Famous CNN Architectures and CNN Visualization

Giacomo Boracchi

giacomo.boracchi@polimi.it

A few popular architectures

AlexNet

VGG

Networks In Networks (and GAP)

Inception

Resnet

Outline

Lecture inspired to:

Notes accompanying the Stanford CS class CS231n: Convolutional Neural Networks for Visual Recognition http://cs231n.github.io/

… and papers cited in here!

ImageNet Classification with Deep Convolutional Neural Networks

Alex Krizhevsky
University of Toronto
kriz@cs.utoronto.ca

Ilya Sutskever
University of Toronto
ilya@cs.utoronto.ca

Geoffrey E. Hinton
University of Toronto
hinton@cs.utoronto.ca

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

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

AlexNet (2012)

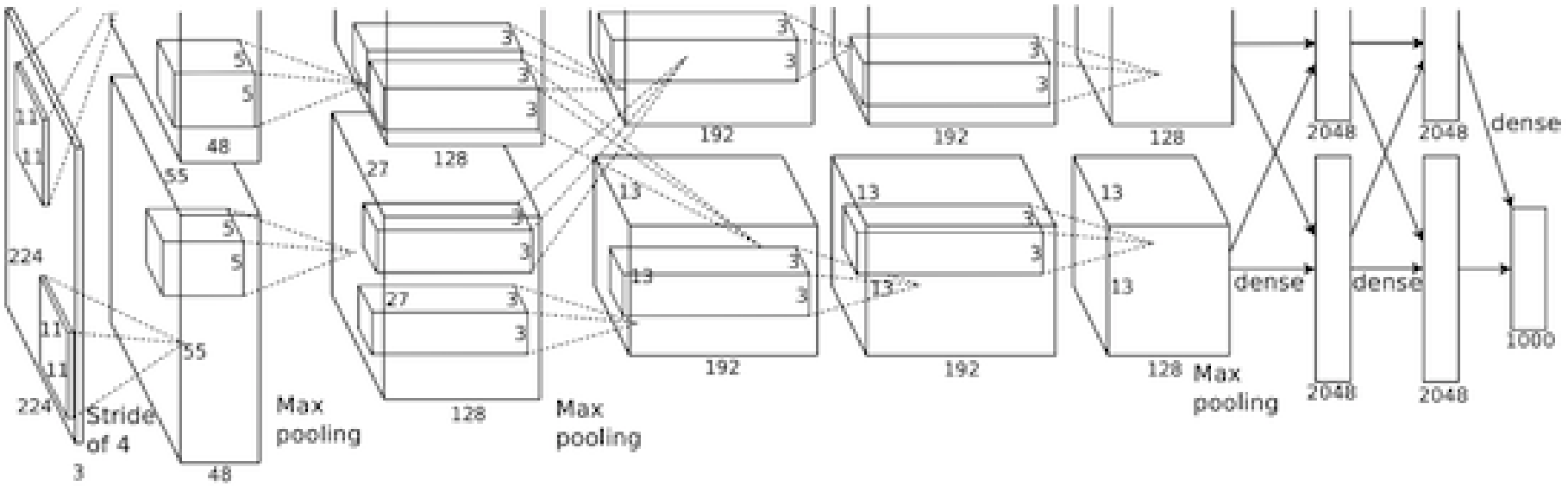
Developed by Alex Krizhevsky et al. in 2012 and won Imagenet competition

Architecture is quite similar to LeNet-5:

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

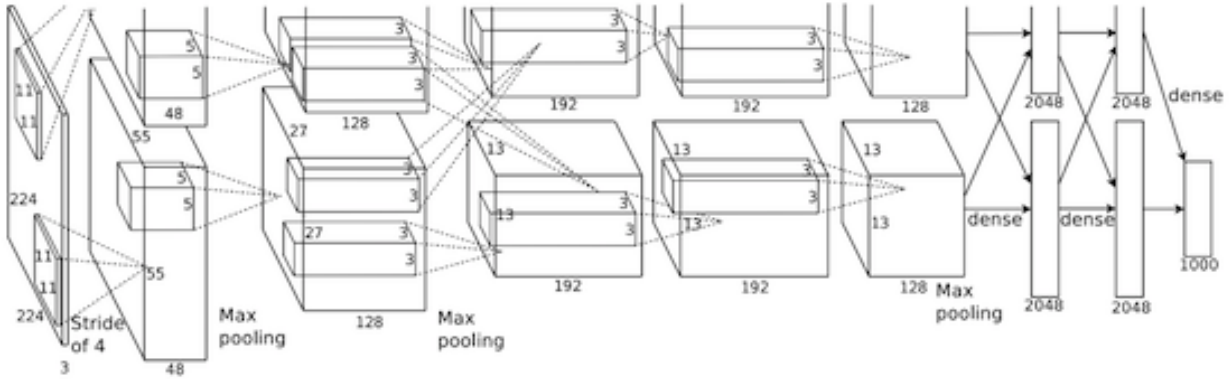
Input size 224 × 224 x 3 (the paper says 227 x 227 x 3)

Parameters: 60 million [**Conv**: 3.7million (6%), **FC**: 58.6 million (94%)]



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

AlexNet (2012)



To counteract overfitting, they introduce:

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

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

VERY DEEP CONVOLUTIONAL NETWORKS FOR LARGE-SCALE IMAGE RECOGNITION

Karen Simonyan* **& Andrew Zisserman+**
Visual Geometry Group, Department of Engineering Science, University of Oxford
{karen,az}@robots.ox.ac.uk

ABSTRACT

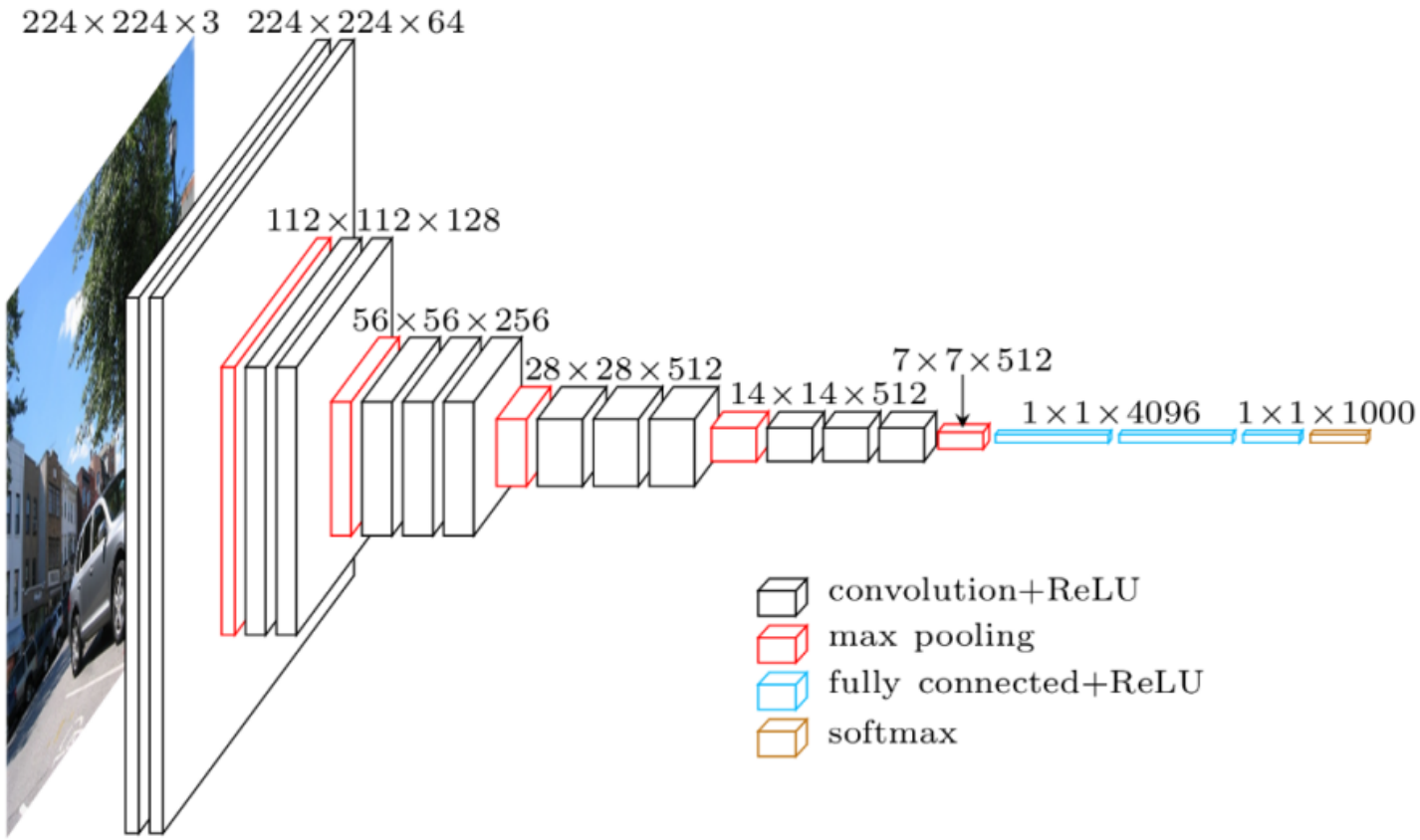
In this work we investigate the effect of the convolutional network depth on its accuracy in the large-scale image recognition setting. Our main contribution is a thorough evaluation of networks of increasing depth using an architecture with very small (3×3) convolution filters, which shows that a significant 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%]



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

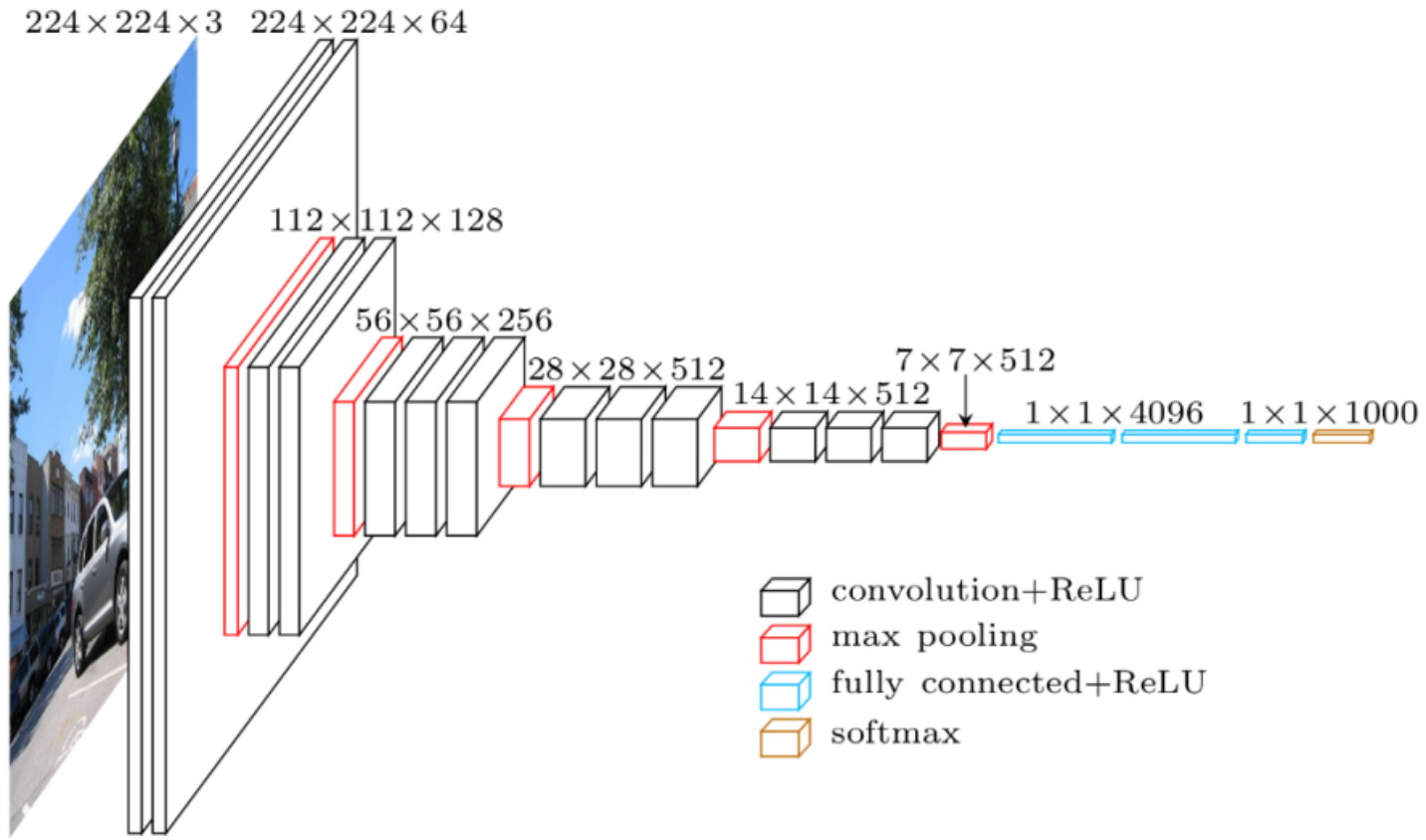
VGG16 (2014)

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%]

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**.

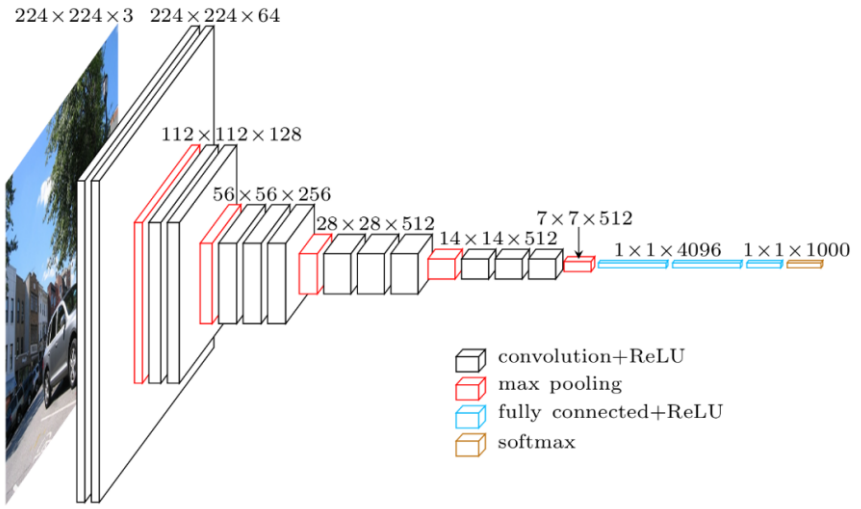
[…]Fix other parameters of the architecture, and steadily increase the depth of the network by adding more convolutional layers, which is feasible due ***to the use of very small (3. × 3) convolution filters in all layers.***

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 parameters	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
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
[…]		

Layer (type)	Output Shape	Param #
[…]		
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
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

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
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
[…]		

Layer (type)	Output Shape	Param #
[…]		
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
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

Many convolutional blocks without maxpooling

G. Boracchi

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
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
[…]		

Layer (type)	Output Shape	Param #
[…]		
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
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

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

G. Boracchi

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)		
block2_conv2 (Conv2D)		
block2_pool (MaxPooling2D)		
block3_conv1 (Conv2D)		
block3_conv2 (Conv2D)		
block3_conv3 (Conv2D)		
block3_pool (MaxPooling2D)		
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
[…]		

Layer (type)	Output Shape	Param #
[…]		
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
	, 14, 512)	2359808
	7, 512)	0
	088)	0
	96)	102764544
	96)	16781312
	00)	4097000

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

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

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

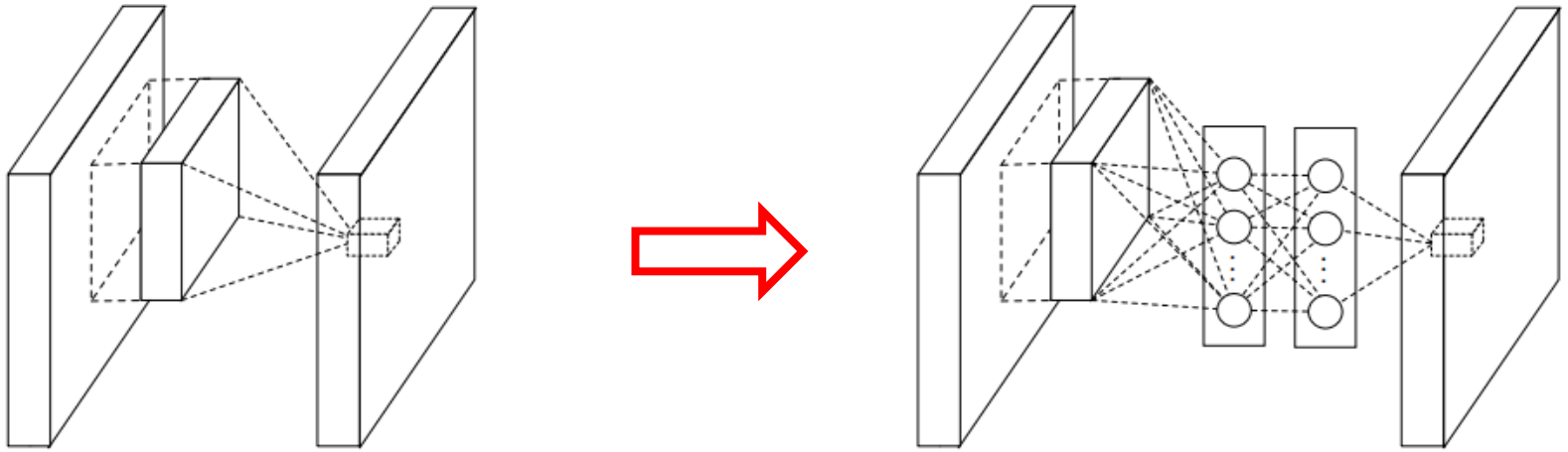
Lin, Min, Qiang Chen, and Shuicheng Yan. "Network in network." *ICLR 2014*

Network in Network

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



(a) Linear convolution layer (b) Mlpconv layer

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

Network in Network

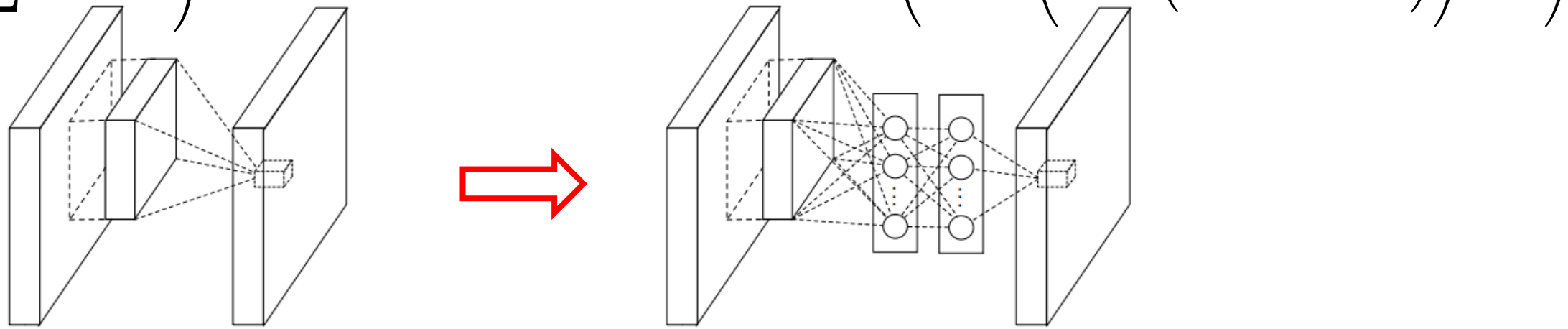
Mlpconv layers: instead of conv layers, use **a sequence of FC + RELU**

- 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

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

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



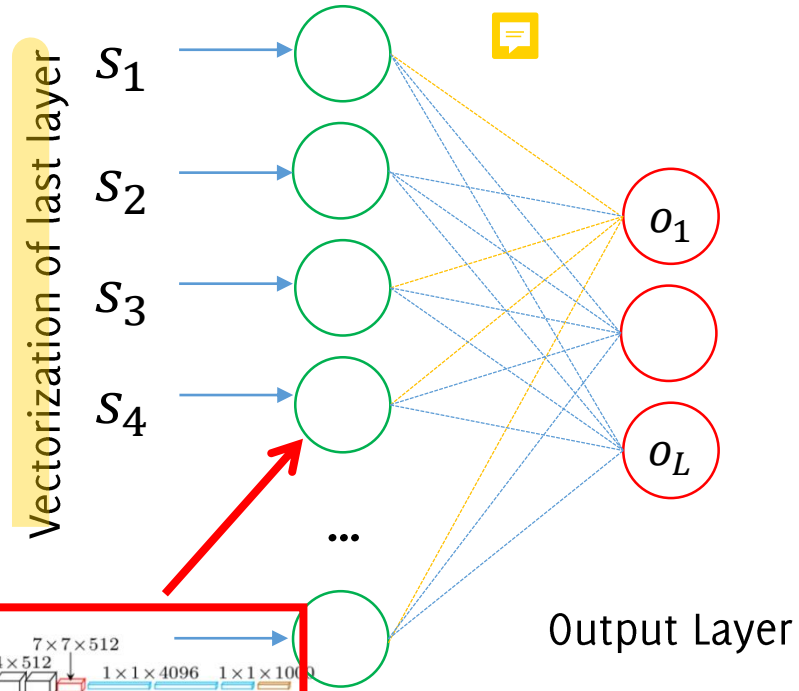
(a) Linear convolution layer (b) Mlpconv layer

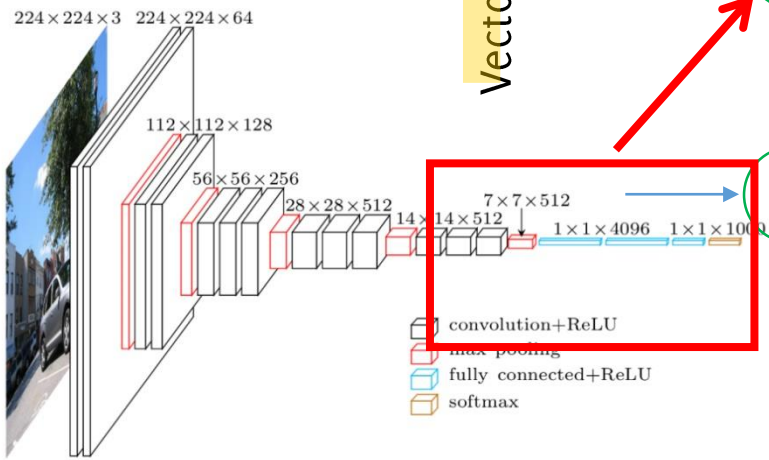
Lin, Min, Qiang Chen, and Shuicheng Yan. "Network in network." *ICLR 2014*

Network in Network

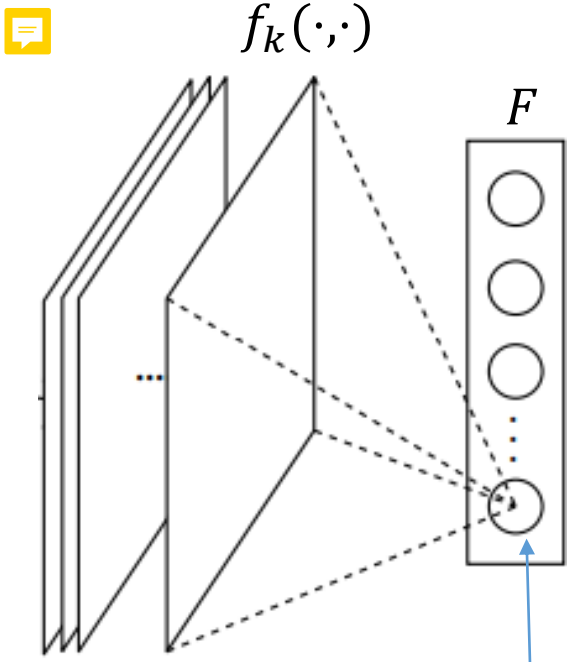
They also introduce Global Averaging Pooling Layers

Fully Connected Layer





Global Averaging Pooling Layer



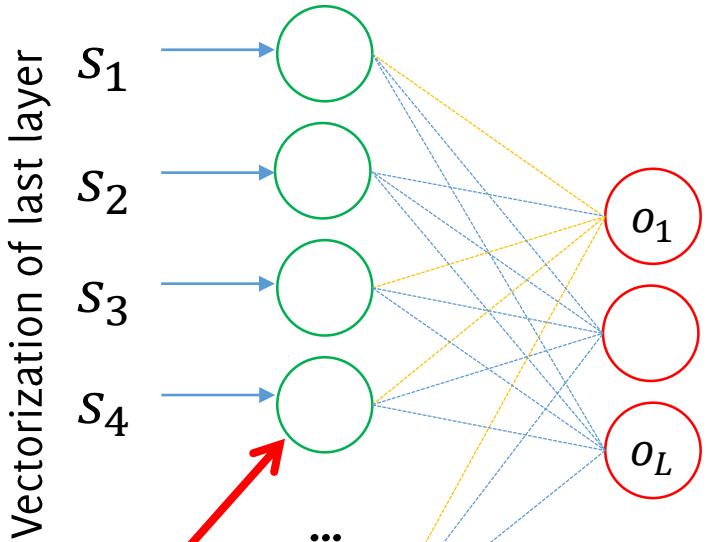
$$F_k = \frac{1}{N} \sum_{(x,y)} f_k(x,y)$$

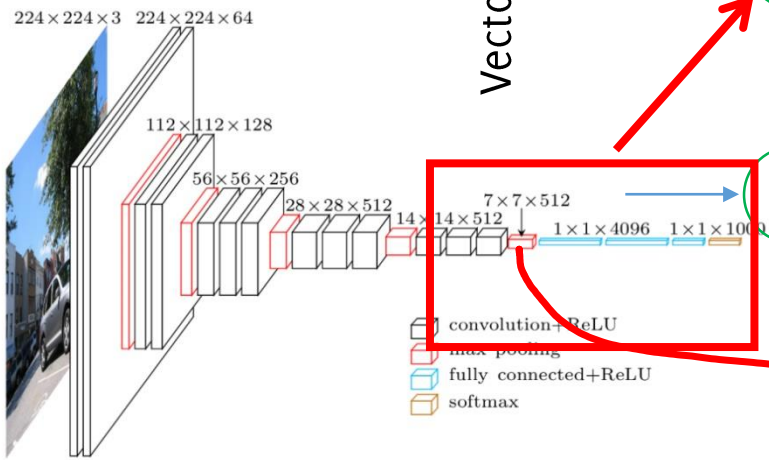
Lin, Min, Qiang Chen, and Shuicheng Yan. "Network in network." *ICLR 2014*

Network in Network

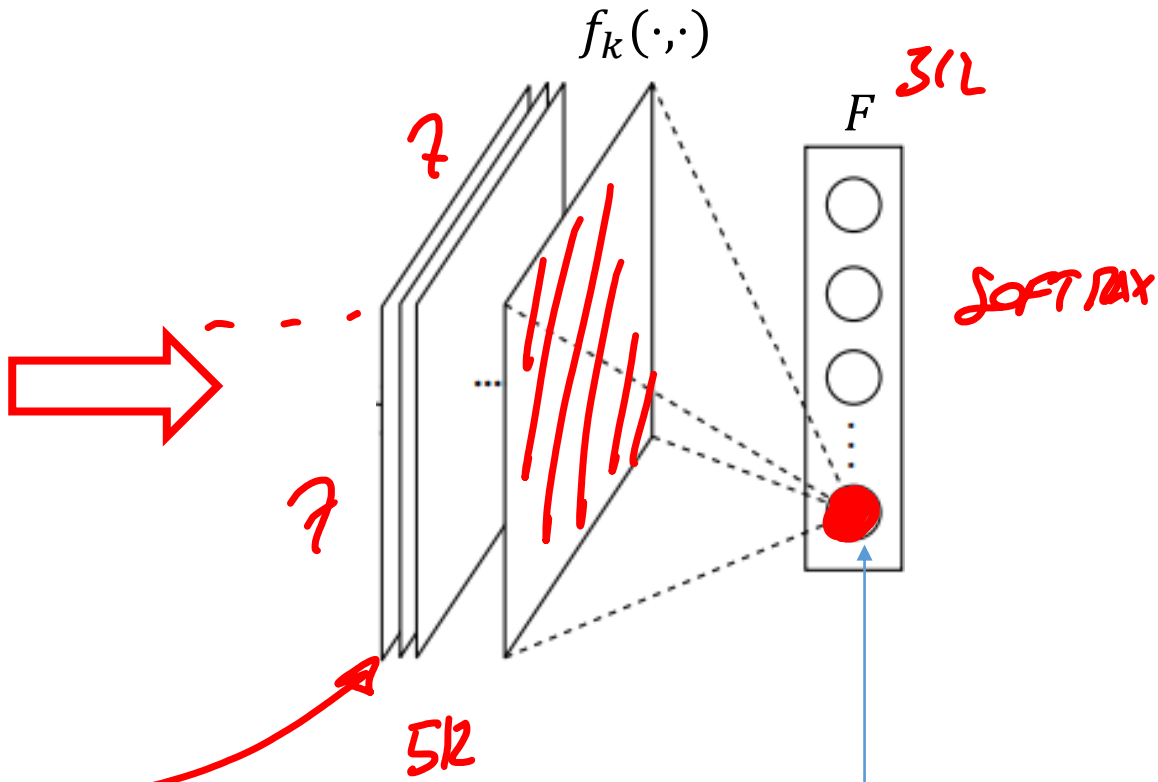
They also introduce Global Averaging Pooling Layers

Fully Connected Layer





GAP: Global Averaging Pooling Layer



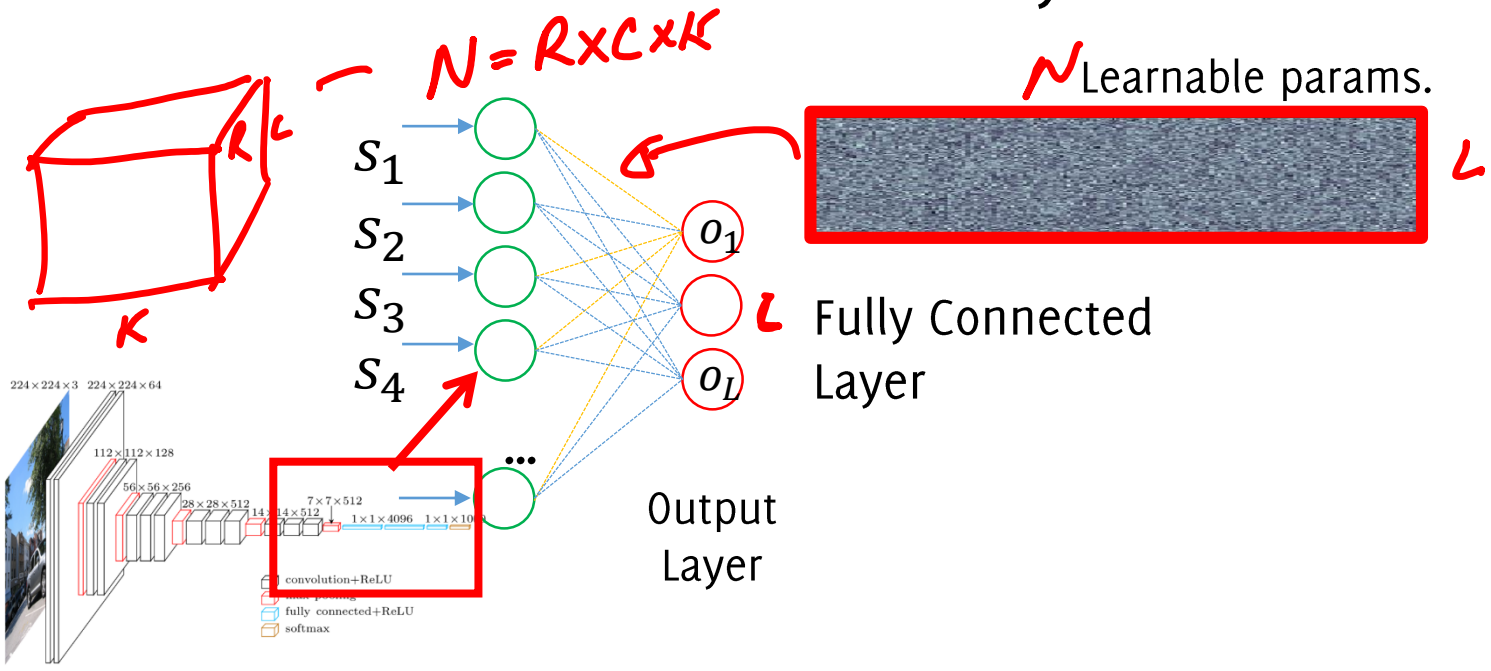
$$F_k = \frac{1}{49}\sum_{(x,y)} f_k(x,y)$$

