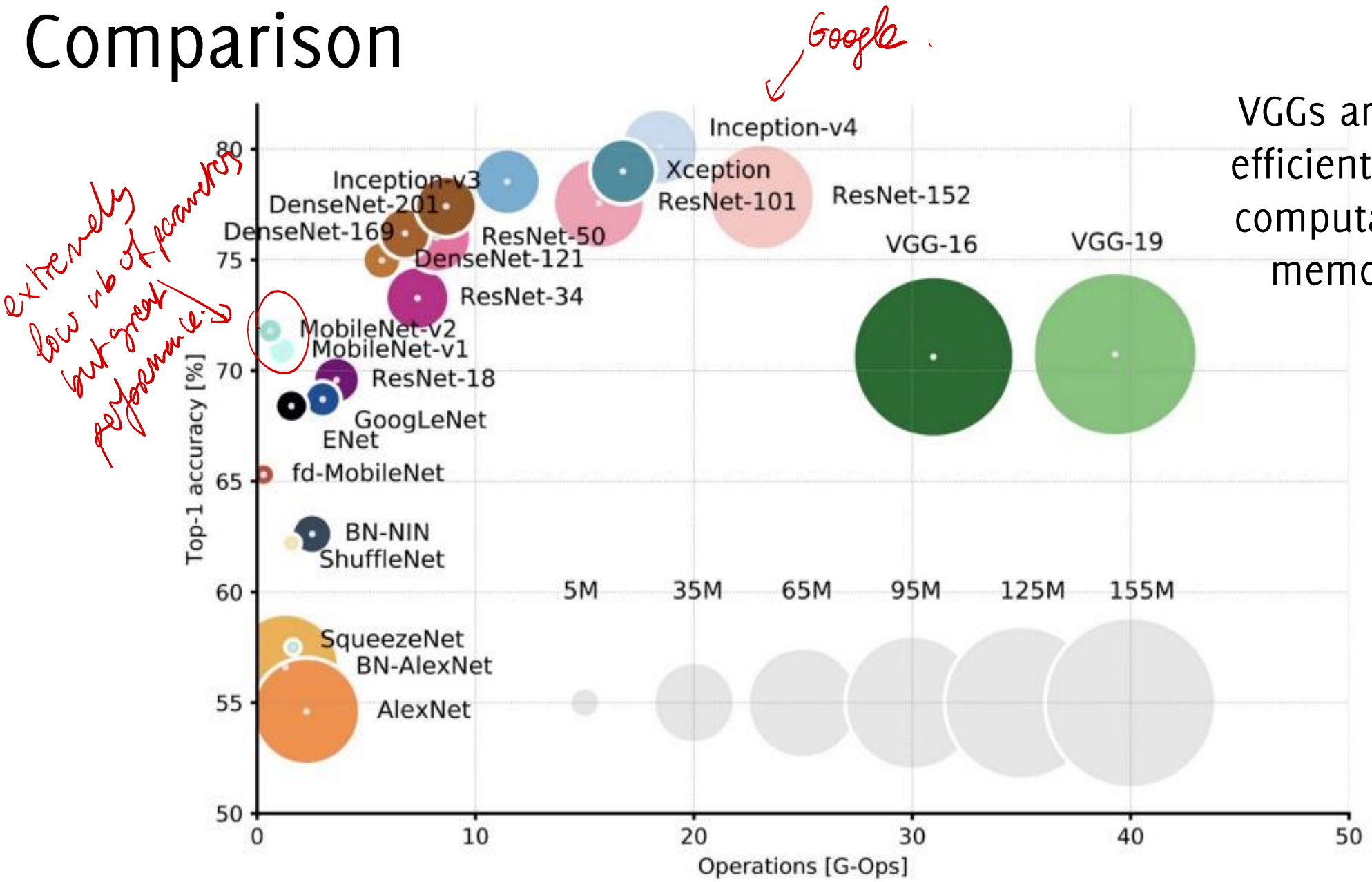
A Comparison

Comparison



Canziani, A, Paszke A., Culurciello E.. "An analysis of deep neural network models for practical applications." *arXiv preprint* (2016).

