THE UNIVERSITY OF BRITISH COLUMBIA

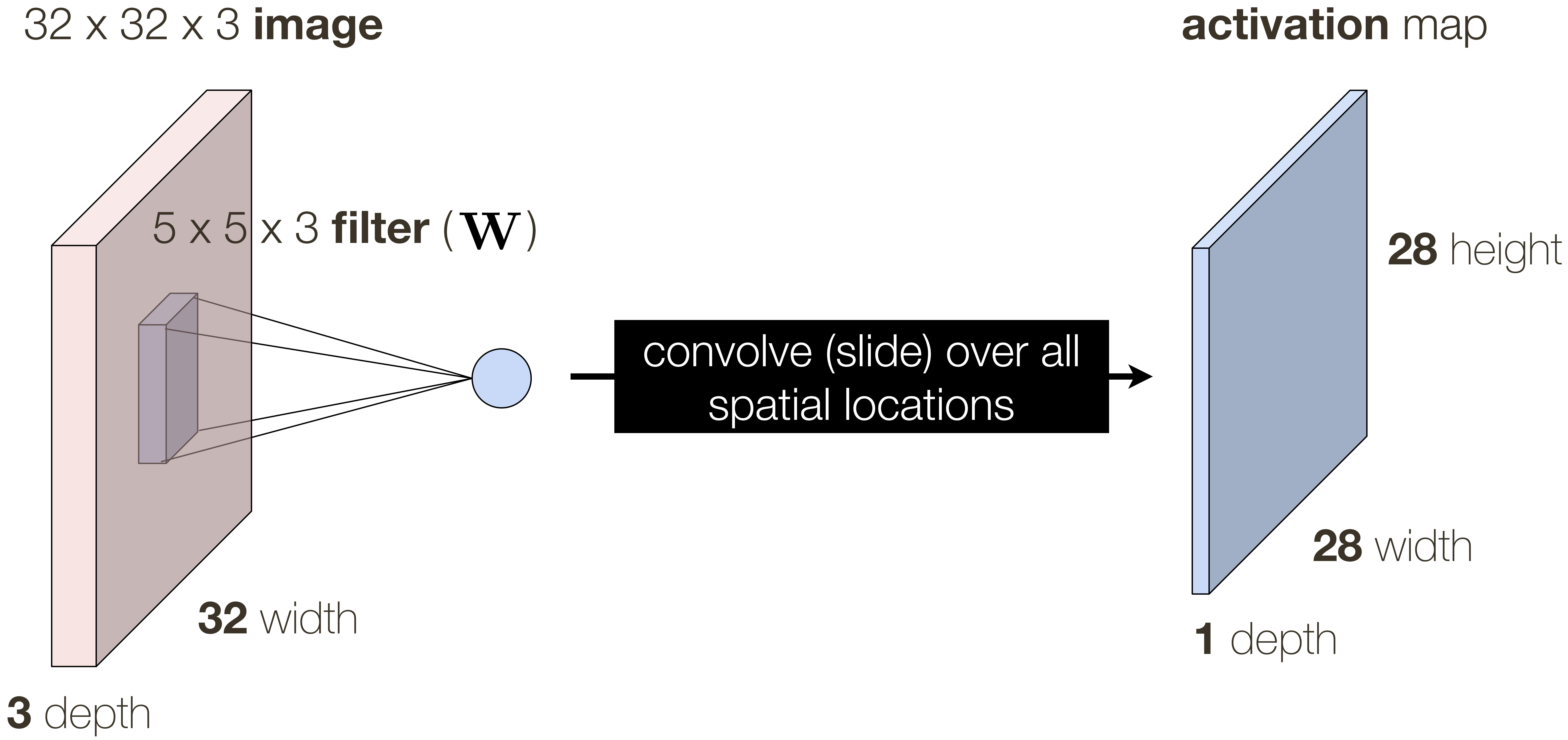
Topics in AI (CPSC 532S): Multimodal Learning with Vision, Language and Sound

Lecture 5: Convolutional Neural Networks (Part 2)

Logistics:

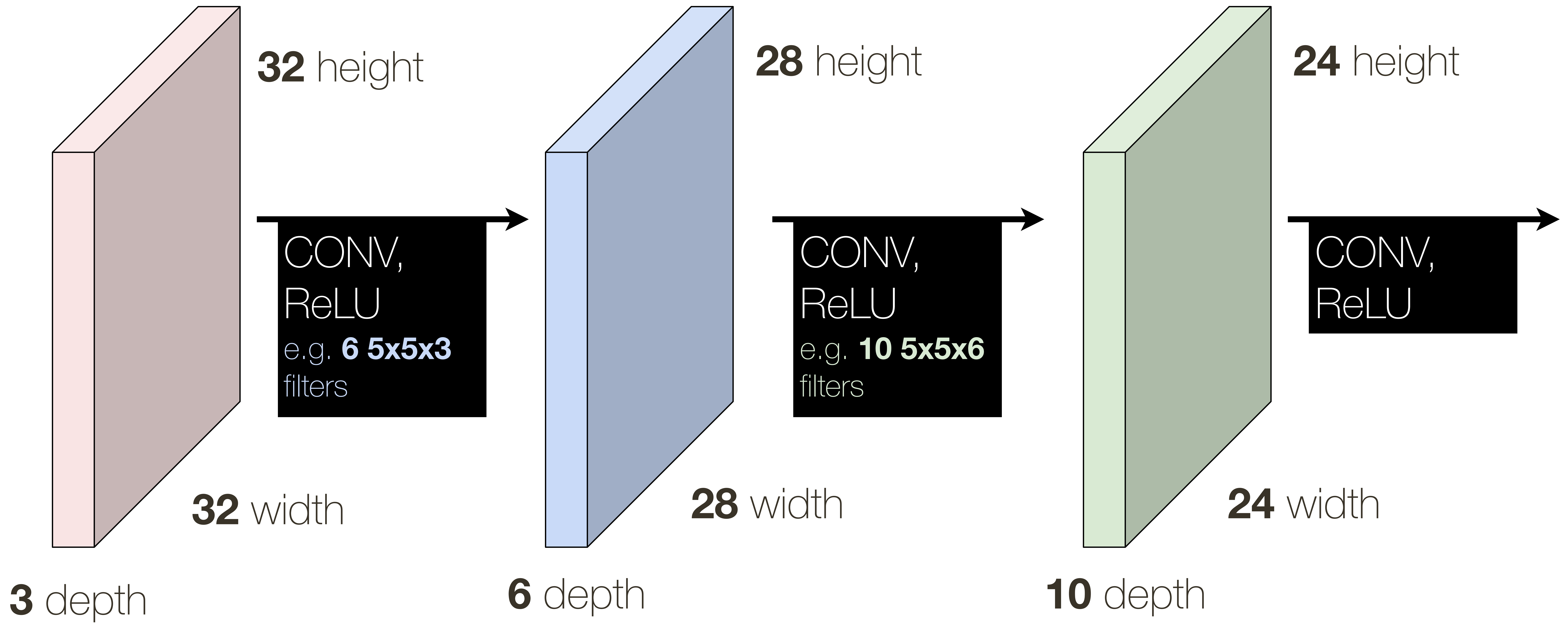
Assignment 2 is out

Last time: Convolutional Layer


32 x 32 x 3 **image**
5 x 5 x 3 **filter** ($\mathbf{W}$)
32 width
3 depth
convolve (slide) over all spatial locations
activation map
28 height
28 width
1 depth

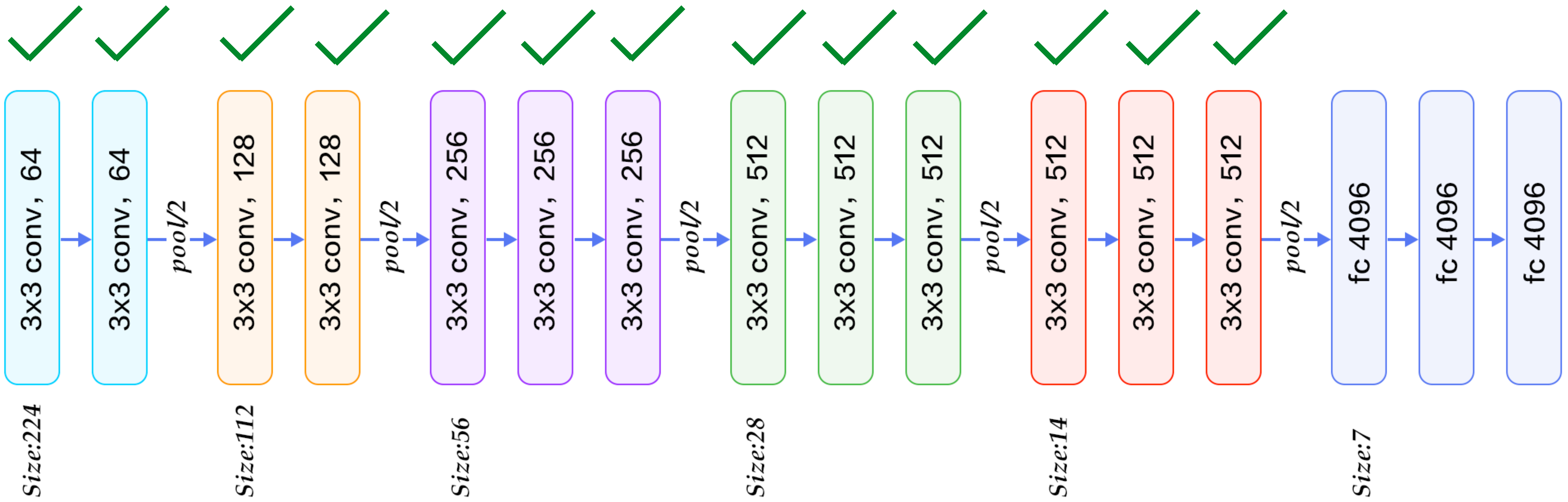
* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

Last time: Convolutional Neural Network (ConvNet)



* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

Convolutional Neural Networks



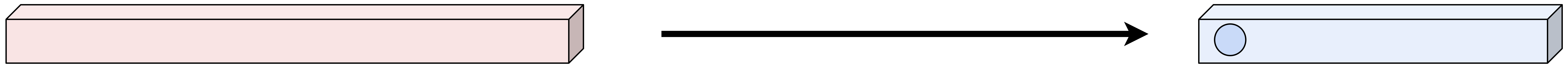
VGG-16 Network

CNNs: Reminder Fully Connected Layers

Input

$\mathbf{W}^T\mathbf{x} + \mathbf{b}, \text{where } \mathbf{W} \in \mathbb{R}^{10\times 3072}$

Activation



3072

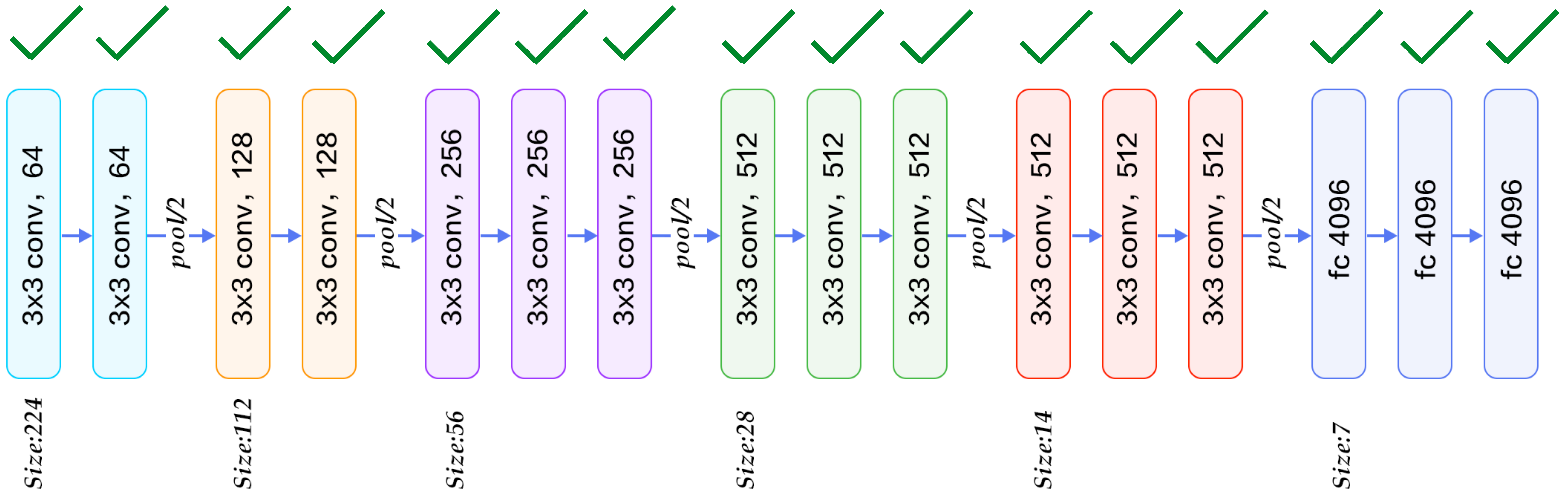
(32 x 32 x 3 image -> stretches to 3072 x 1)

each neuron looks at the full input volume

10

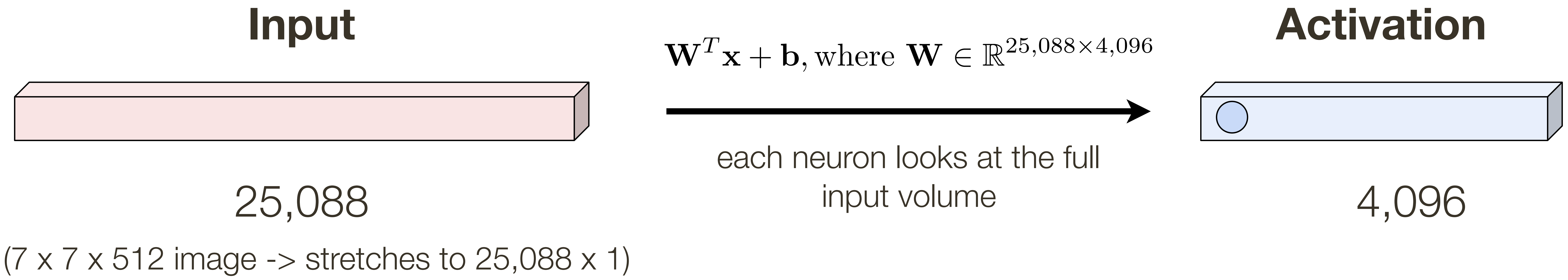
* adopted from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

Convolutional Neural Networks



VGG-16 Network

CNNs: Reminder Fully Connected Layers

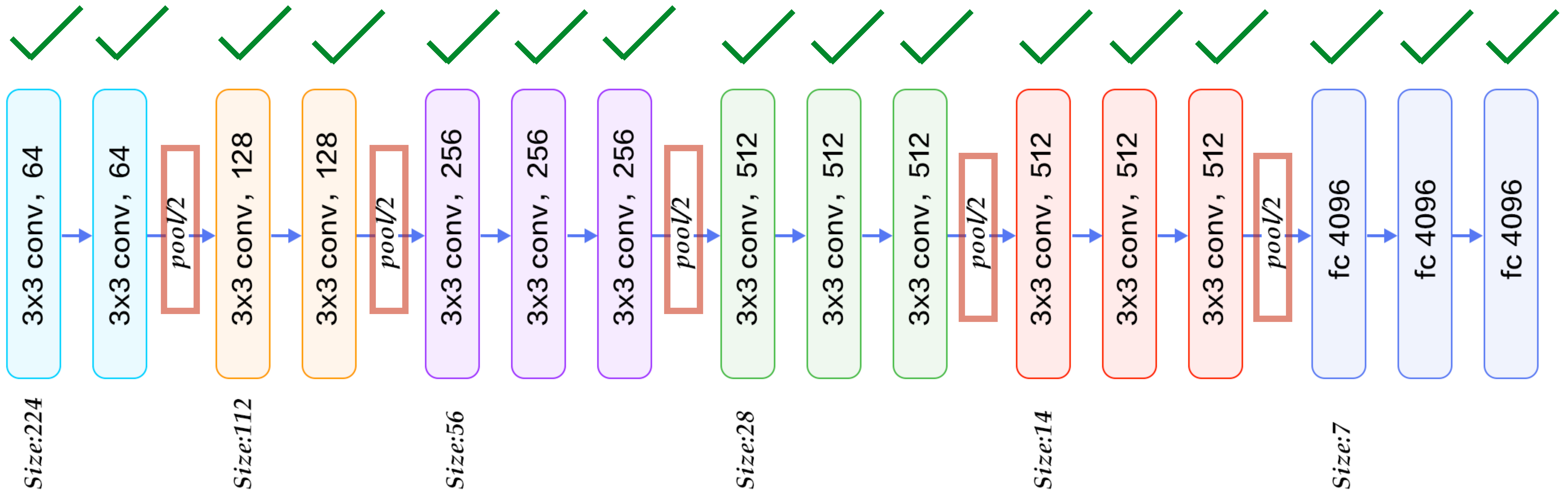


Input
25,088
(7 x 7 x 512 image -> stretches to 25,088 x 1)
Activation
4,096
each neuron looks at the full input volume

$\mathbf{W}^T\mathbf{x} + \mathbf{b}$, where $\mathbf{W} \in \mathbb{R}^{25,088 \times 4,096}$

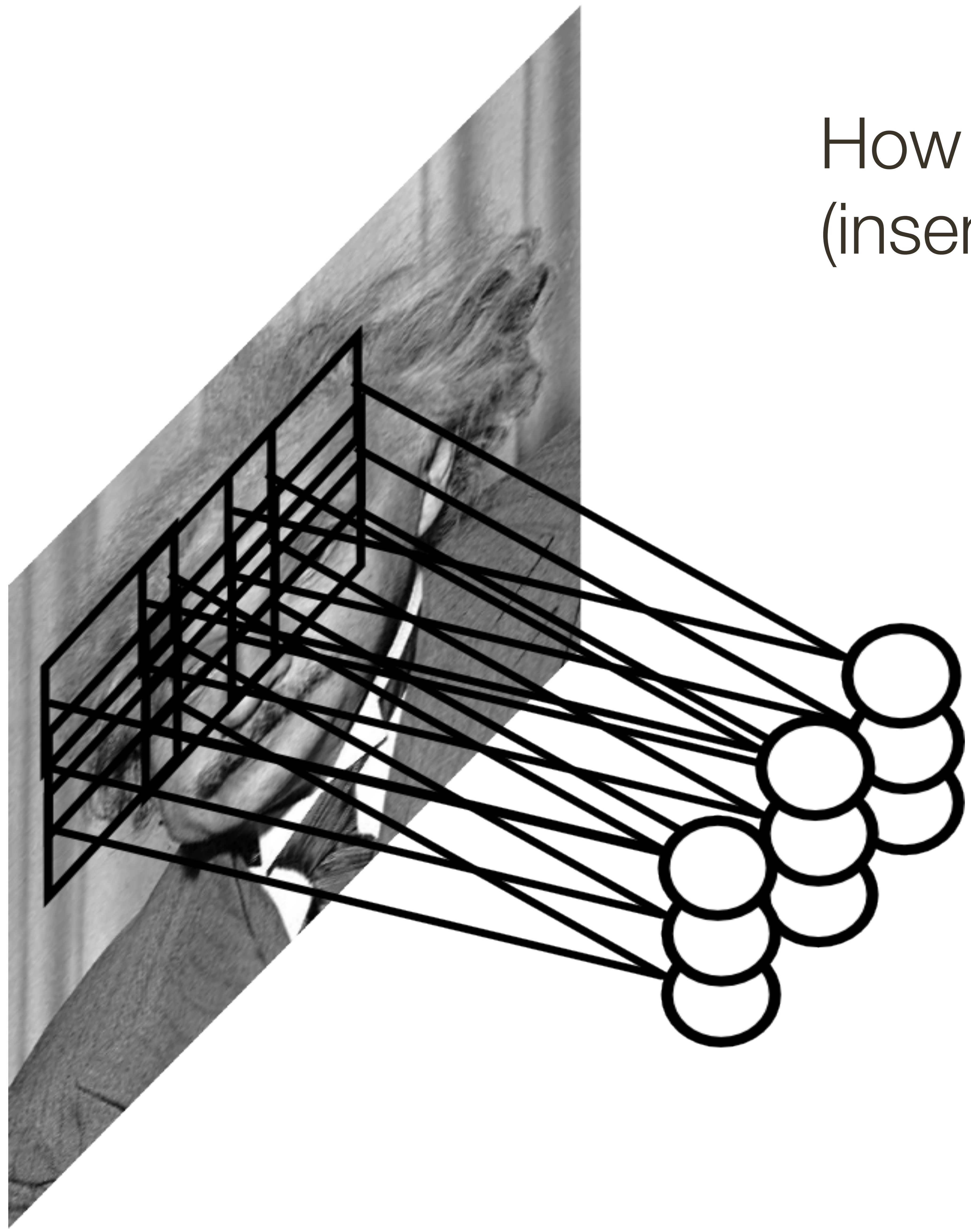
102,760,448 parameters!