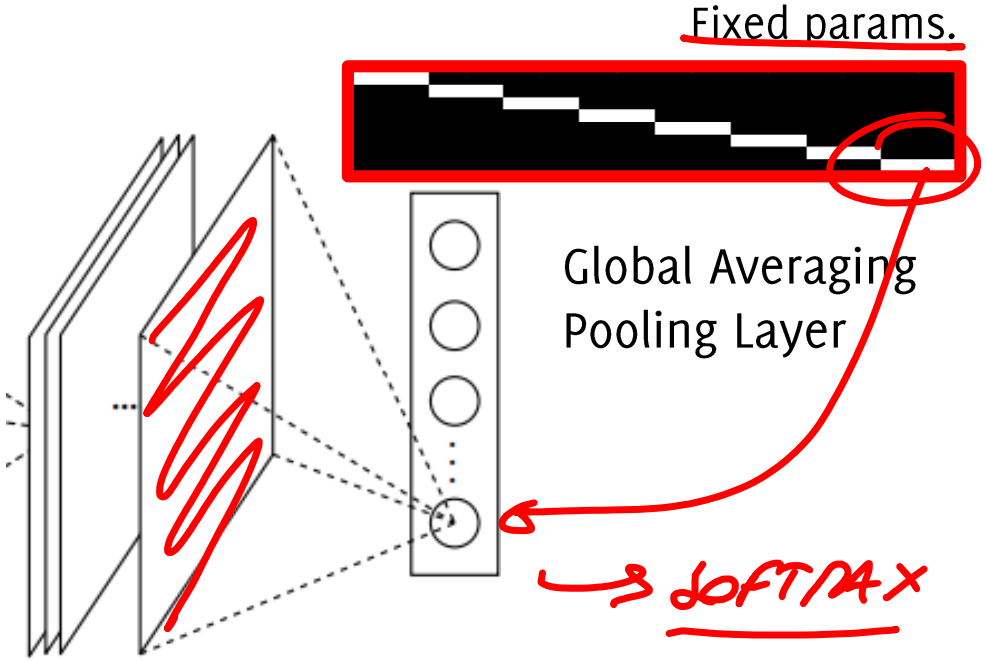
Lin, Min, Qiang Chen, and Shuicheng Yan. "Network in network." *ICLR 2014*

Network in Network: GAP

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

- The transformation corresponding **to GAP is a block diagonal, constant matrix** (consider the input unrolled layer-wise in a vector)
- The transformation of each layer in **MLP corresponds to a 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 regularized 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.**

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

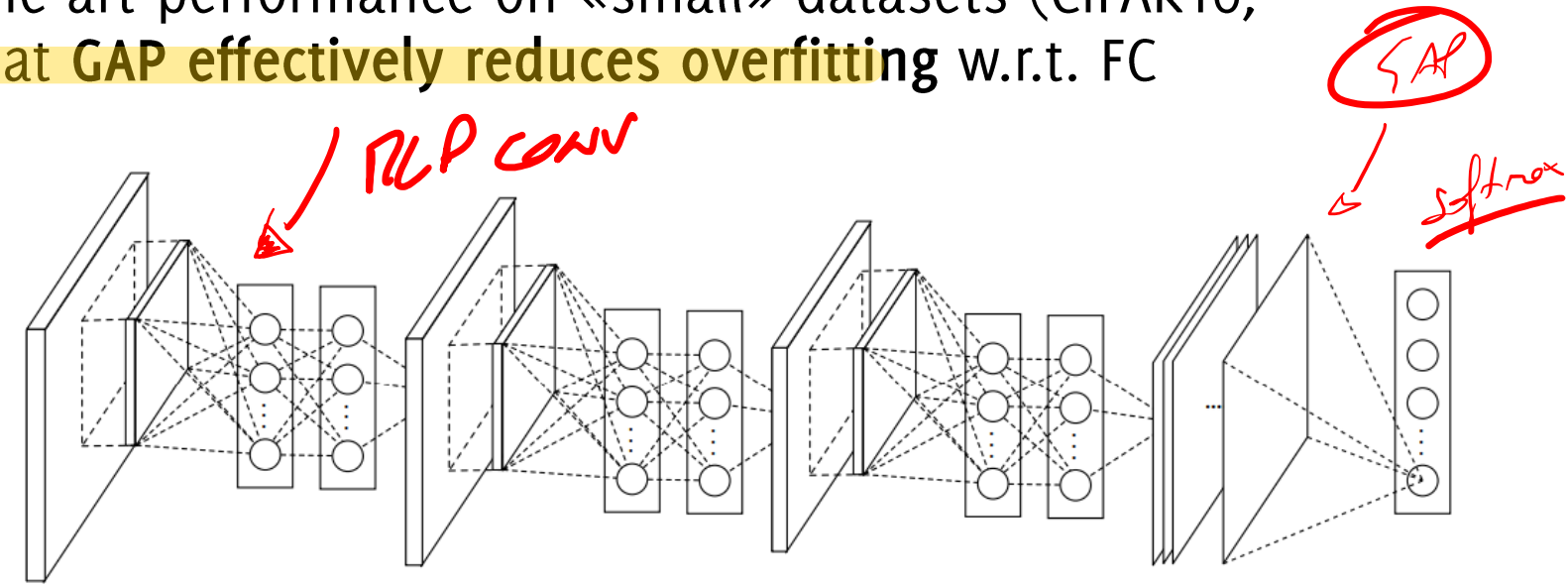
- mlpconv layers (RELU) + dropout
- Maxpooling

} 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

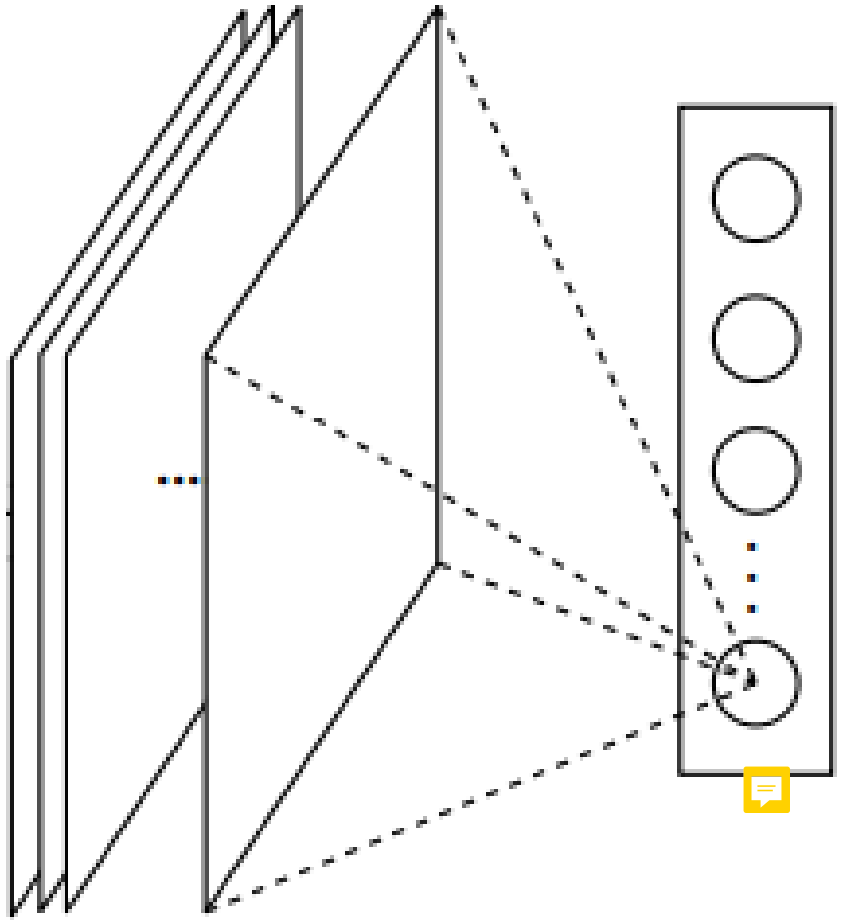


Lin, Min, Qiang Chen, and Shuicheng Yan. "Network in network." *ICLR 2014*

The Global Averaging Pooling (GAP) Layer

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

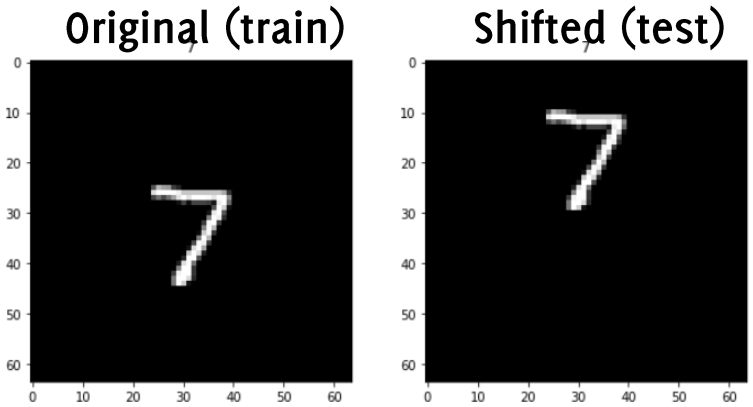
Method	Testing Error
mlpconv + Fully Connected	11.59%
mlpconv + Fully Connected + Dropout	10.88%
mlpconv + Global Average Pooling	10.41%



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 and the two images lead to the same or very similar features

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 same 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

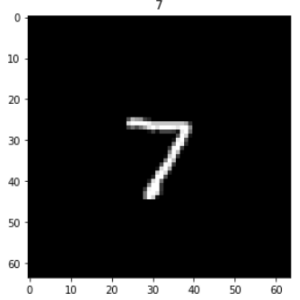
Credits Eugenio Lomurno

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
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

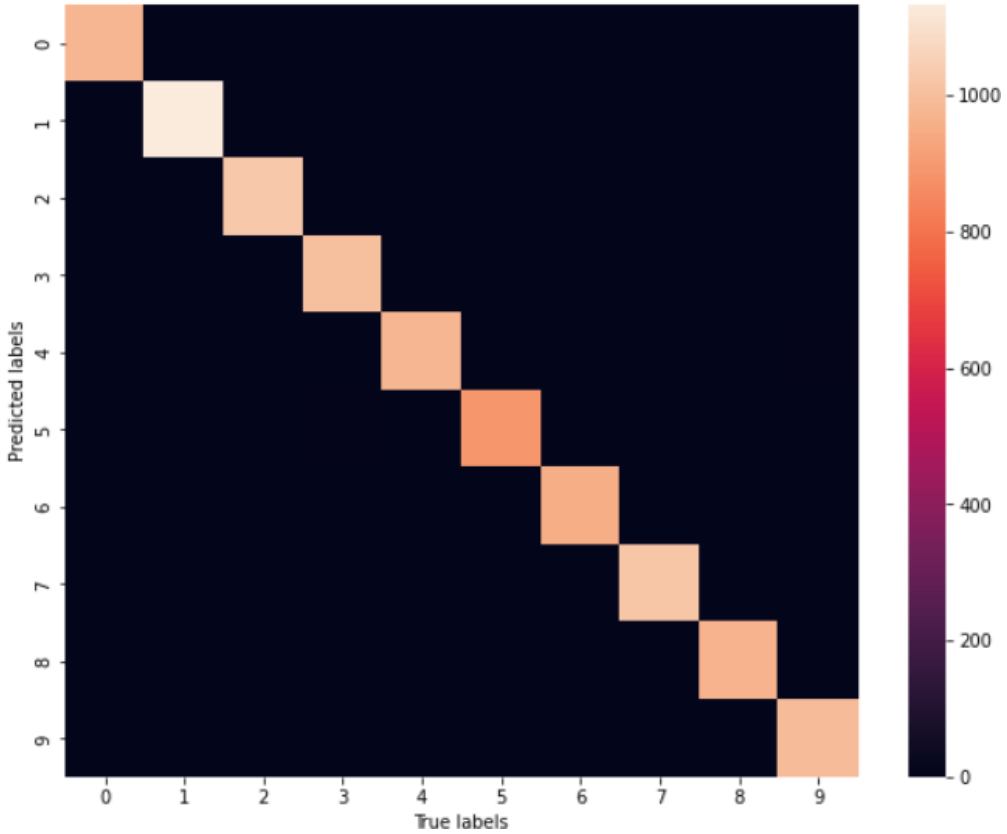
Total params: 101,578
Trainable params: 101,578
Non-trainable params: 0

Accuracy over Original Test Set



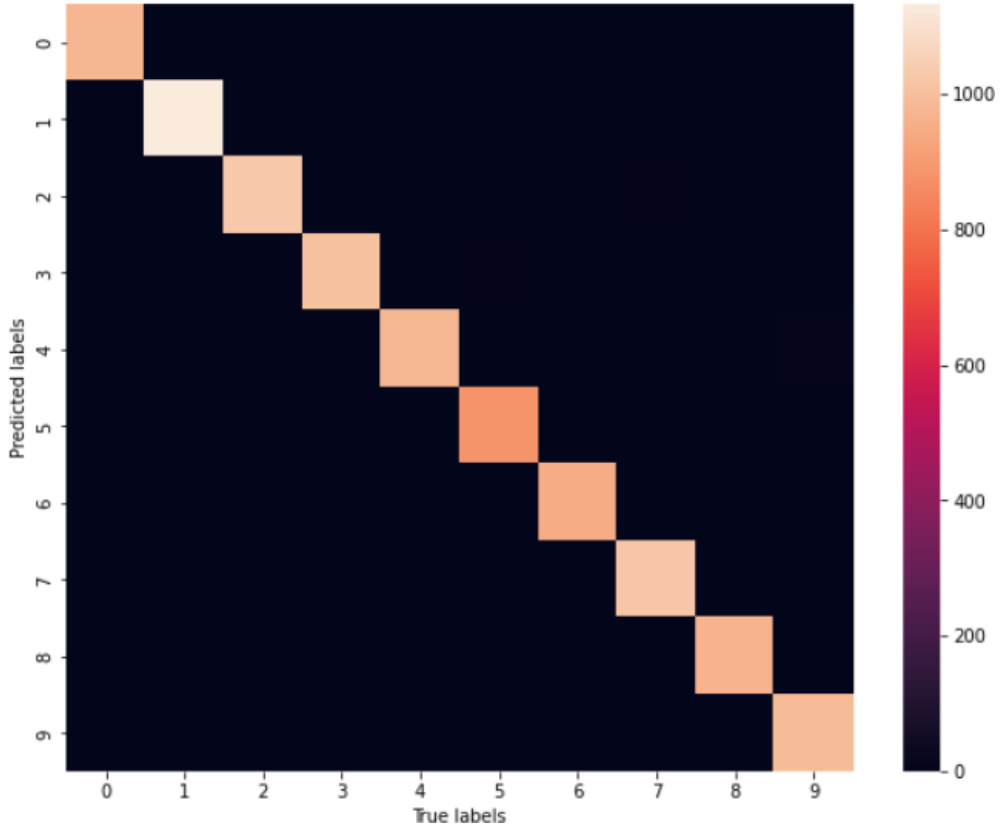
CNN-flattening:

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



CNN-GAP

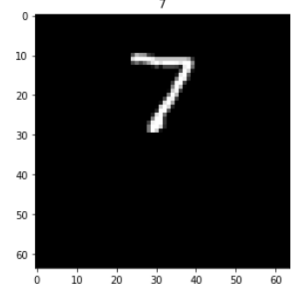
Accuracy: 0.9934
Precision: 0.9934
Recall: 0.9933
F1: 0.9933



Credits Eugenio Lomurno

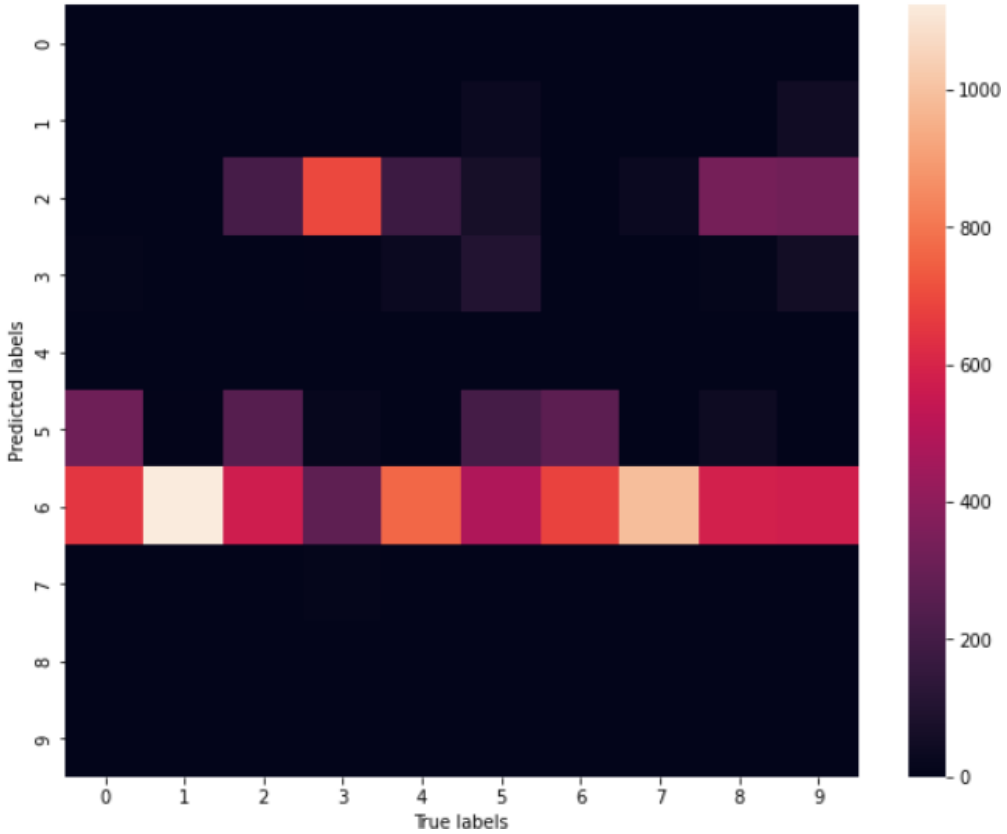
G. Boracchi

Accuracy over Shifted Test Set



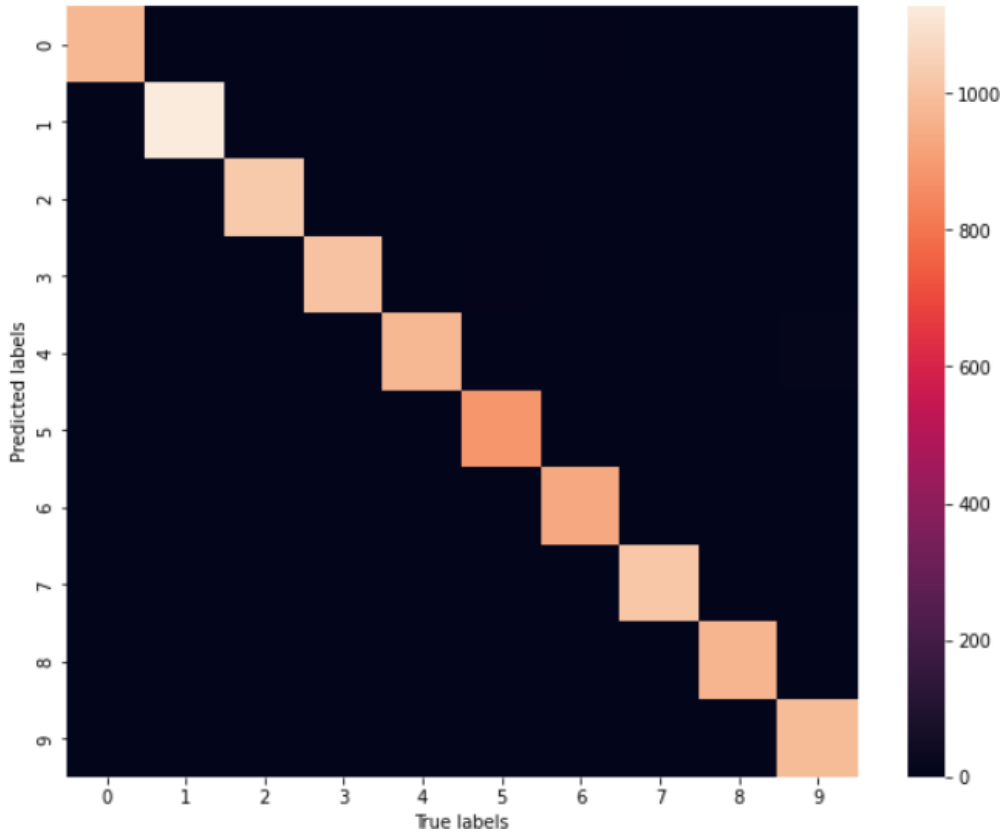
CNN-flattening:

```
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
```



Credits Eugenio Lomurno

G. Boracchi

https://colab.research.google.com/drive/1s108-oylignuFBNTscfj9ZgDymi5sU0X?usp=sharing

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

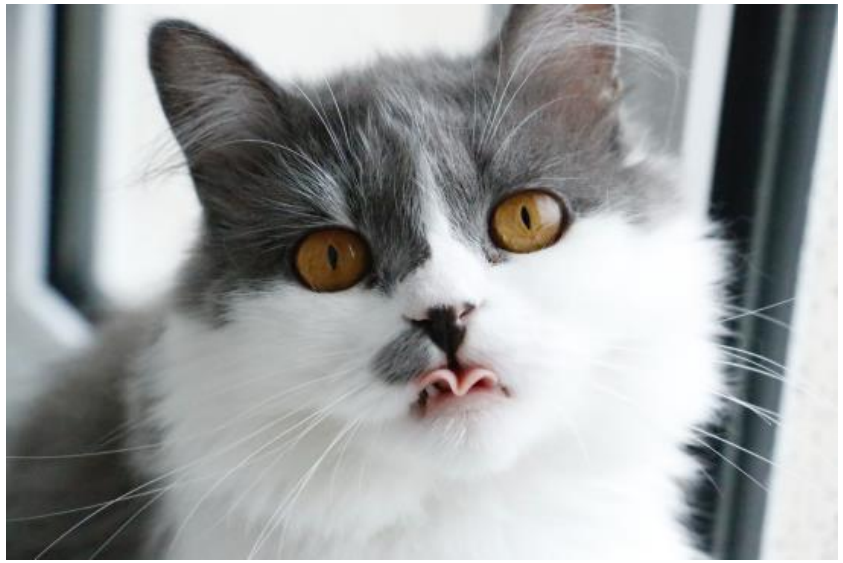
dramatically increase in the use of computational resources

Moreover image features might appear at different scale, 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

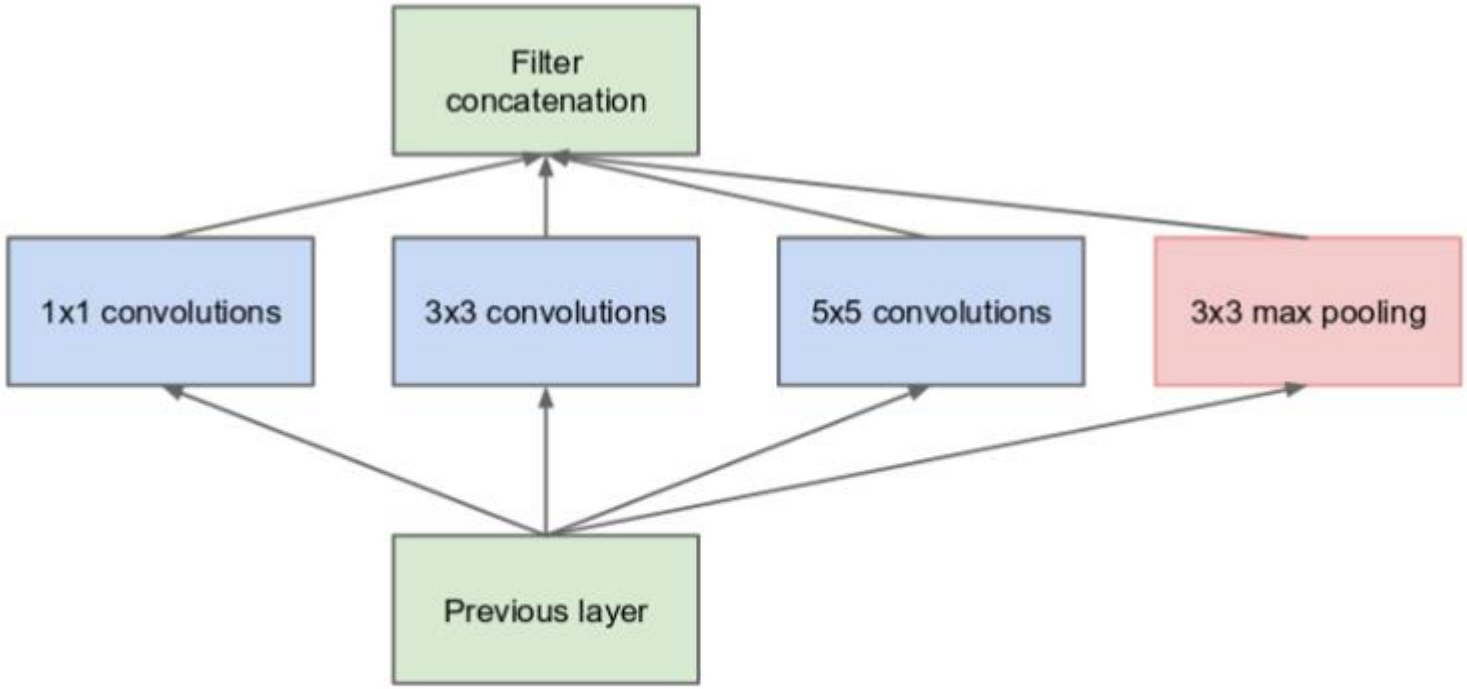
Won 2014 ILSVR-classification challenge (6,7% top 5 classification error)

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

GoogLeNet and Inception v1 (2014)

It is based on inception modules, which are sort of «networks inside the network» or «local modules»

Concatenation preserves spatial resolution



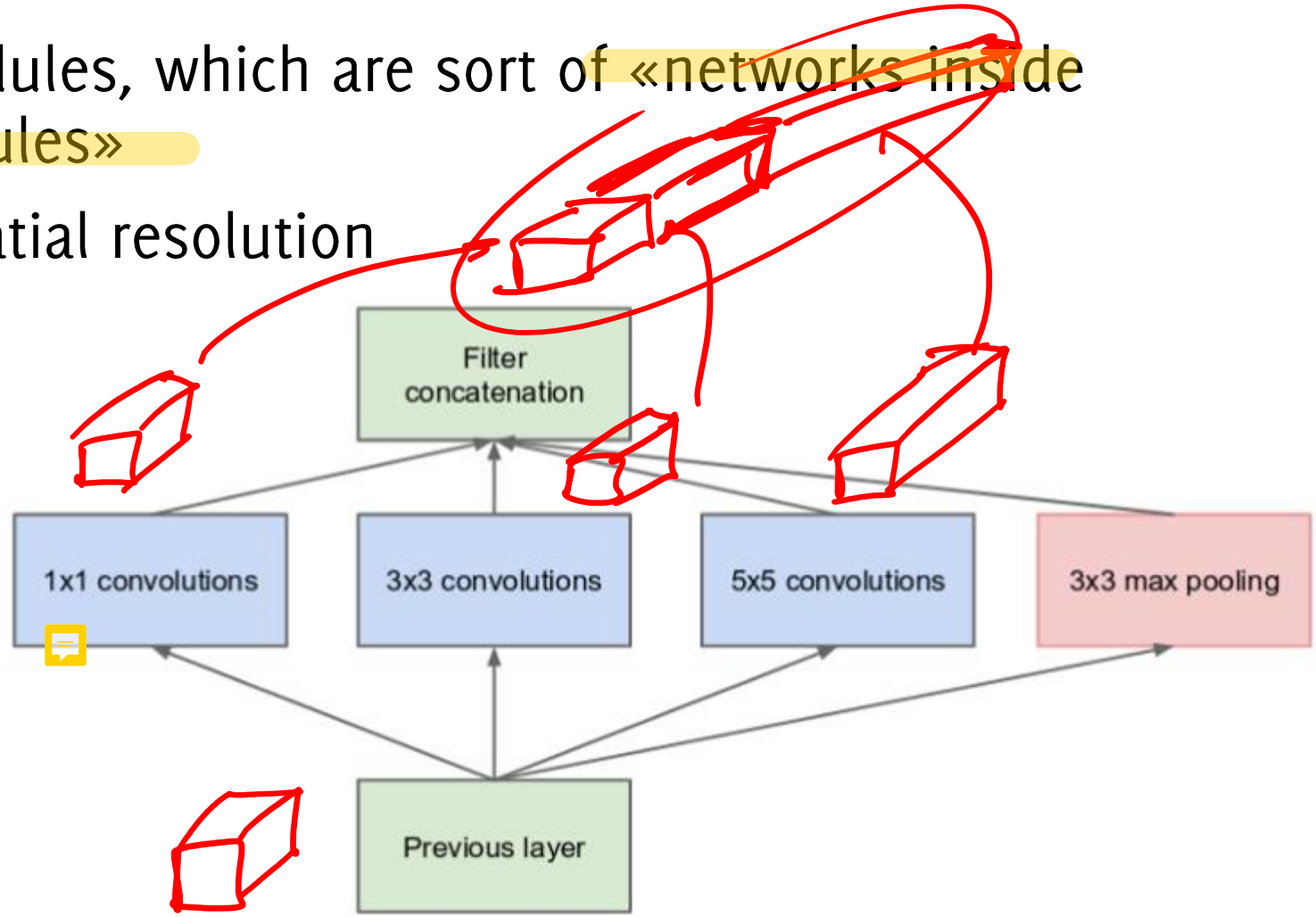
(a) Inception module, naïve version

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

GoogLeNet and Inception v1 (2014)

It is based on inception modules, which are sort of «networks inside the network» or «local modules»

Concatenation preserves spatial resolution



(a) Inception module, naïve version

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

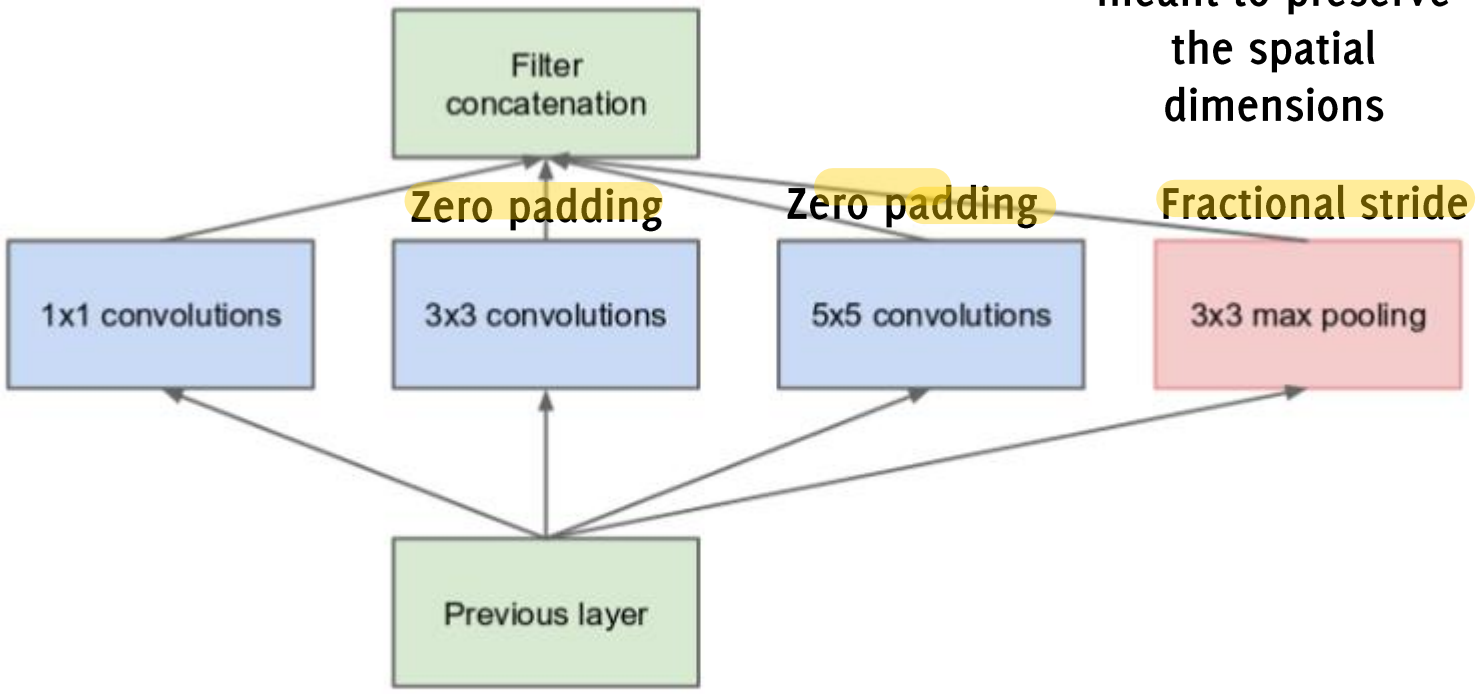
Inception Module (2014)