Comparison

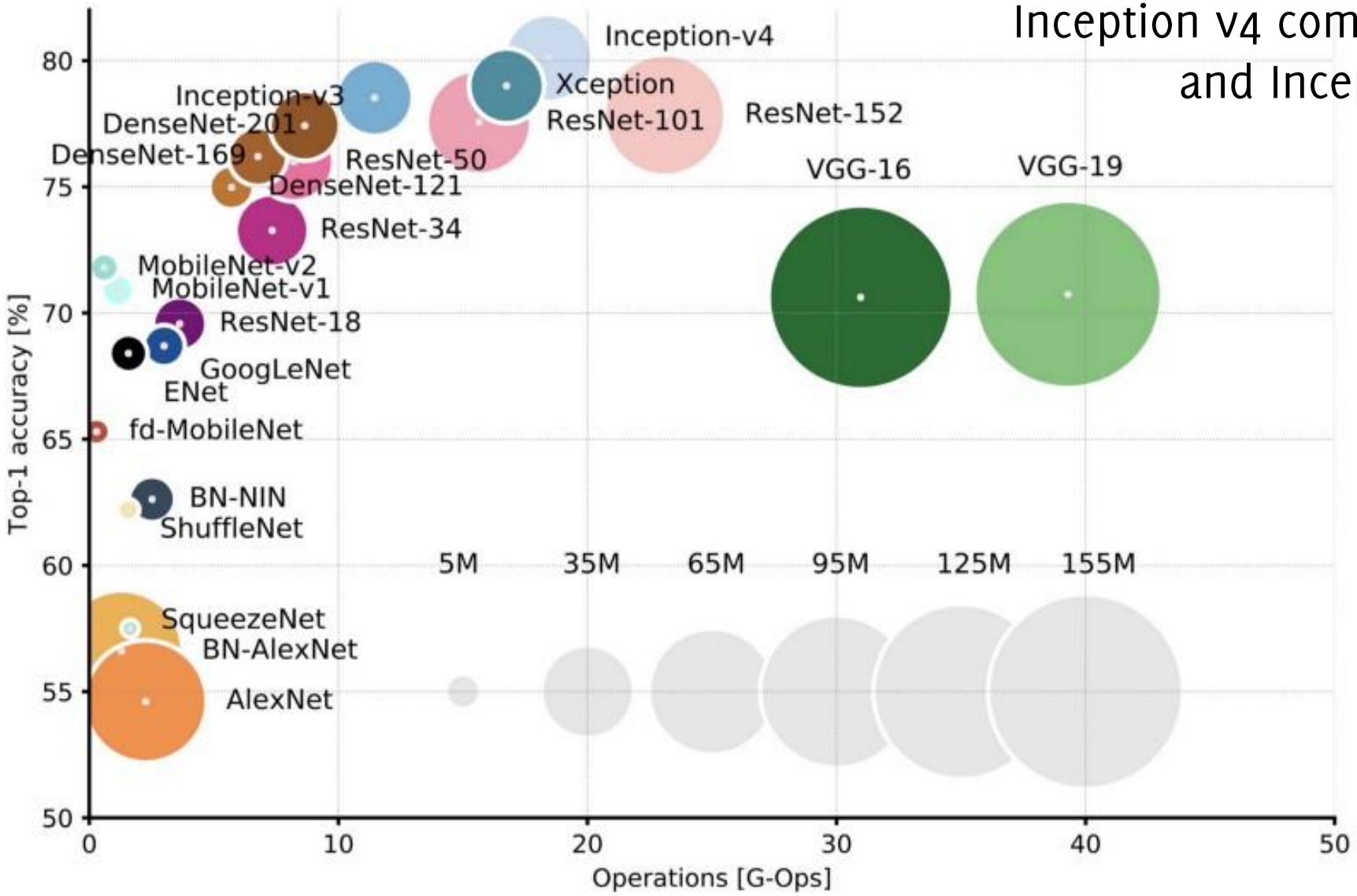


VGGs are the least efficient: very large computational and memory usage

Canziani, A, Paszke A., Culurciello E.. "An analysis of deep neural network models for practical applications." *arXiv preprint* (2016).

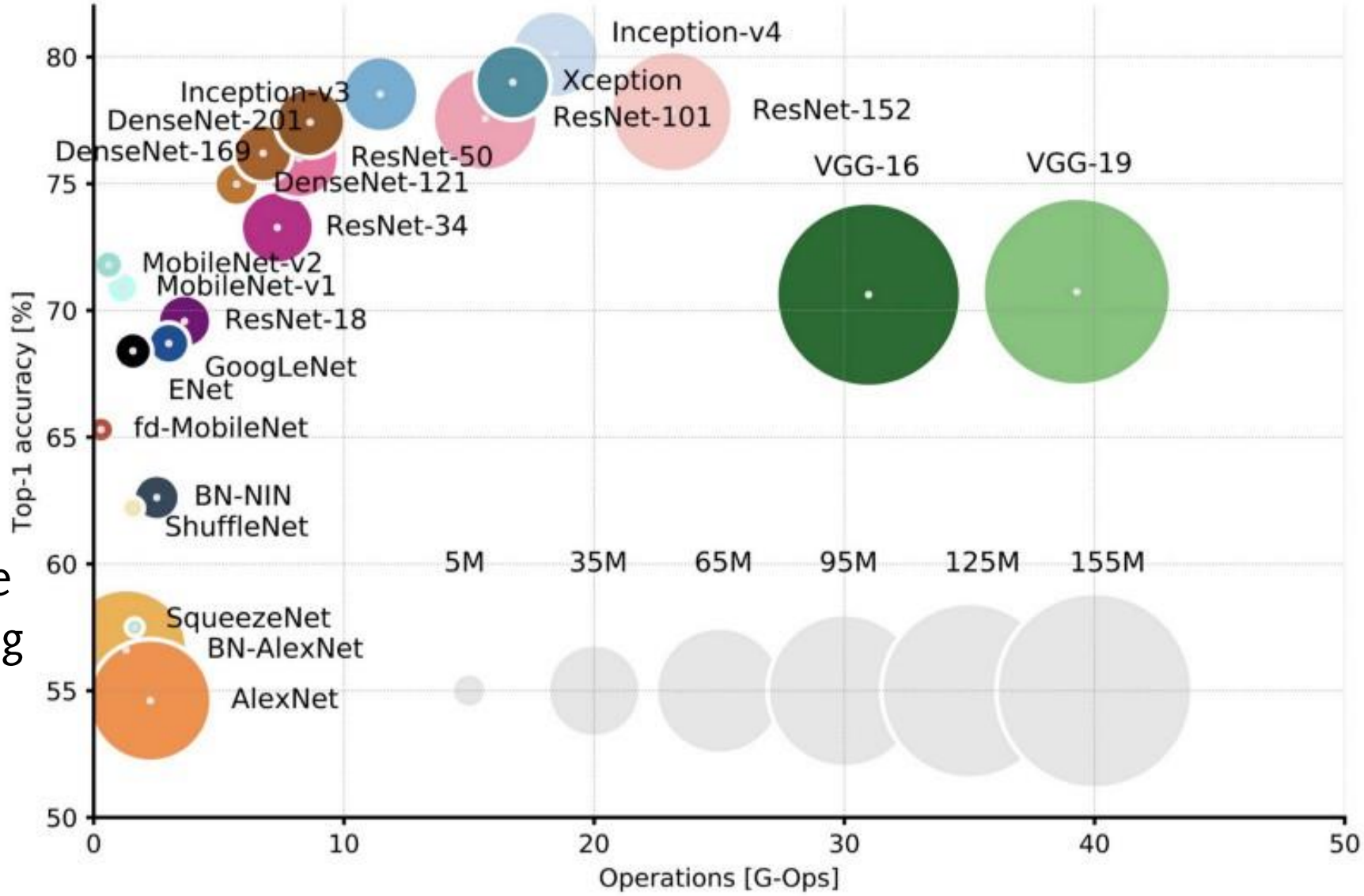
Comparison

Inception models are the most efficient and best performing
Inception v4 combines ResNet and Inception



Canziani, A, Paszke A., Culurciello E.. "An analysis of deep neural network models for practical applications." *arXiv preprint* (2016).