Convolutional Neural Networks



VGG-16 Network

Pooling Layer

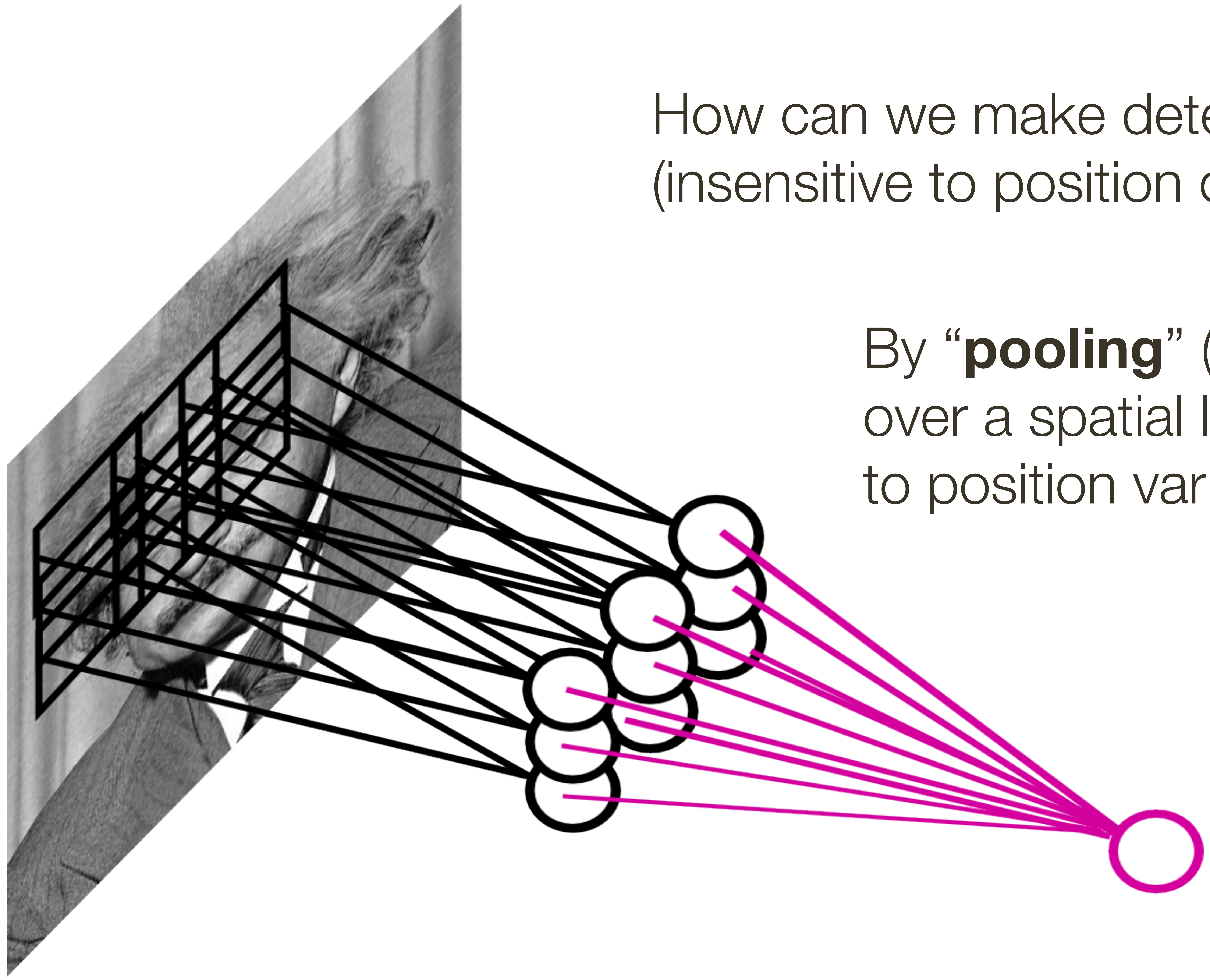


Let us assume the filter is an “eye” detector

How can we make detection spatially invariant (insensitive to position of the eye in the image)

* slide from Marc’Aurelio Renzato

Pooling Layer



Let us assume the filter is an "eye" detector

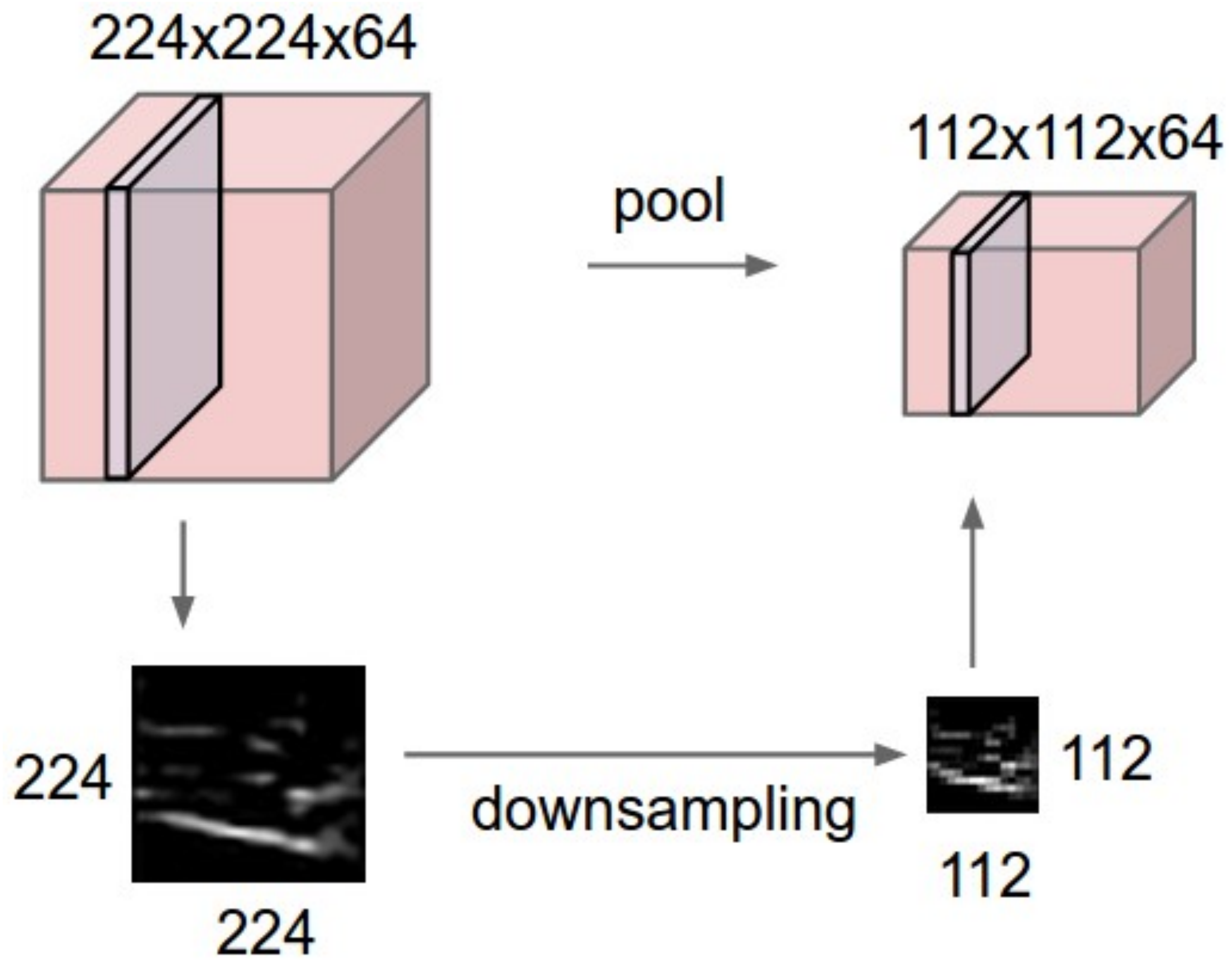
How can we make detection spatially invariant (insensitive to position of the eye in the image)

By "**pooling**" (e.g., taking a max) response over a spatial locations we gain robustness to position variations

* slide from Marc'Aurelio Renzato

Pooling Layer

- Makes representation smaller, more manageable and spatially invariant
- Operates over each activation map independently



How many **parameters**?

None!

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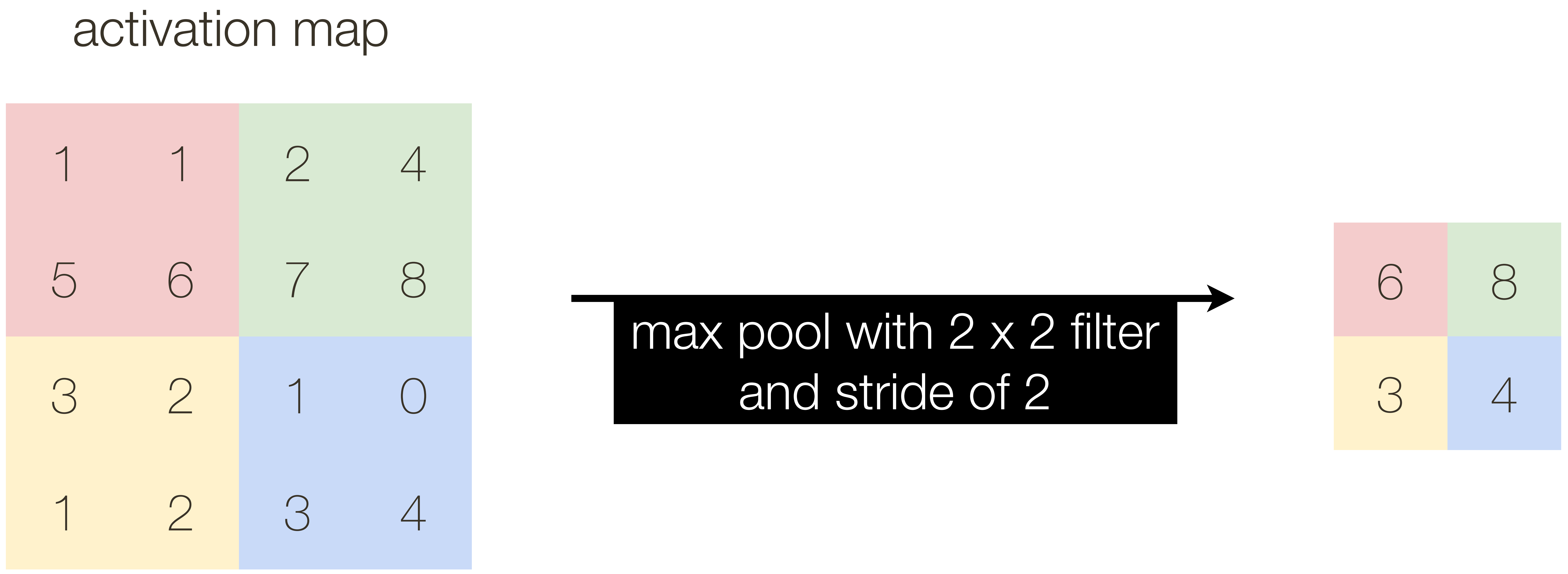
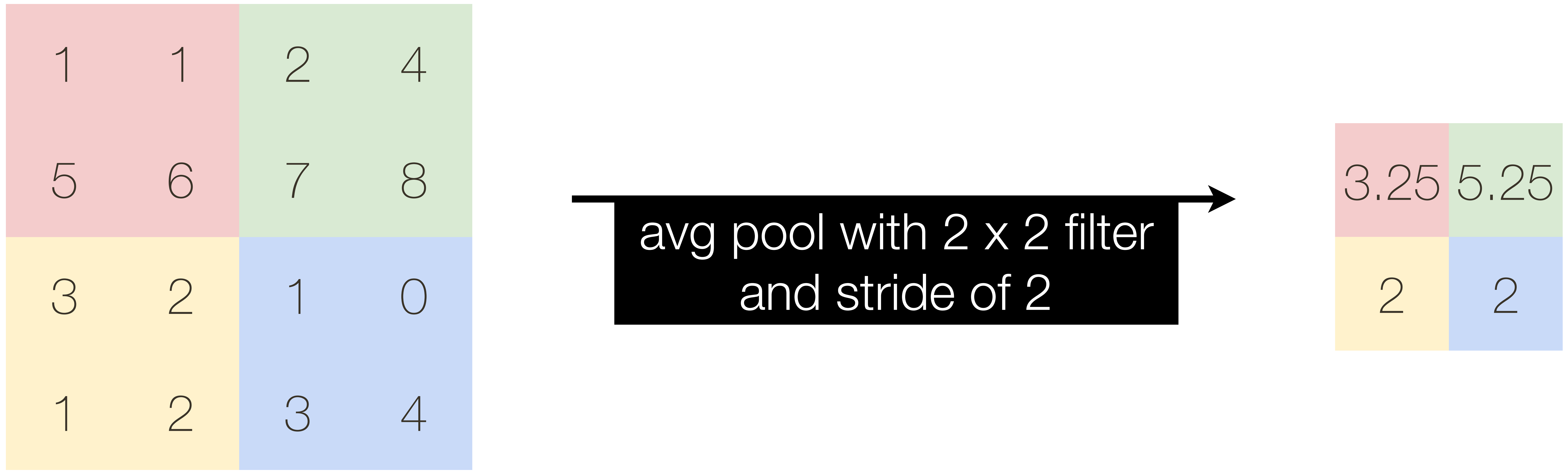
Max **Pooling**



activation map
1 1 2 4
5 6 7 8
3 2 1 0
1 2 3 4
max pool with 2 x 2 filter and stride of 2
6 8
3 4

Average **Pooling**

activation map

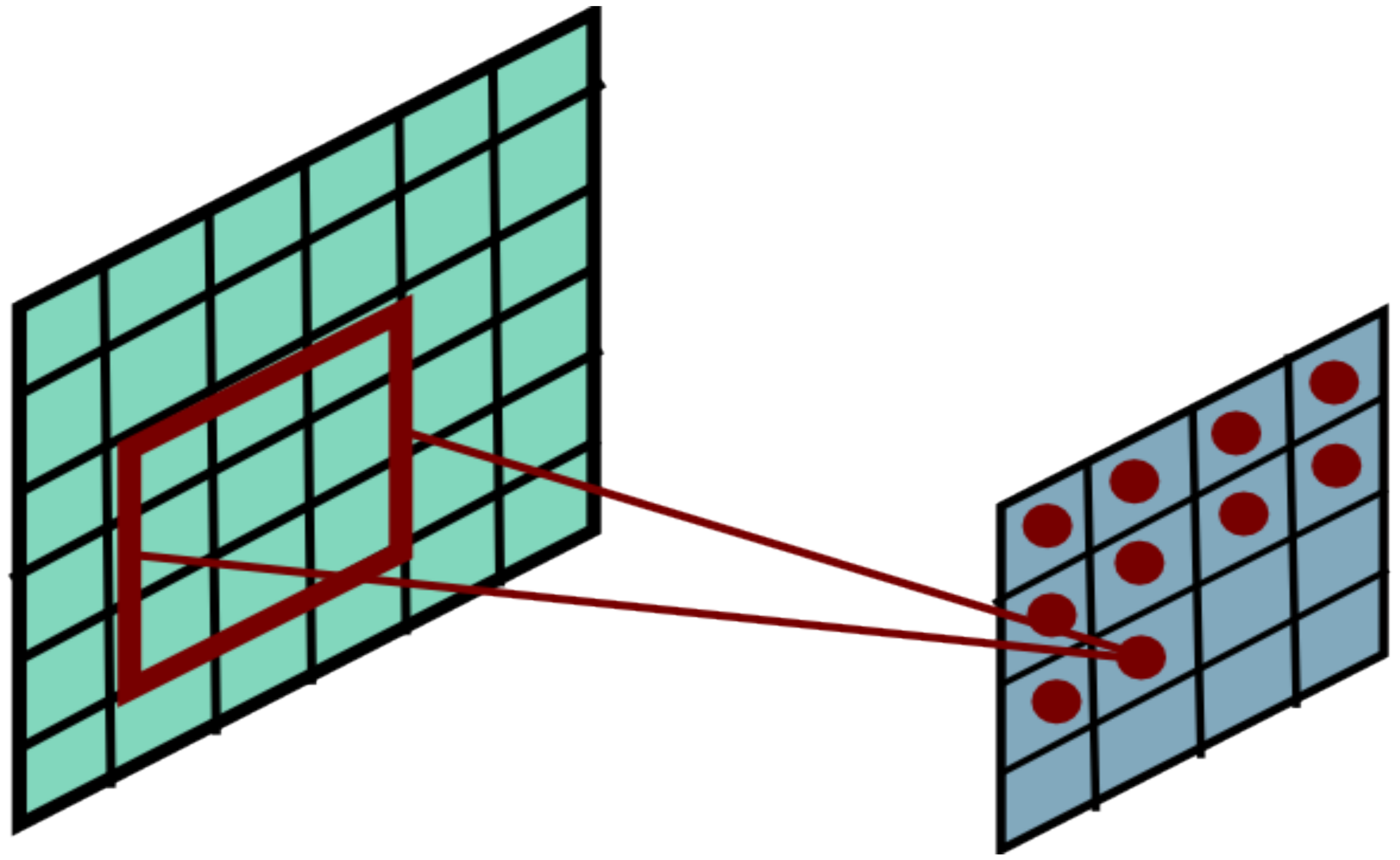


1	1	2	4
5	6	7	8
3	2	1	0
1	2	3	4

3.25	5.25
2	2

Pooling Layer **Receptive Field**

If convolutional filters have size KxK and stride 1, and pooling layer has pools of size PxP, then each unit in the pooling layer depends upon a patch (at the input of the preceding conv. layer) of size: **(P+K-1)x(P+K-1)**