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

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

Fractional strides are meant to preserve the spatial dimensions



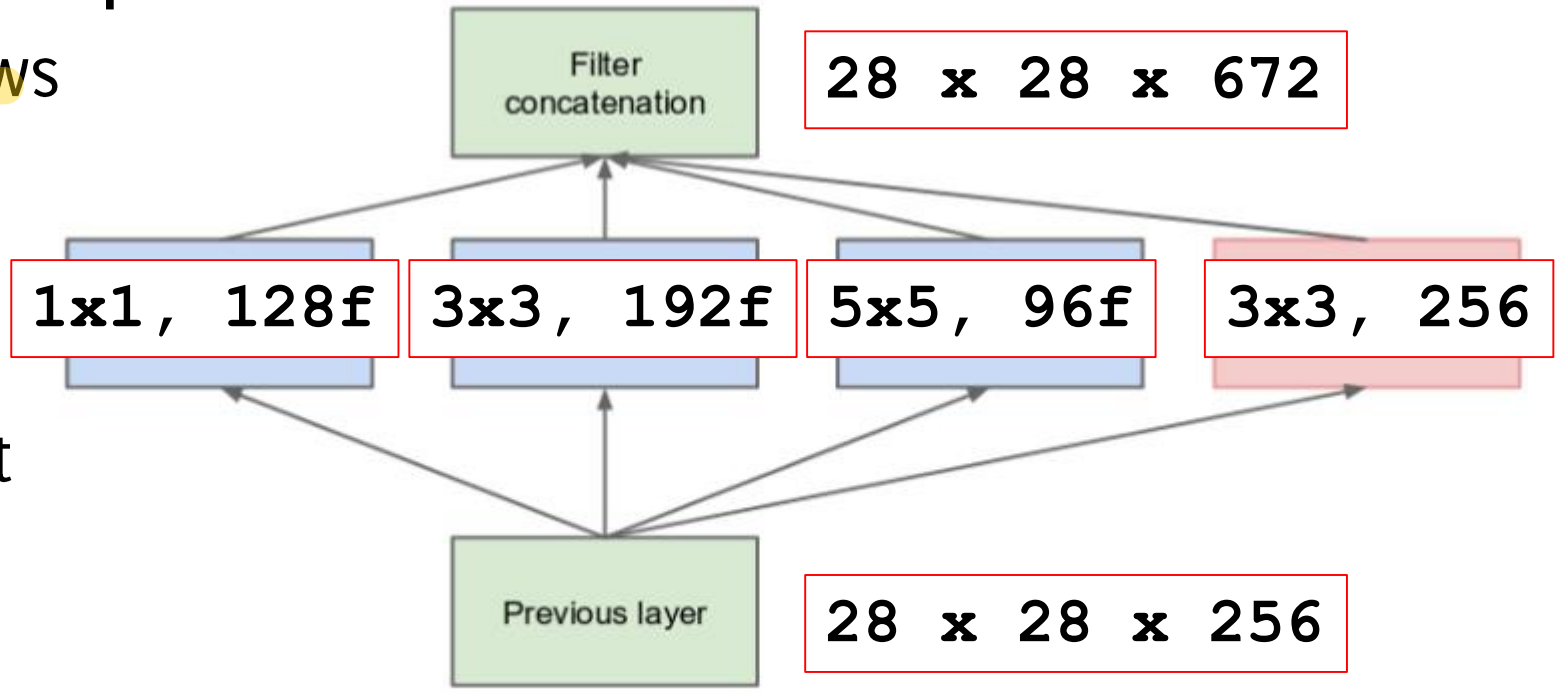
(a) Inception module, naïve version

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

- **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

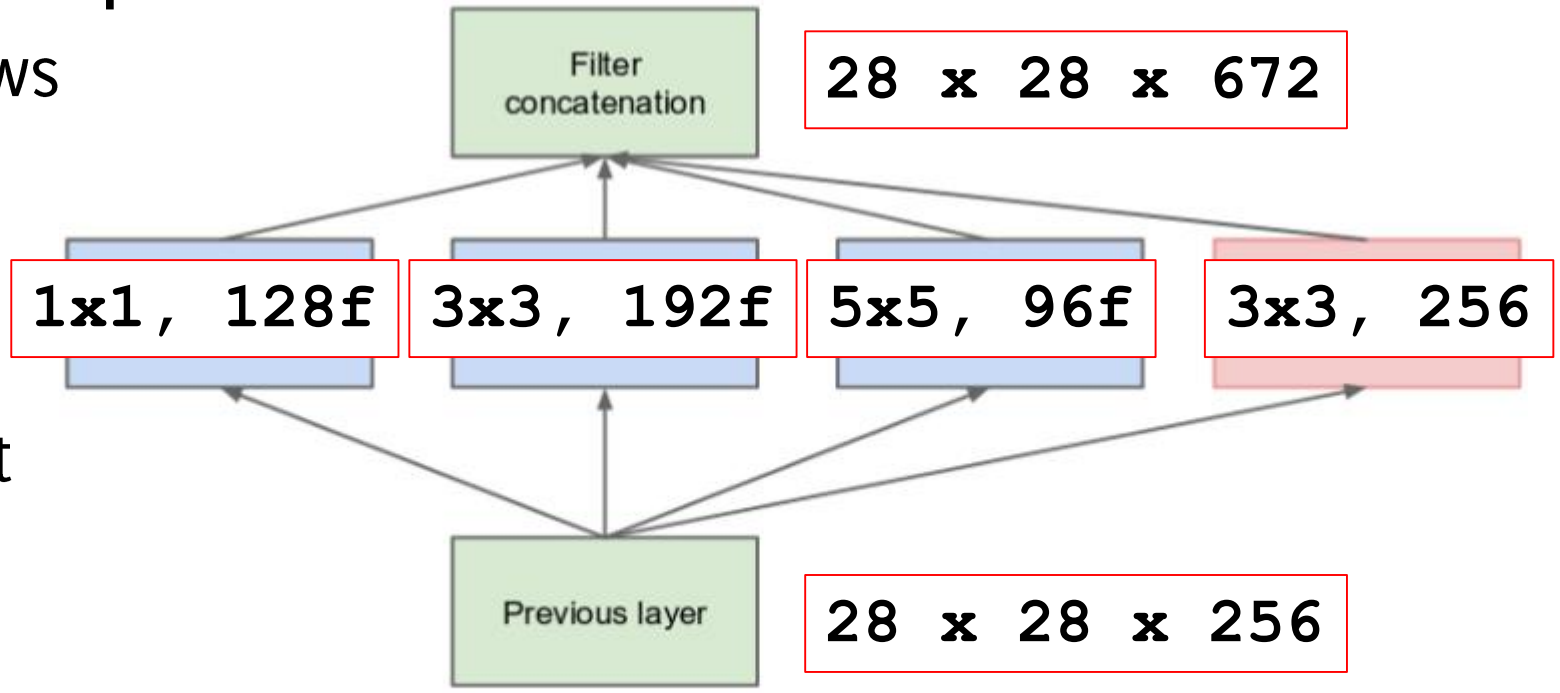
Szegedy et al. "Going deeper with convolutions." *CVPR 2015*

Inception Module (2014)

The sol… 3x3, 5x5) an… togethe…

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

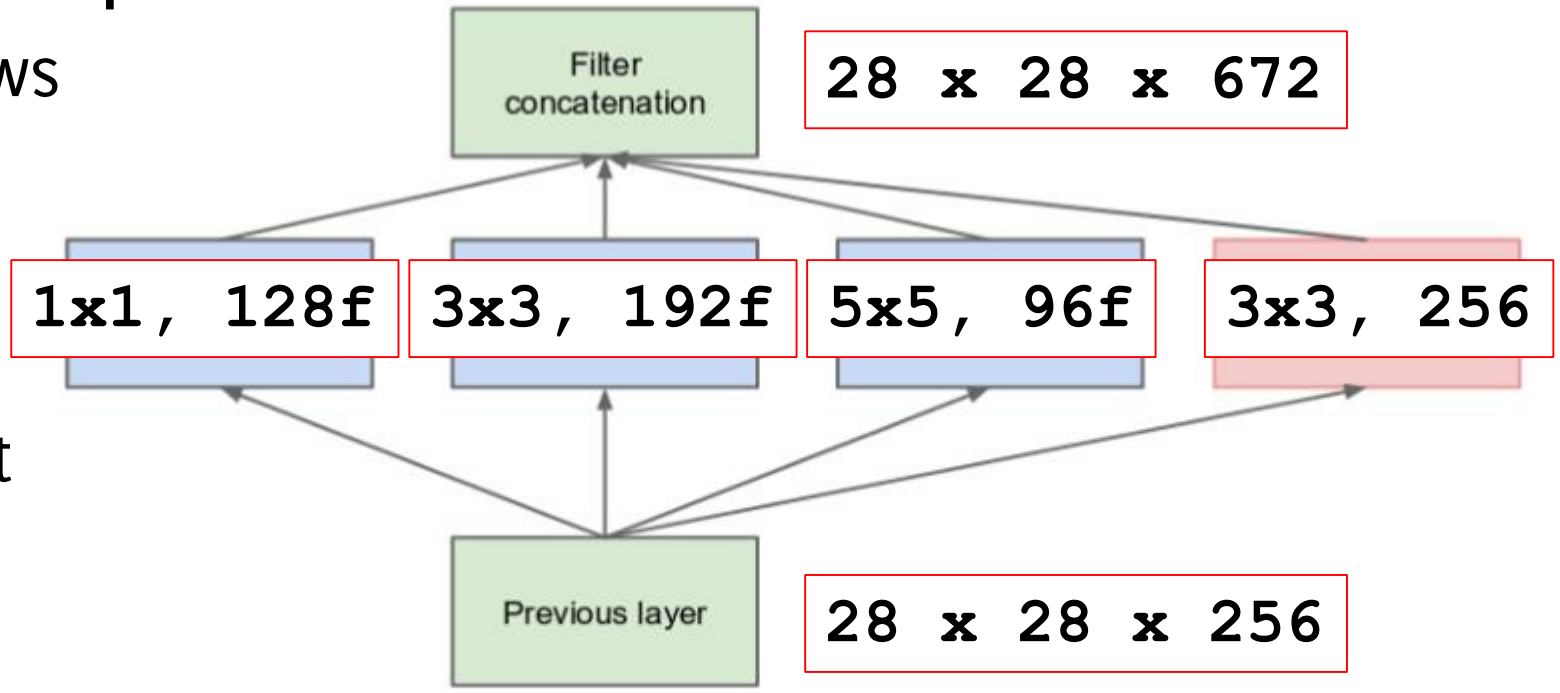
Szegedy et al. "Going deeper with convolutions." *CVPR 2015*

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



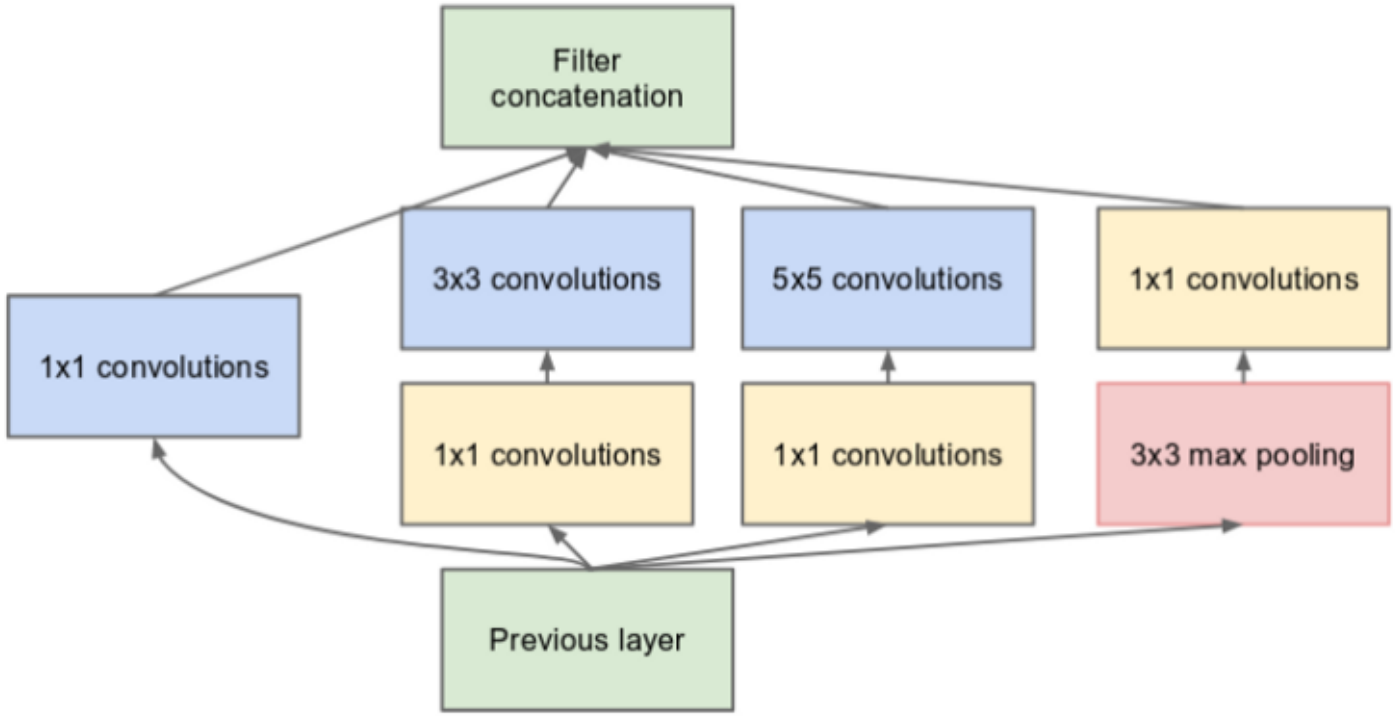
(a) Inception module, naïve version

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

Inception Module (2014)

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

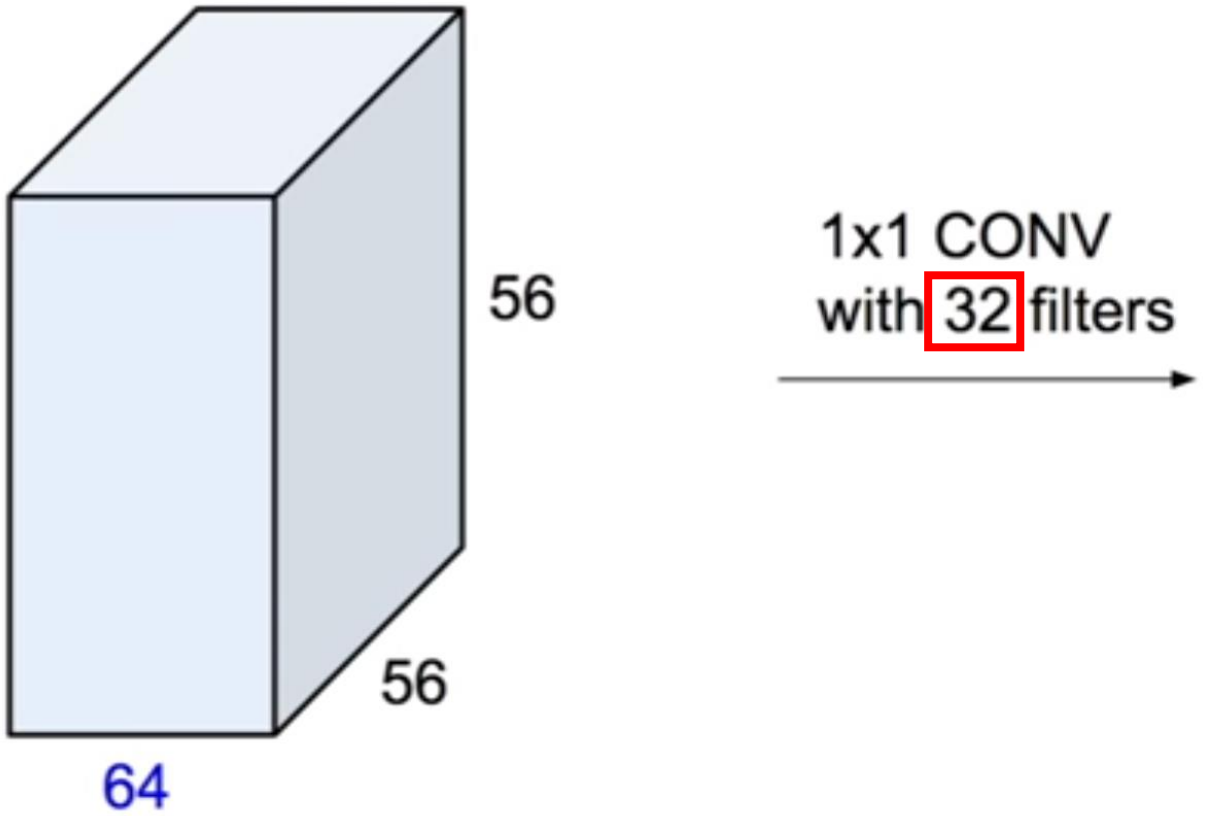
Using these 1x1 conv is referred to as "**bottleneck" layer**



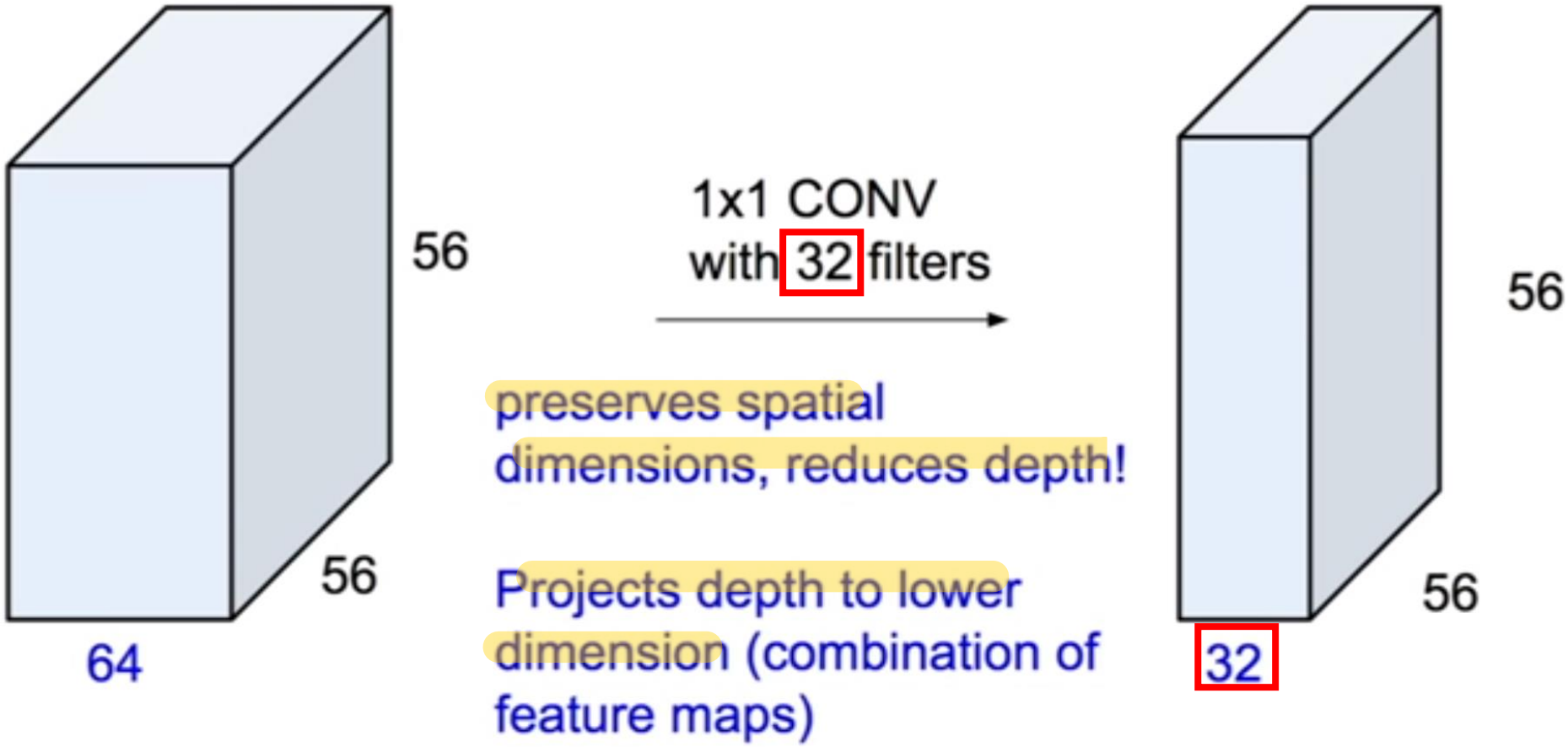
(b) Inception module with dimension reductions

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

1x1 convolution layers as bottleneck



1x1 convolution layers as bottleneck

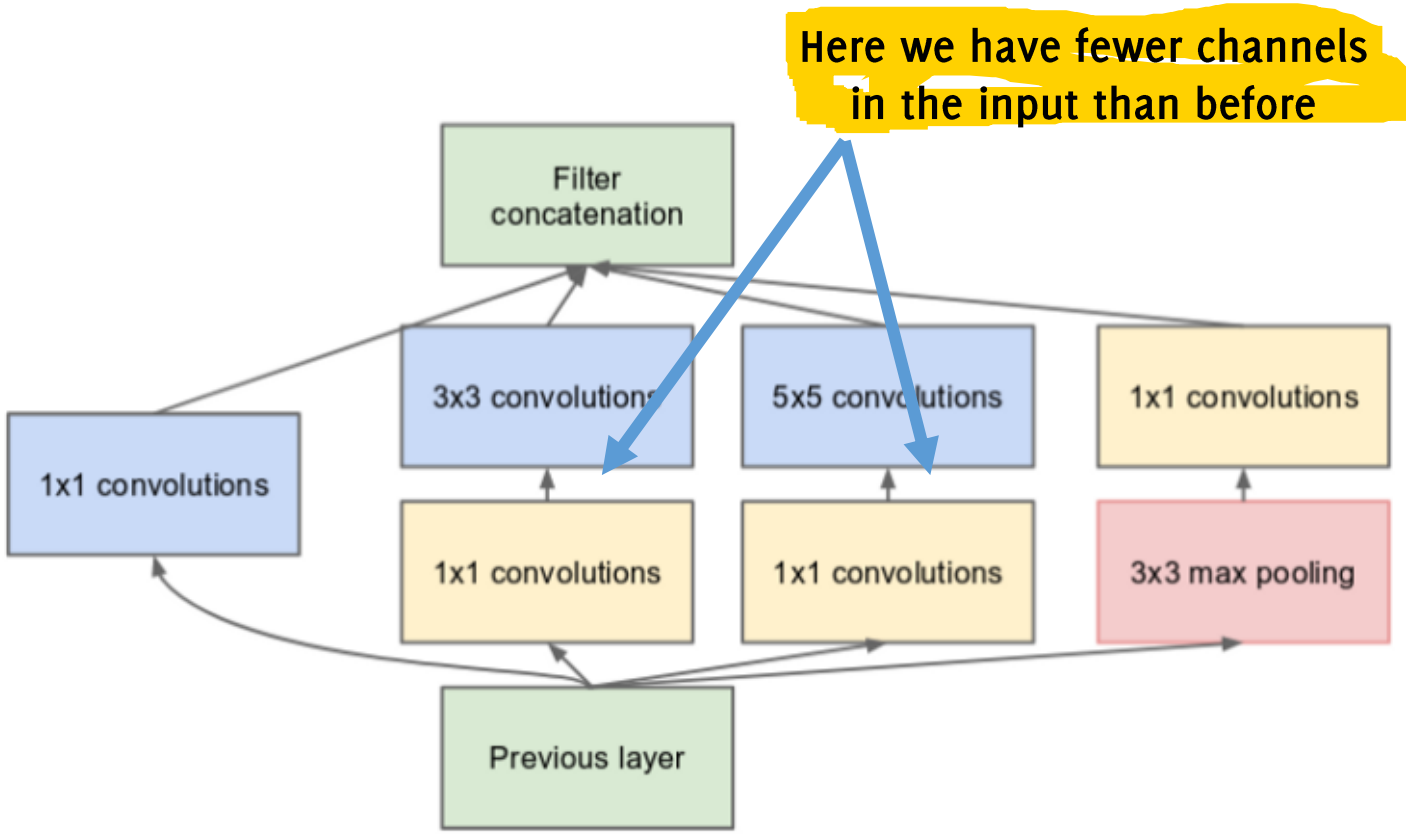


Inception Module (2014)

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



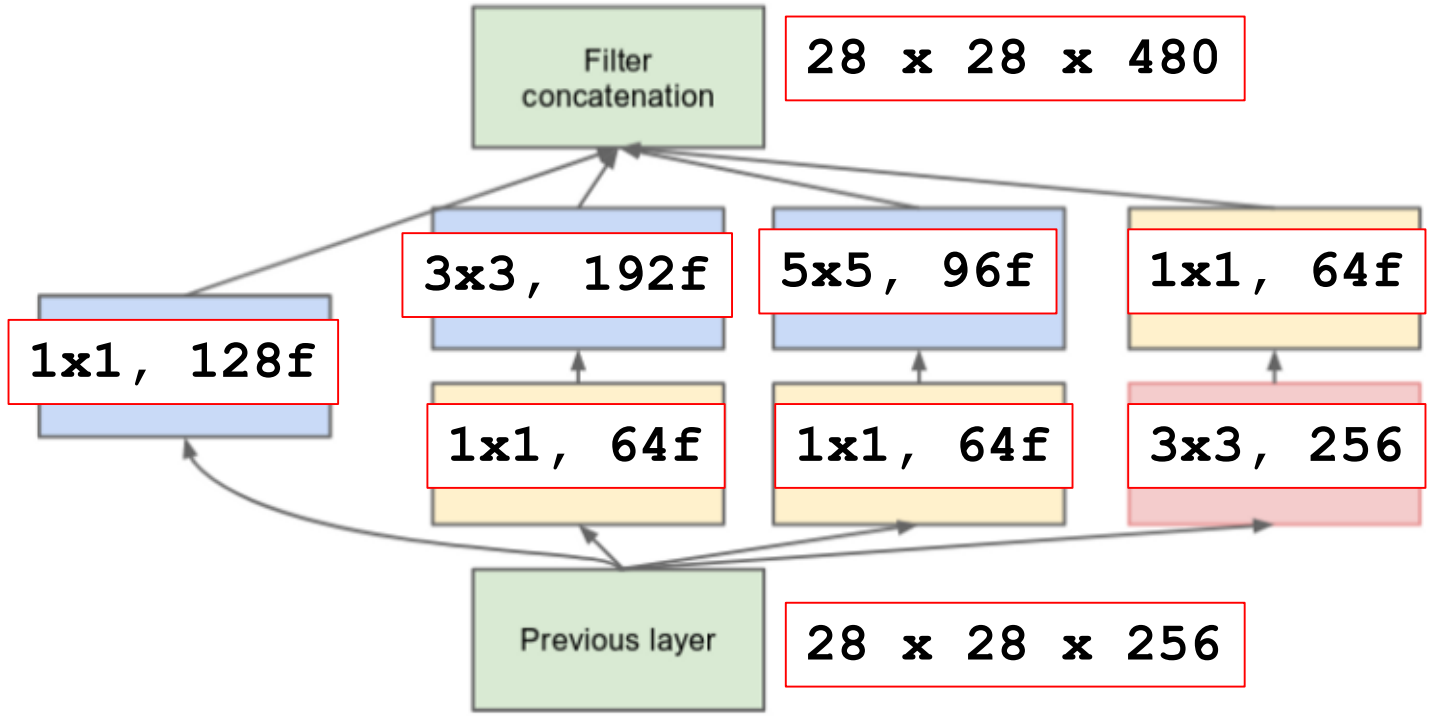
(b) Inception module with dimension reductions

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

Inception Module (2014)

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



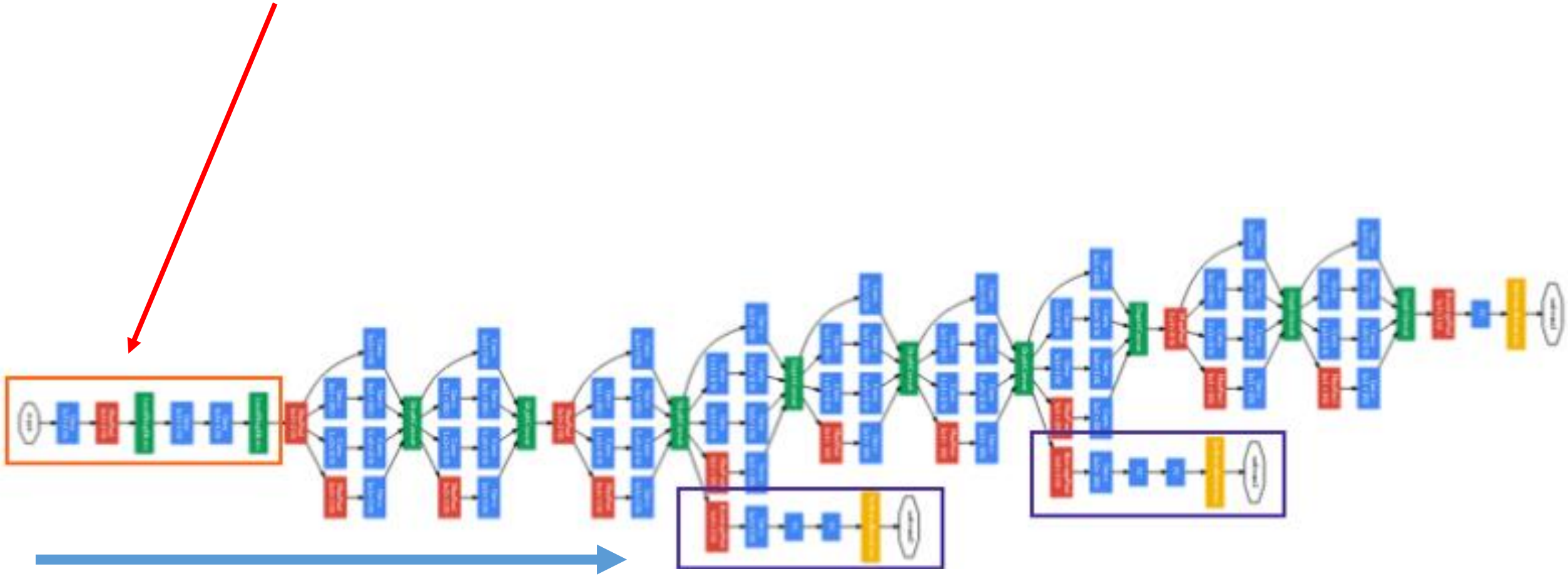
(b) Inception module with dimension reductions

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

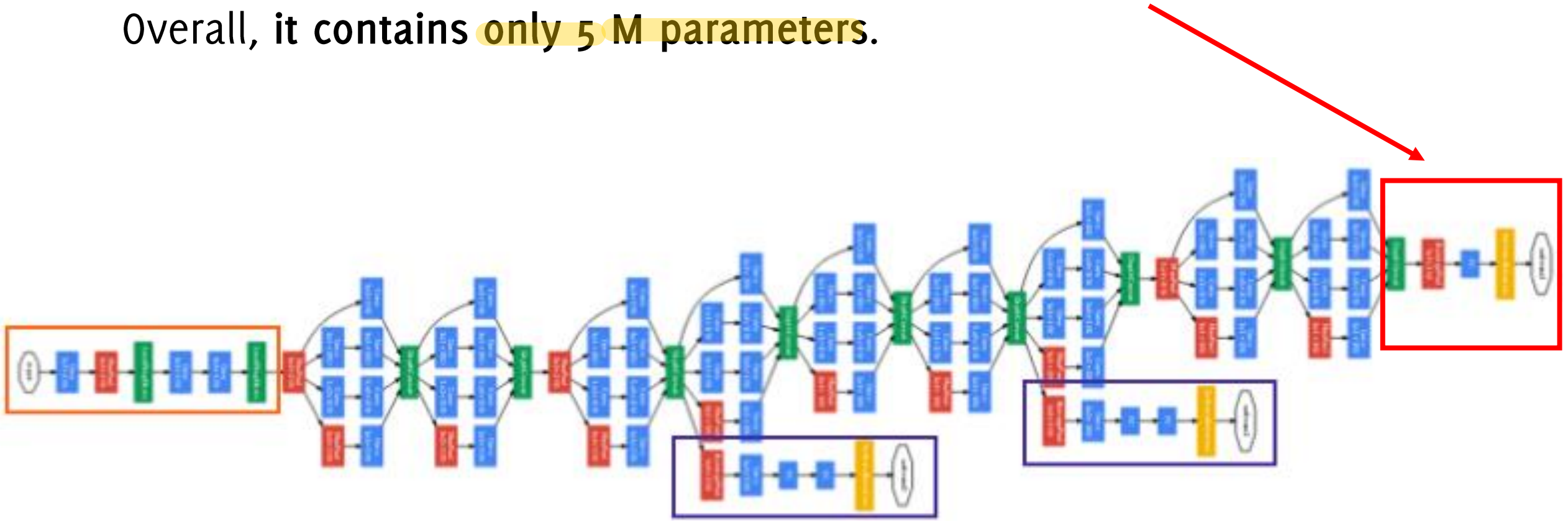
Szegedy et al. "Going deeper with convolutions." *CVPR 2015*

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**.