Comparison

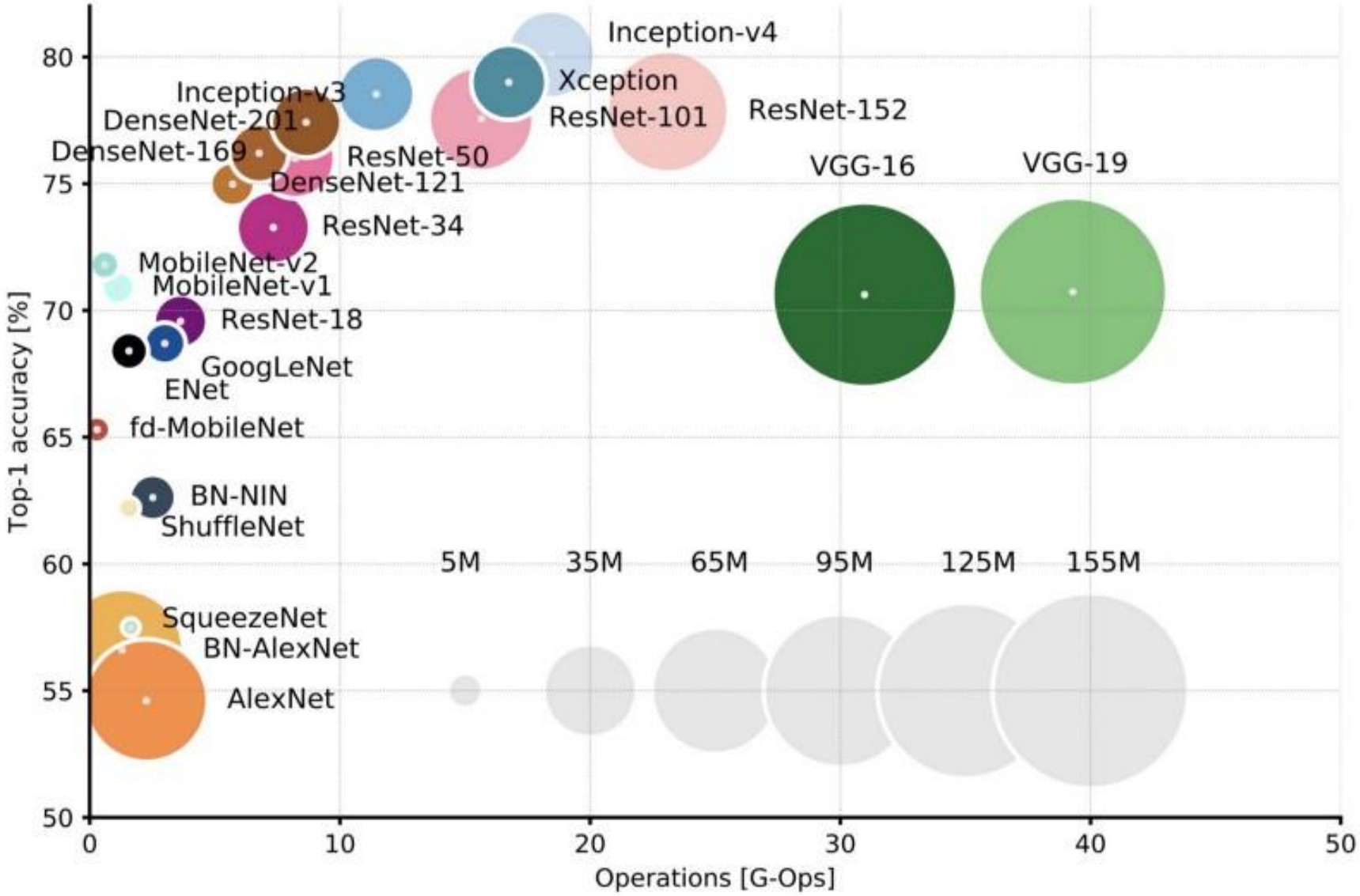


AlexNet are the least performing and not particularly efficient

Canziani, A, Paszke A., Culurciello E.. "An analysis of deep neural network models for practical applications." *arXiv preprint* (2016).

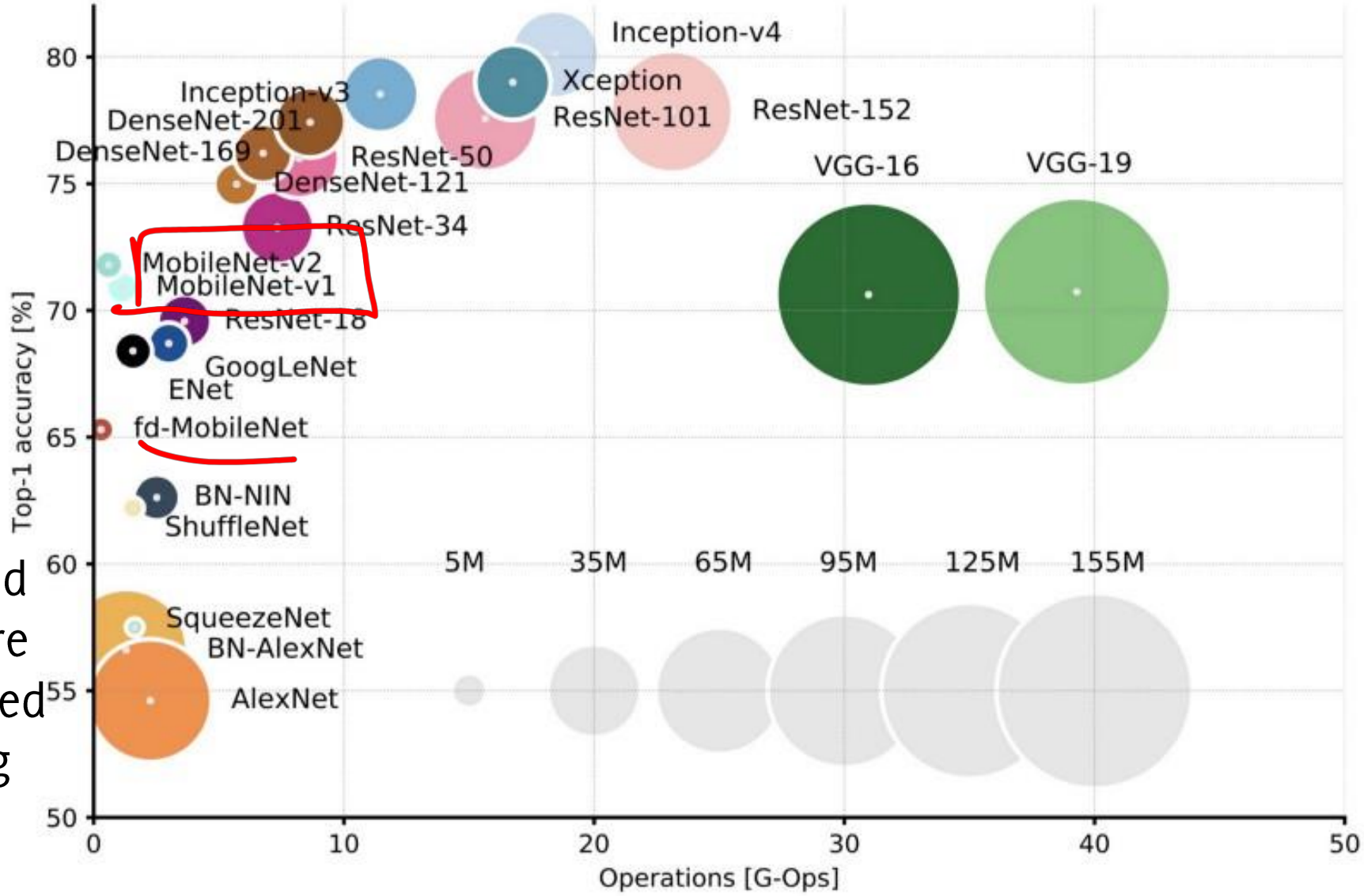
Comparison

Inception-v4:
Resnet + Inception



Canziani, A, Paszke A., Culurciello E.. "An analysis of deep neural network models for practical applications." *arXiv preprint* (2016).

Comparison



Mobile net and squeezenet are instead designed for improving efficiency

Canziani, A, Paszke A., Culurciello E.. "An analysis of deep neural network models for practical applications." *arXiv preprint* (2016).