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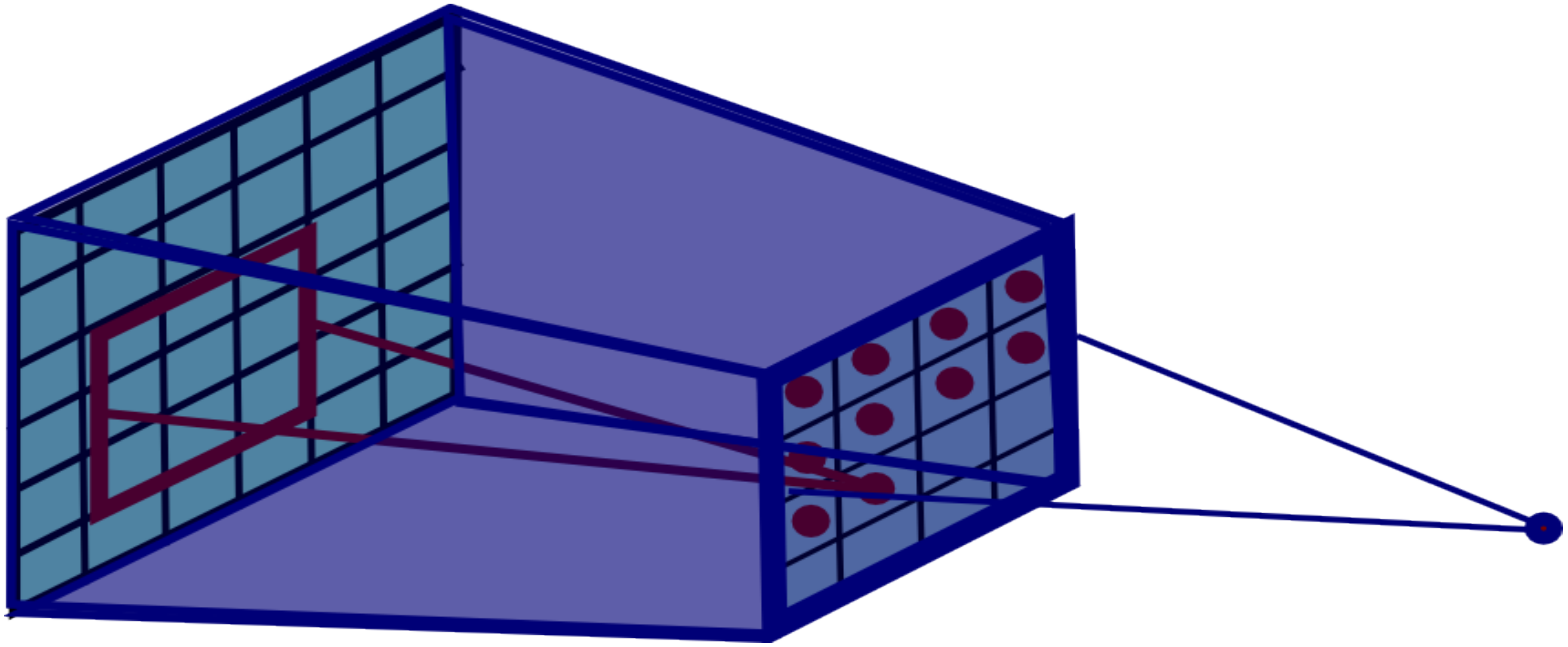


* slide from Marc'Aurelio Renzato

Pooling Layer **Summary**

Accepts a volume of size: $W_i \times H_i \times D_i$

Requires hyperparameters:

— Spatial extent of filters: K

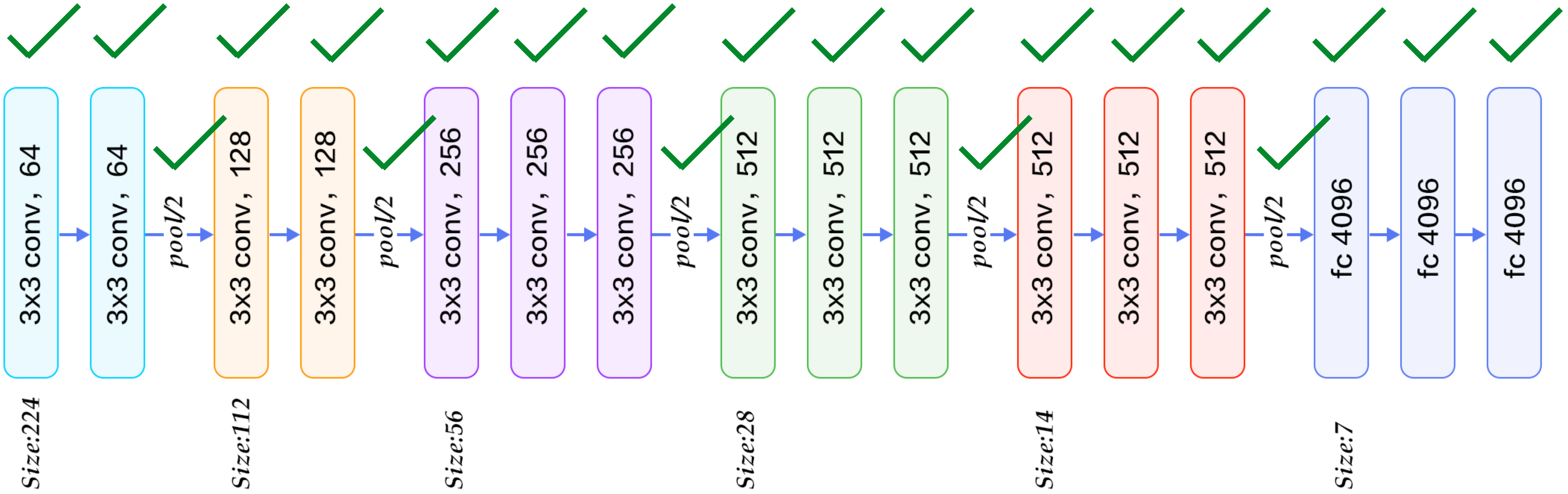
— Stride of application: F

Produces a volume of size: $W_o \times H_o \times D_o$

$$W_o = (W_i - F)/S + 1 \qquad H_o = (H_i - F)/S + 1 \qquad D_o = D_i$$

Number of total learnable parameters: 0

Convolutional Neural Networks

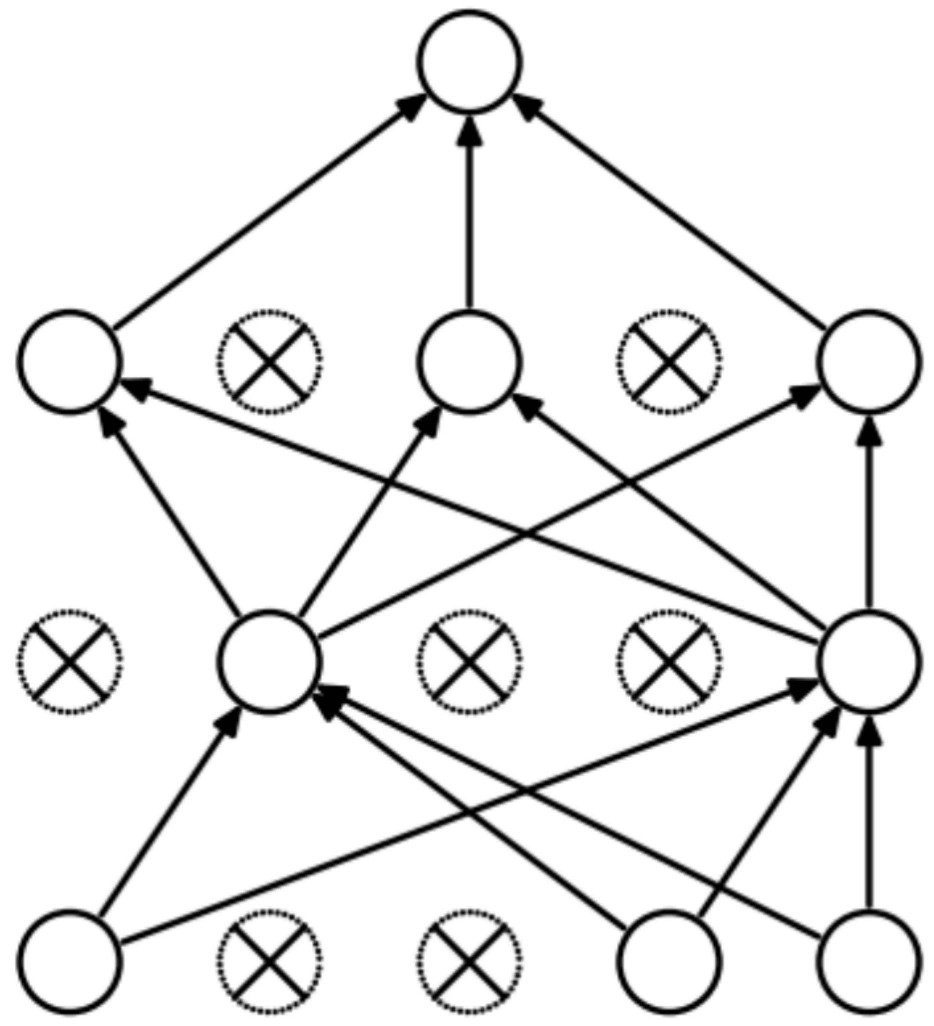


VGG-16 Network

Improving **Single Model**

Regularization

- L2, L1
- Dropout / Inverted Dropout
- Data augmentation


Dropout

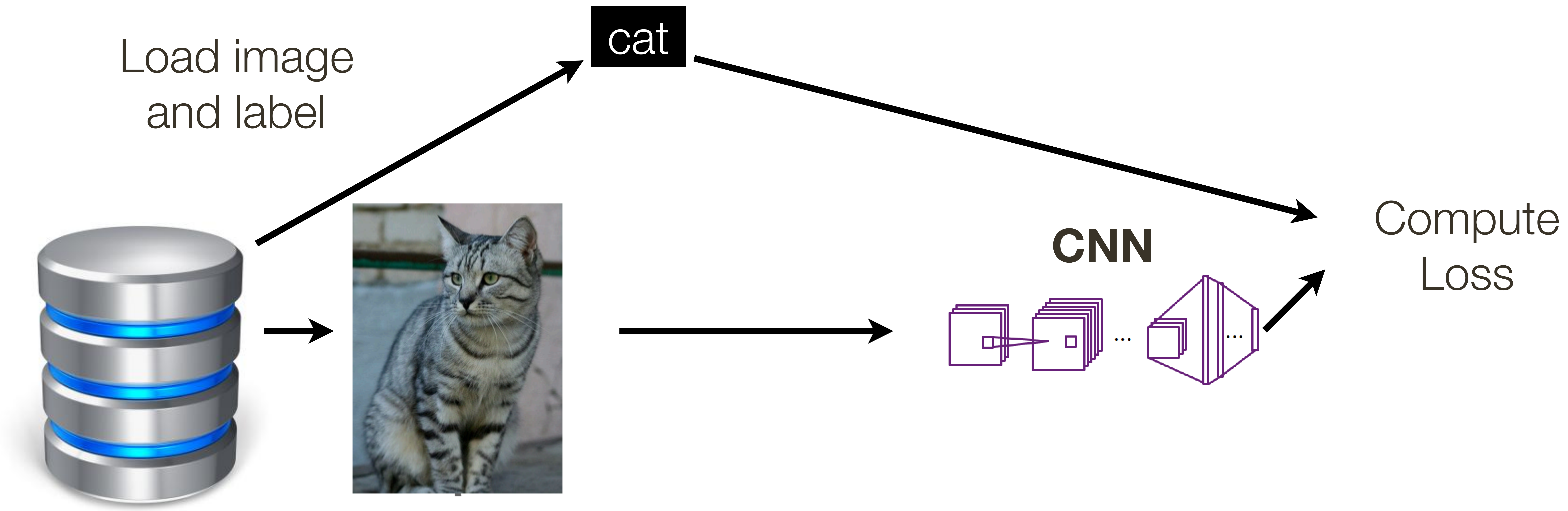
L2 Regularization: Learn a more (dense) distributed representation

$$R(\mathbf{W}) = ||\mathbf{W}||_2 = \sum_i \sum_j \mathbf{W}_{i,j}^2$$

L1 Regularization: Learn a sparse representation (few non-zero wight elements)

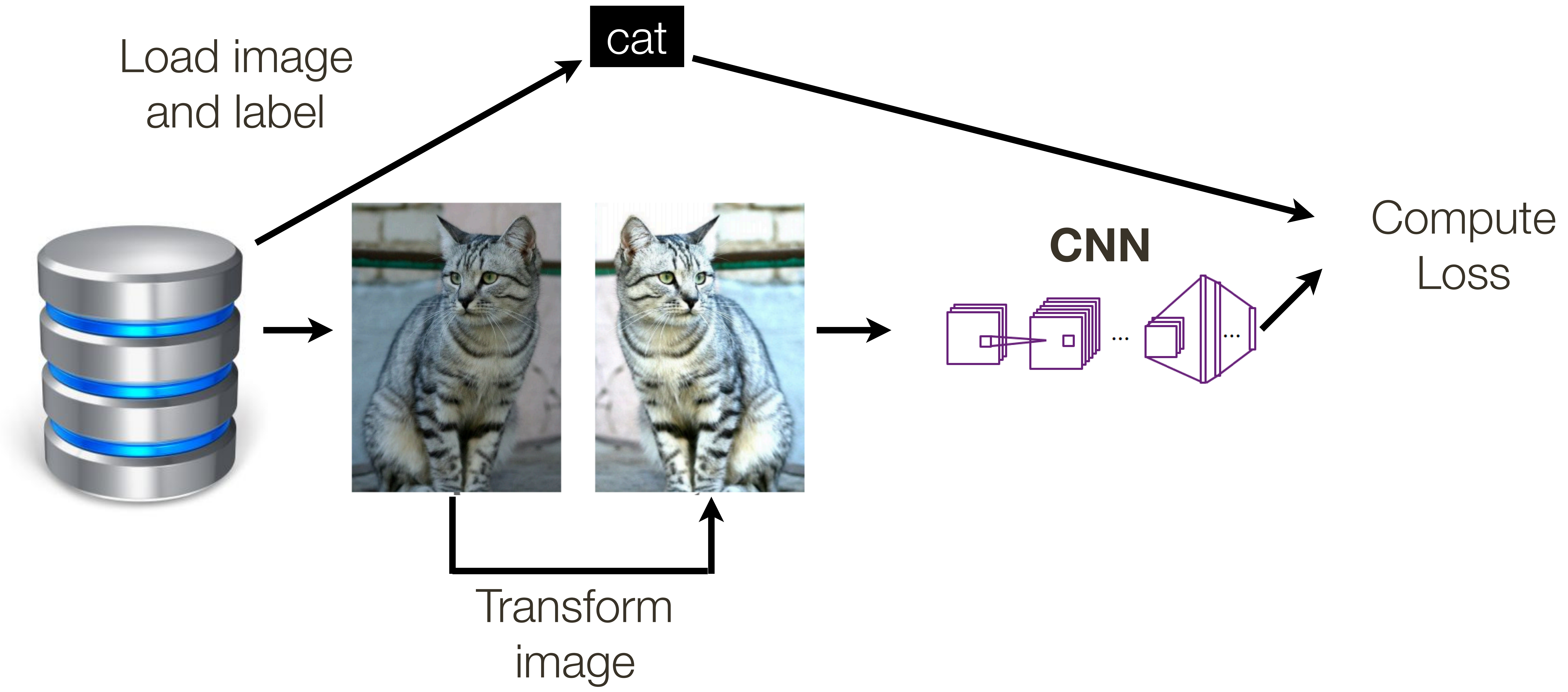
$$R(\mathbf{W}) = ||\mathbf{W}||_1 = \sum_i \sum_j |\mathbf{W}_{i,j}|$$

Regularization: Data Augmentation



* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

Regularization: Data Augmentation



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Regularization: Data Augmentation

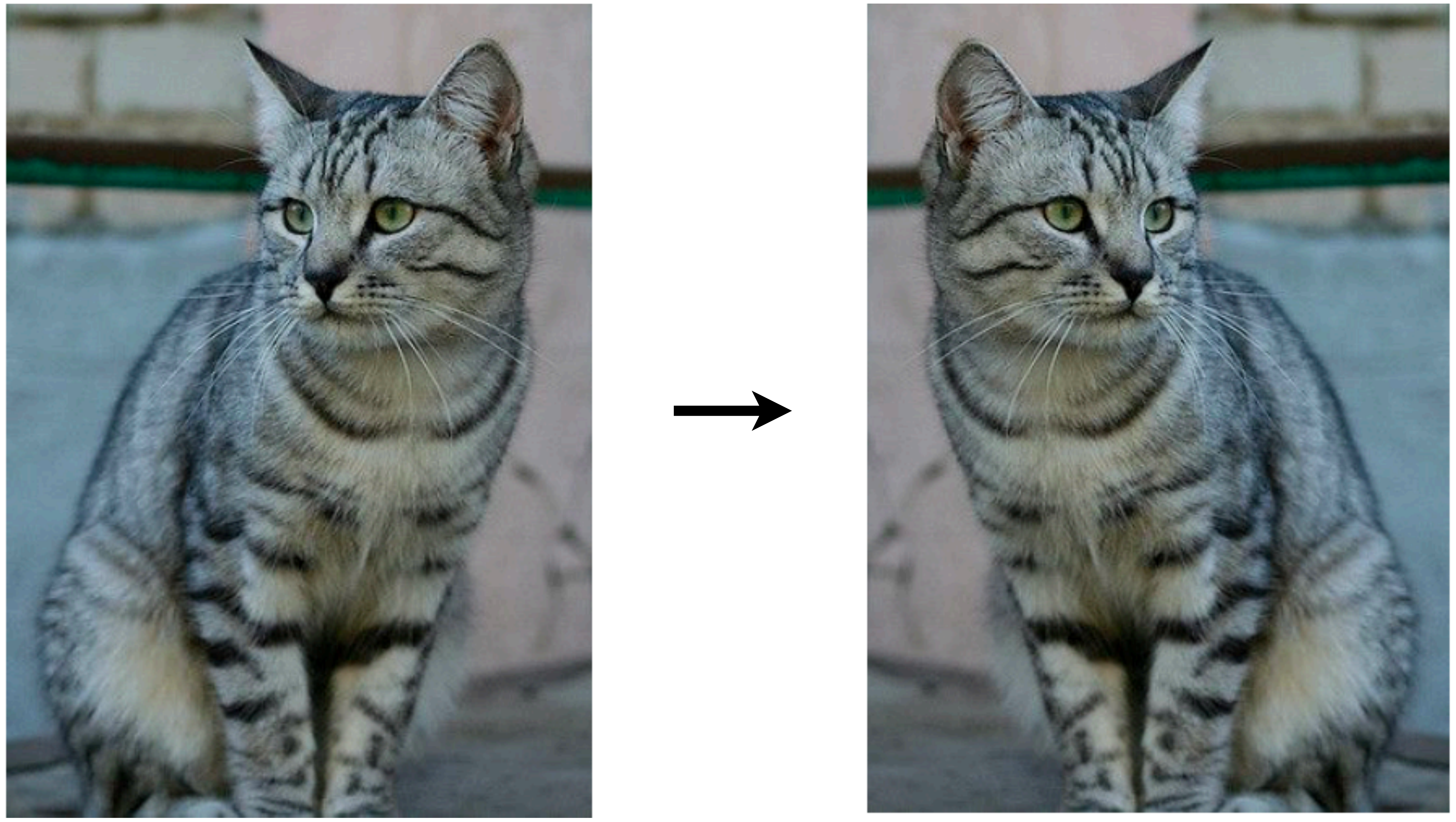
Horizontal flips

Random crops & scales

Color Jitter

Regularization: Data Augmentation

Horizontal flips Random crops & scales Color Jitter



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Regularization: Data Augmentation