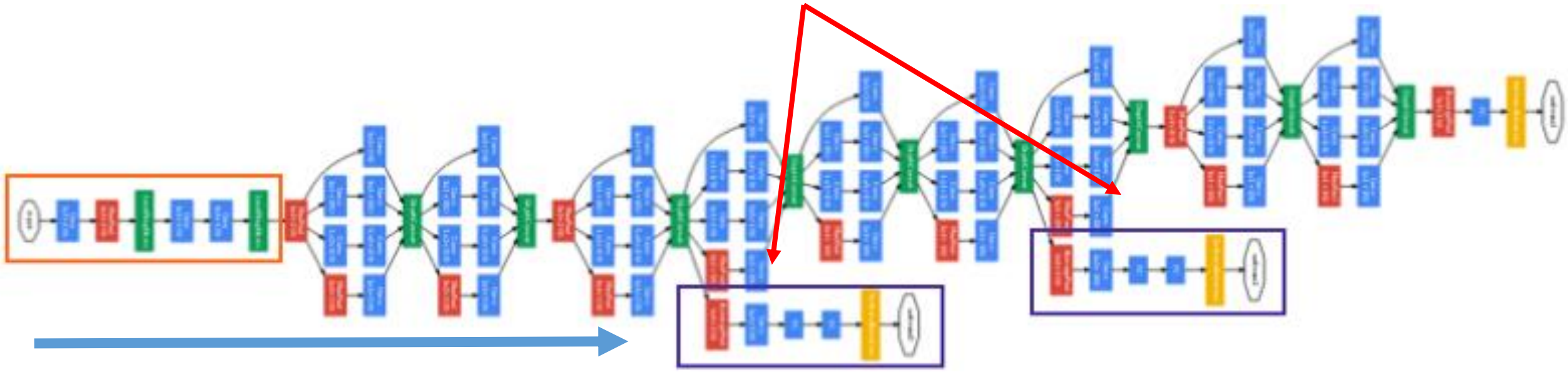


Szegedy et al. "Going deeper with convolutions." *CVPR 2015*

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.



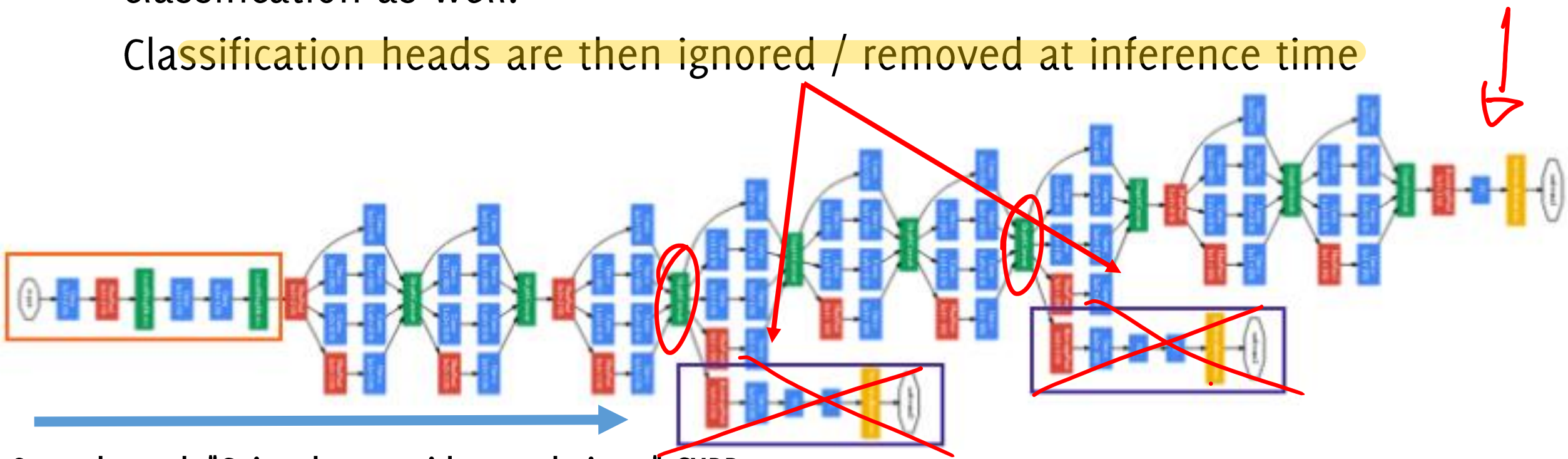
Szegedy et al. "Going deeper with convolutions." *CVPR 2015*

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*

Deep Residual Learning for Image Recognition

Kaiming He Xiangyu Zhang Shaoqing Ren Jian Sun
Microsoft Research
{kahe, v-xiangz, v-shren, jiansun}@microsoft.com

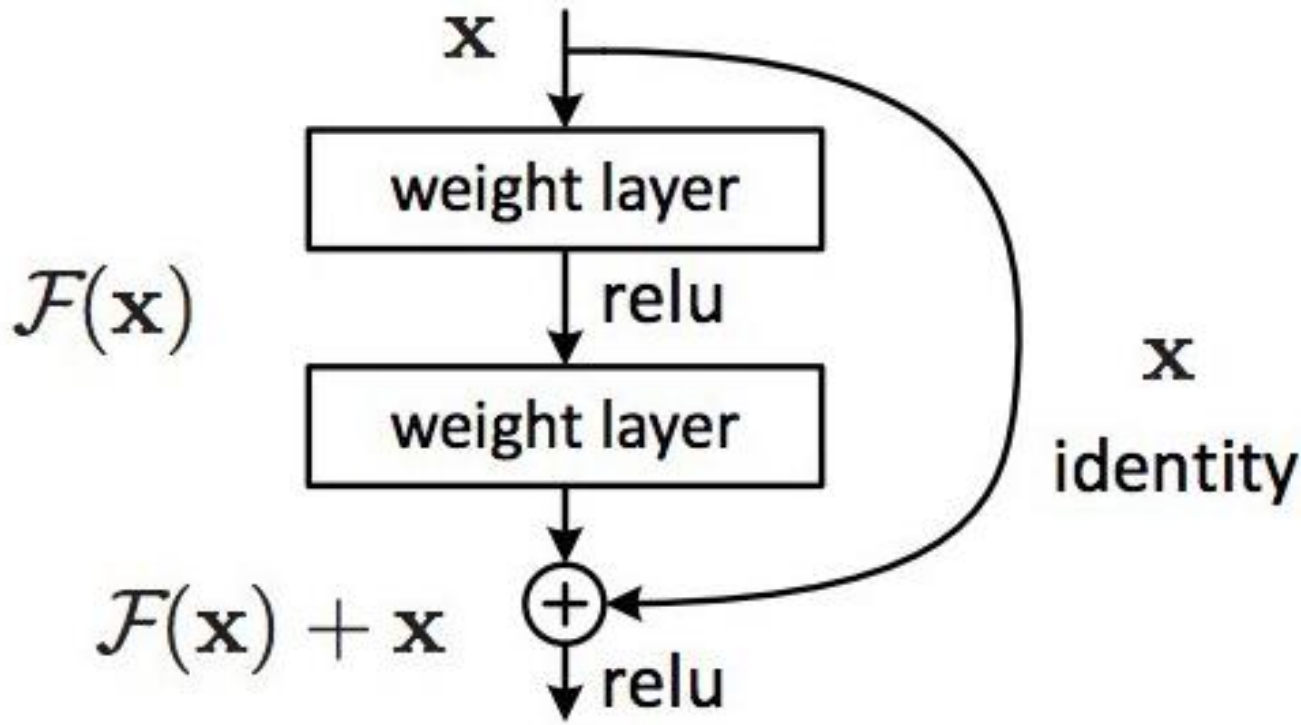
ResNet (2015)

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***

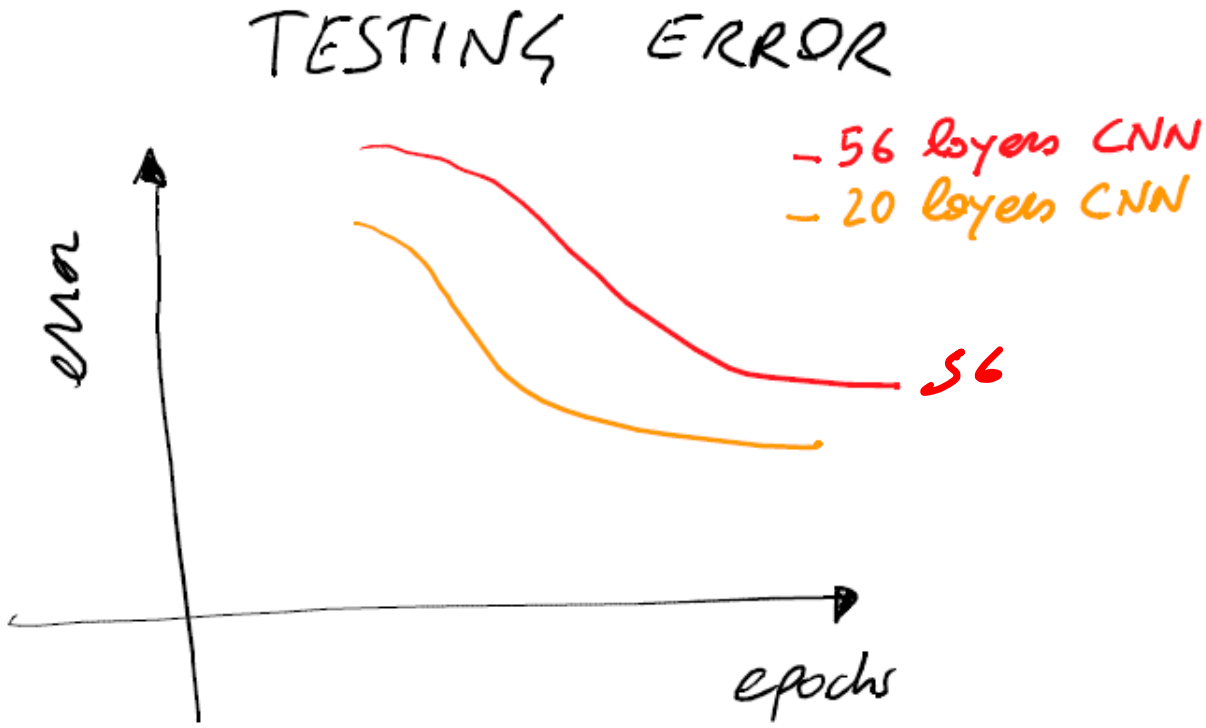
The main investigation was:
is it possible to continuosly improve accuracy by stacking more and more layers



Kaiming He, et al. "Deep Residual Learning for Image Recognition“ CVPR 2016

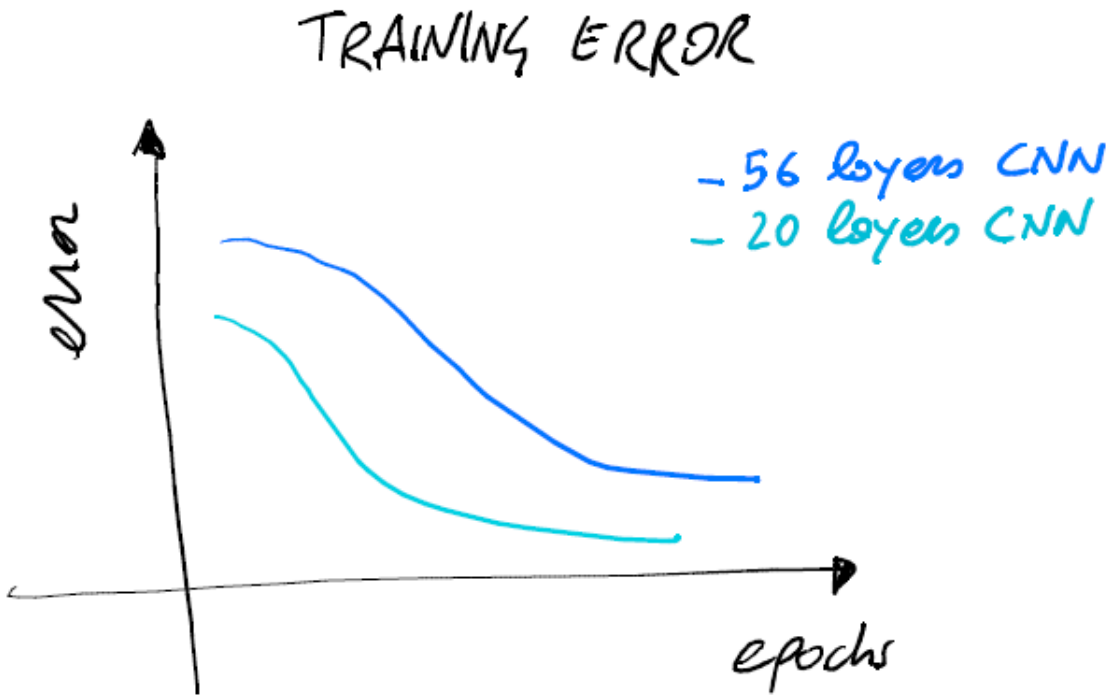
ResNet (2015): The rationale

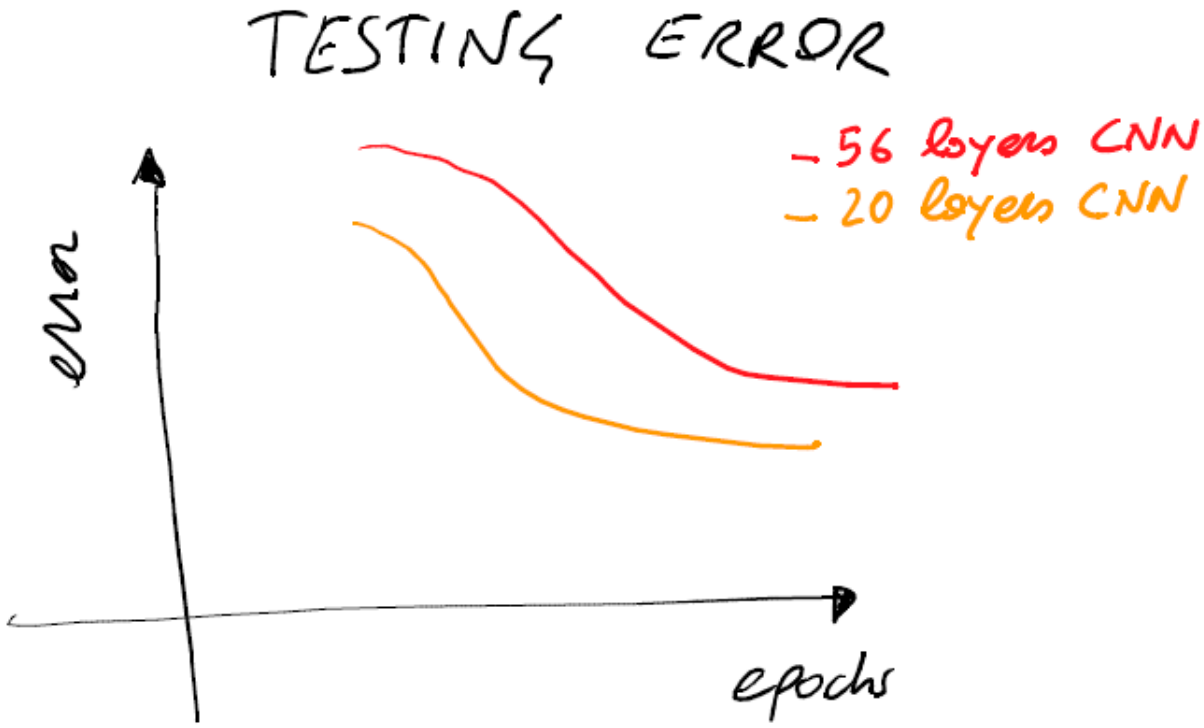
Increasing the network depth, by stacking an increasingly number of layers, **does not always improve performance**



ResNet (2015): The rationale

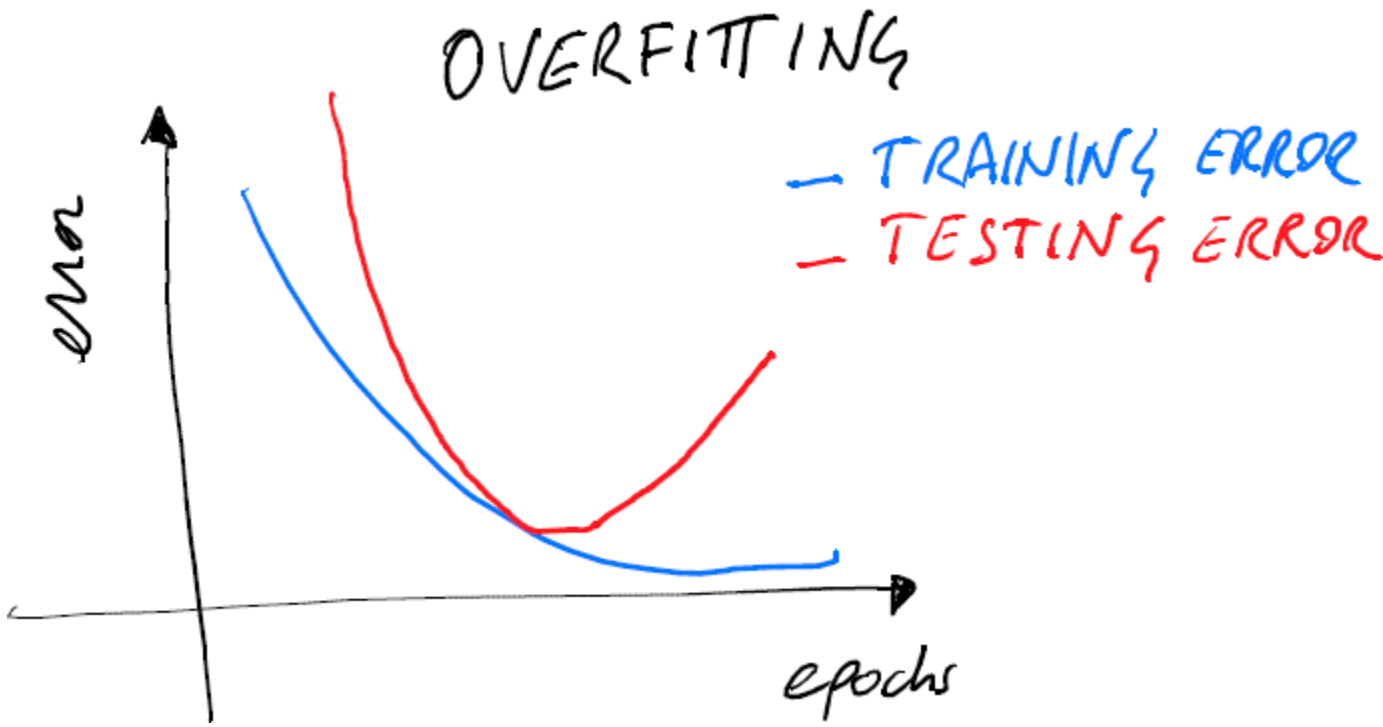
But **this is not due to overfitting**, since the same trend is shown in the training error





ResNet (2015): The rationale

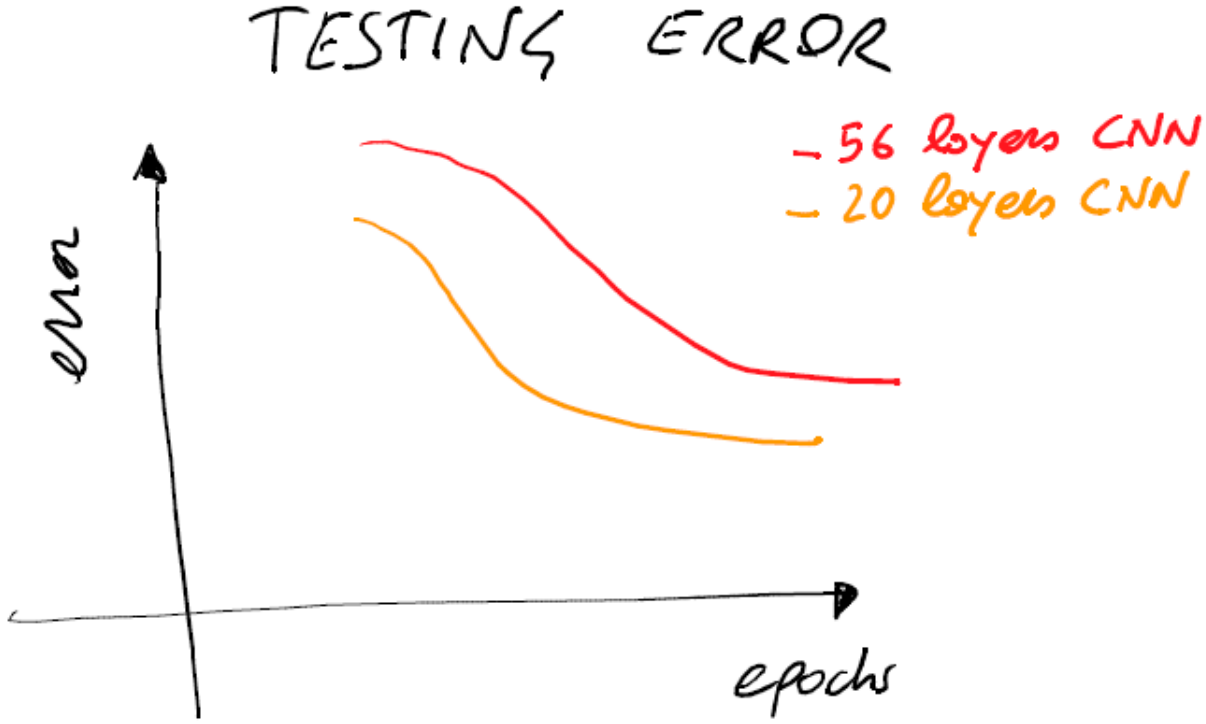
But **this is not due to overfitting**, since the same trend is shown in the training error, while for overfitting we have that training and test error diverge



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**.



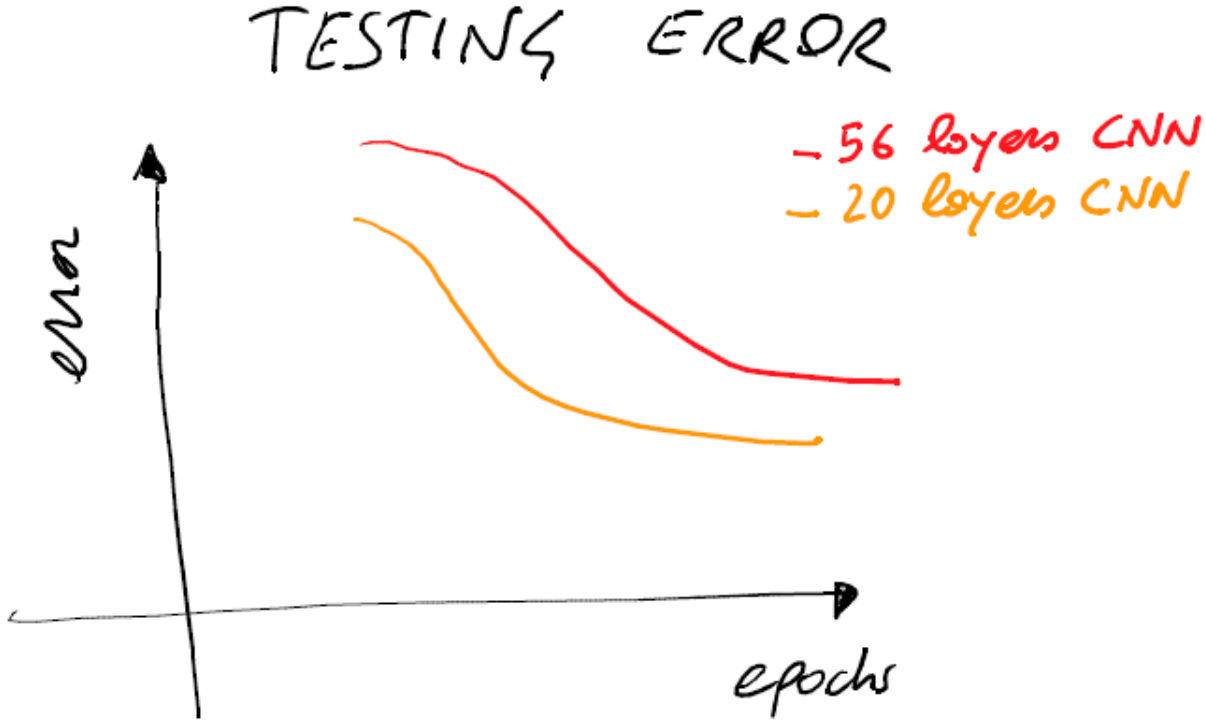
ResNet (2015): the intuition

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

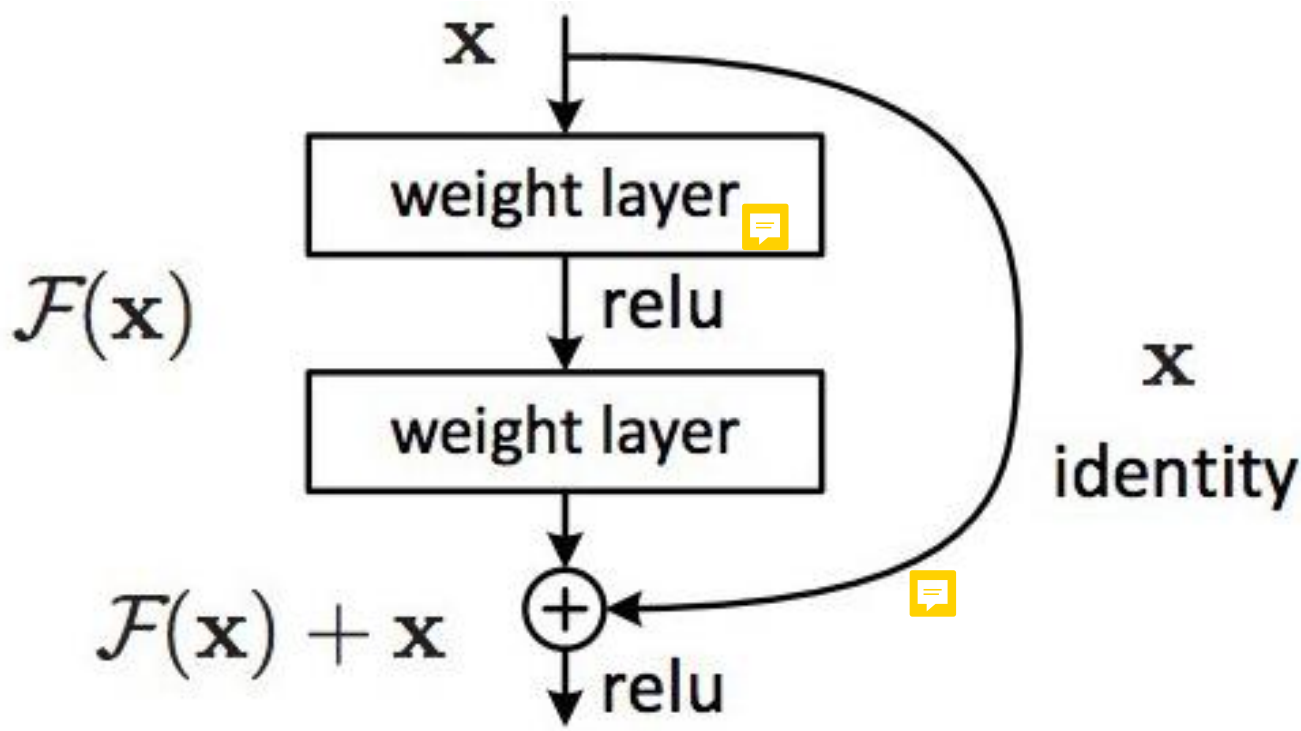
Since the experimental evidence, is different **the identity function is not easy to learn!**



ResNet: Very deep by residual connections

Adding an "identity shortcut connection":

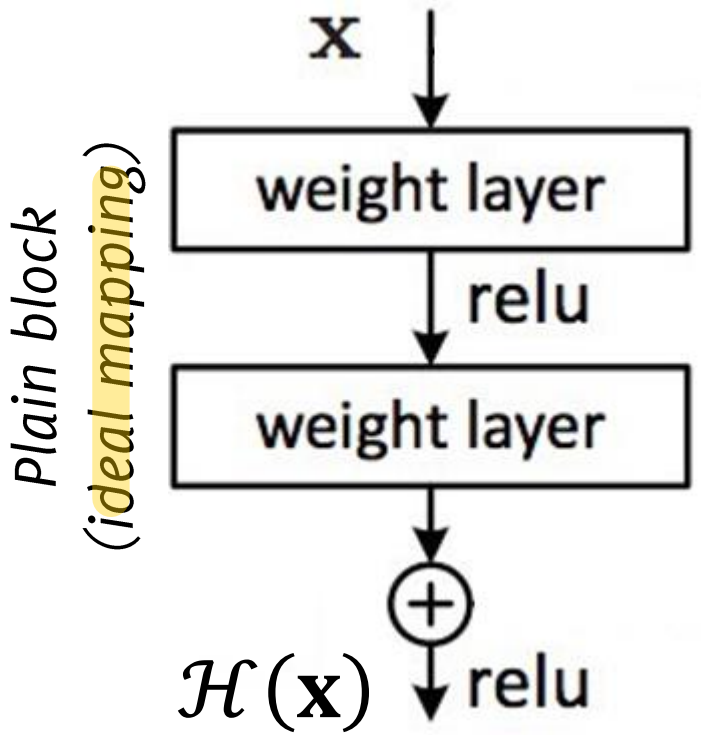
- helps in **mitigating the vanishing gradient problem** and enables deeper architectures
- Does not add parameters
- In case the **previous network was optimal**, the **weights to be learned goes to zero** and information is propagated by the identity
- The network can still be trained through back-propagation

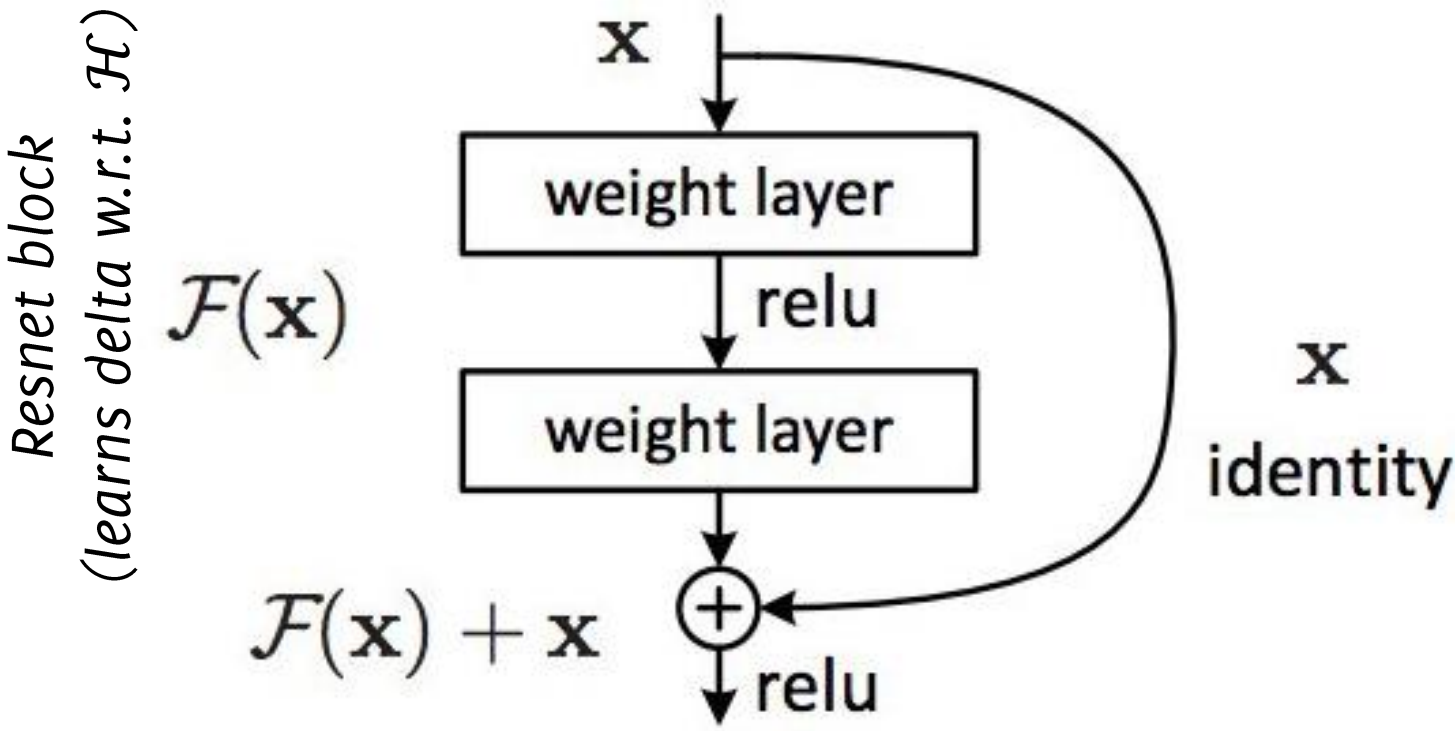


Kaiming He, et al. "Deep Residual Learning for Image Recognition" CVPR 2016

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 $\mathcal{F}(\mathbf{x}) = \mathcal{H}(\mathbf{x}) - \mathbf{x}$.**