Latest Developments in Image Classification

G. Boracchi

Aggregated Residual Transformations for Deep Neural Networks

Saining Xie[1] Ross Girshick[2] Piotr Dollár[2] Zhuowen Tu[1] Kaiming He[2]

[1]UC San Diego [2]Facebook AI Research

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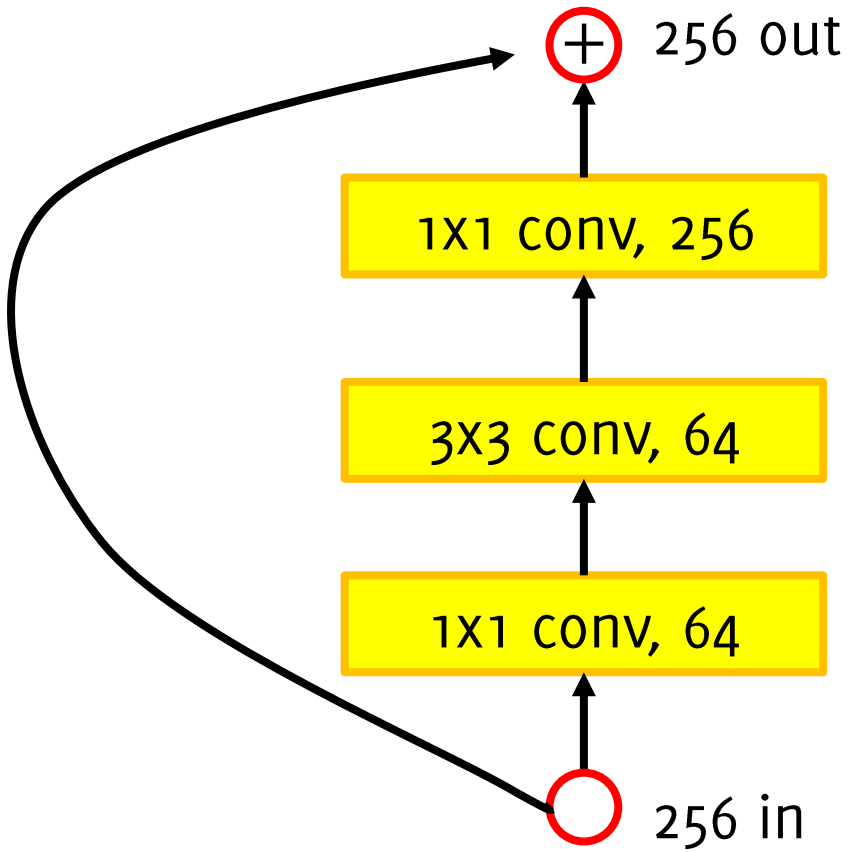
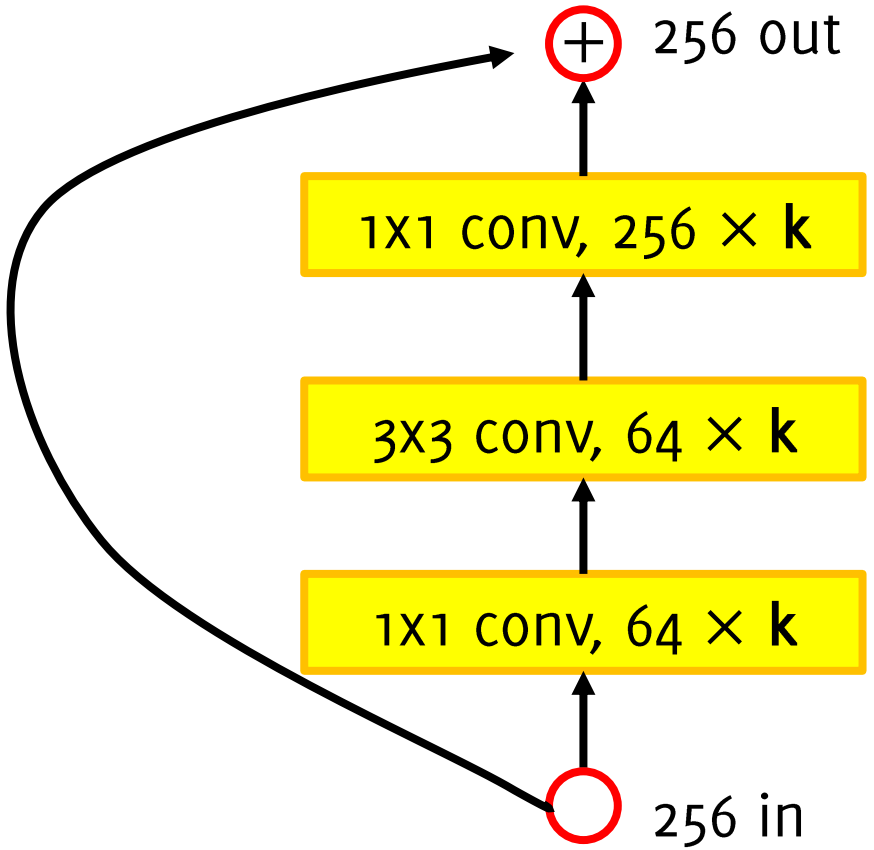
Wide Resnet