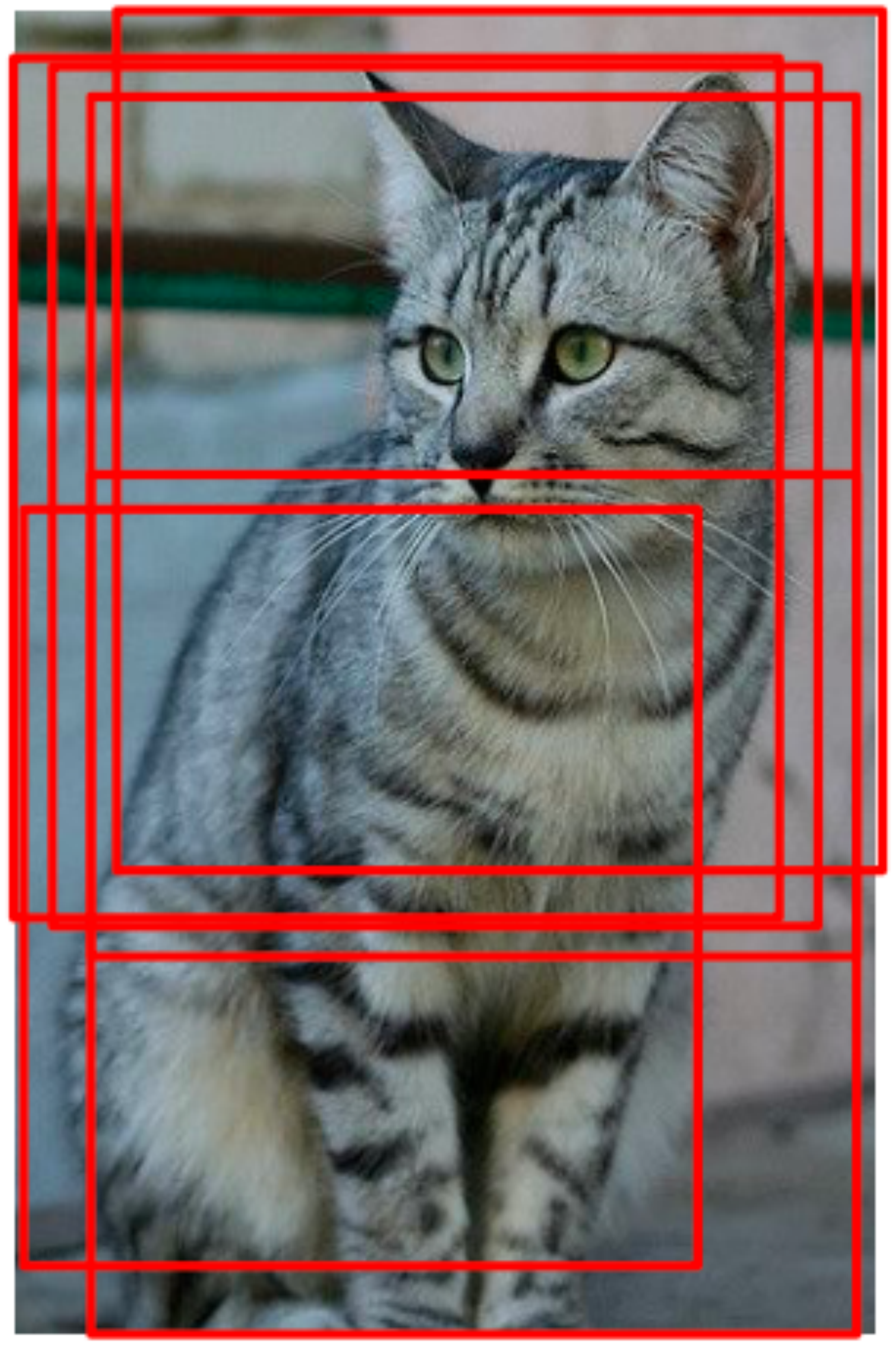
Horizontal flips | **Random crops & scales** | Color Jitter

Training: sample random crops and scales
e.g., ResNet:

1. Pick random L in range [256, 480]
2. Resize training image, short size = L
3. Sample random 224x224 patch

Testing: average a fix set of crops
e.g., ResNet:

1. Resize image to 5 scales (224, 256, 384, 480, 640)
2. For each image use 10 224x224 crops: 4 corners + center, + flips



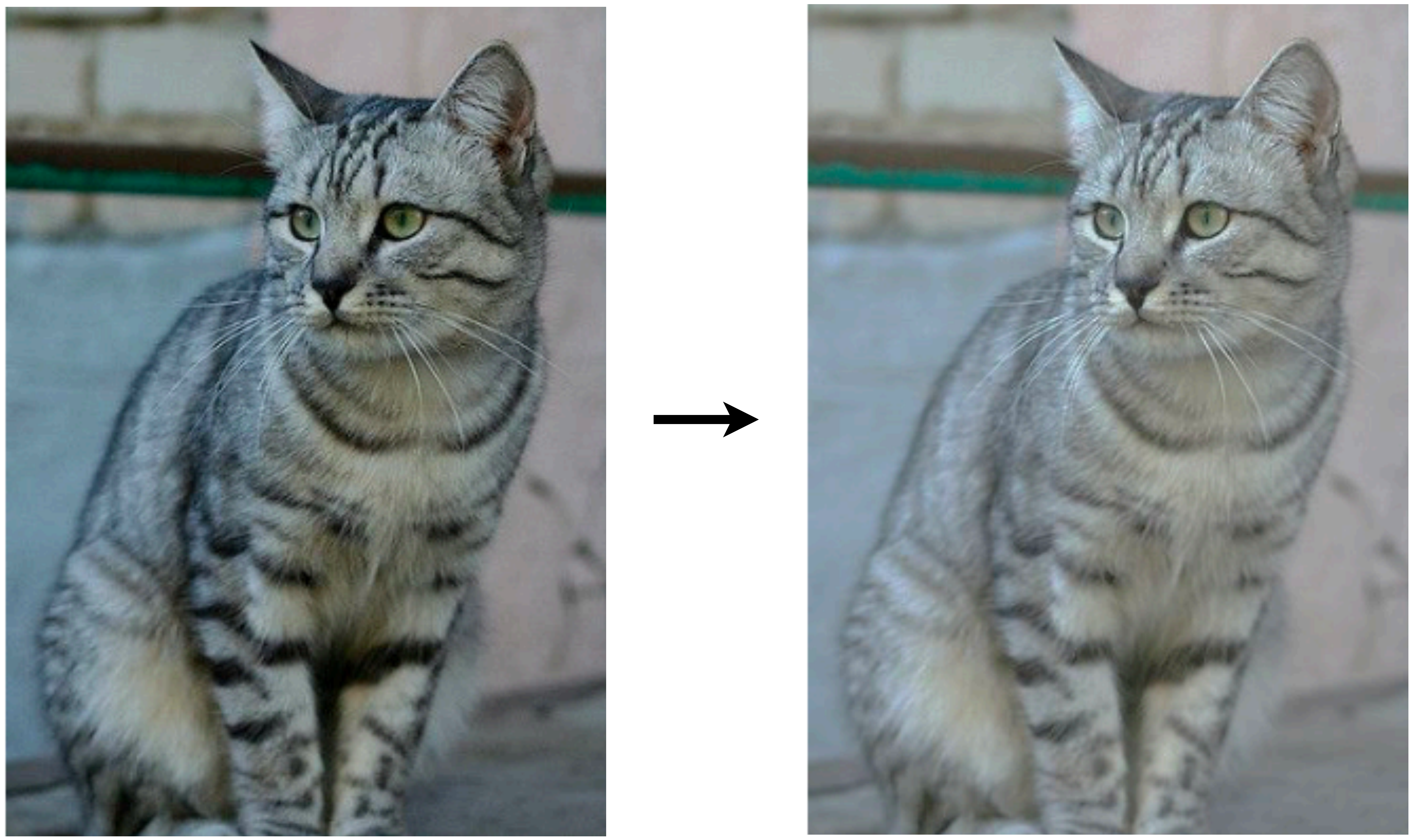
Regularization: Data Augmentation

Horizontal flips

Random crops & scales

Color Jitter

Random perturbations in contrast and brightness



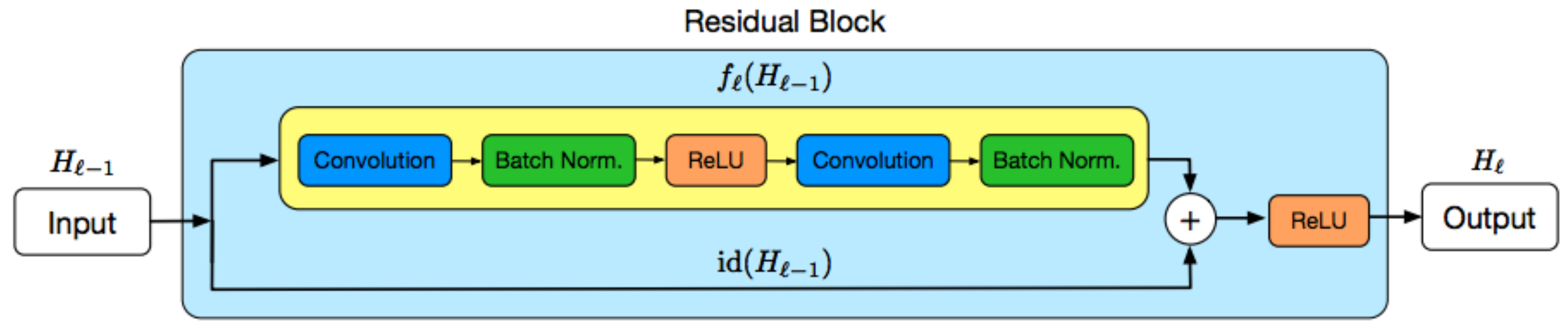
Regularization: Stochastic Depth

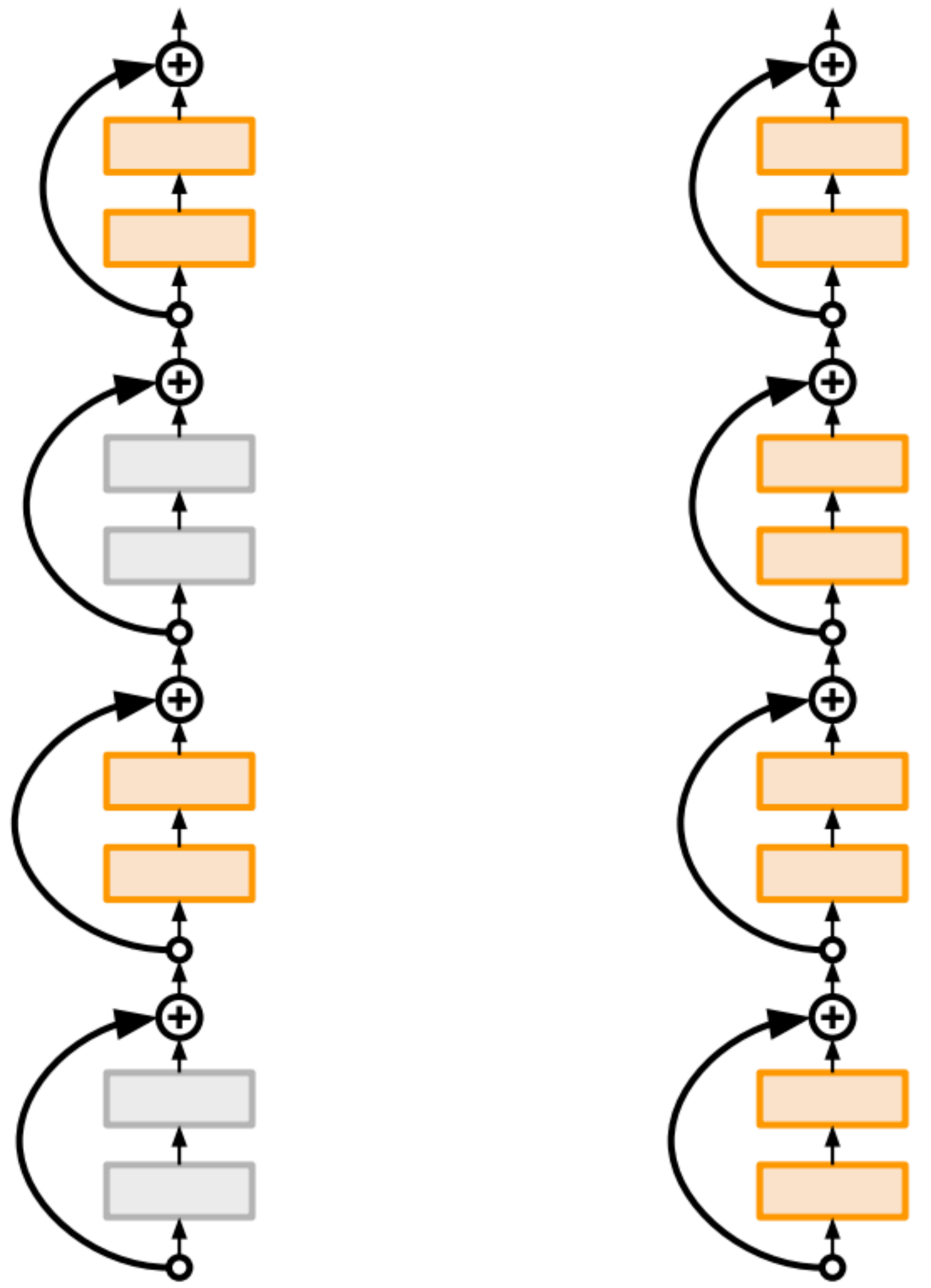
[Huang et al., ECCV 2016]

Effectively "dropout" but for layers

Stochastically with some probability **turn off some layer** (for each batch)

Effectively trains a collection of neural networks





* adopted from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

Transfer Learning with CNNs

Common "Wisdom": You need a lot of data to train a CNN

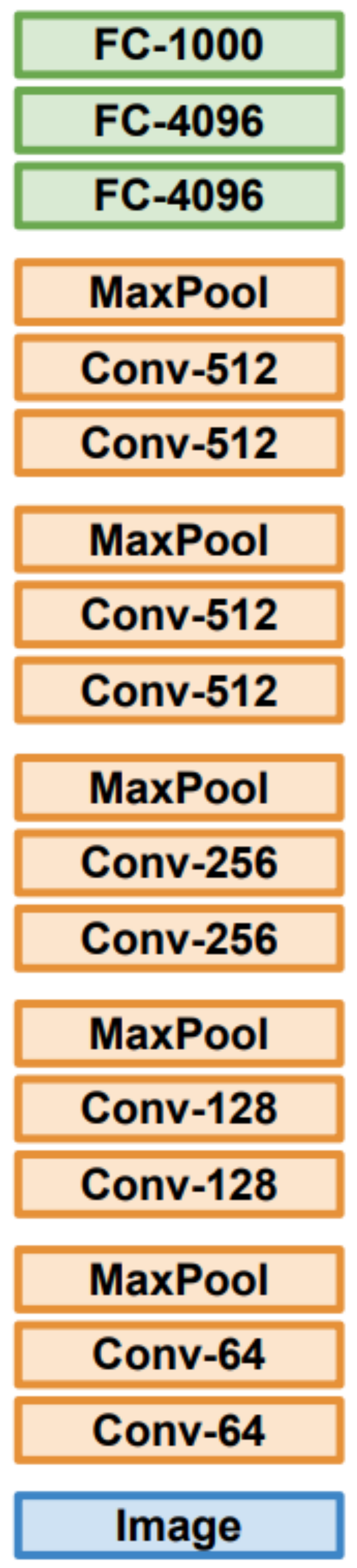
Solution: Transfer learning — taking a model trained on the task that has lots of data and adopting it to the task that may not

This strategy is PERVASIVE.

Transfer Learning with CNNs

[Yosinski et al., NIPS 2014]
[Donahue et al., ICML 2014]
[Razavian et al., CVPR Workshop 2014]

Train on **ImageNet**



Why on **ImageNet**?