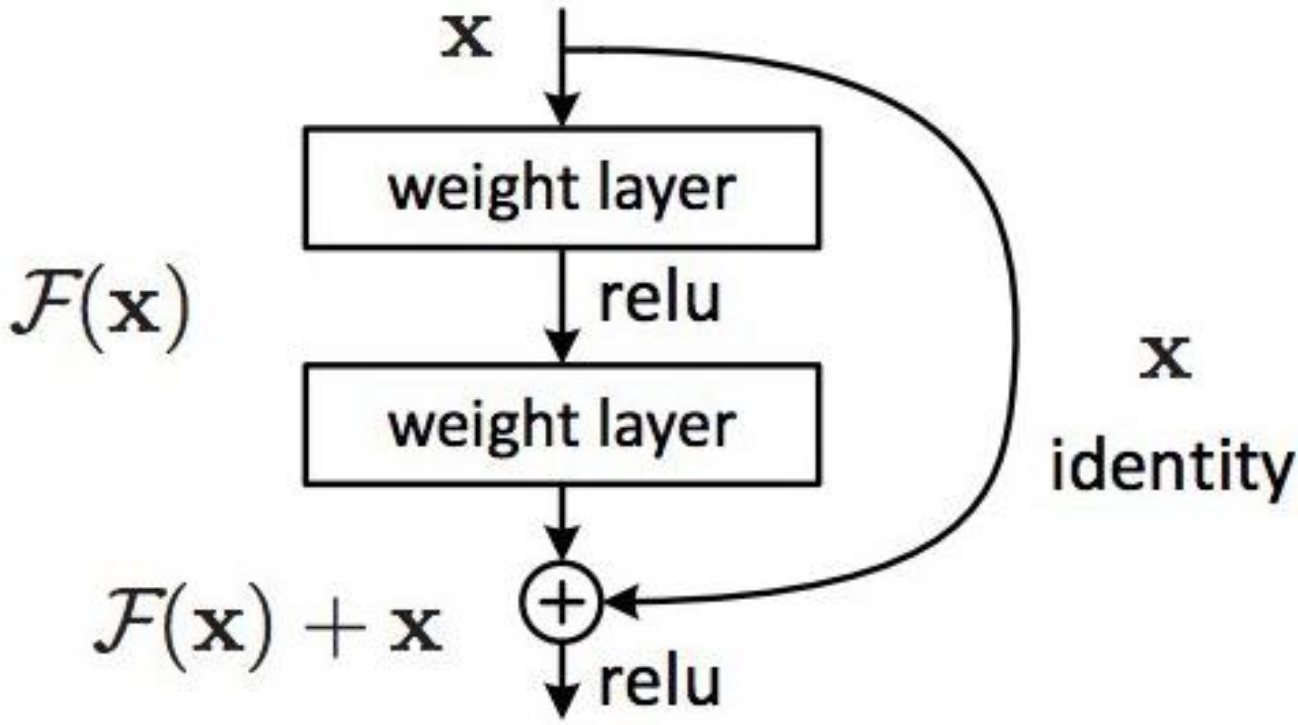




Kaiming He, et al. "Deep Residual Learning for Image Recognition" CVPR 2016

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., $F(\mathbf{x})$ to improve over the solution that can be achieved by a shallow network**
- The weights (convolutional layers) are such that to **preserve dimension depth-wise or are re-arranged by 1x1 convolutions**

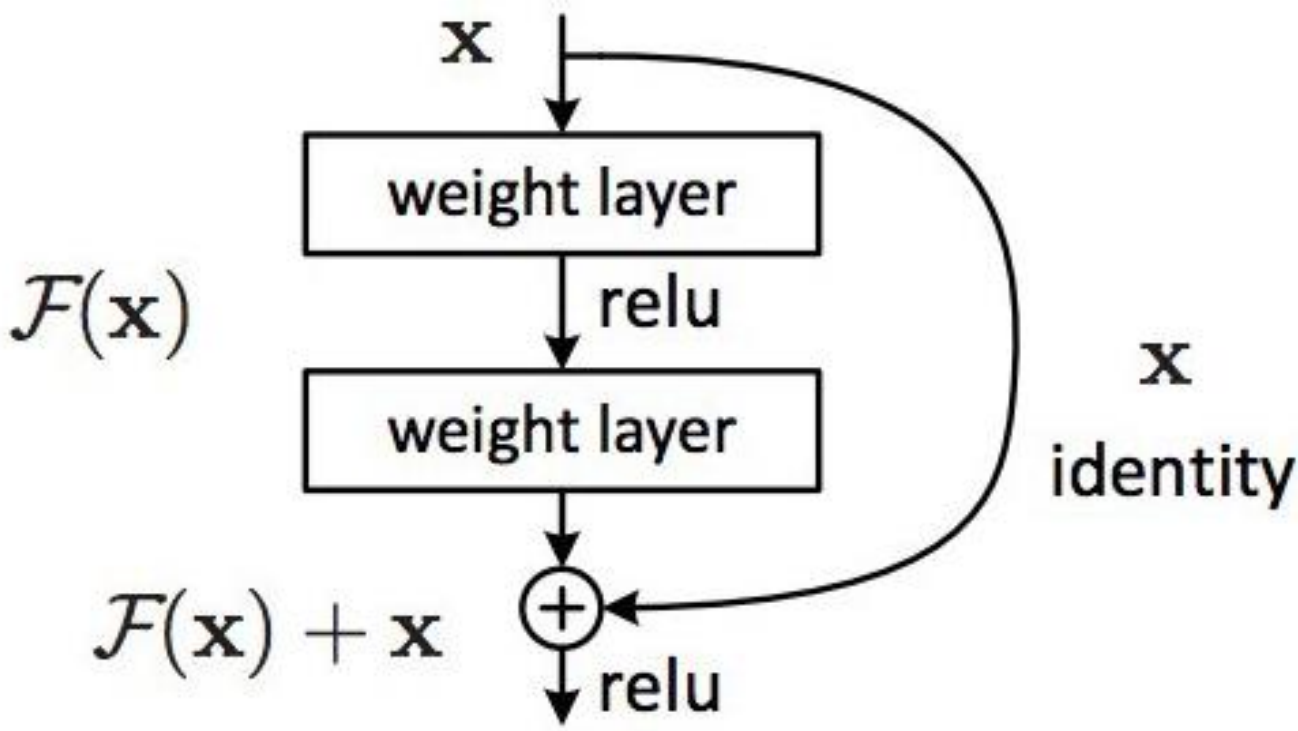


Kaiming He, et al. "Deep Residual Learning for Image Recognition" CVPR 2016

ResNet (2015)

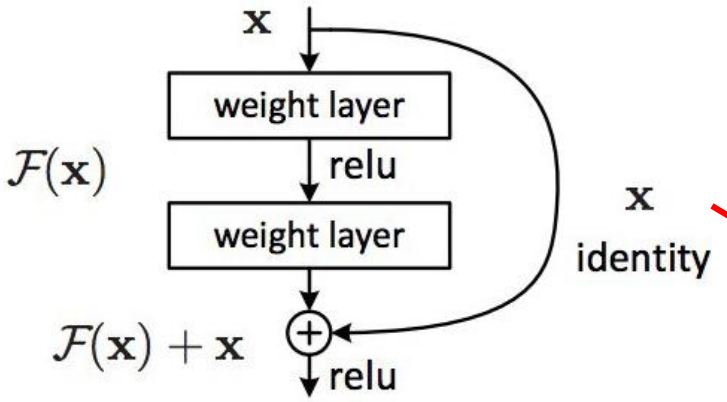
The rationale behind adding this identity mapping is that:

- 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 thee deep layers have to be close to the identity!**



Kaiming He, et al. "Deep Residual Learning for Image Recognition“ CVPR 2016

ResNet (2015)



The ResNet is a stack of
152 layers of this module

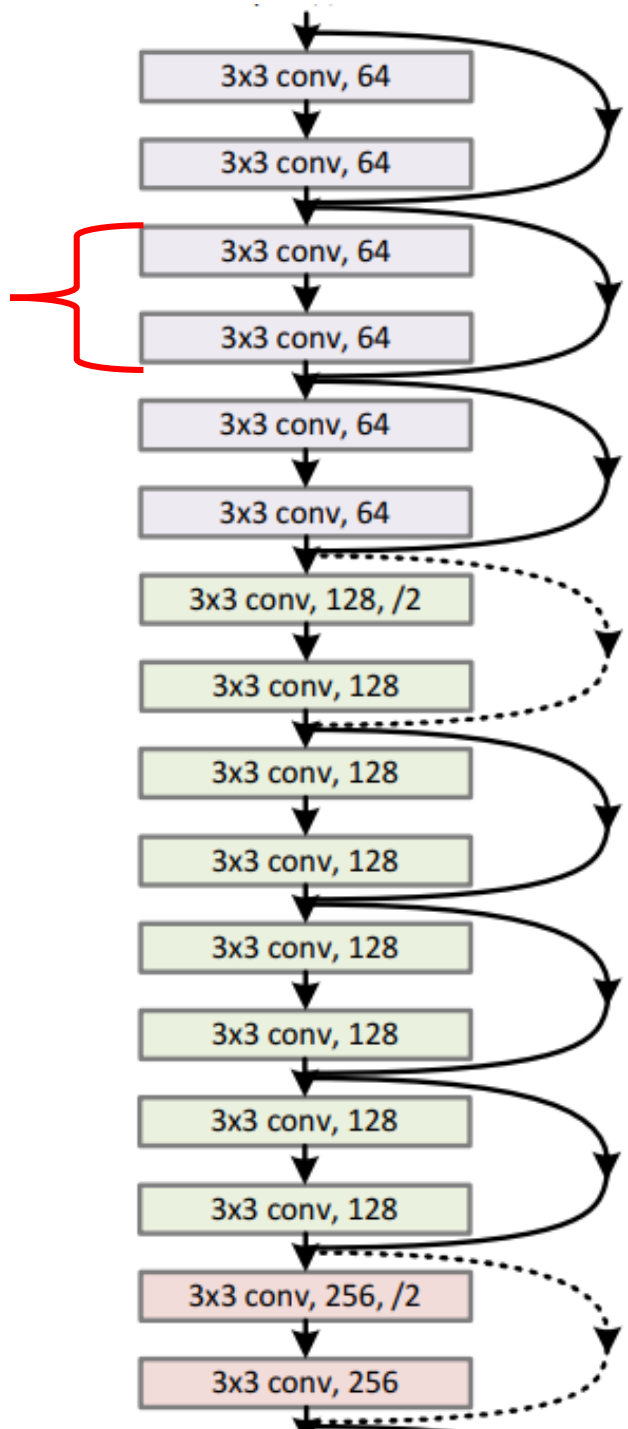
The network alternates

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

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

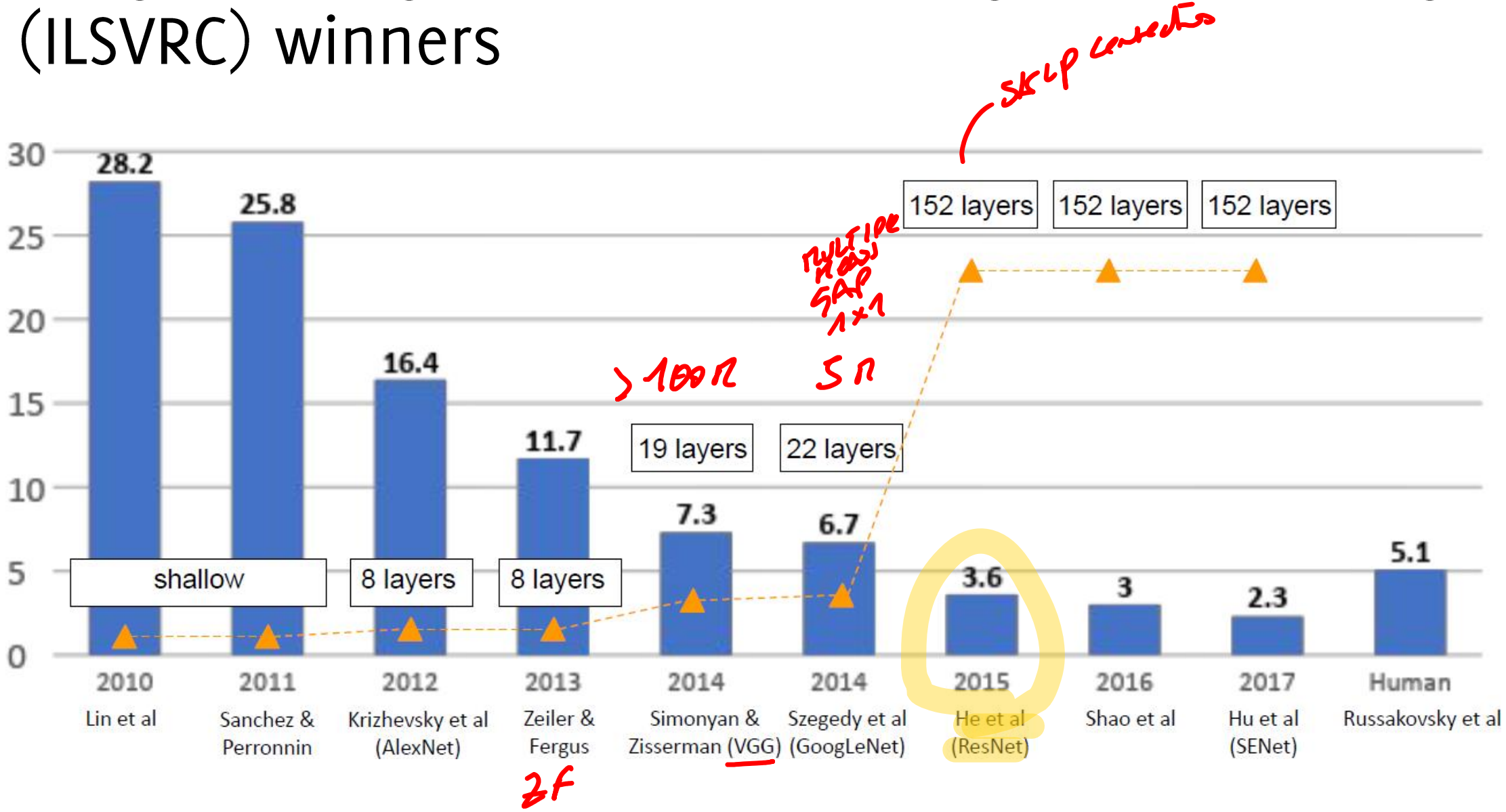
At the end, no FC but just a **GAP to be fed in the final softmax**

Deeper networks are able to achieve lower errors as expected



Kaiming He, et al. "Deep Residual Learning for Image Recognition" CVPR 2016

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



Aggregated Residual Transformations for Deep Neural Networks

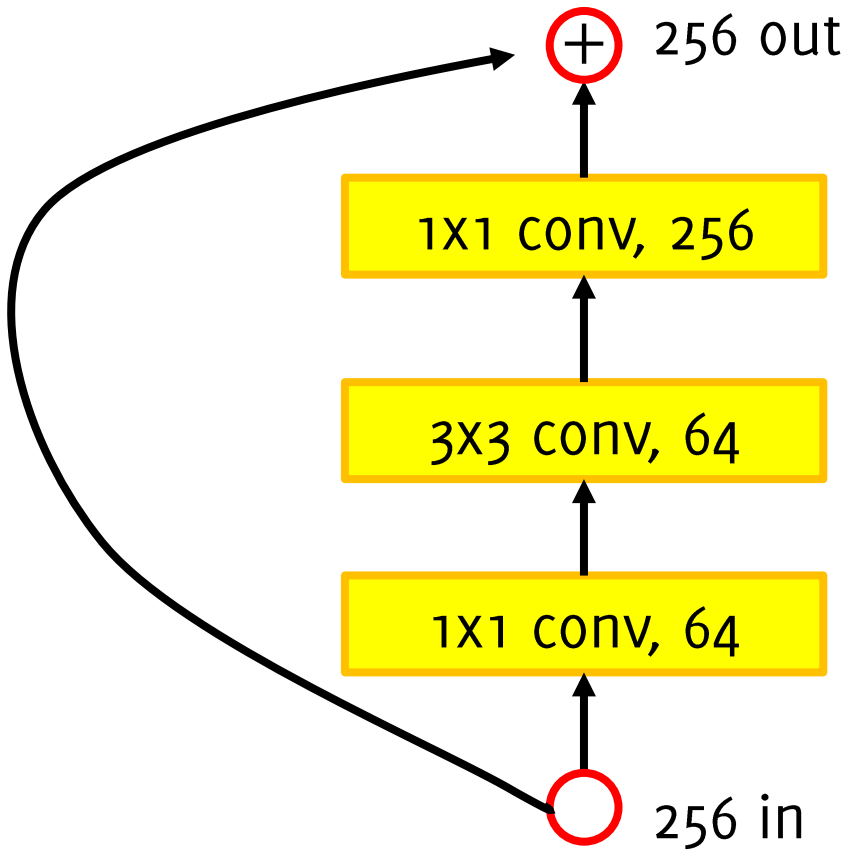
Saining Xie[1] Ross Girshick[2] Piotr Dollár[2] Zhuowen Tu[1] Kaiming He[2]

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

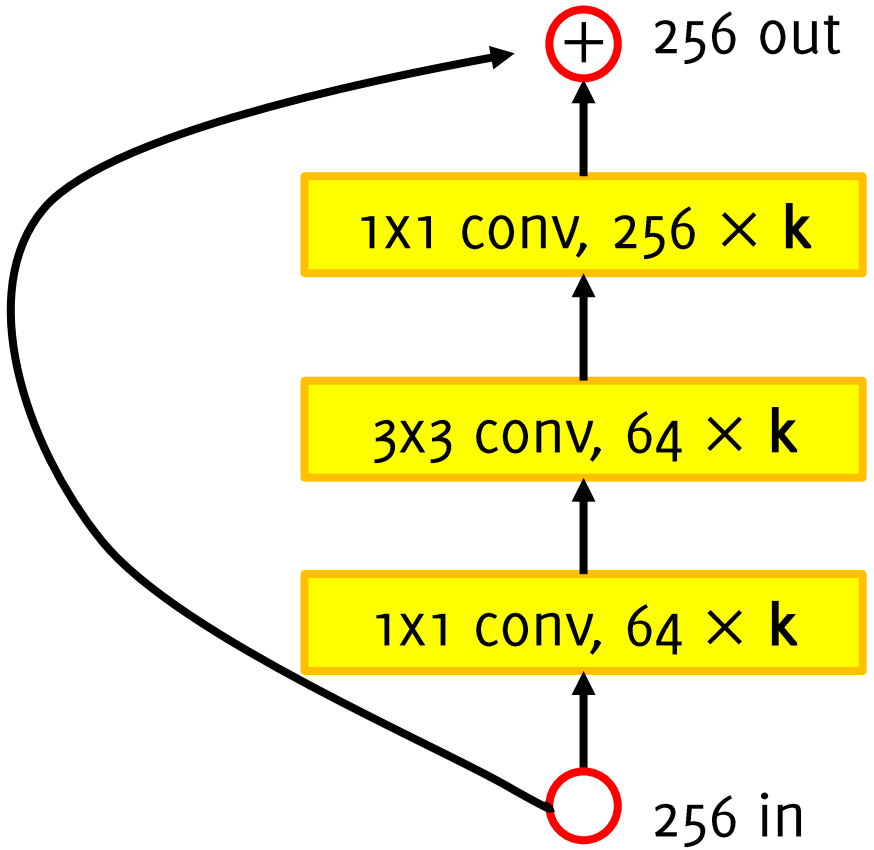
{s9xie,ztu}@ucsd.edu {rbg,pdollar,kaiminghe}@fb.com

Wide Resnet

ResNet Module



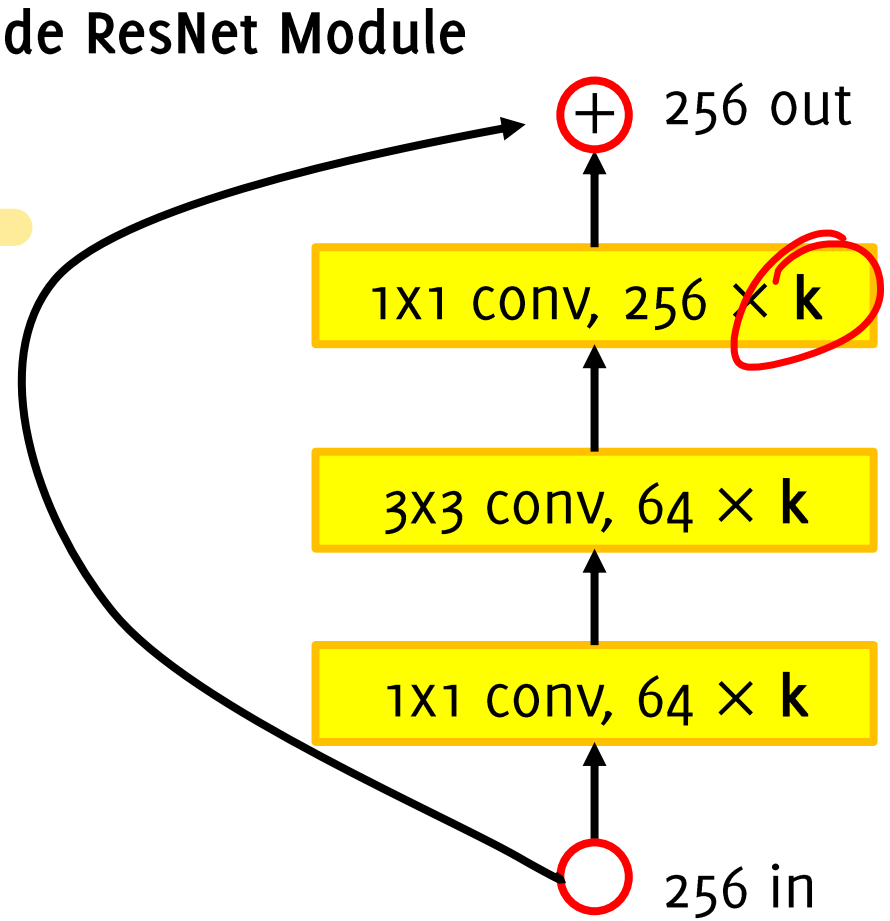
Wide ResNet Module



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

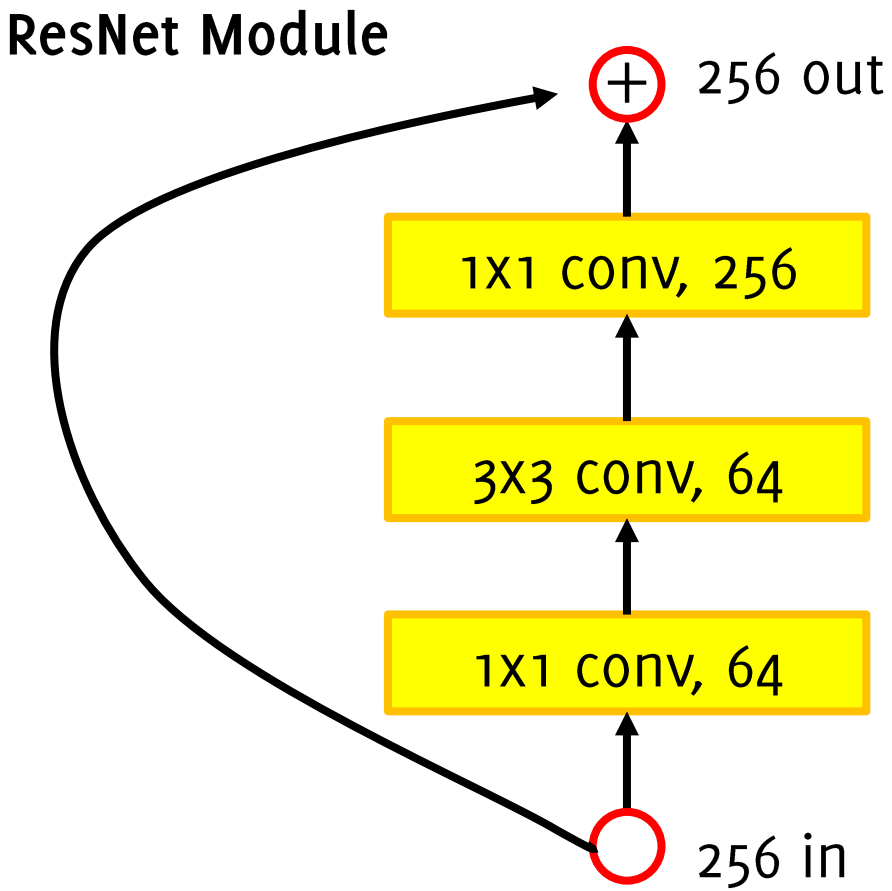
Wide Resnet

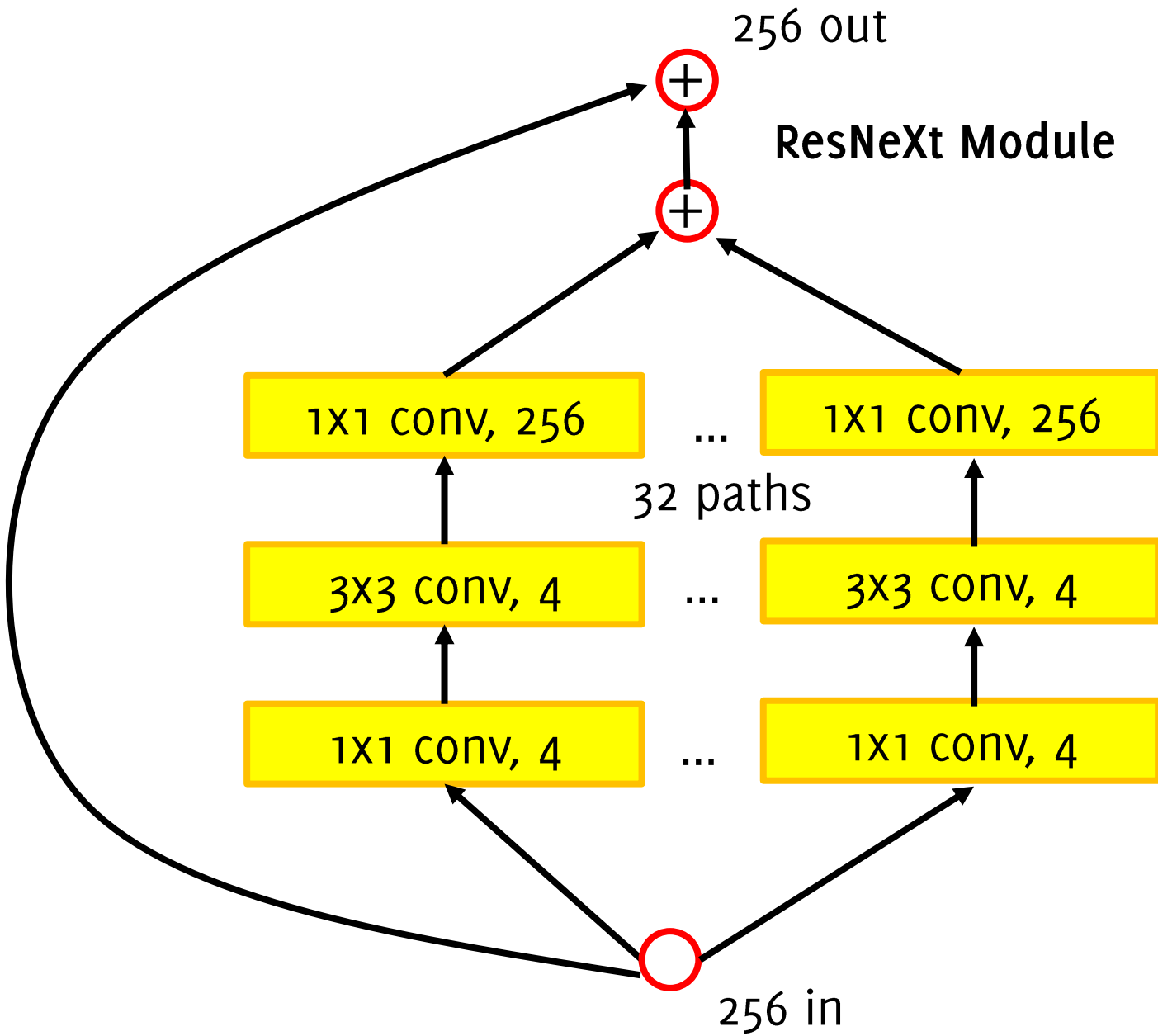
- Use wider residual blocks (F x k filters instead of F filters in each layer)
- 50-layer wide ResNet outperforms 152-layer original ResNet
- Increasing width instead of depth more computationally efficient (parallelizable)



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

ResNeXt





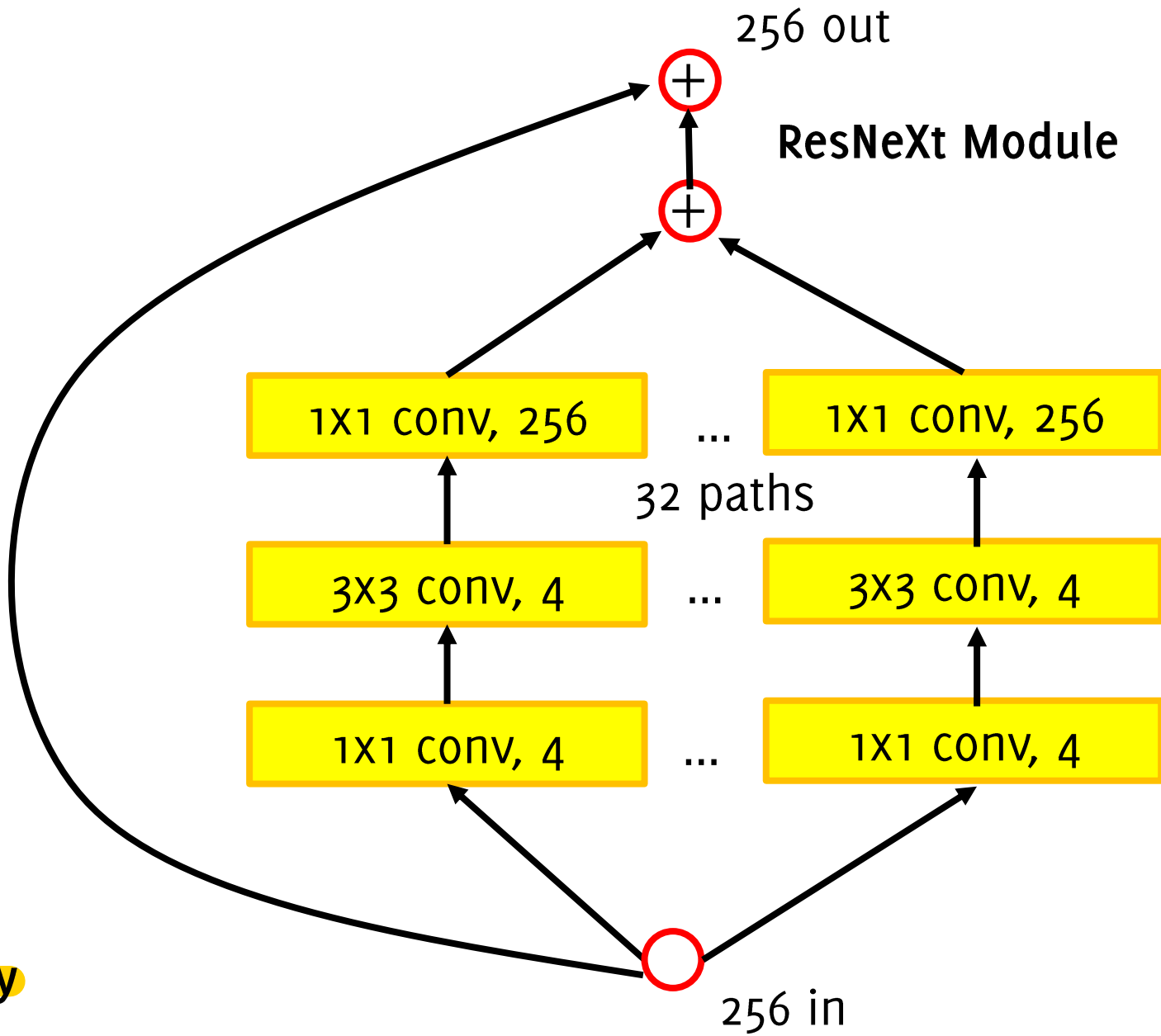
Xie et al "Aggregated Residual Transformations for Deep Neural Networks", CVPR 2017

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 perf. 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