ResNet Module



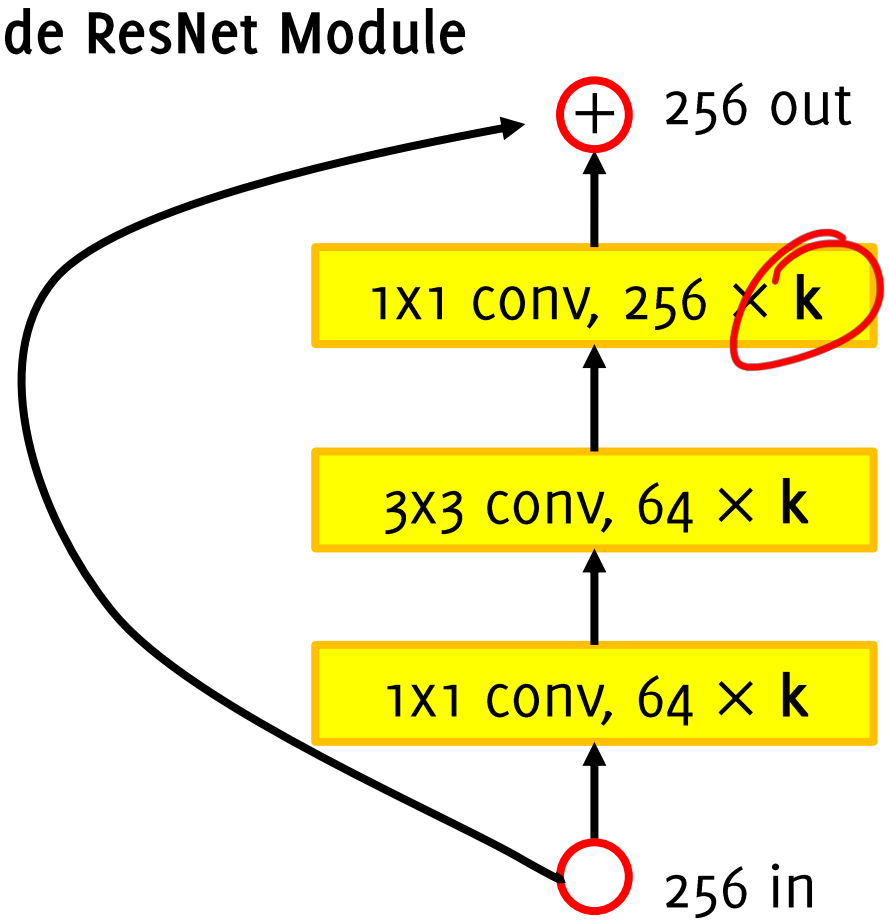
Wide ResNet Module



Xie et al "Aggregated Residual Transformations for Deep Neural Networks", CVPR 2017

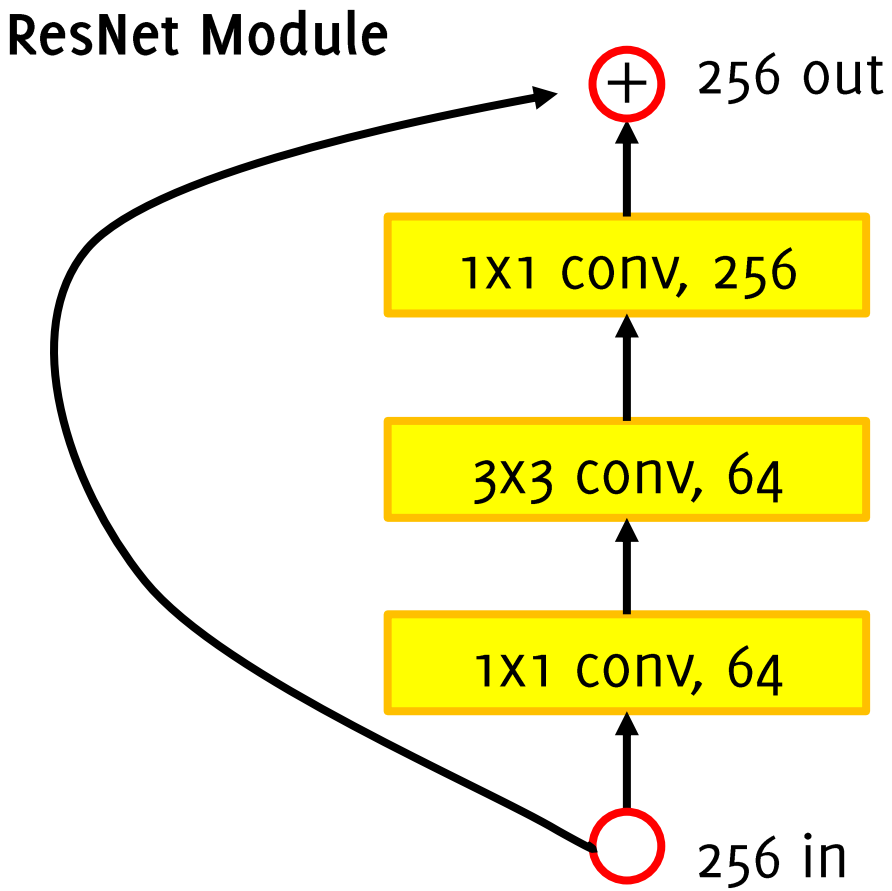
Wide Resnet

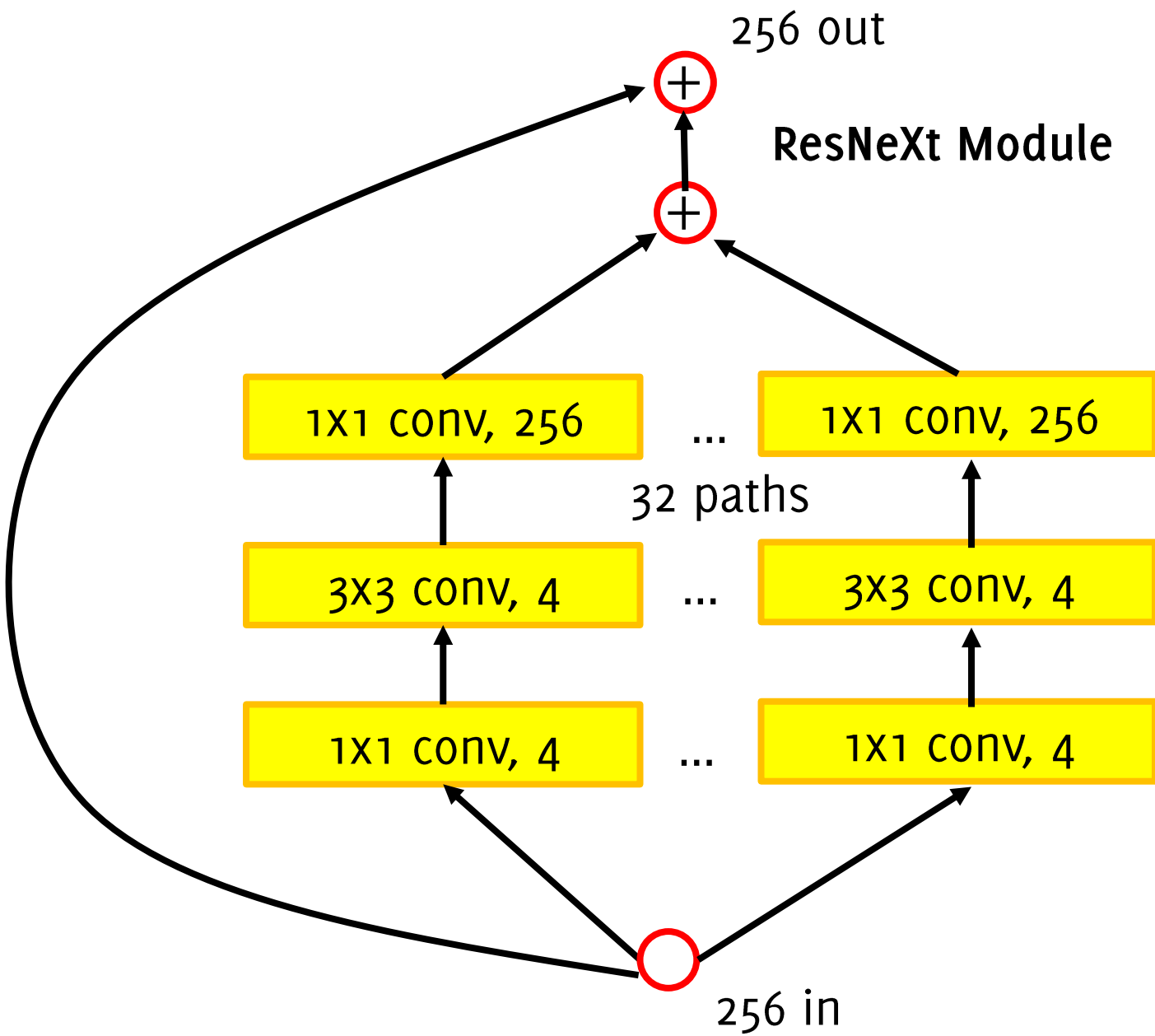
- Use wider residual blocks (F x k filters instead of F filters in each layer)
- **50-layer wide ResNet outperforms 152-layer original ResNet**
- Increasing width instead of depth more computationally efficient (parallelizable)