- Convenience, lots of **data**
- We know how to **train these well**

However, for some tasks we would need to start with something else (e.g., videos for optical flow)

Transfer Learning with CNNs

[Yosinski et al., NIPS 2014]
[Donahue et al., ICML 2014]
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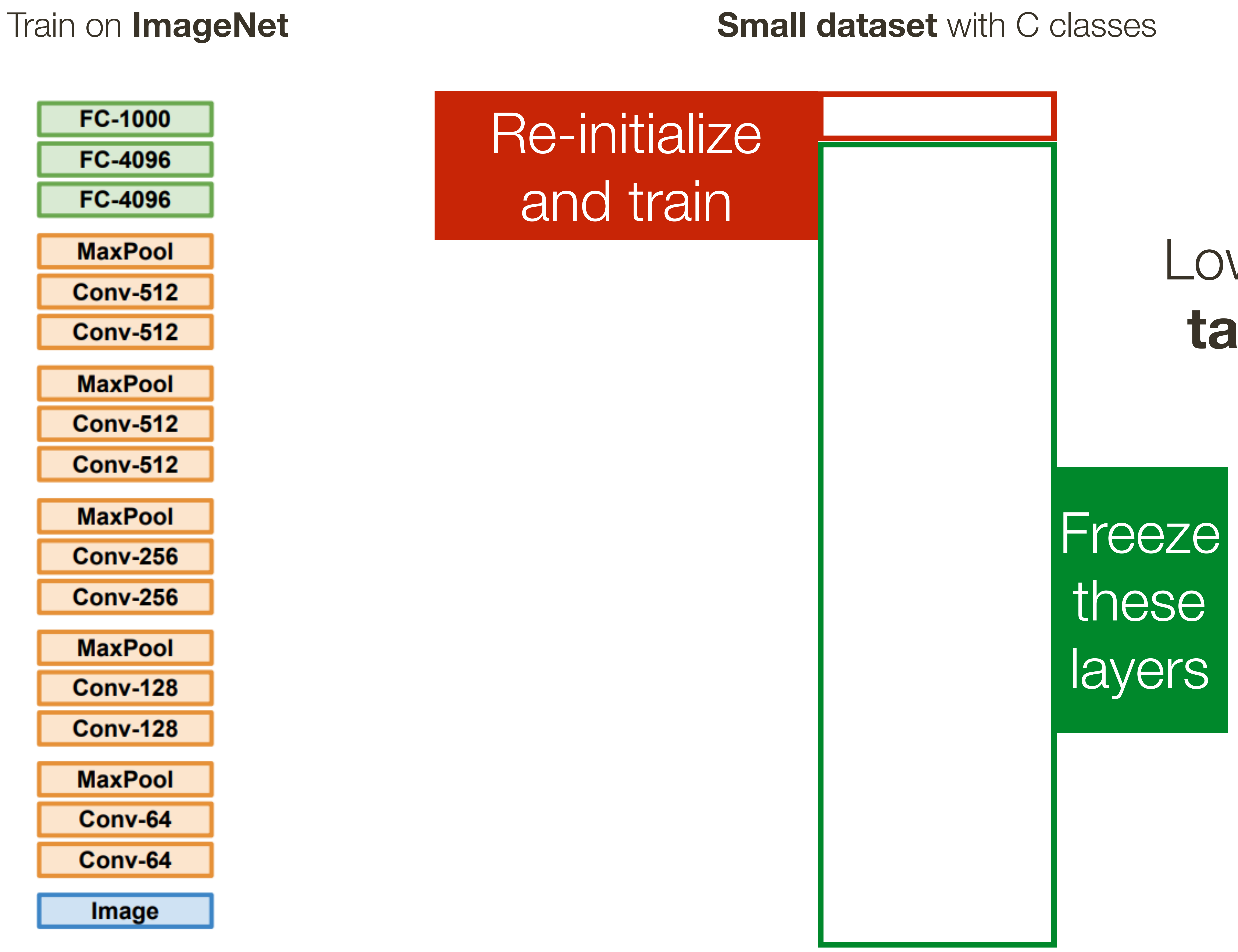
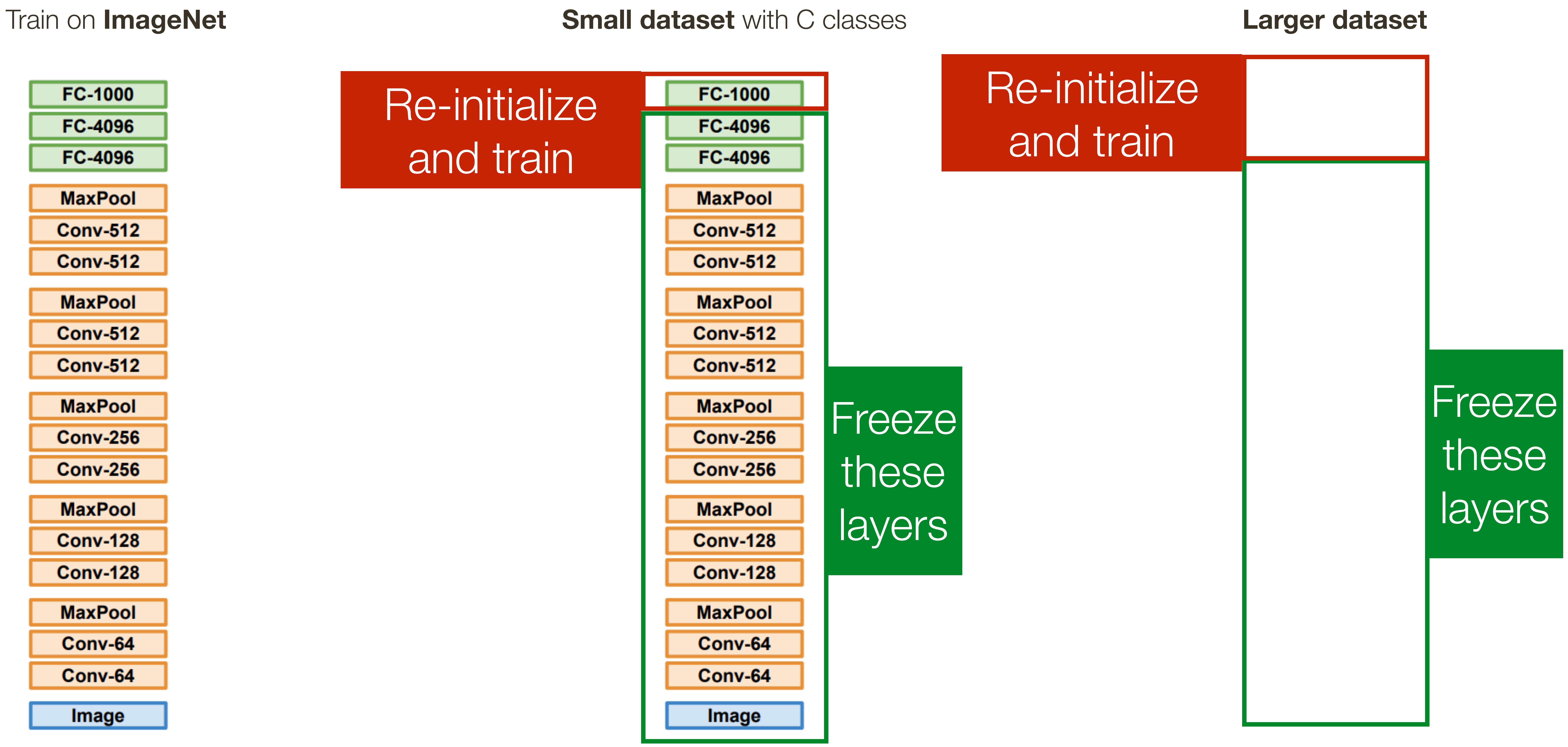


Lower levels of the CNN are at **task independent** anyways

Transfer Learning with CNNs

[Yosinski et al., NIPS 2014]
[Donahue et al., ICML 2014]
[Razavian et al., CVPR Workshop 2014]



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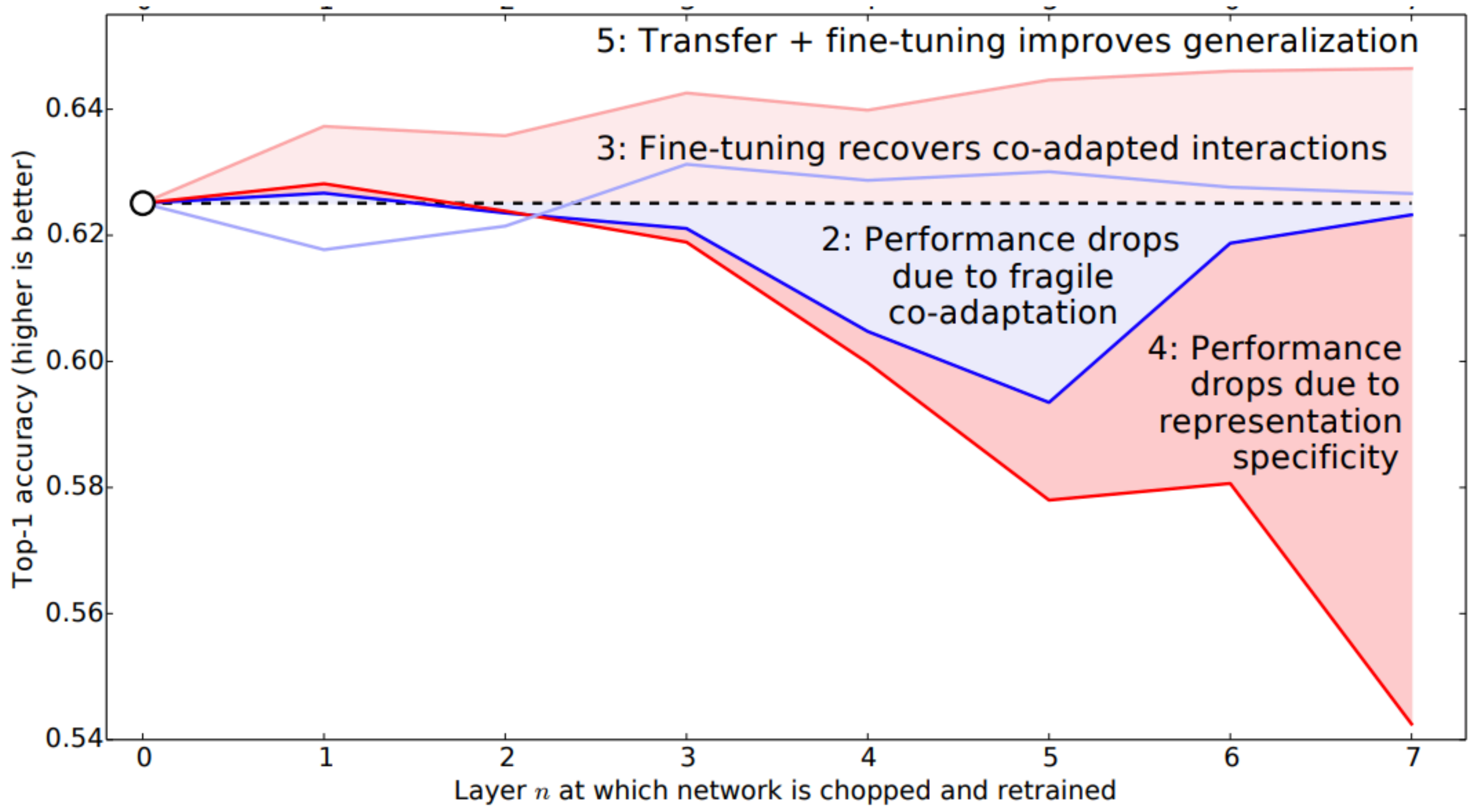
Transfer Learning with CNNs



[Yosinski et al., NIPS 2014]

Model **Ensemble**

Training: Train multiple independent models

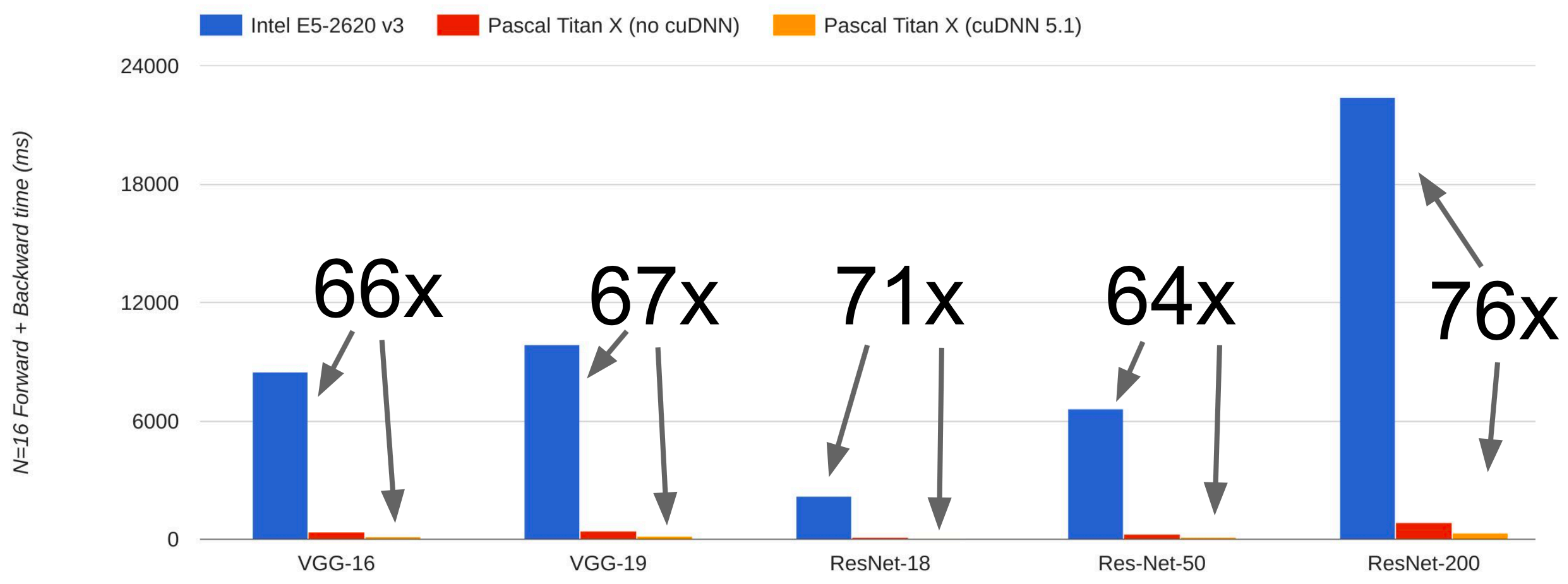
Test: Average their results

~ 2% improved performance in practice

Alternative: Multiple snapshots of the single model during training!

Improvement: Instead of using the actual parameter vector, keep a moving average of the parameter vector and use that at test time (Polyak averaging)

CPU vs. **GPU** (Why do we need Azure?)



Data from https://github.com/jcjohnson/cnn-benchmarks

* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

Frameworks: Super quick overview

1. Easily **build computational graphs**

2. Easily **compute gradients** in computational graphs

3. **Run it all efficiently** on a GPU (weap cuDNN, cuBLAS, etc.)

Frameworks: Super quick overview

Core DNN Frameworks		
Caffe (UC Berkeley)	Caffe 2 (Facebook)	Puddle (Baidu)
Torch (NYU/Facebook)	**PyTorch** (Facebook)	CNTK (Microsoft)
Theano (U Montreal)	**TensorFlow** (Google)	MXNet (Amazon)