Gao Huang*
Cornell University
gh349@cornell.edu

Zhuang Liu*
Tsinghua University
liuzhuang13@mails.tsinghua.edu.cn

Laurens van der Maaten
Facebook AI Research
lvdmaaten@fb.com

Kilian Q. Weinberger
Cornell University
kqw4@cornell.edu

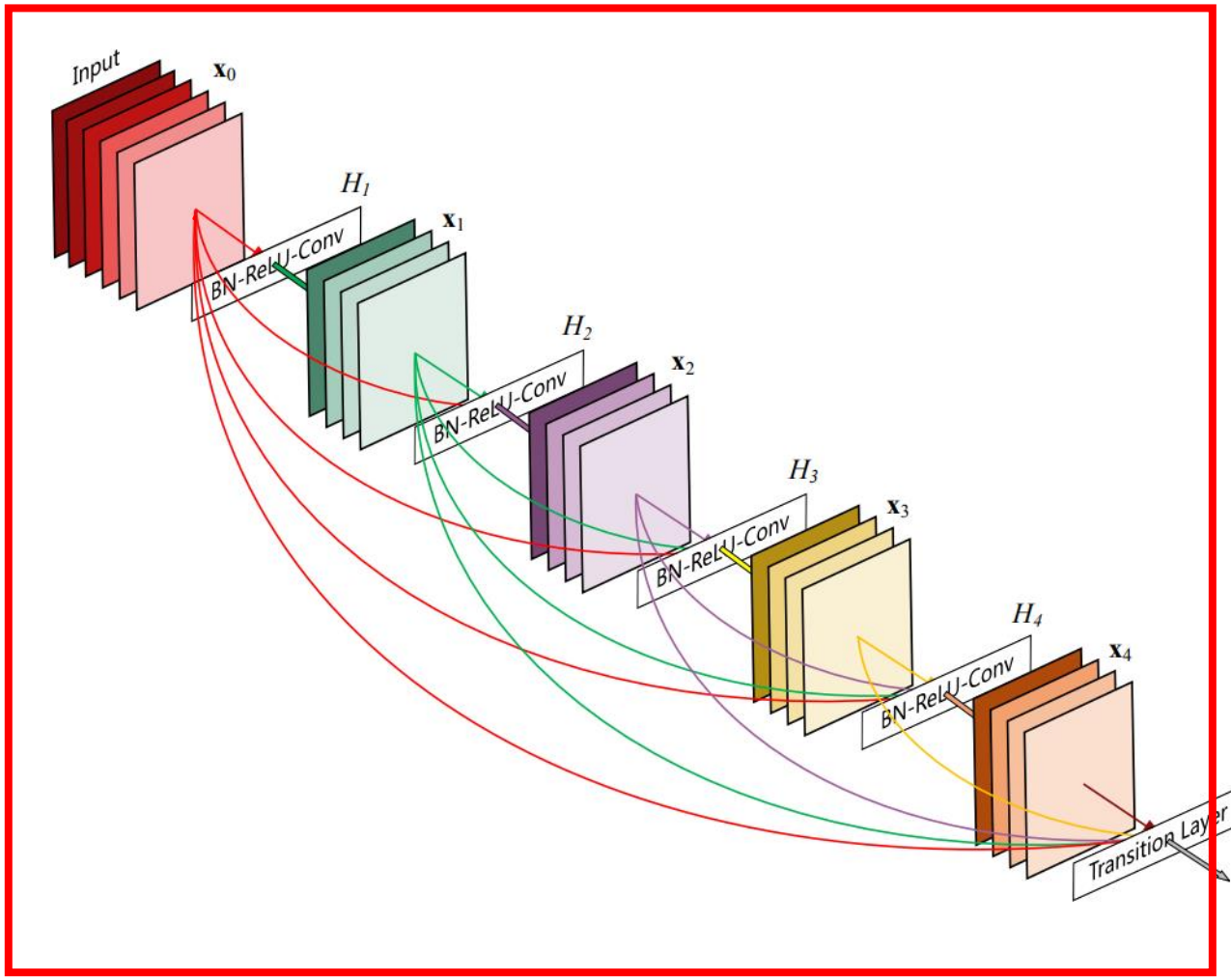
DenseNet

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



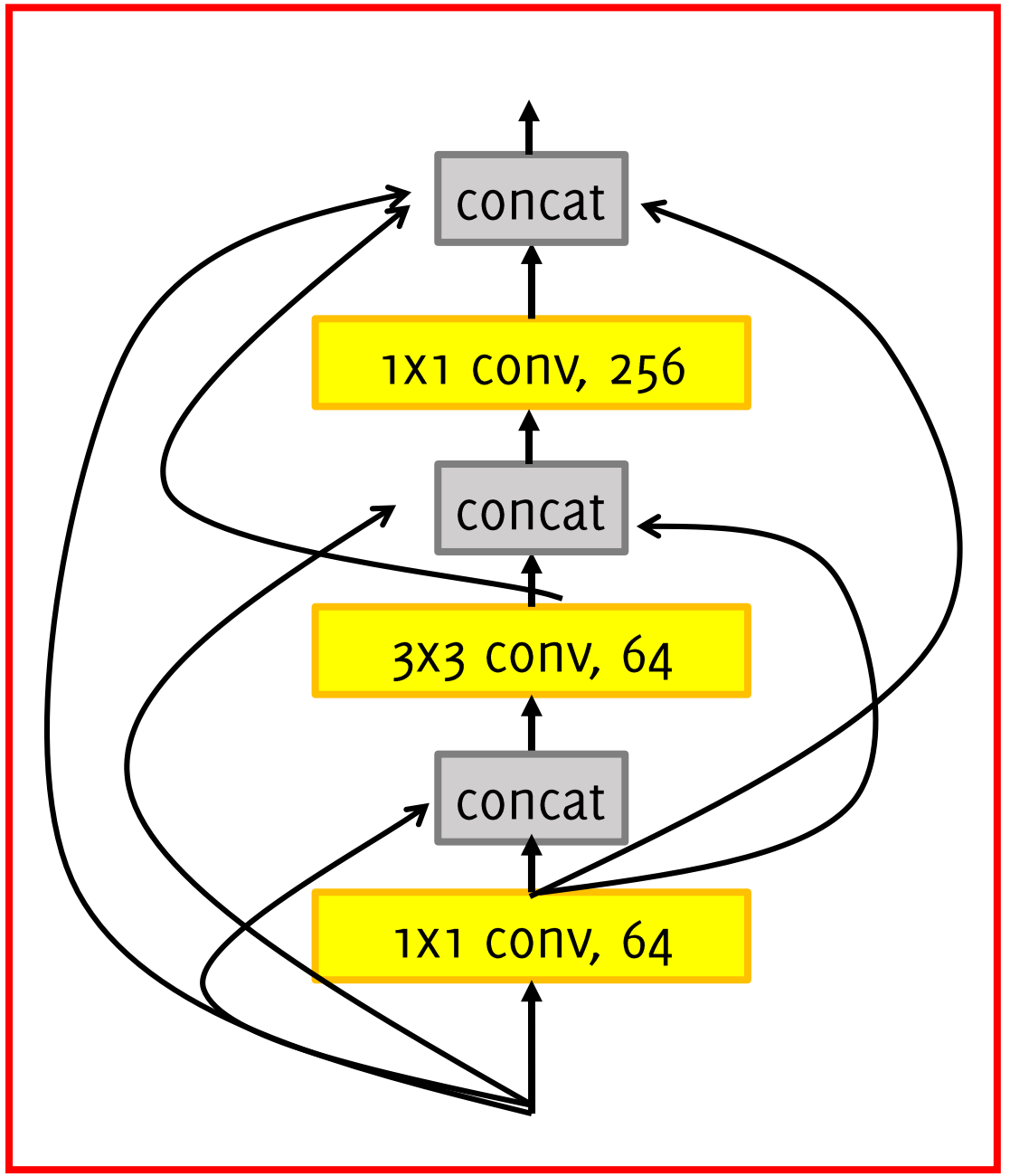
Huang G. et al, "Densely Connected Convolutional Network" CVPR 2017

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

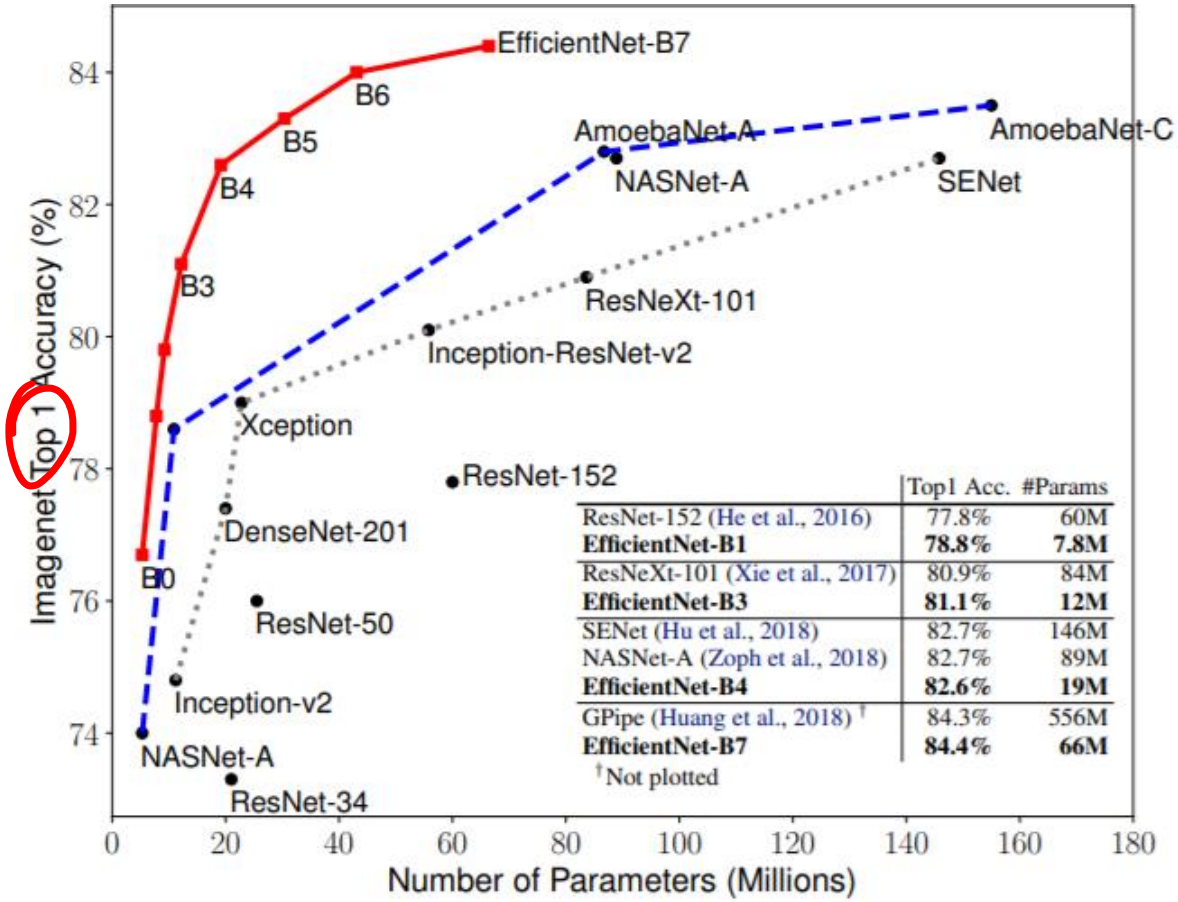
This alleviates vanishing gradient problem, promotes feature re-use since each feature is spread through the network



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

EfficientNet:

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



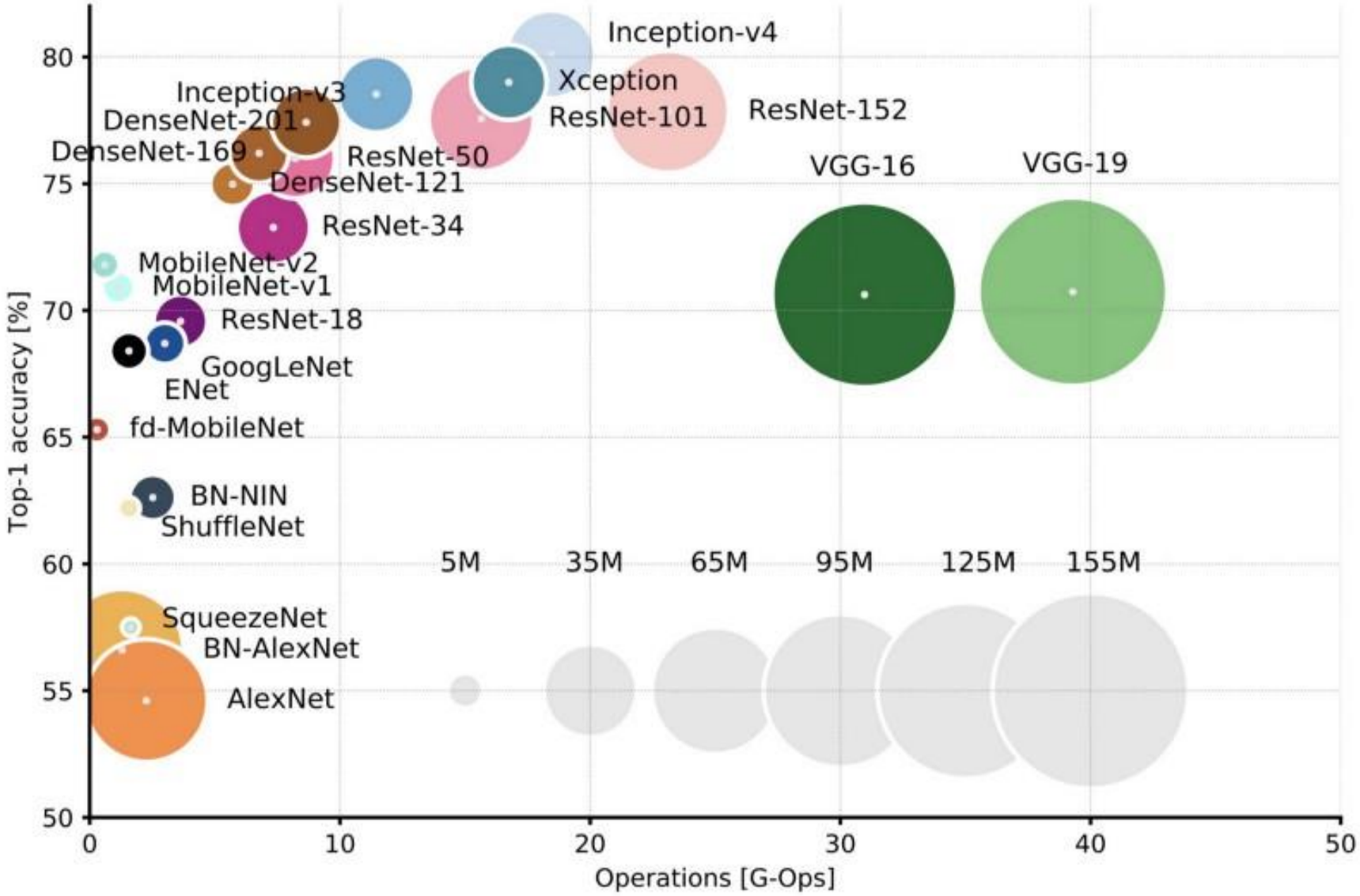
	Top1 Acc.	#Params
ResNet-152 (He et al., 2016)	77.8%	60M
EfficientNet-B1	**78.8%**	**7.8M**
ResNeXt-101 (Xie et al., 2017)	80.9%	84M
EfficientNet-B3	**81.1%**	**12M**
SENet (Hu et al., 2018)	82.7%	146M
NASNet-A (Zoph et al., 2018)	82.7%	89M
EfficientNet-B4	**82.6%**	**19M**
GPipe (Huang et al., 2018)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

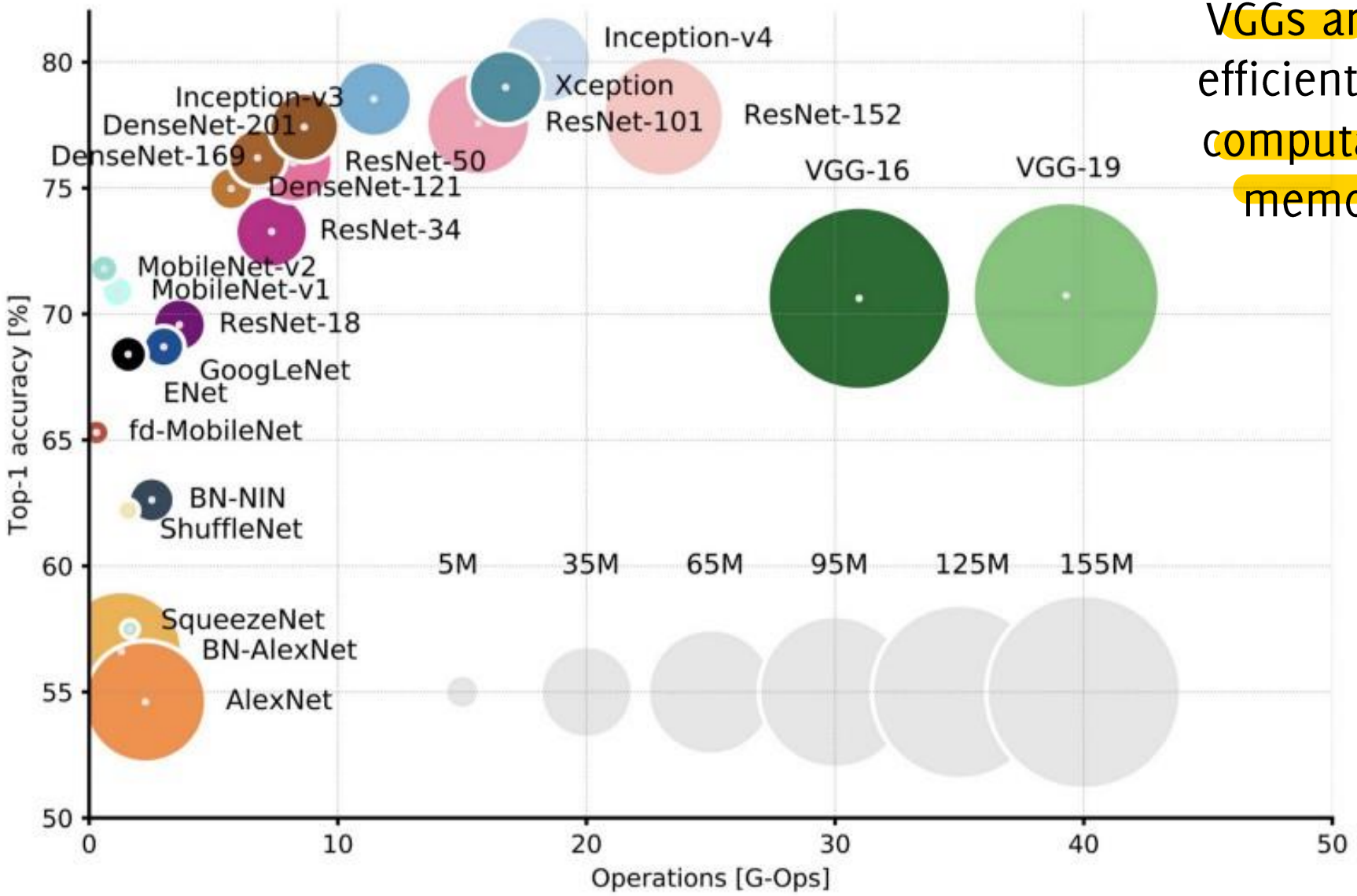
Tan, Mingxing, and Quoc Le. "Efficientnet: Rethinking model scaling for convolutional neural networks." *International Conference on Machine Learning*. PMLR, 2019.

Comparison



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

Comparison

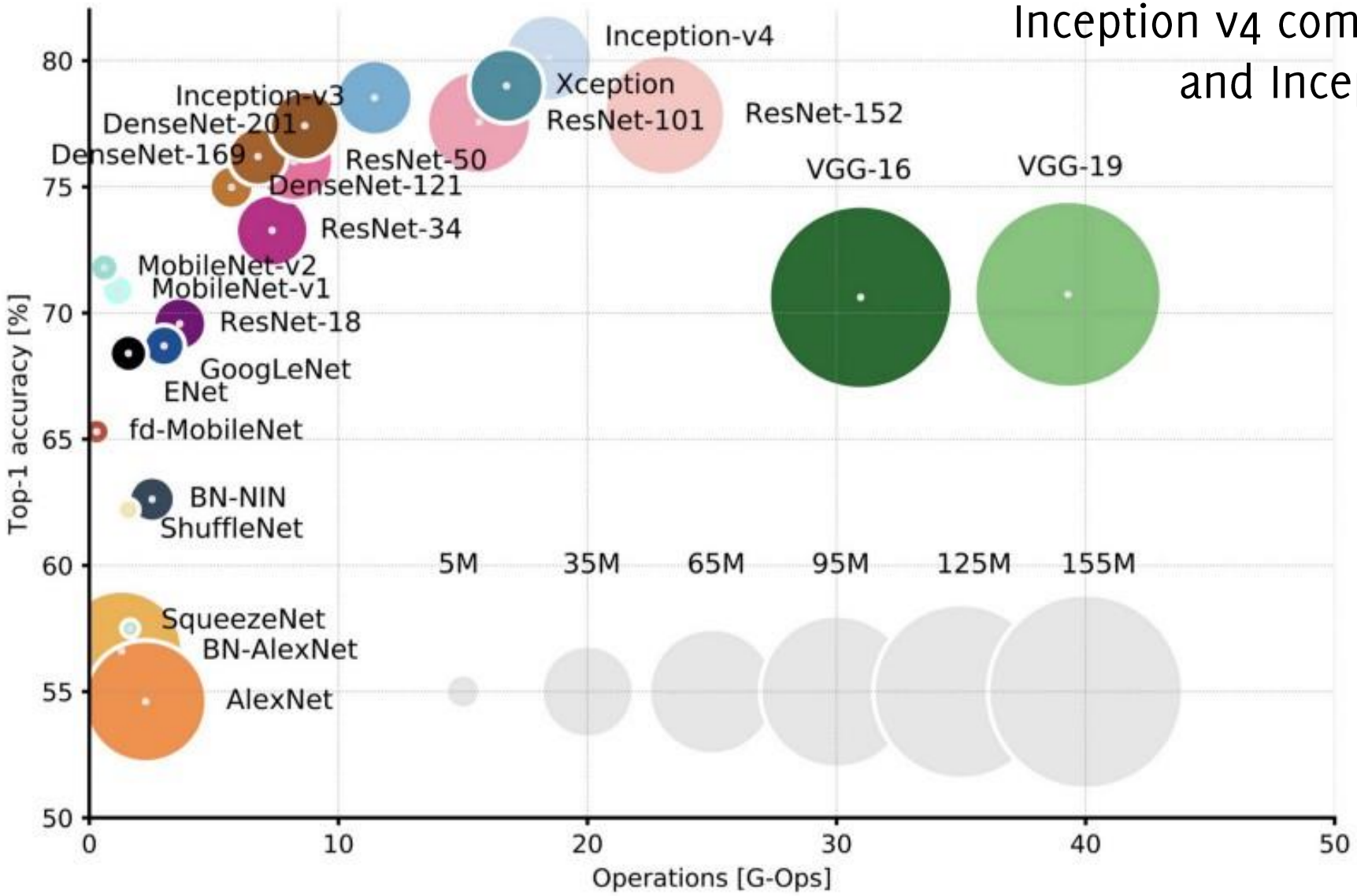


VGGs are the least efficient: very large computational and memory usage

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

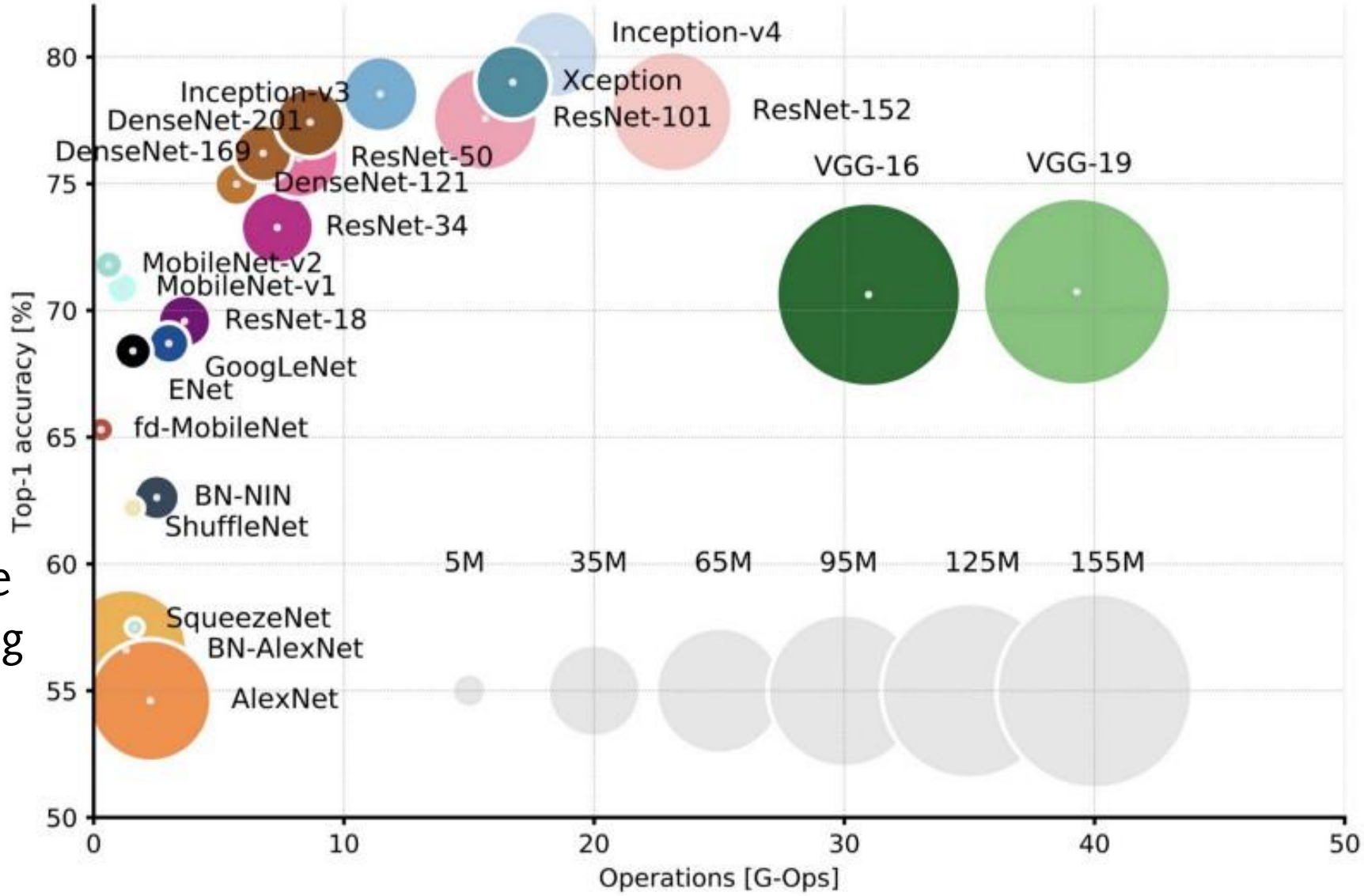
Comparison

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

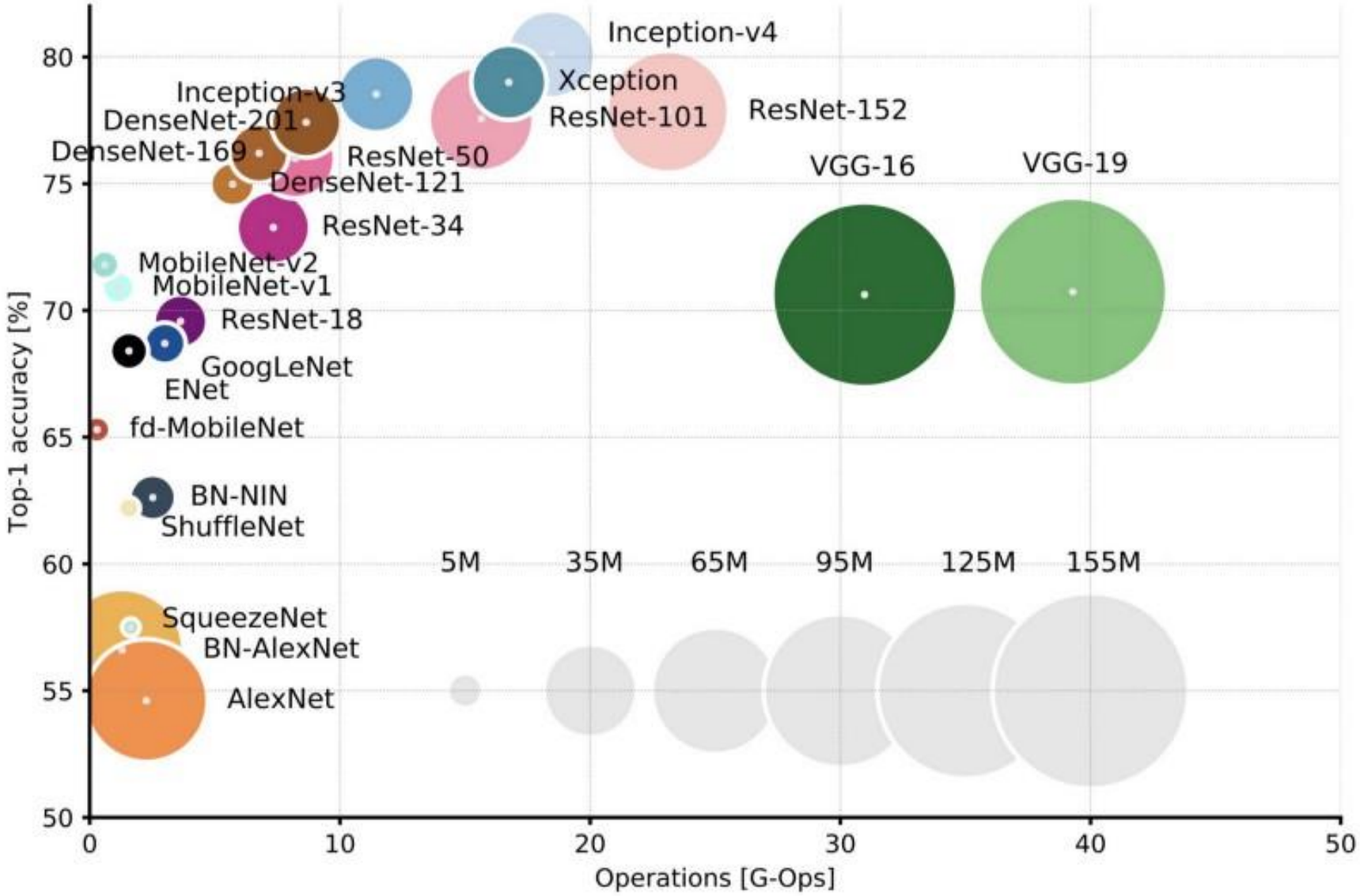


AlexNet are the least performing and not particularly efficient

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

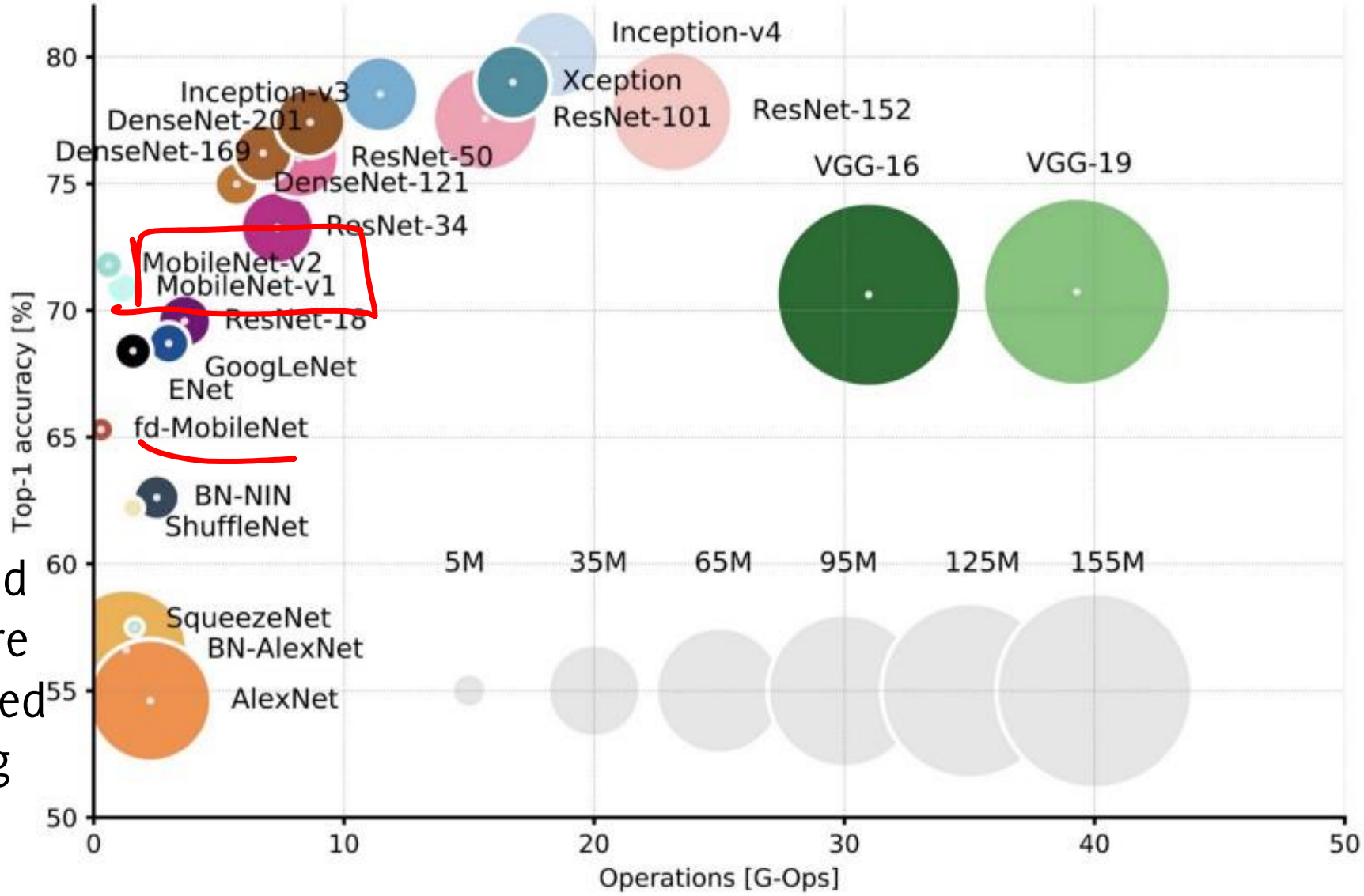
Comparison

Inception-v4:
Resnet + Inception



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

Comparison



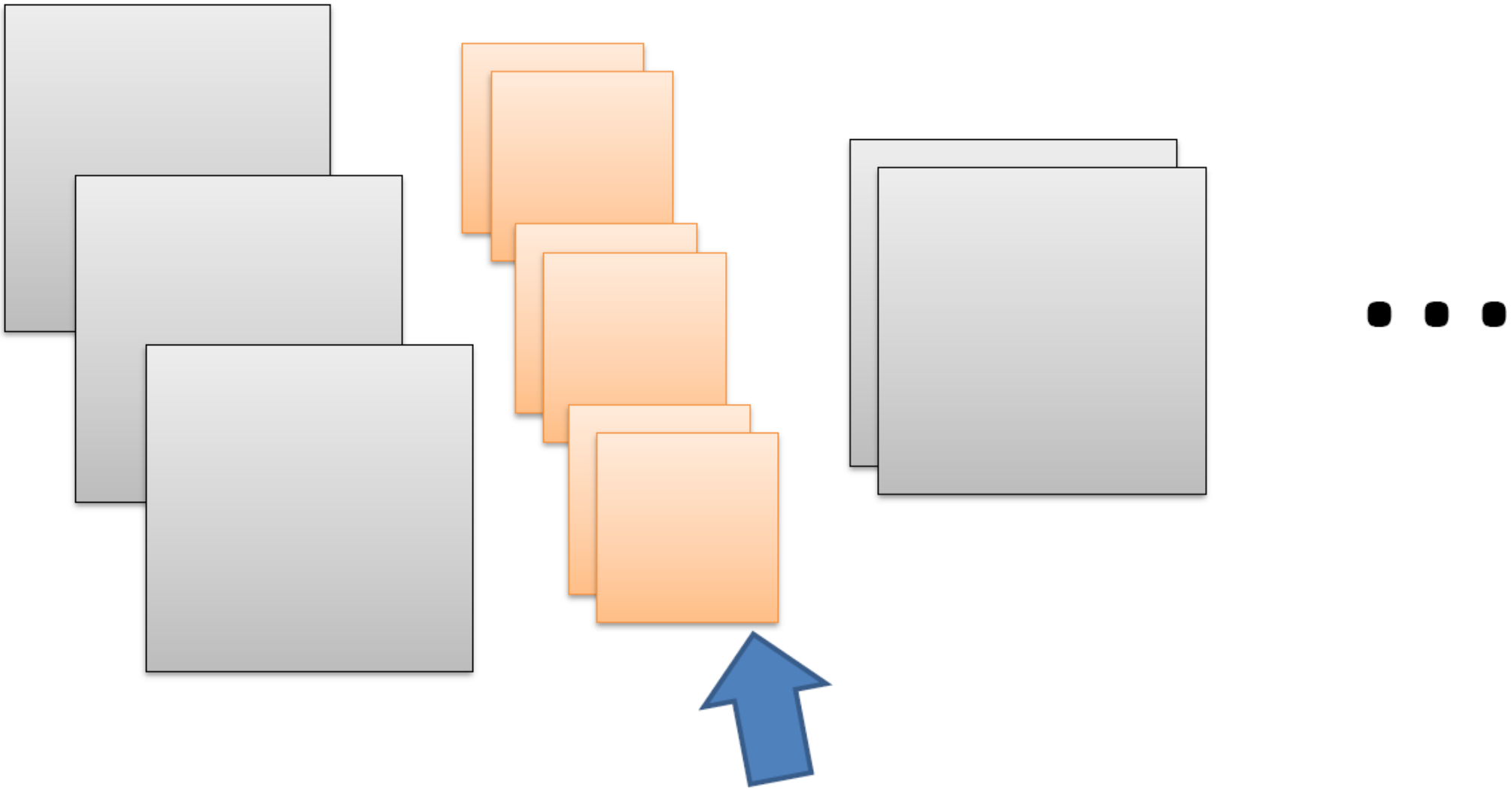
Mobile net and squeezenet are instead designed for improving efficiency