Xie et al "Aggregated Residual Transformations for Deep Neural Networks", CVPR 2017

ResNeXt





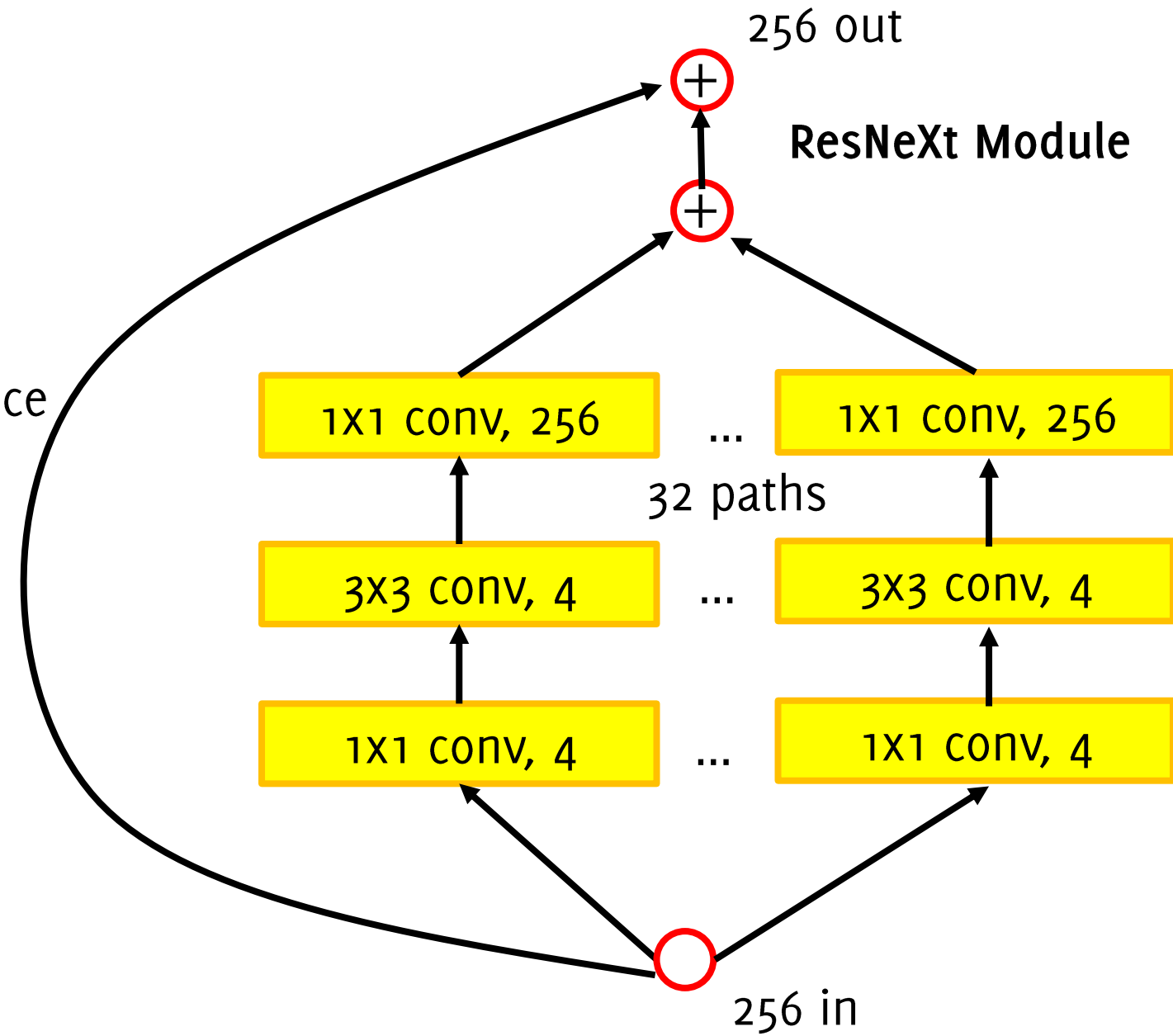
Xie et al "Aggregated Residual Transformations for Deep Neural Networks", CVPR 2017

ResNeXt

Widen the ResNet module by adding multiple pathways in parallel (previous wide Resnet was just increasing the number of filters and showing it achieves similar performance with fewer blocks)

Similar to inception module where the **activation maps are being processed in parallel**

Different from inception module, all the paths share the same topology



Xie et al "Aggregated Residual Transformations for Deep Neural Networks", CVPR 2017