Wrapper Libraries

Keras
TFLearn
TensorLayer
tf.layers
TF-Slim
tf.contrib.learn
Pretty Tensor

* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

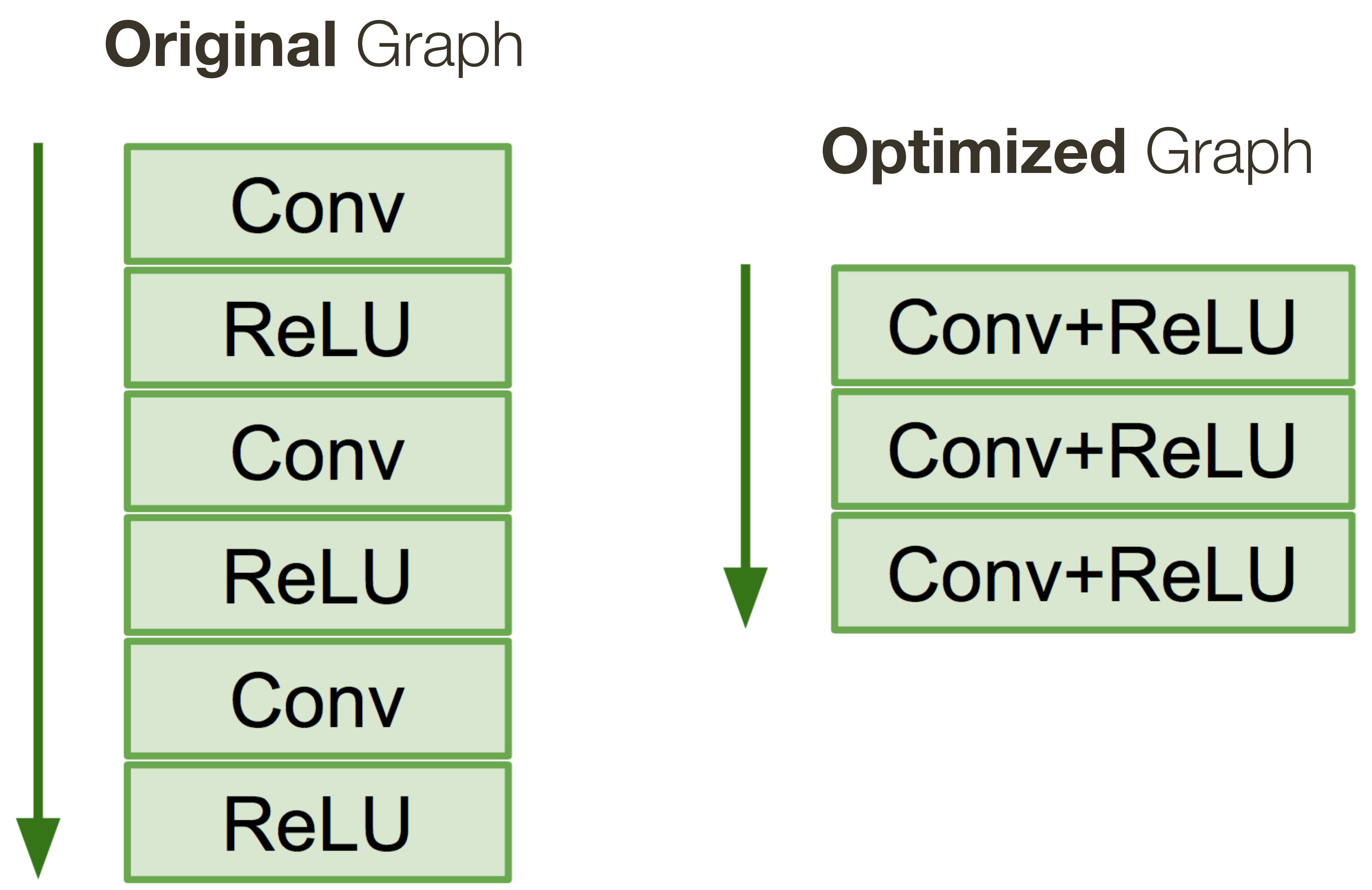
Frameworks: PyTorch vs. TensorFlow

Dynamic vs. Static computational graphs

Frameworks: PyTorch vs. TensorFlow

Dynamic vs. **Static** computational graphs

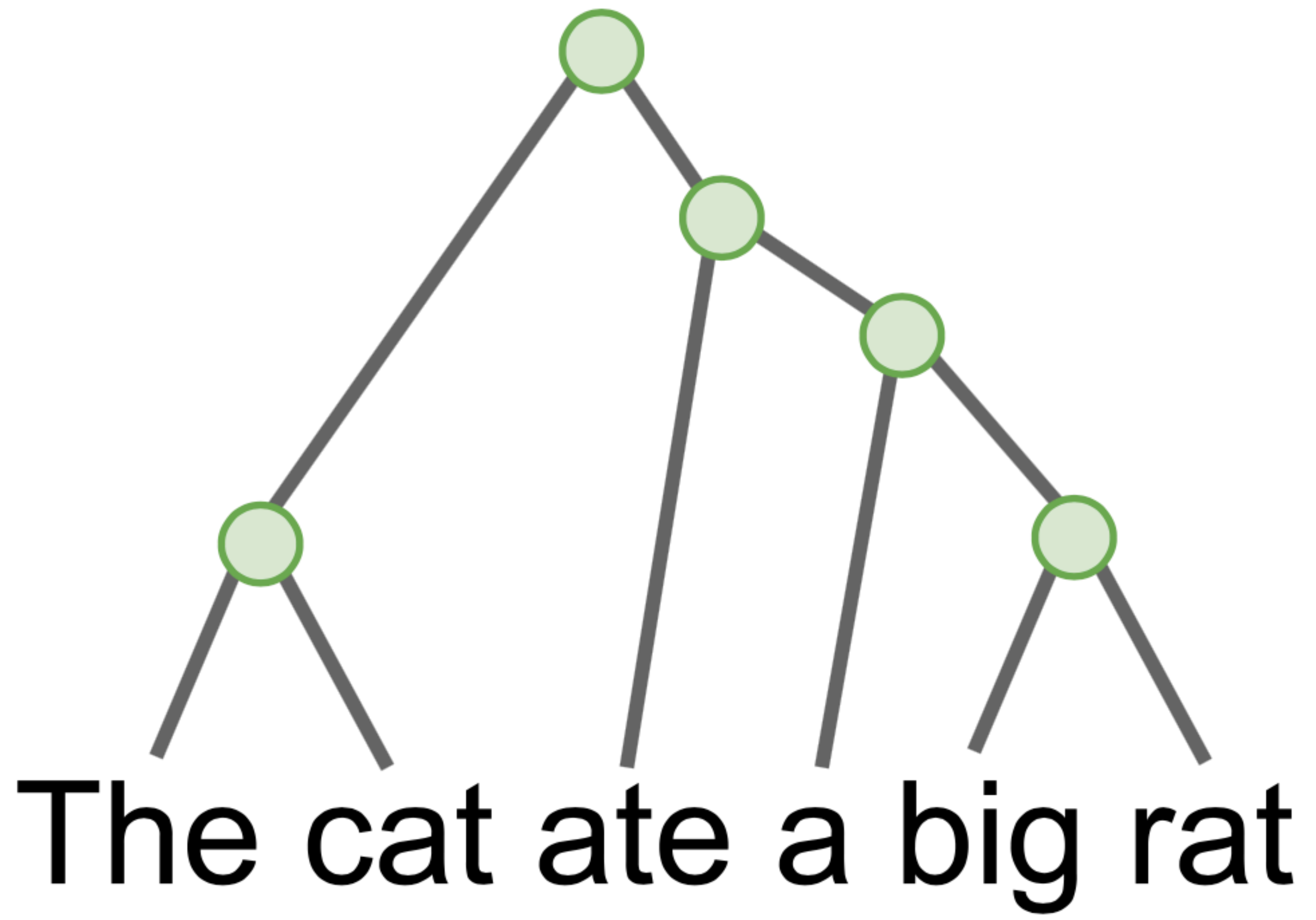
With static graphs, framework can **optimize** the graph for you before it runs!



Frameworks: PyTorch vs. TensorFlow

Dynamic vs. Static computational graphs

Graph building and execution is intertwined. Graph can be different for every sample.



PyTorch: Three levels of abstraction

Tensor: Imperative ndarray, but runs on GPU

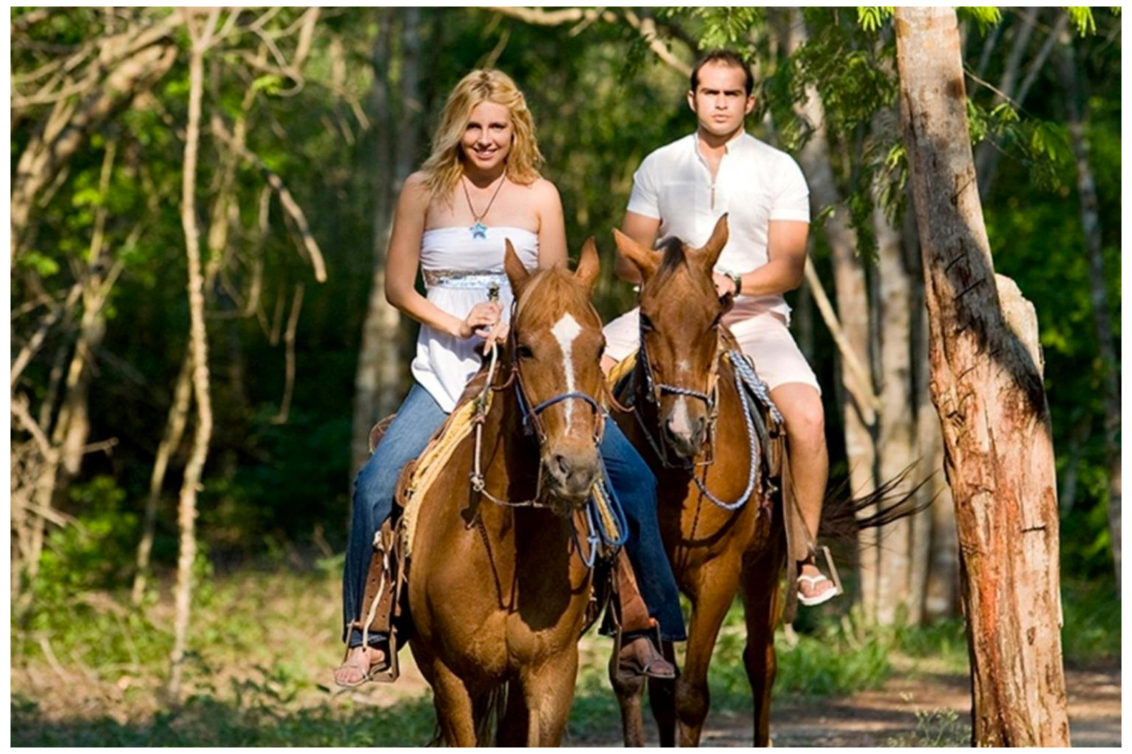
Variable: Node in a computational graph; stores data and gradients

Module: A neural network layer; may store state or learnable weights

Computer **Vision Problems** (no language for now)

Computer **Vision Problems** (no language for now)

Categorization



Multi-**class:**	Horse
	Church
	Toothbrush
	Person

IMAGENET

Multi-**label**:	**Horse**
	Church
	Toothbrush
	Person

Computer **Vision Problems** (no language for now)

Categorization

Multi-**class**: Horse
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IMAGENET

Multi-**label**: **Horse**
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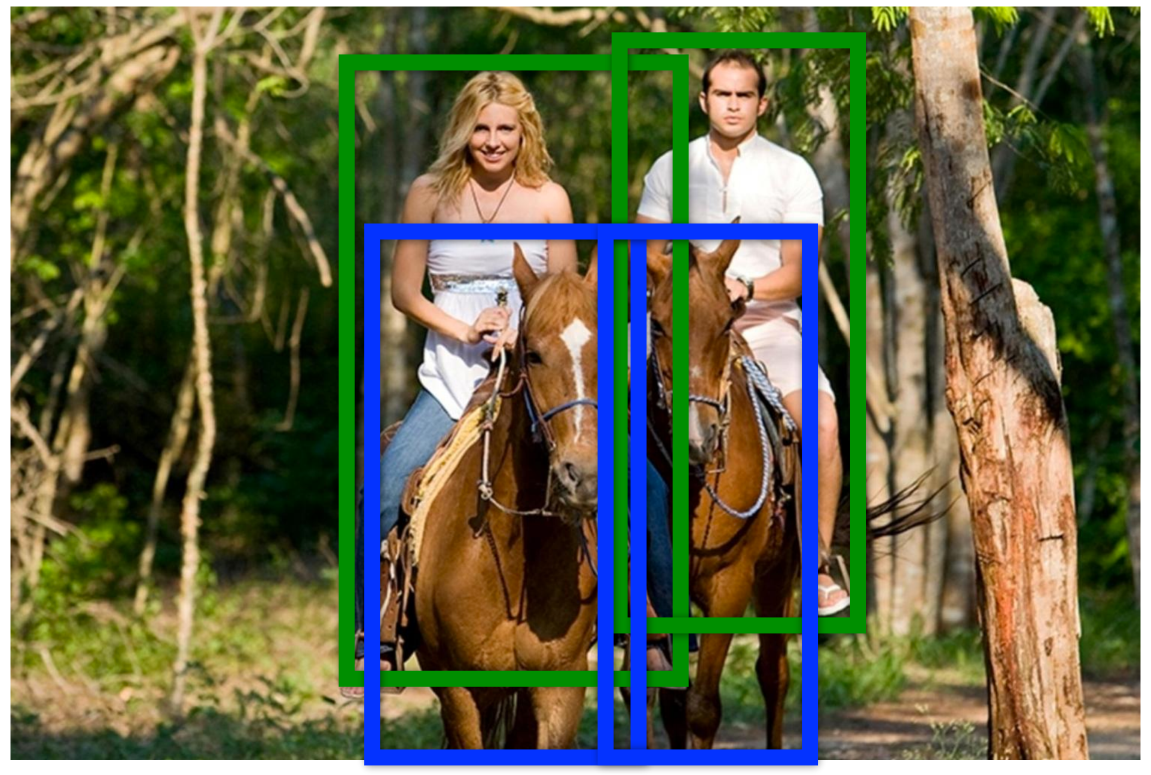
Detection



Horse (x, y, w, h)
Horse (x, y, w, h)
Person (x, y, w, h)
Person (x, y, w, h)

COCO
Common Objects in Context

Computer **Vision Problems** (no language for now)

Categorization

Multi-**class**: Horse
Church
Toothbrush
Person

IMAGENET

Multi-**label**: **Horse**
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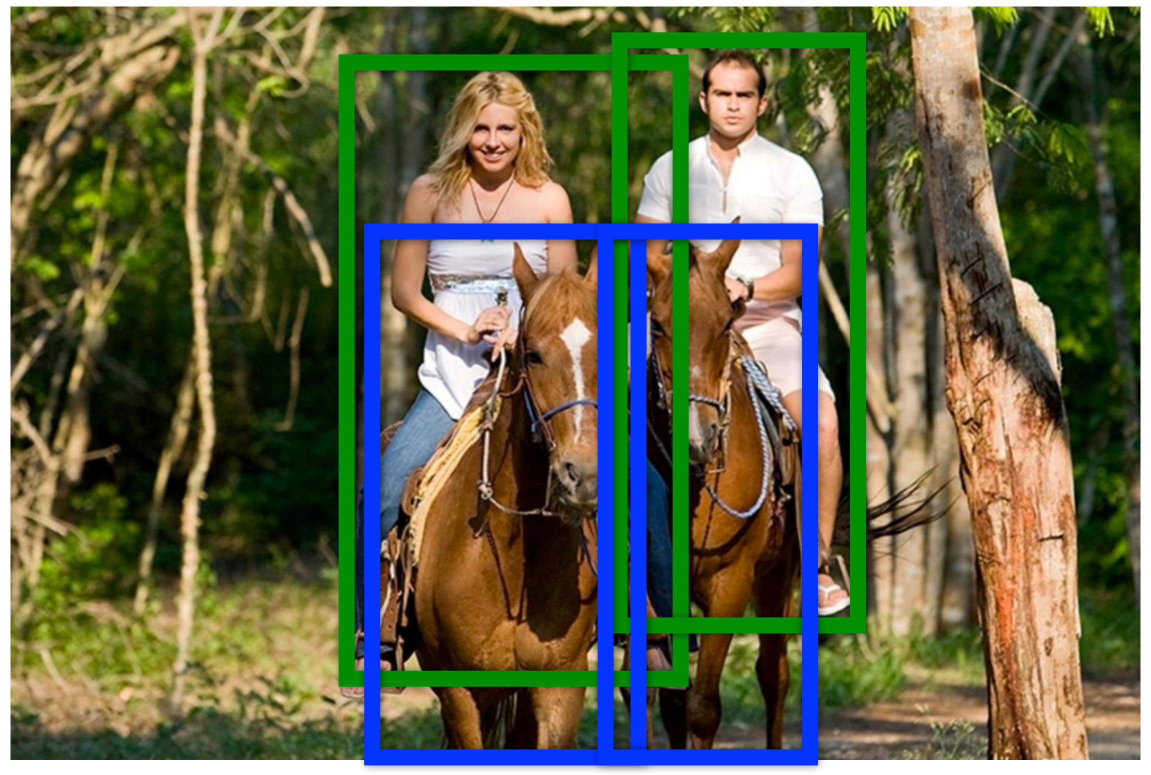
Toothbrush
Person

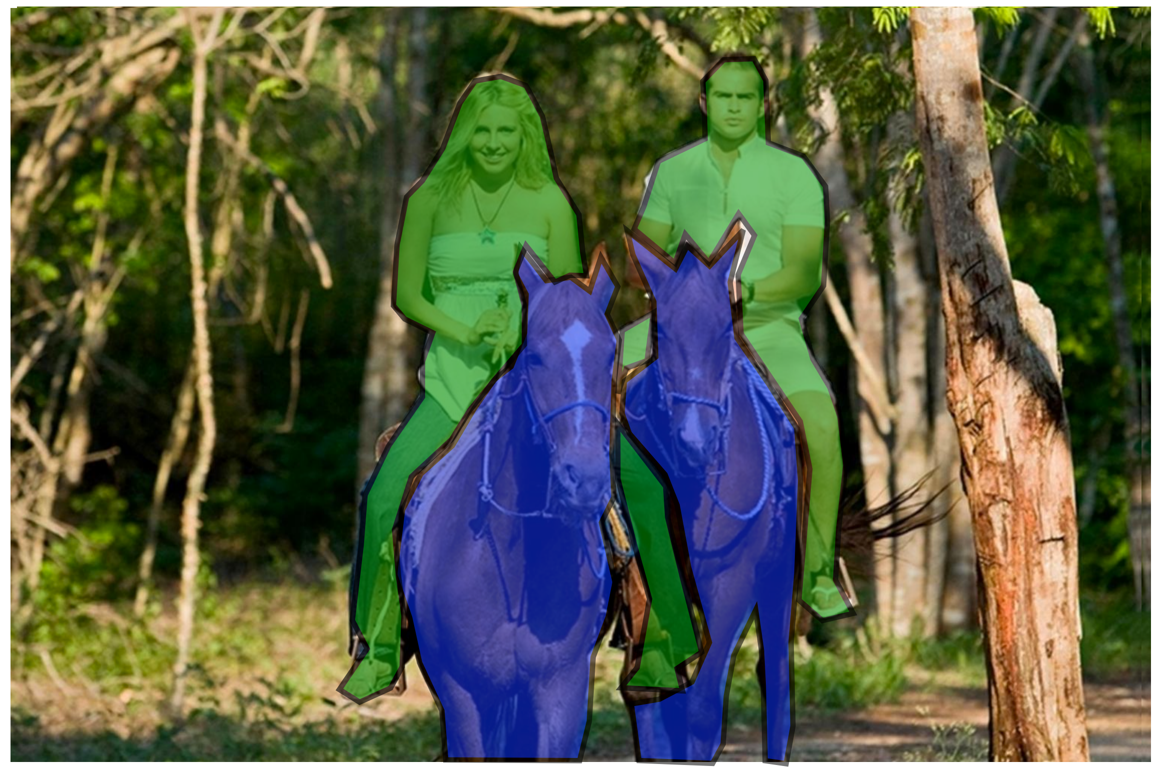
Detection



Horse (x, y, w, h)
Horse (x, y, w, h)
Person (x, y, w, h)
Person (x, y, w, h)