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

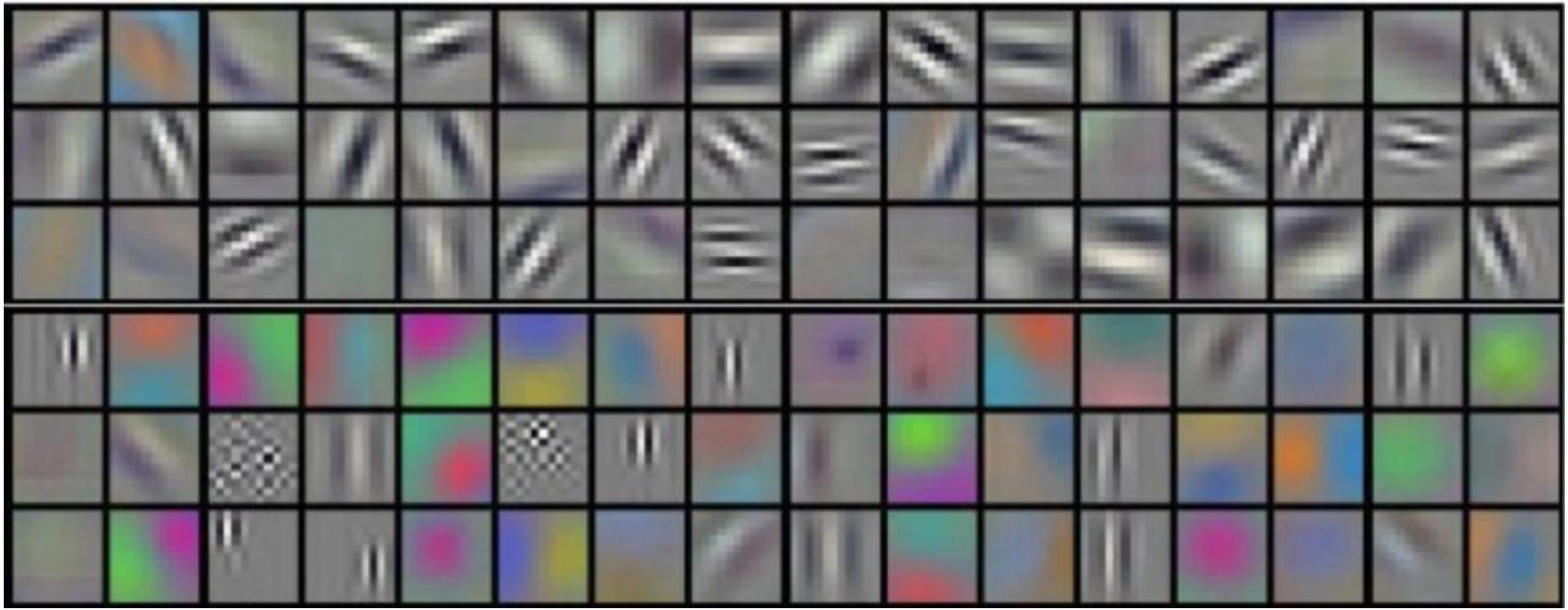
CNN Visualization

G. Boracchi

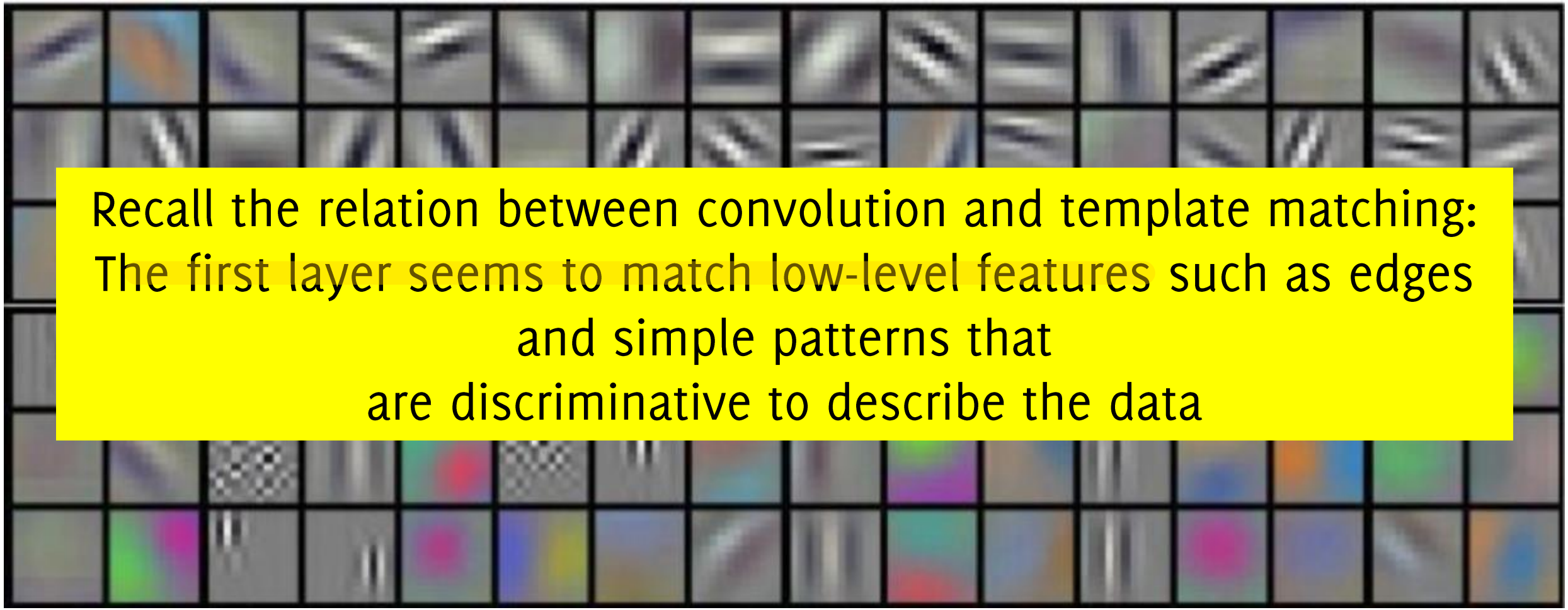
Visualizing CNN Filters



11x11x3 filters (visualized in RGB) extracted from the first convolutional layer

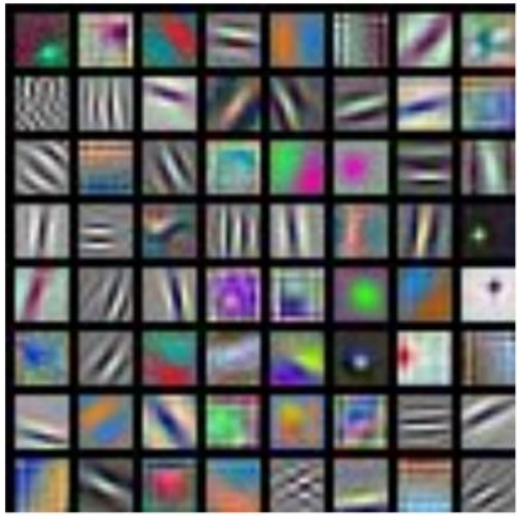


11x11x3 filters (visualized in RGB) extracted from the first convolutional layer



Recall the relation between convolution and template matching:
The first layer seems to match low-level features such as edges and simple patterns that
are discriminative to describe the data

First layer's filters are often like these

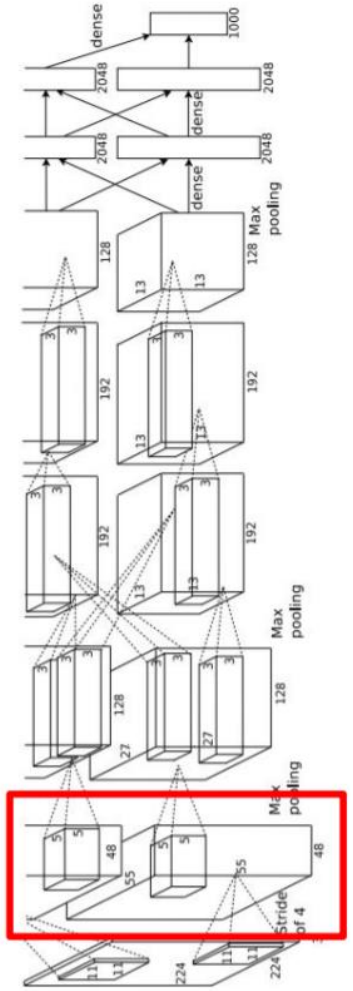


AlexNet:
64 x 3 x 11 x 11

ResNet-18:
64 x 3 x 7 x 7

ResNet-101:
64 x 3 x 7 x 7

DenseNet-121:
64 x 3 x 7 x 7



Krizhevsky, "One weird trick for parallelizing convolutional neural networks", arXiv 2014
He et al, "Deep Residual Learning for Image Recognition", CVPR 2016
Huang et al, "Densely Connected Convolutional Networks", CVPR 2017

Difficult to interpret deeper layers

Weights:

layer 1 weights

16 x 3 x 7 x 7

Weights:

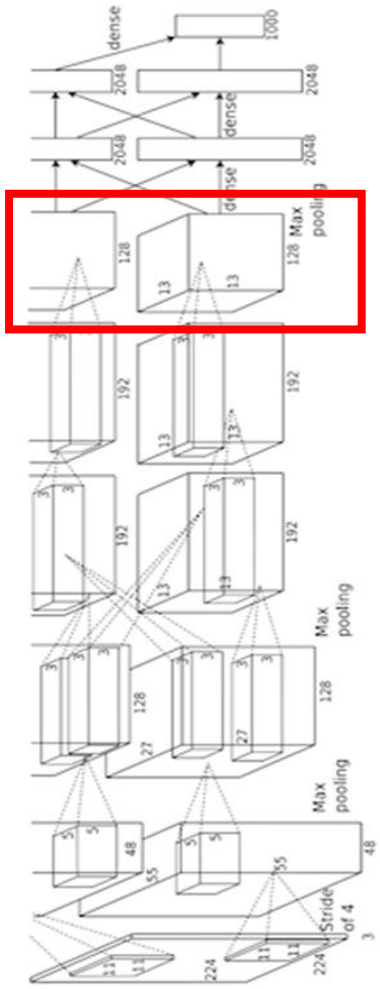
layer 2 weights

20 x 16 x 7 x 7

Weights:

layer 3 weights

20 x 20 x 7 x 7

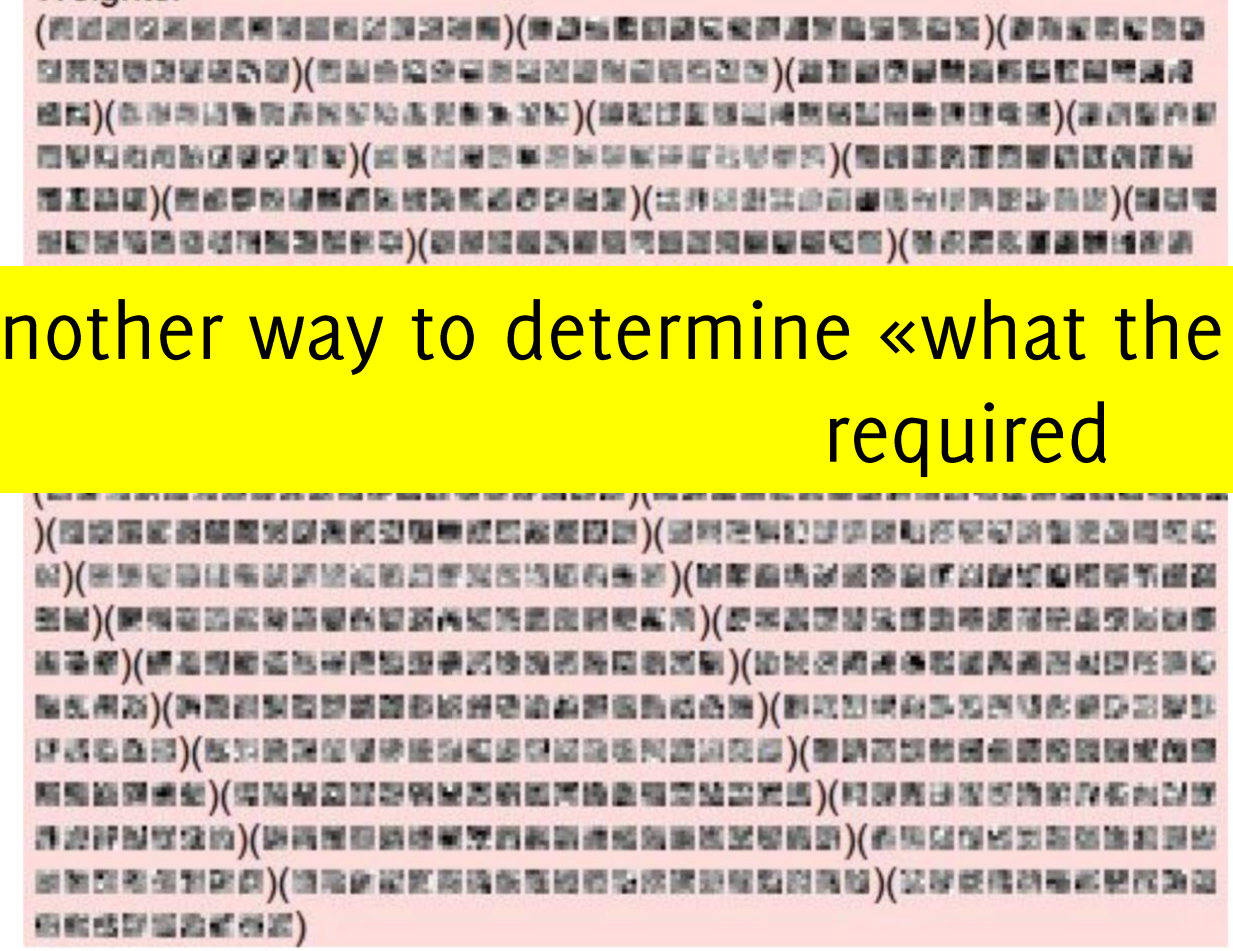


CS231n: Convolutional Neural Networks for Visual Recognition http://cs231n.github.io/

Difficult to interpret deeper layers

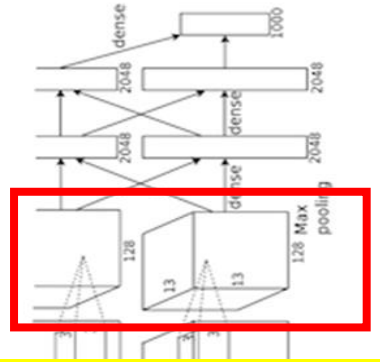
Weights:

Weights:



layer 1 weights

16 x 3 x 7 x 7

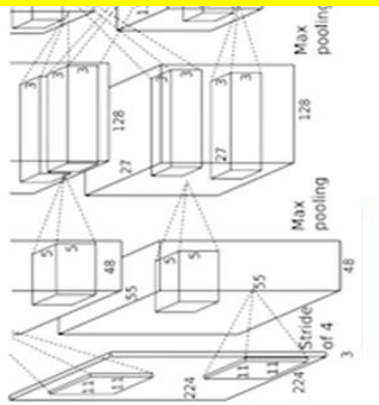


layer 2 weights

Another way to determine «what the deepest layer see» is required

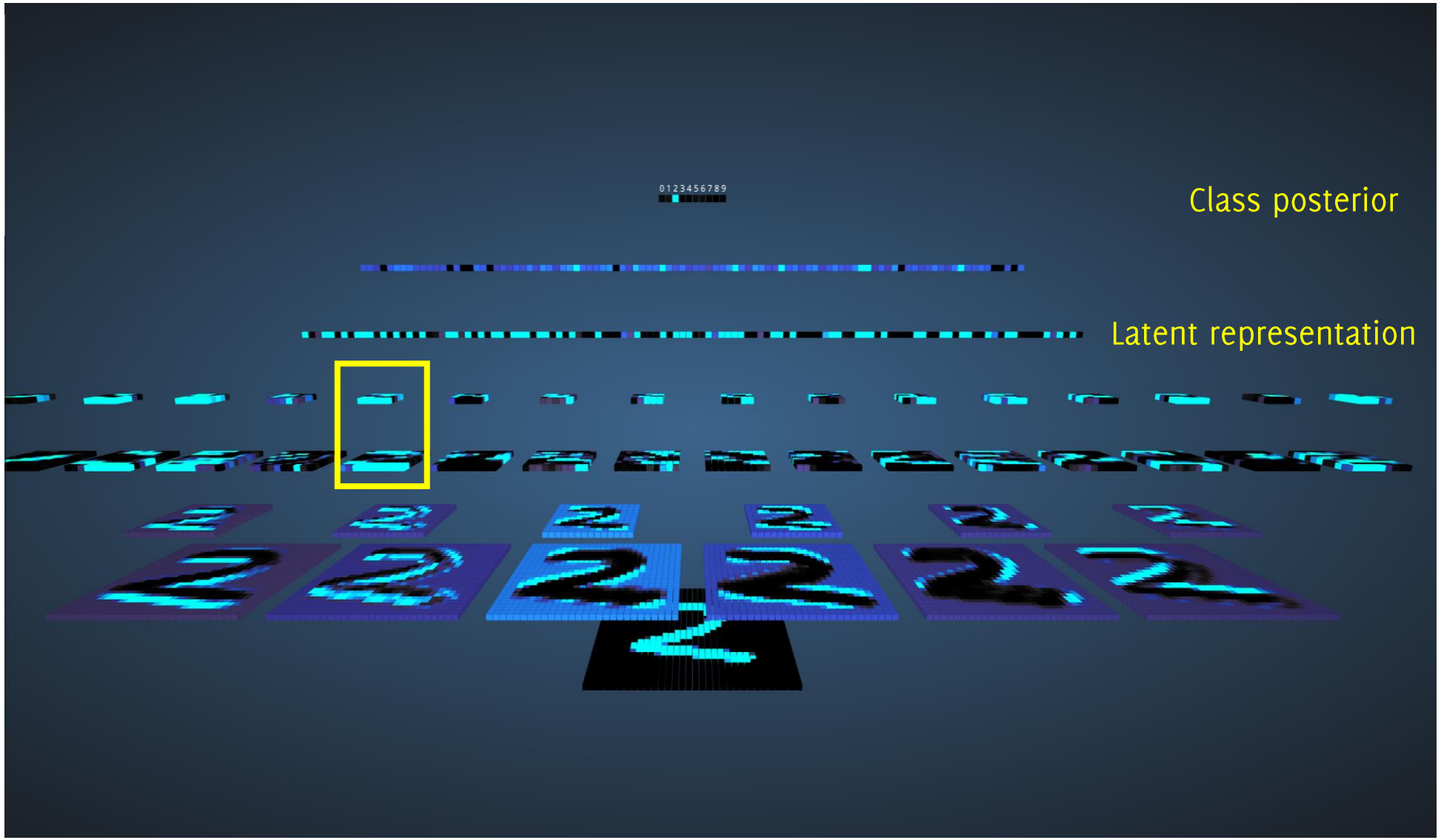
layer 3 weights

20 x 20 x 7 x 7



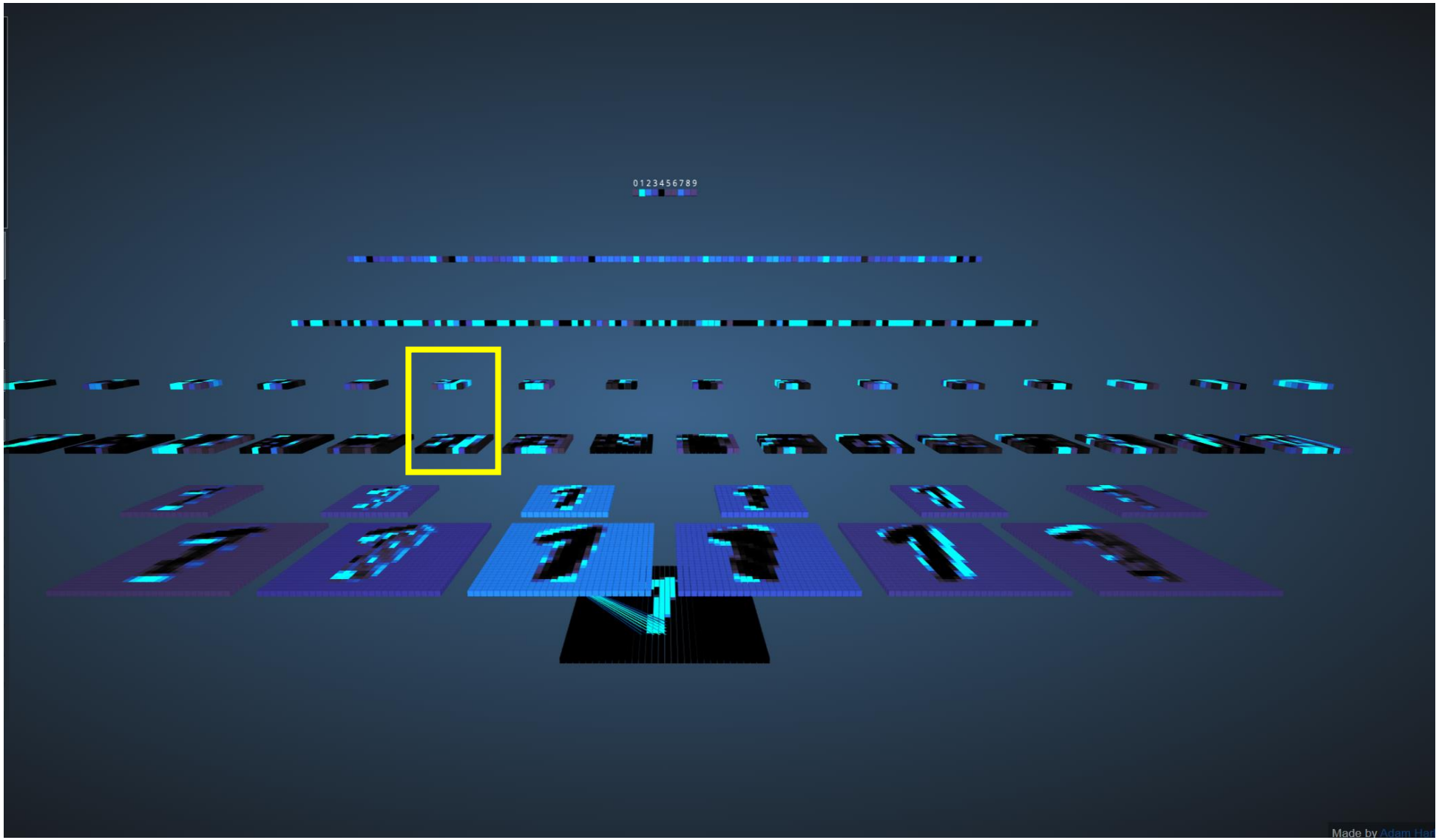
CS231n: Convolutional Neural Networks for Visual Recognition http://cs231n.github.io/

What if we look at the activations?



https://www.cs.ryerson.ca/~aharley/vis/conv/

What if we look at the activations?



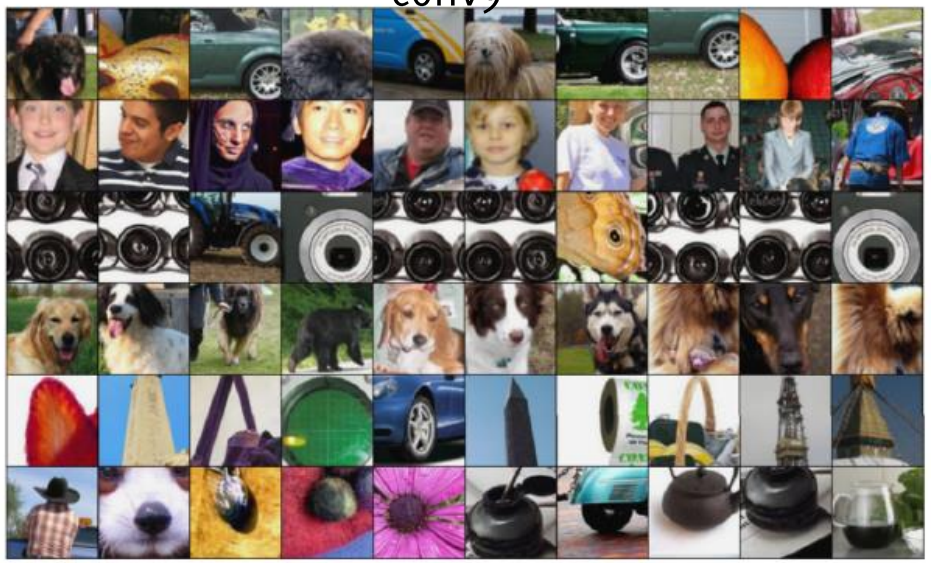
https://www.cs.ryerson.ca/~aharley/vis/conv/

Visualizing Maximally Activating Patches

1. Select a neuron in a deep layer of a pre-trained CNN on ImageNet
2. Perform inference and store the activations for each input image.
3. Select the images yielding the maximum activation.
4. Show the region (patches) corresponding to the receptive field of the neuron.
5. Iterate for many neurons.