Densely Connected Convolutional Networks

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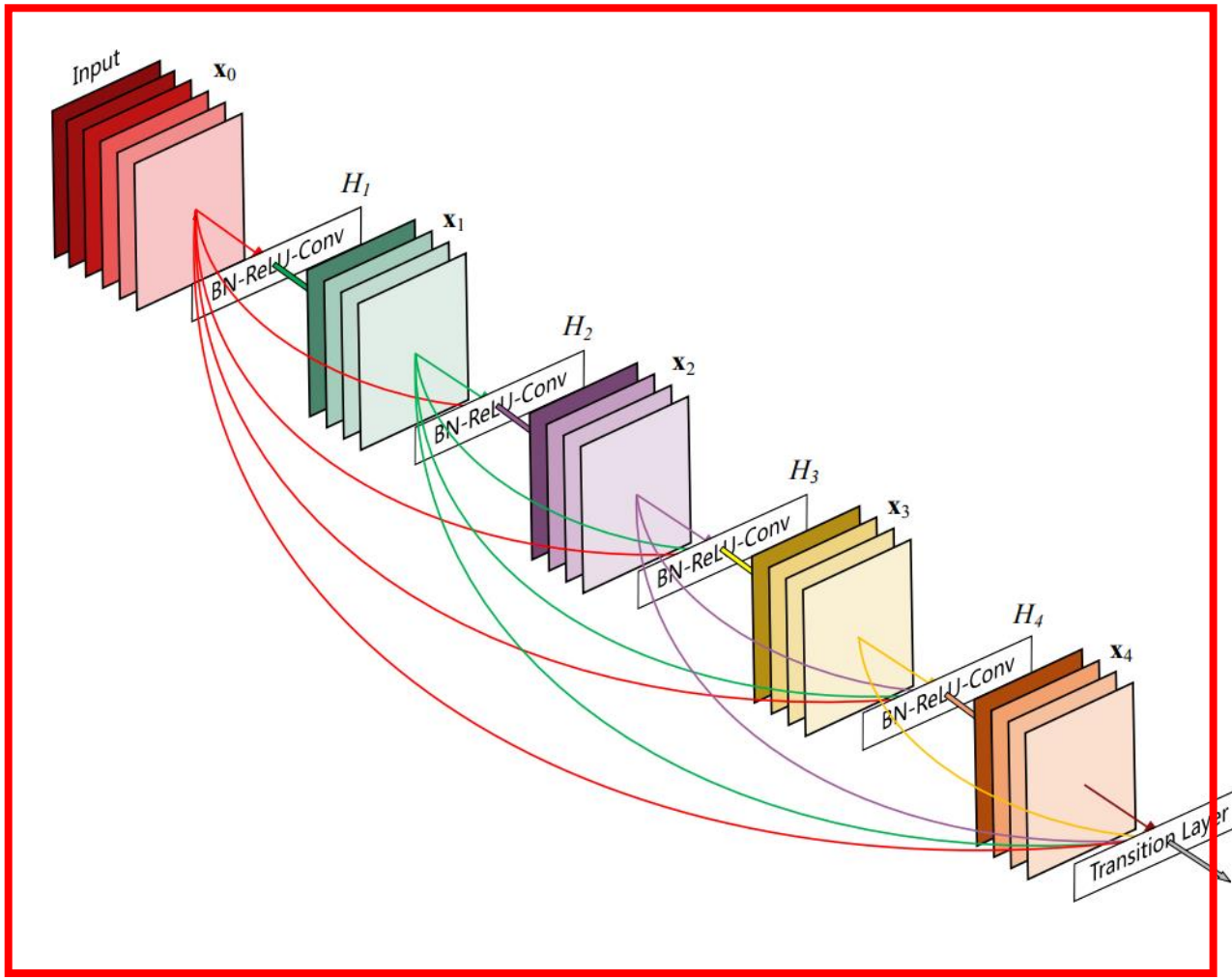
DenseNet

In **each block** of a DenseNet, **each convolutional layer takes as input the output of the previous layers**

Short connections between convolutional layers of the network

Each layer is connected to every other layer in a feed-forward fashion

Dense block



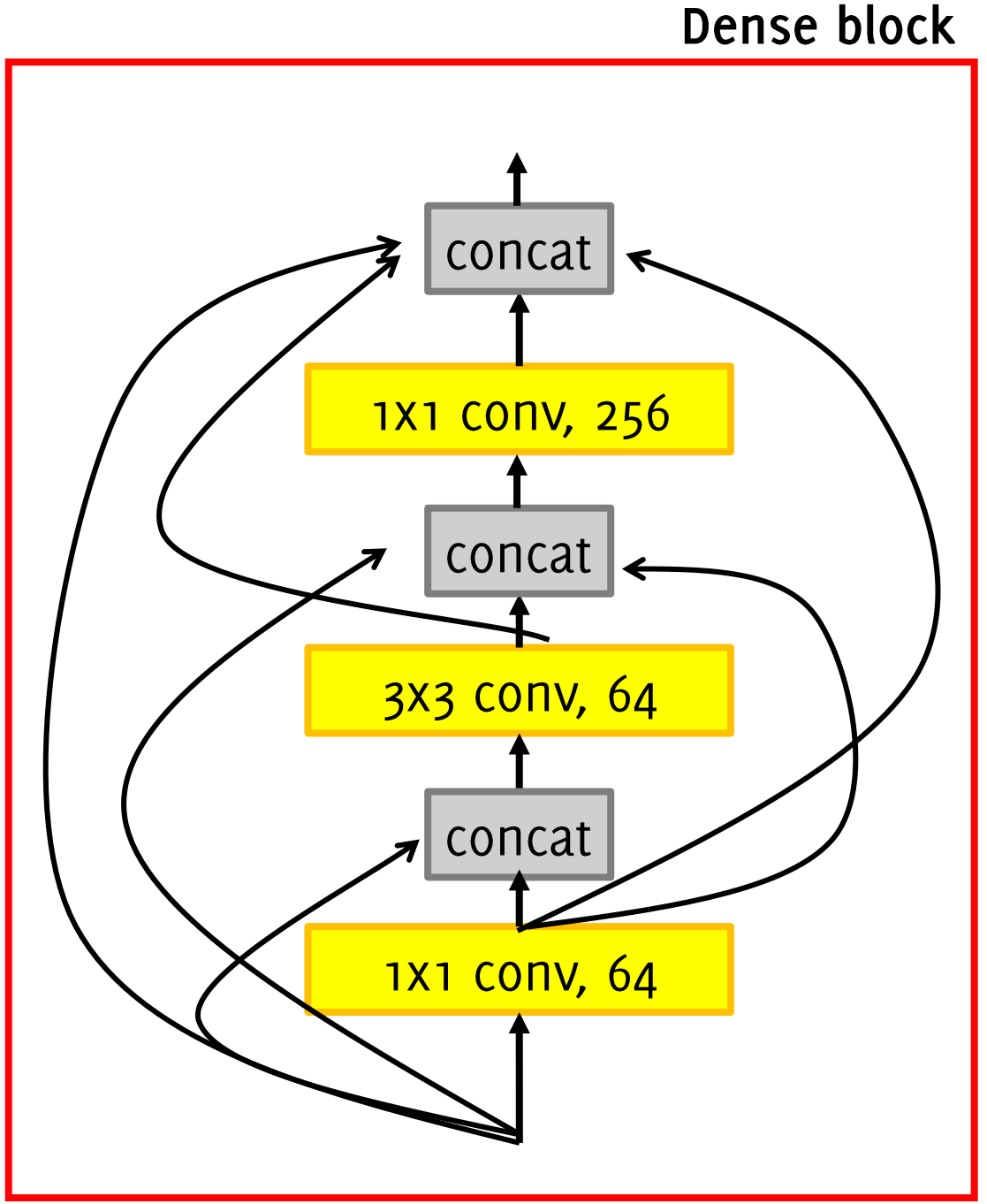
Huang G. et al, "Densely Connected Convolutional Network" CVPR 2017

DenseNet

In each block a DenseNet, each **convolutional layer takes as input the output of the previous layers**

Each layer is connected to every other layer in a feed-forward fashion

This alleviates vanishing gradient problem, promotes feature re-use since each feature is spread through the network