COCO Common Objects in Context

Segmentation

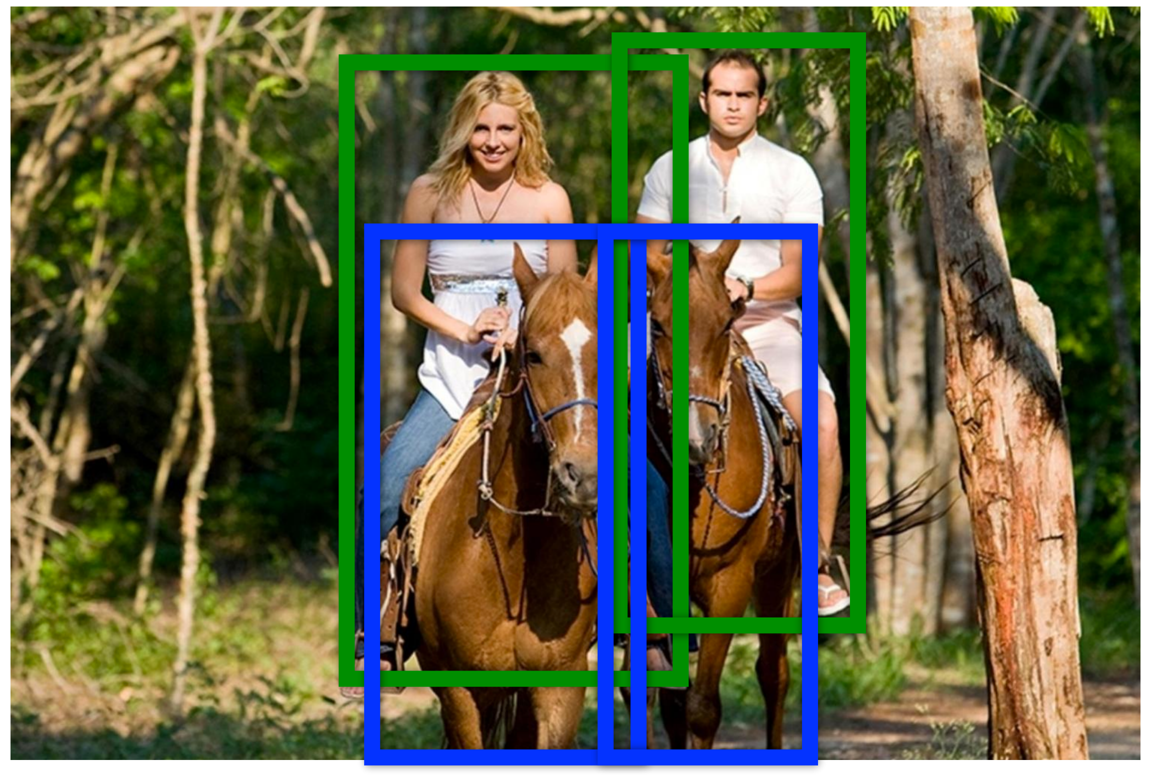


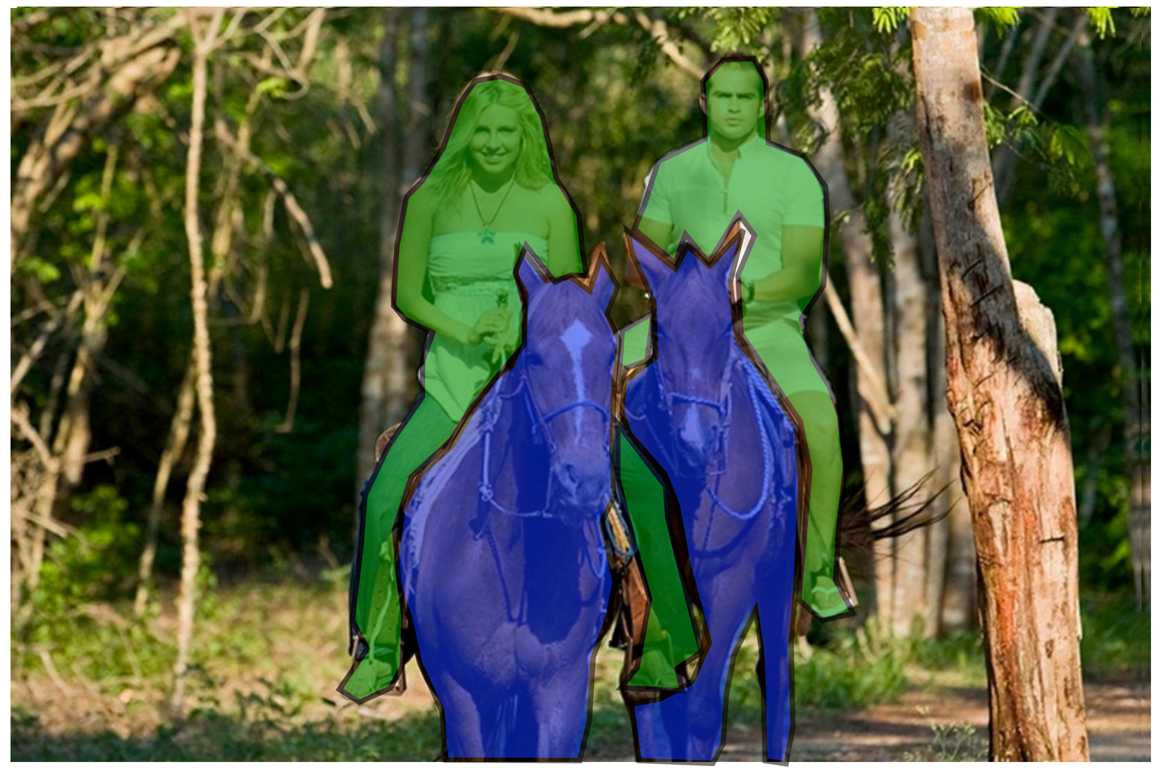
Horse
Person

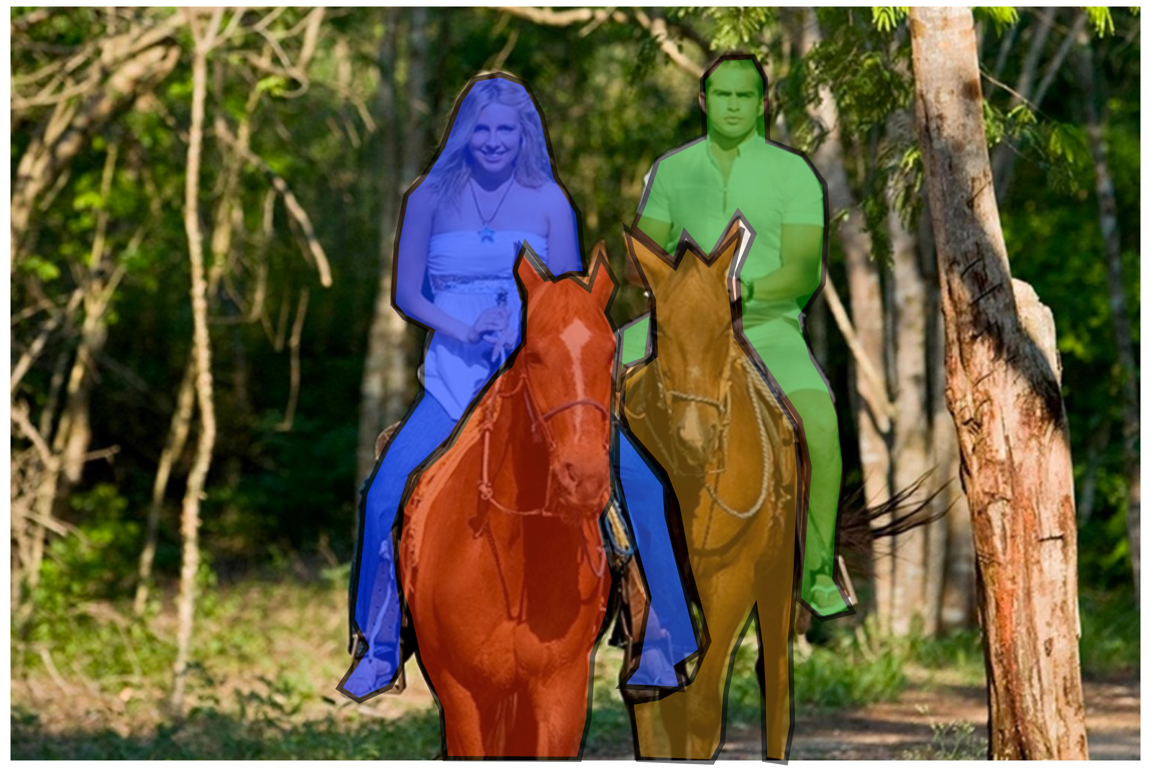
COCO Common Objects in Context

Computer **Vision Problems** (no language for now)

Categorization	Detection	Segmentation	Instance Segmentation







Multi-**class:** Horse
Church
Toothbrush
Person

IMAGENET

Multi-**label**: **Horse**
Church
Toothbrush
Person

Horse (x, y, w, h)
Horse (x, y, w, h)
Person (x, y, w, h)
Person (x, y, w, h)

COCO Common Objects in Context

Horse
Person

COCO Common Objects in Context

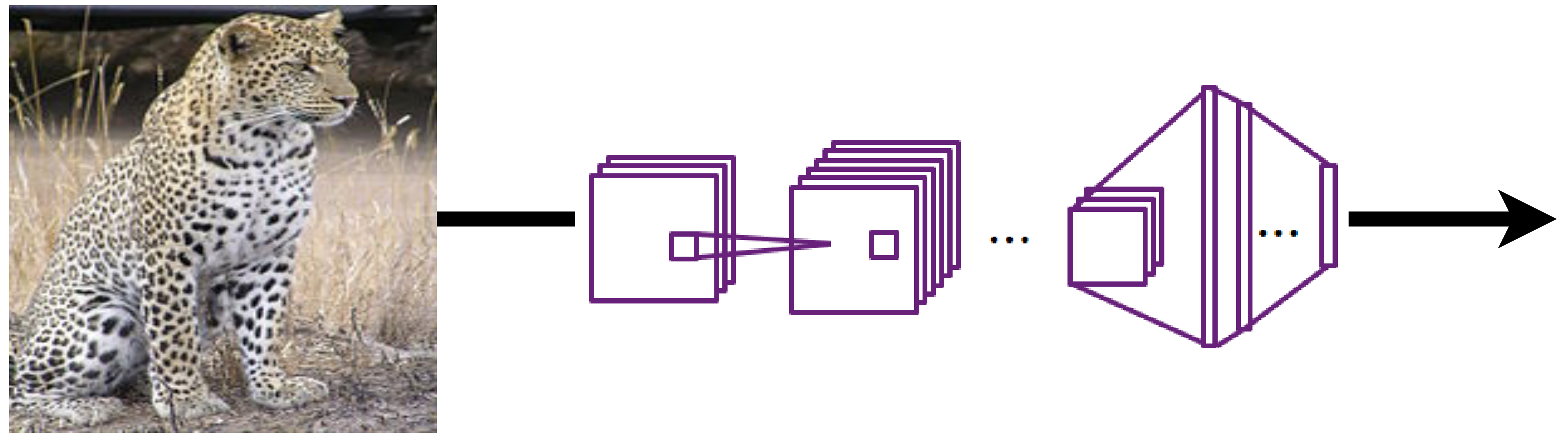
Horse1
Horse2
Person1
Person2

Object **Classification**

Category	**Prediction**
Dog	No
Cat	No
Couch	No
Flowers	No
Leopard	**Yes**
…	…

Problem: For each image predict which category it belongs to out of a fixed set

Object **Classification**



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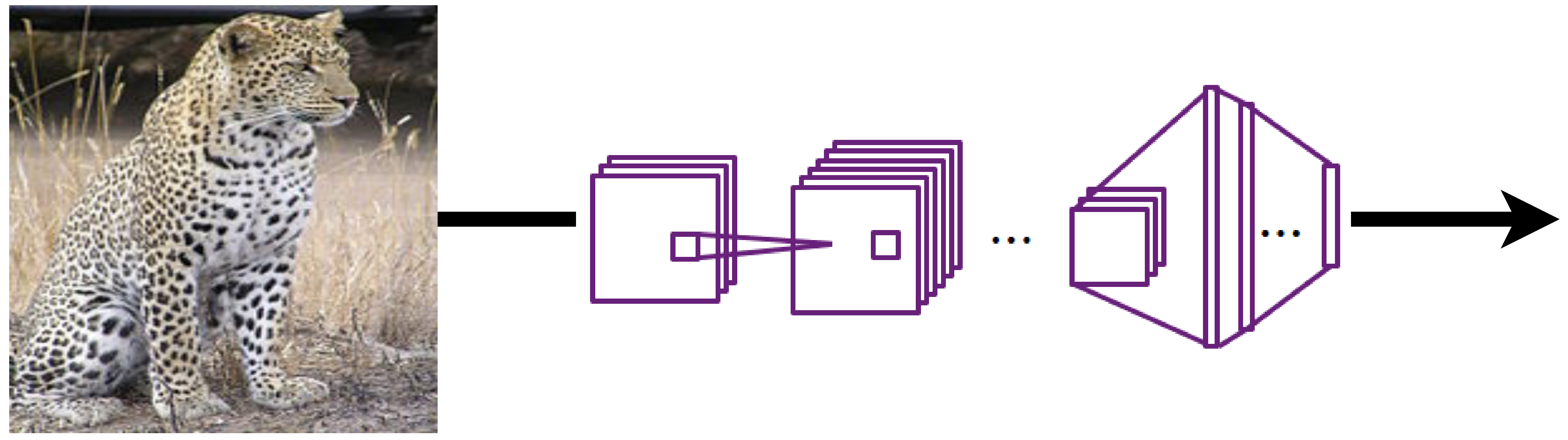
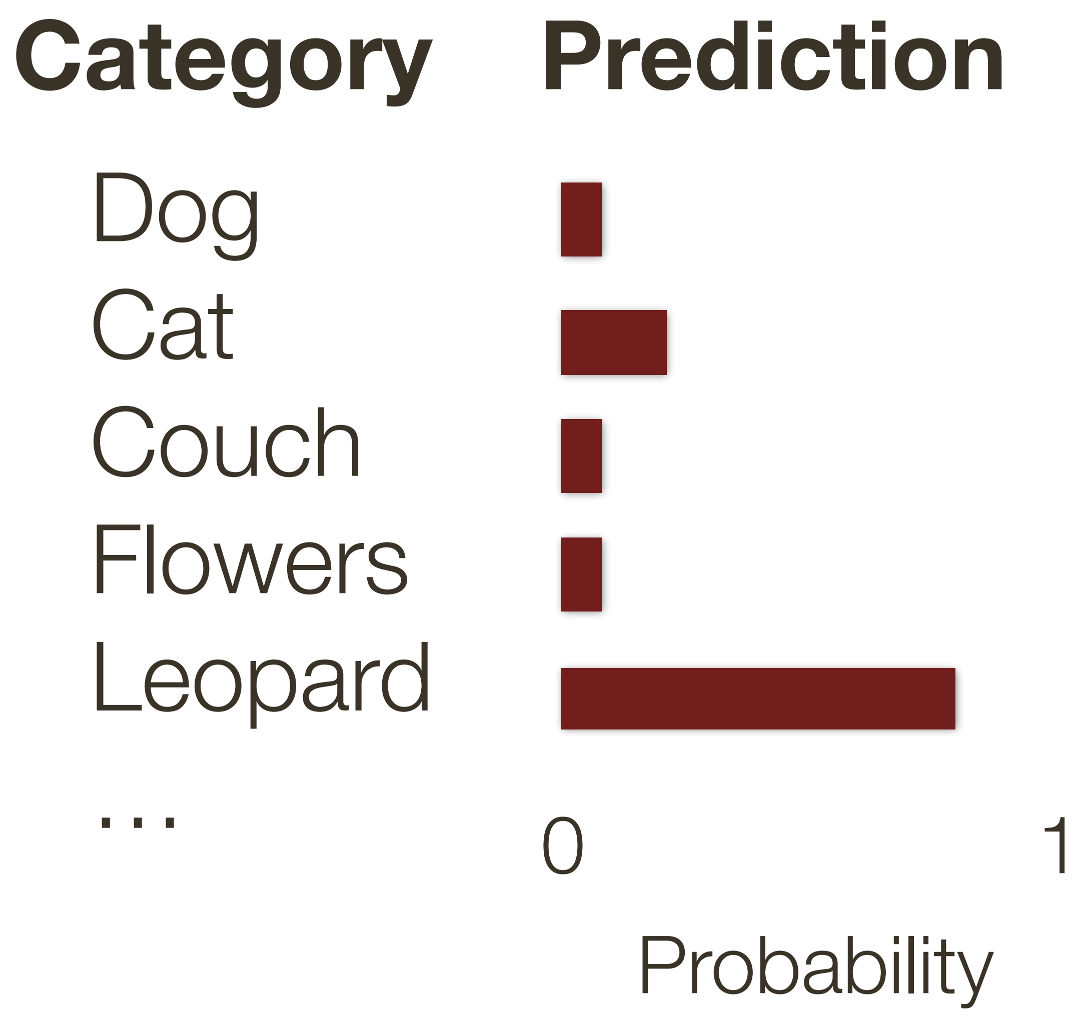
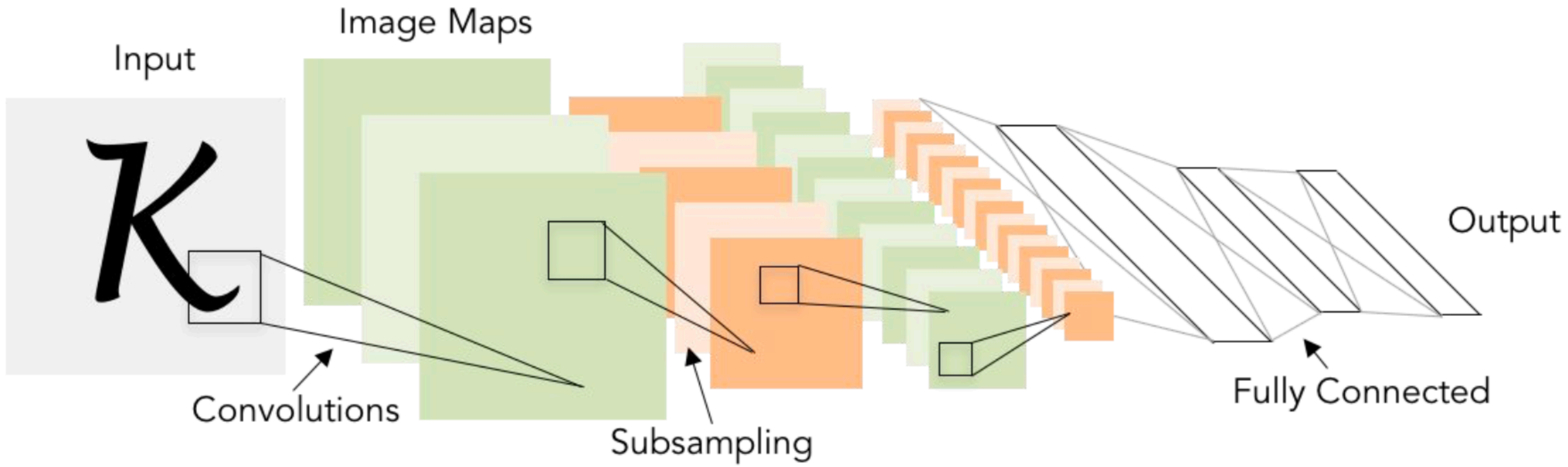




Problem: For each image predict which category it belongs to out of a fixed set

CNN Architectures: LeNet-5

[LeCun et al., 1998]



Architecture: CONV —> POOL —> CONV —> POOL —> FC —> FC

Conv filters: 5x5, Stride: 1

Pooling: 2x2, Stride: 2

ImageNet **Dataset**

Over **14 million** (high resolution) web **images**

Roughly labeled with **22K synset** categories

Labeled on Amazon Mechanical Turk (AMT)

Popular Synsets

Animal

fish
bird
mammal
invertebrate

Plant

tree
flower
vegetable

Activity

sport

Material

fabric

Instrumentation

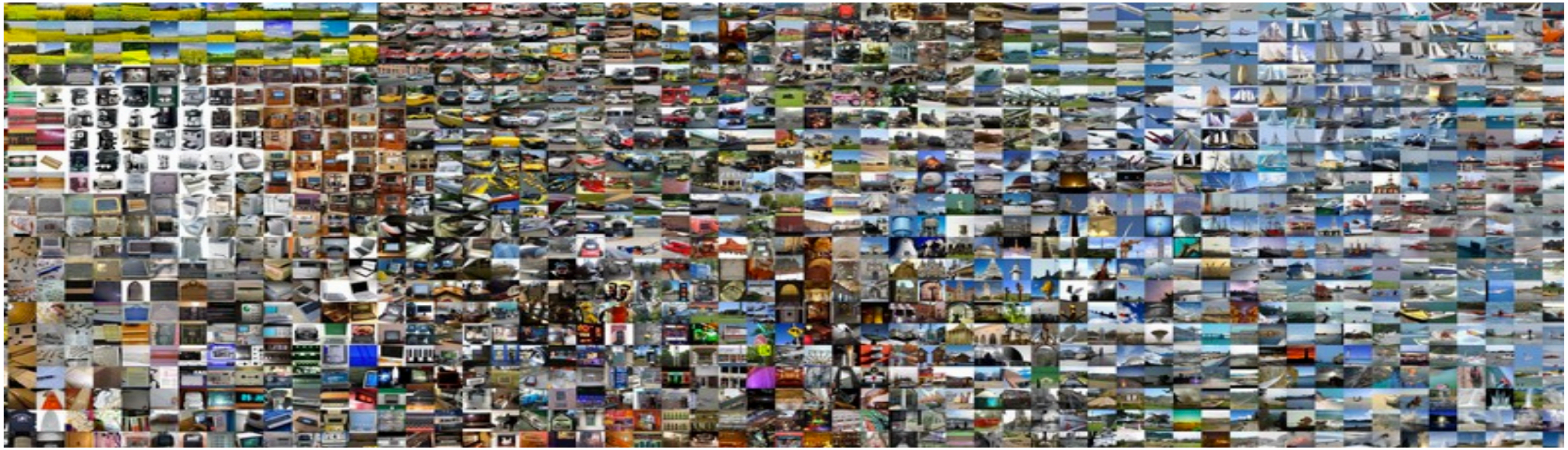
utensil
appliance
tool
musical instrument