conv6

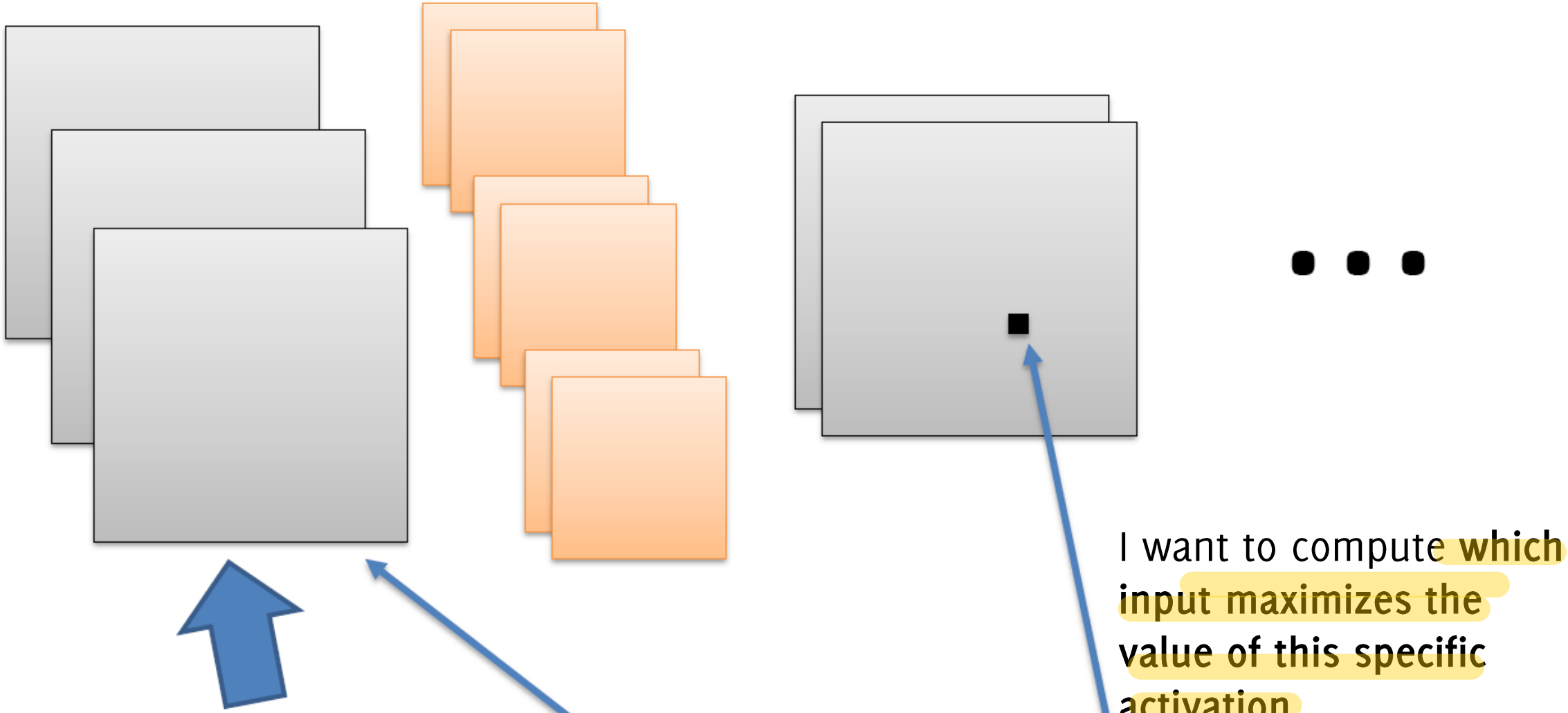
conv9



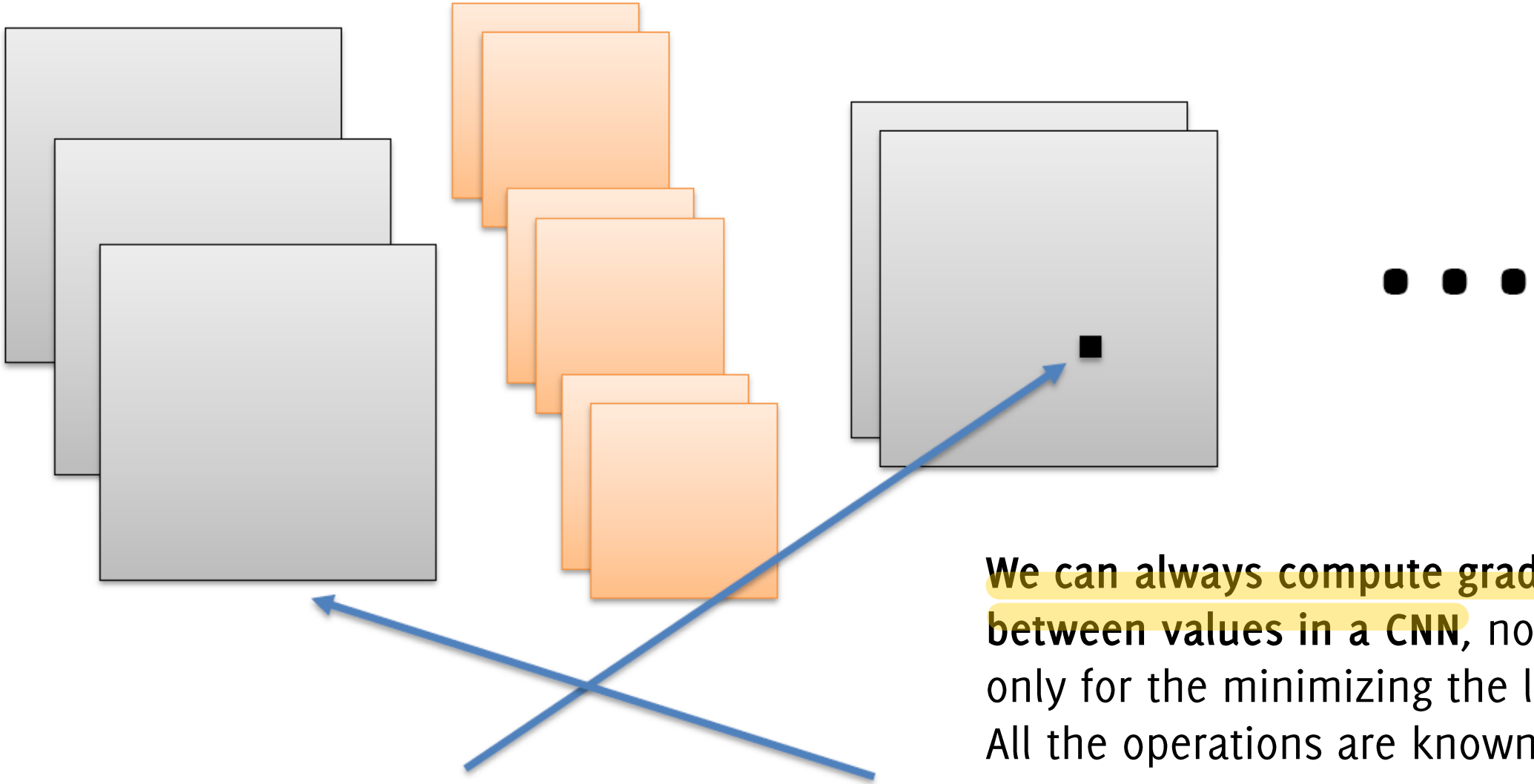
Each row in these images corresponds to the different outputs of the same filter

Springenberg et al, “Striving for Simplicity: The All Convolutional Net”, ICLR Workshop 2015

Computing Input maximally activating a neuron

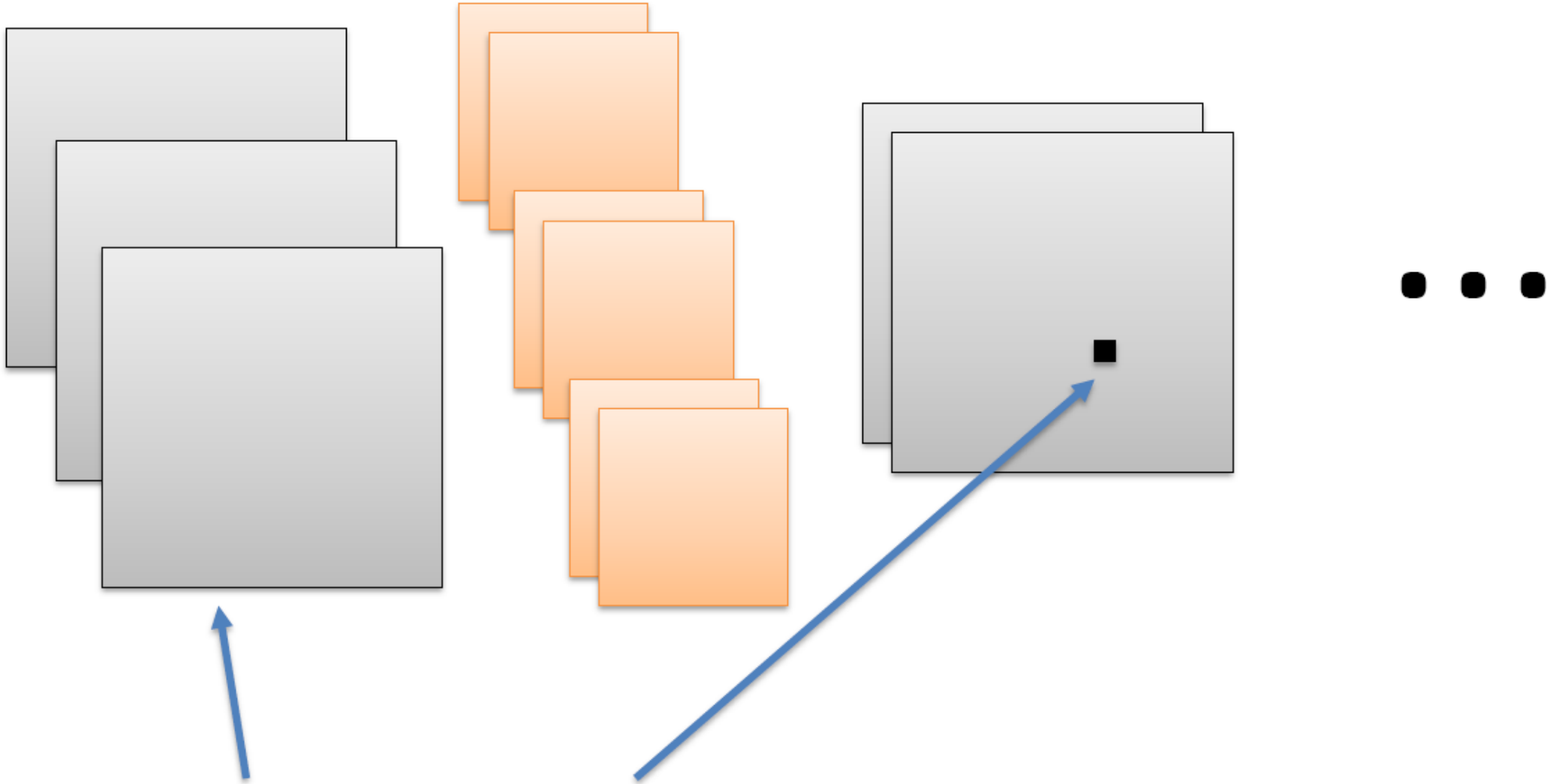


Step 1



We can always compute gradient between values in a CNN, not only for the minimizing the loss. All the operations are known

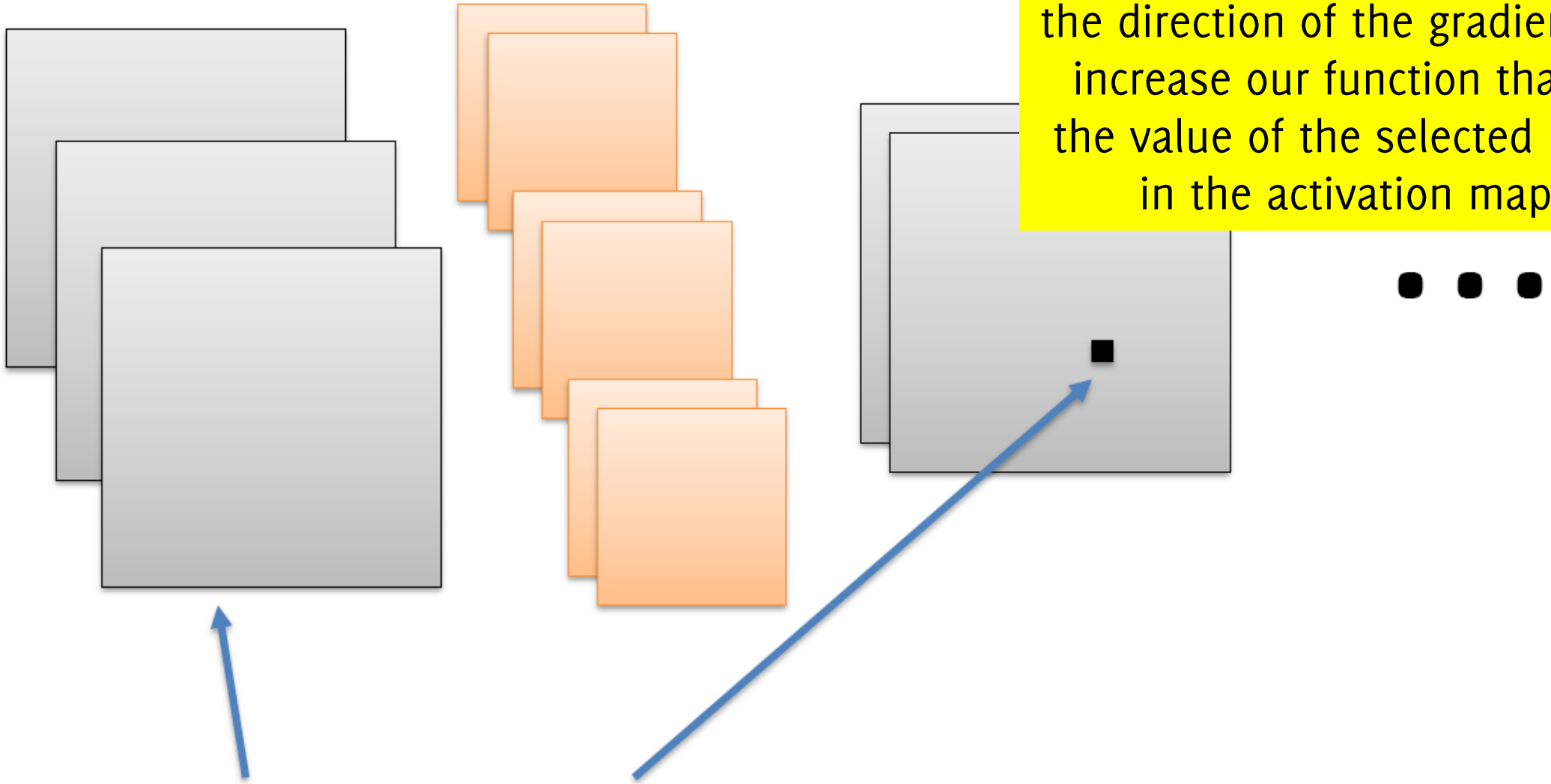
Step 2



Nudge the input accordingly: our guy will increase its activation

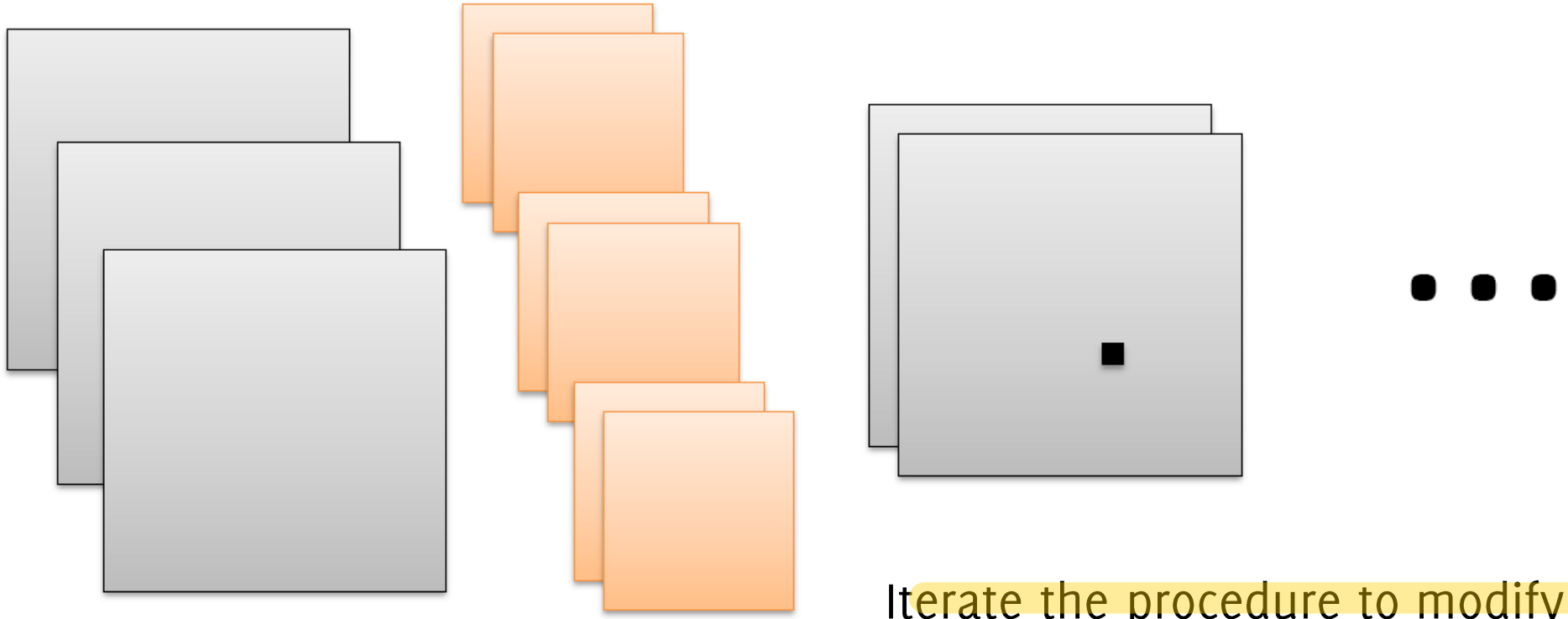
Step 2

Now we perform gradient ascent, we modify the input in the direction of the gradient, to increase our function that is the value of the selected pixel in the activation map



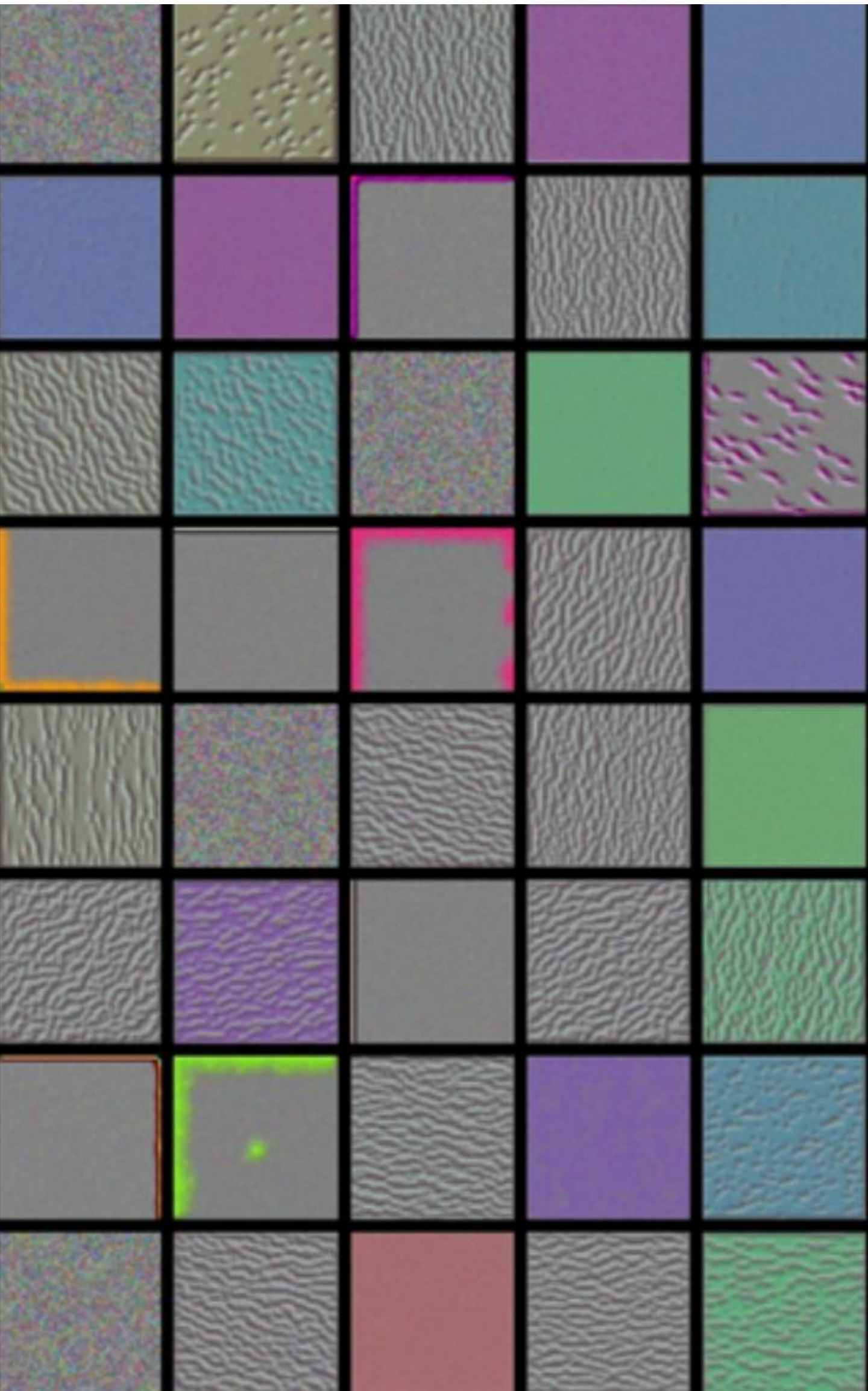
Nudge the input accordingly: our guy will increase its activation

Back to step 1 and iterate

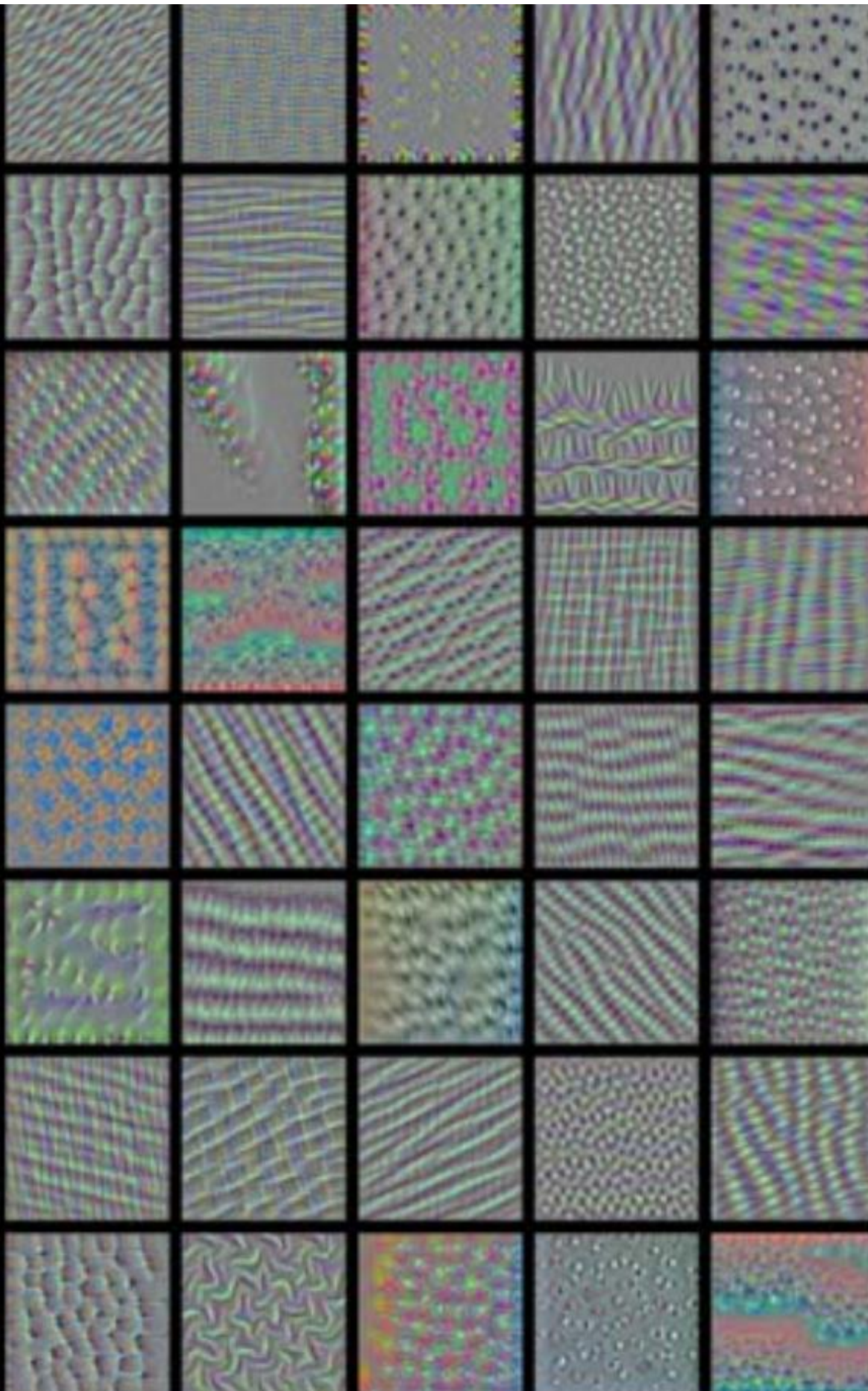


Iterate the procedure to modify the input. Some form of regularization can be added to the selected pixel value to steer the input to look more like a natural image

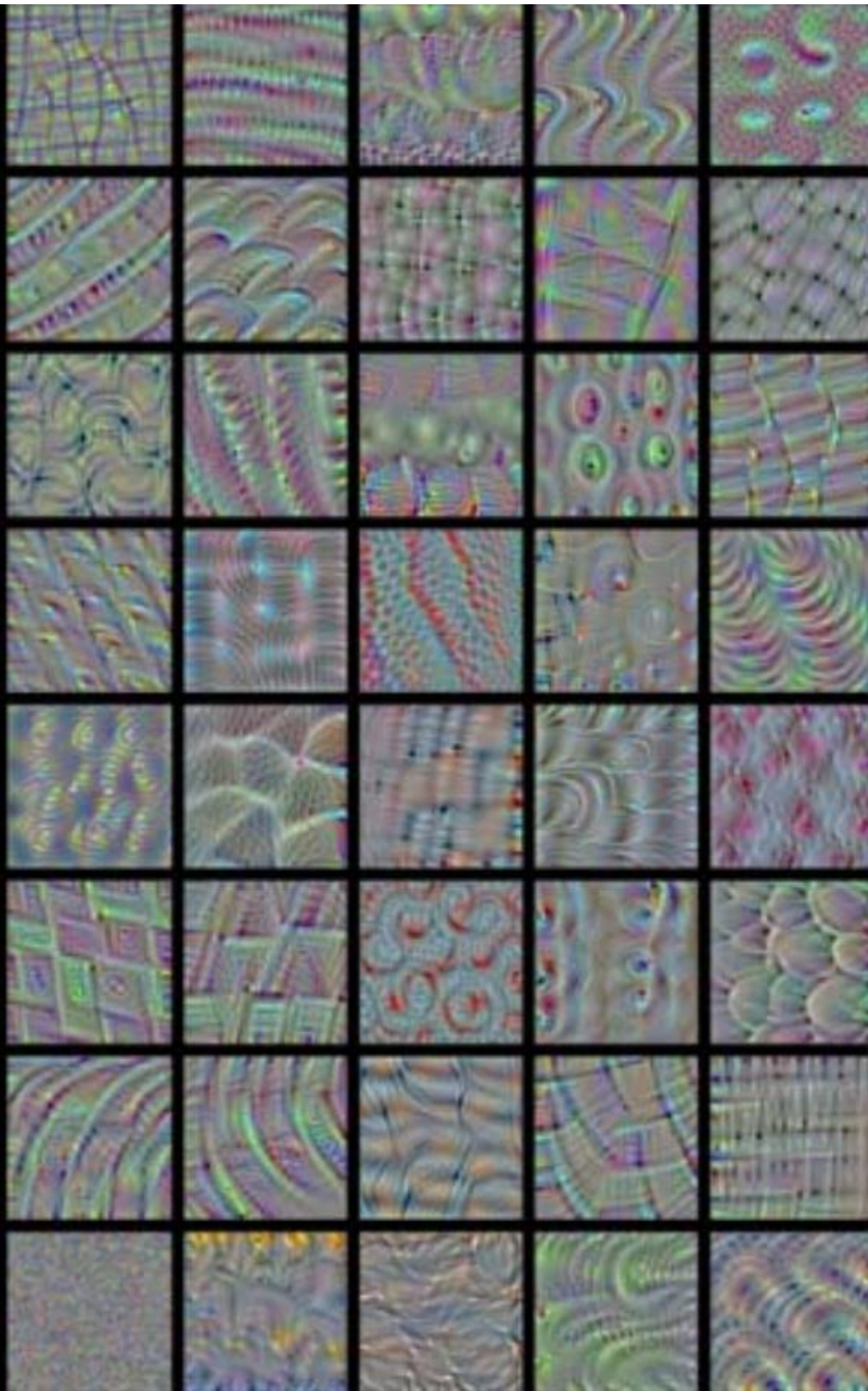
Shallow layers respond to fine, low-level patterns



Intermediate layers ...



Deep layers respond to complex, high-level patterns



Computing Images maximally activating softmax input

Adopt gradient descent to maximally activate a neuron before the softmax (thus the network «score», which indicates the prediction)

$$\hat{I} = \underset{I}{\operatorname{argmax}} S_c(I) + \lambda \|I\|_2^2$$

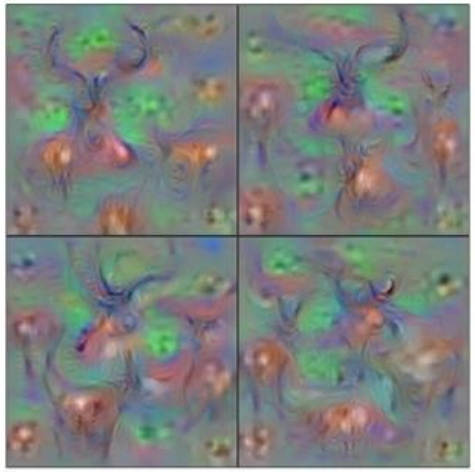
Being $\lambda > 0$ regularization parameter, c is a given output class

We add the regularization term $\lambda \|I\|_2^2$ to obtain smoother images

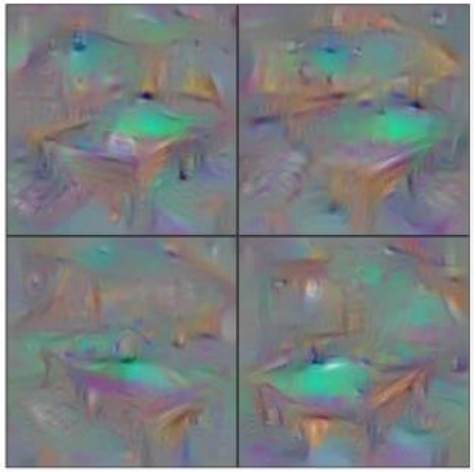
Optimize this through gradient ascent from the network for different classes c

Yosinski et al, “Understanding Neural Networks Through Deep Visualization”, ICML DL Workshop 2014.

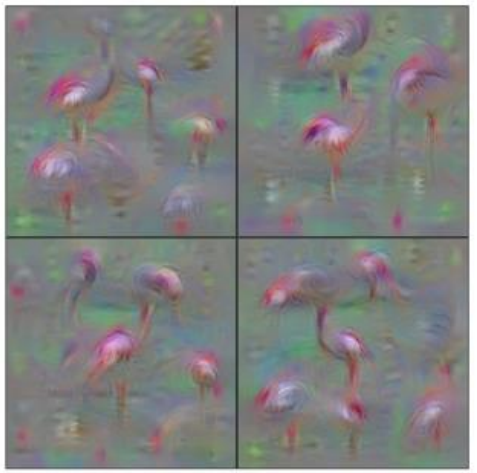
Images maximally activating softmax input



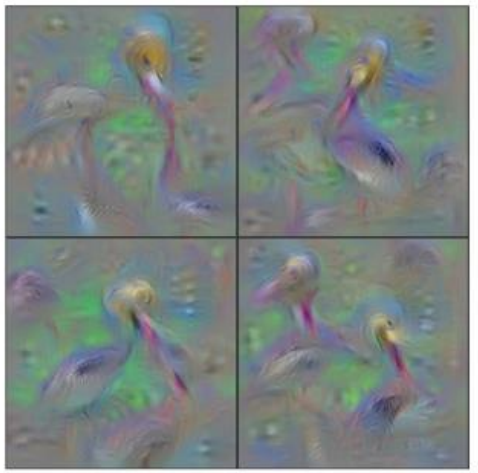
Hartebeest



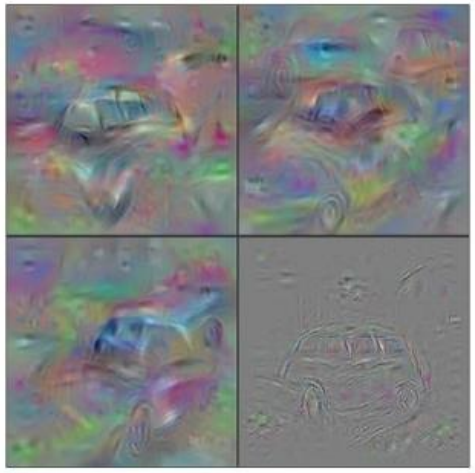
Billiard Table



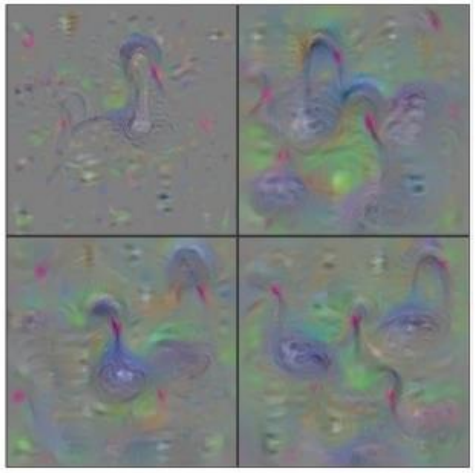
Flamingo



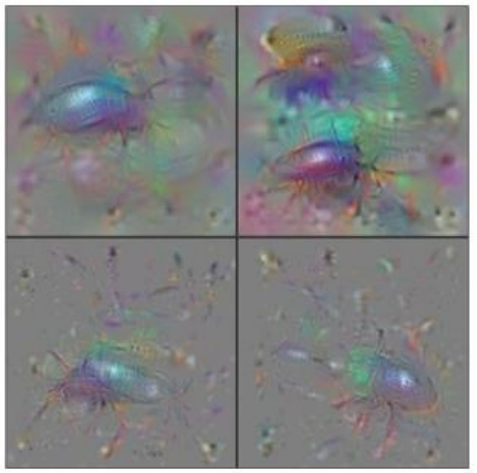
Pelican



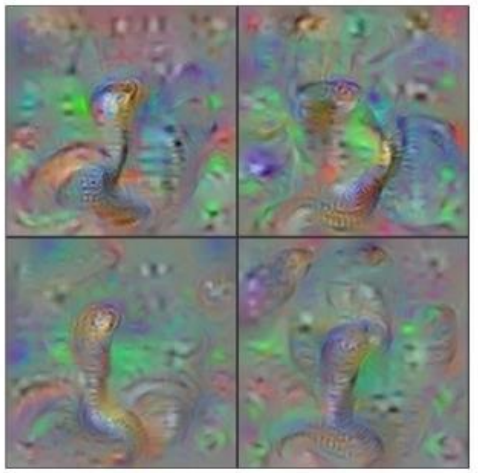
Station Wagon



Black Swan



Ground Beetle



Indian Cobra

Yosinski et al, “Understanding Neural Networks Through Deep Visualization”, ICML DL Workshop 2014.

Why CNNs work

Convnets learn a **hierarchy** of **translation-invariant** spatial pattern detectors