Huang G. et al, "Densely Connected Convolutional Network" CVPR 2017

EfficientNet: a family of networks

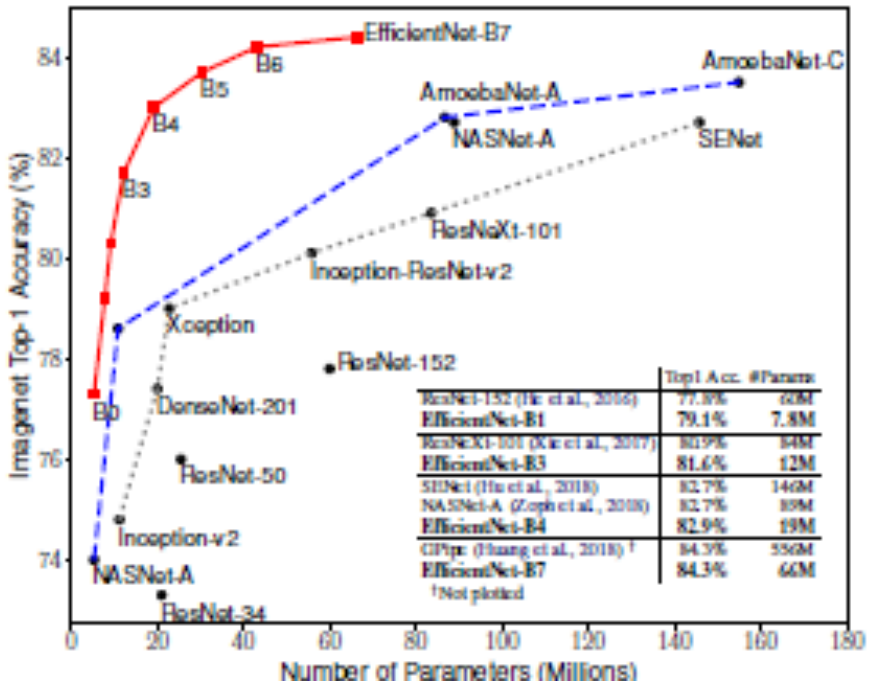
G. Boracchi

EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks

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

Abstract

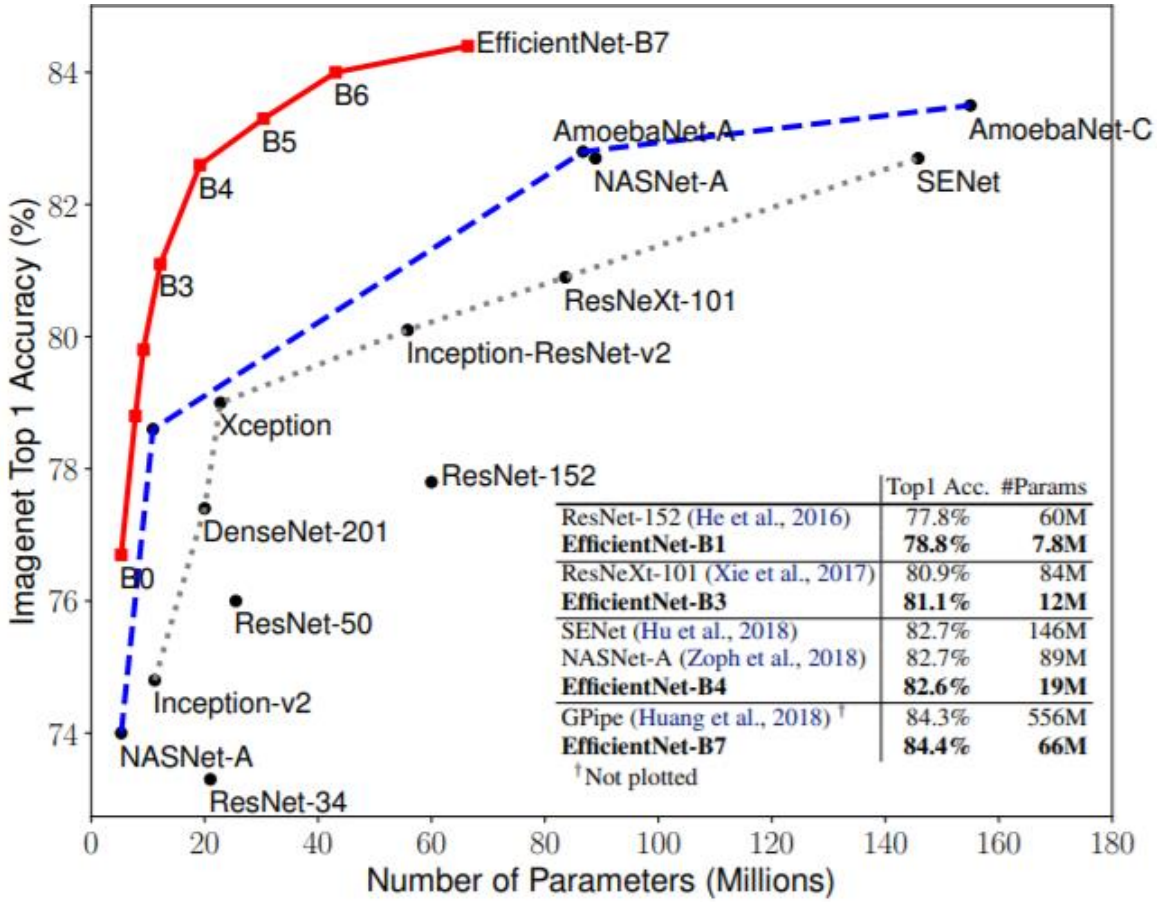
Convolutional Neural Networks (ConvNets) are commonly developed at a fixed resource budget, and then scaled up for better accuracy if more resources are available. In this paper, we systematically study model scaling and identify that carefully balancing network depth, width, and resolution can lead to better performance. Based on this observation, we propose a new scaling method that uniformly scales all dimensions of depth/width/resolution using a simple yet highly effective *compound coefficient*. We demonstrate the effectiveness of this method on scaling up MobileNets and ResNet.



Tan, Mingxing, and Quoc Le. "Efficientnet: Rethinking model scaling for convolutional neural networks." ICML, 2019.

EfficientNet:

We propose a new scaling method that uniformly scales all dimensions of depth/width/resolution using a simple yet highly effective compound coefficient



	Top1 Acc.	#Params
ResNet-152 (He et al., 2016)	77.8%	60M
EfficientNet-B1	**78.8%**	**7.8M**
ResNeXt-101 (Xie et al., 2017)	80.9%	84M
EfficientNet-B3	**81.1%**	**12M**
SENet (Hu et al., 2018)	82.7%	146M
NASNet-A (Zoph et al., 2018)	82.7%	89M
EfficientNet-B4	**82.6%**	**19M**
GPipe (Huang et al., 2018) †	84.3%	556M
EfficientNet-B7	**84.4%**	**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 84.4% 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.

Next time: segmentation, object detection ...

Tan, Mingxing, and Quoc Le. "Efficientnet: Rethinking model scaling for convolutional neural networks." ICML, 2019.