Scene

room
geological formation

Food

beverage

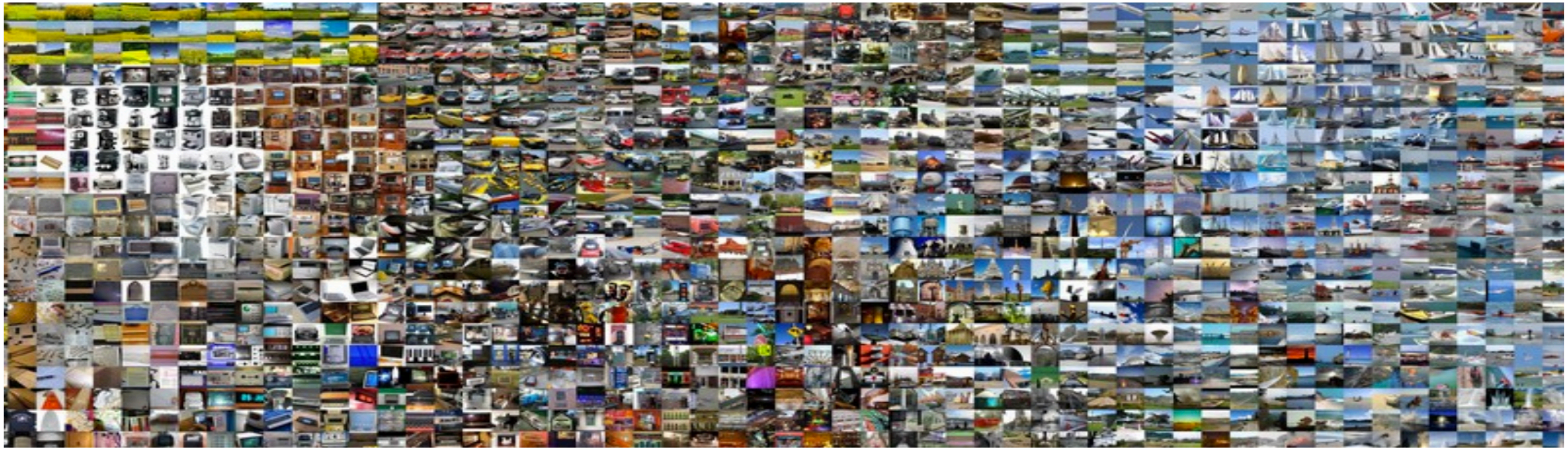


ImageNet **Competition** (ILSVRC)

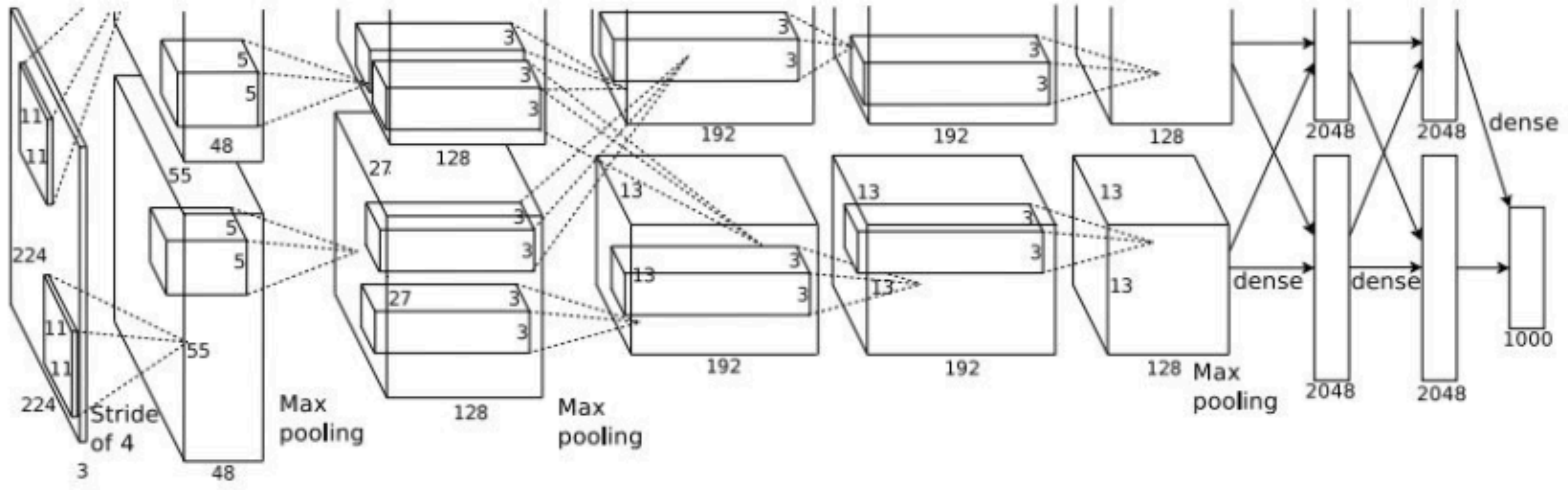
Annual competition of image classification at scale

Focuses on a subset of **1K synset** categories

Scoring: need to predict true label within top K (K=5)



AlexNet



[Krizhevsky et al., 2012]

Architecture:
CONV1
MAX POOL1
NORM1
CONV2
MAX POOL2
NORM2
CONV3
CONV4
CONV5
Max POOL3
FC6
FC7
FC8

Input: 227 x 227 x 3 images

CONV1: 96 11 x 11 filters applied at stride 4

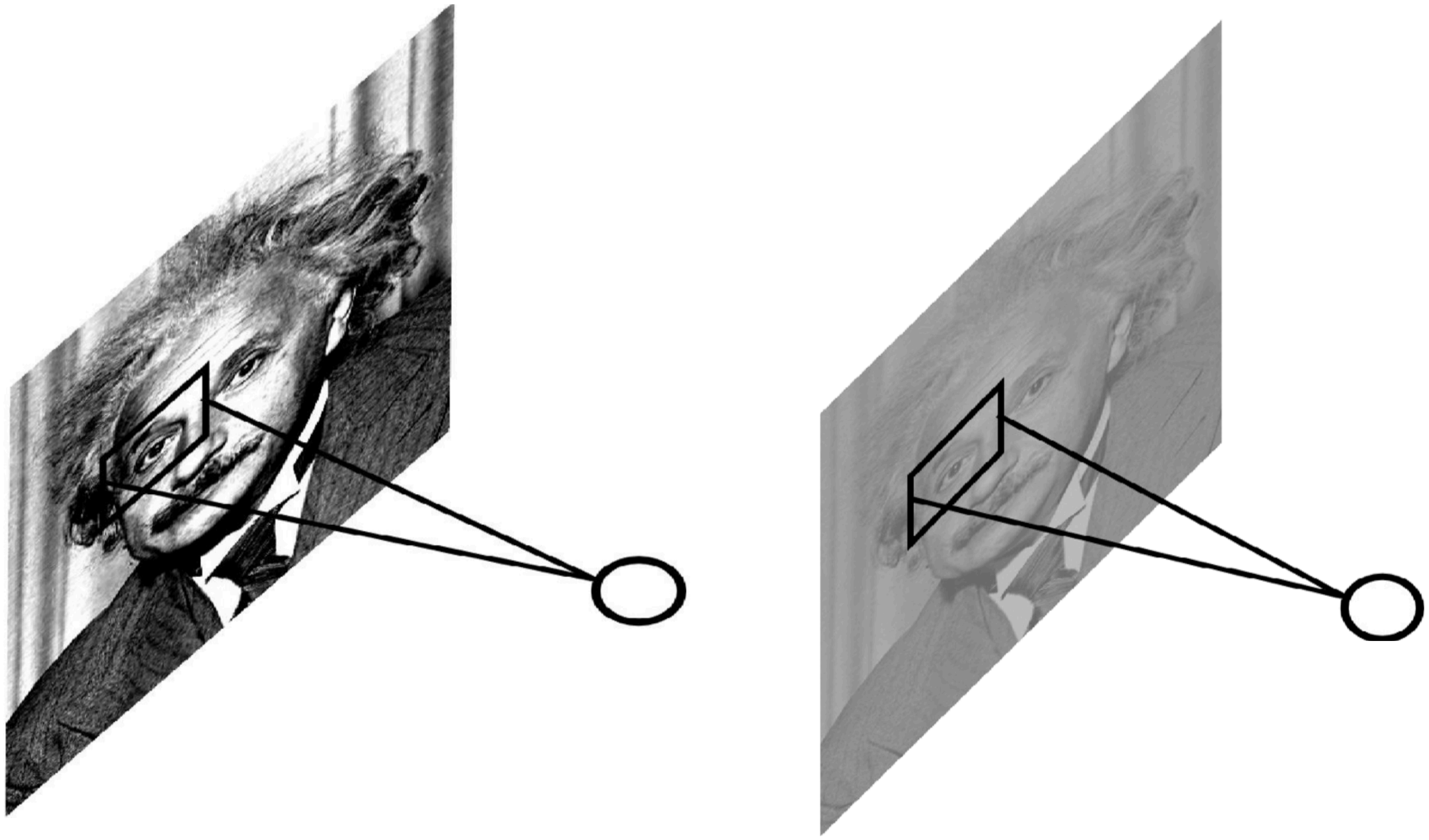
Output: 55 x 55 x 96 **Parameters:** 35K

MAX POOL1: 96 11 x 11 filters applied at stride 4

Output: 27 x 27 x 96 **Parameters:** 0

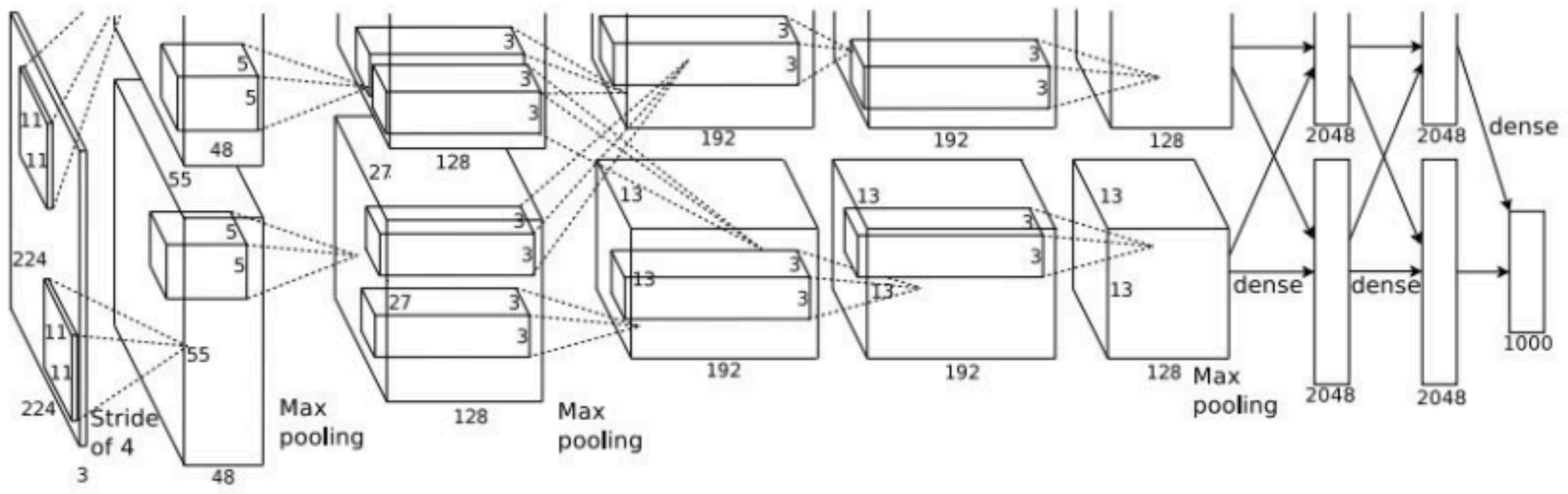
Local **Contrast Normalization** Layer

ensures response is the same in both case (details omitted, no longer popular)



* images from Marc’Aurelio Renzato

AlexNet

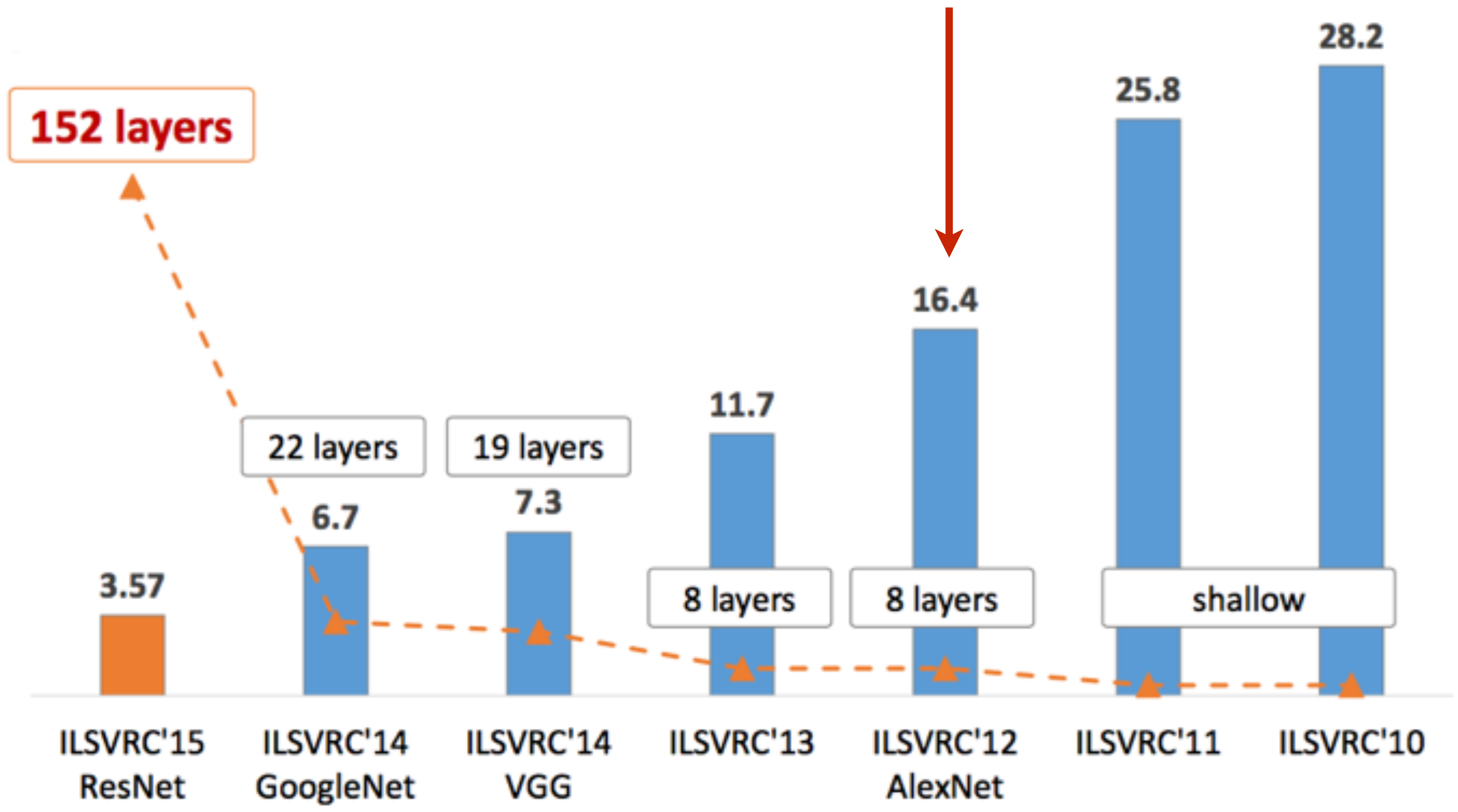


[Krizhevsky et al., 2012]

Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

Details / Comments
— First use of ReLU
— Used contrast normalization layers
— Heavy data augmentation
— Dropout of 0.5
— Batch size of 128
— SGD Momentum (0.9)
— Learning rate (1e-2) reduced by 10 manually when validation accuracy plateaus
— L2 weight decay
— 7 CNN ensamble: 18.2% -> 15.4%

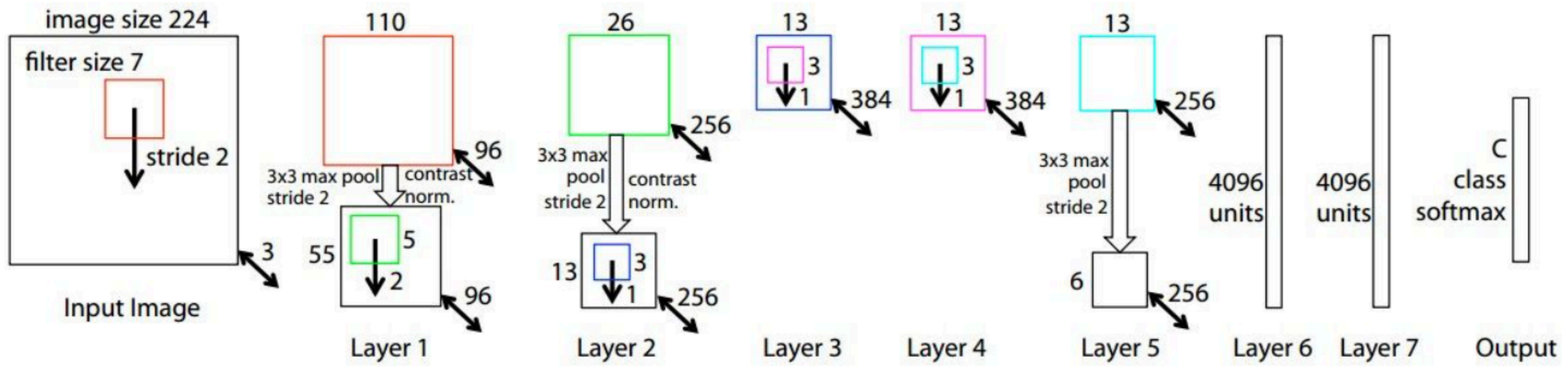
ILSVRC winner 2012



* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

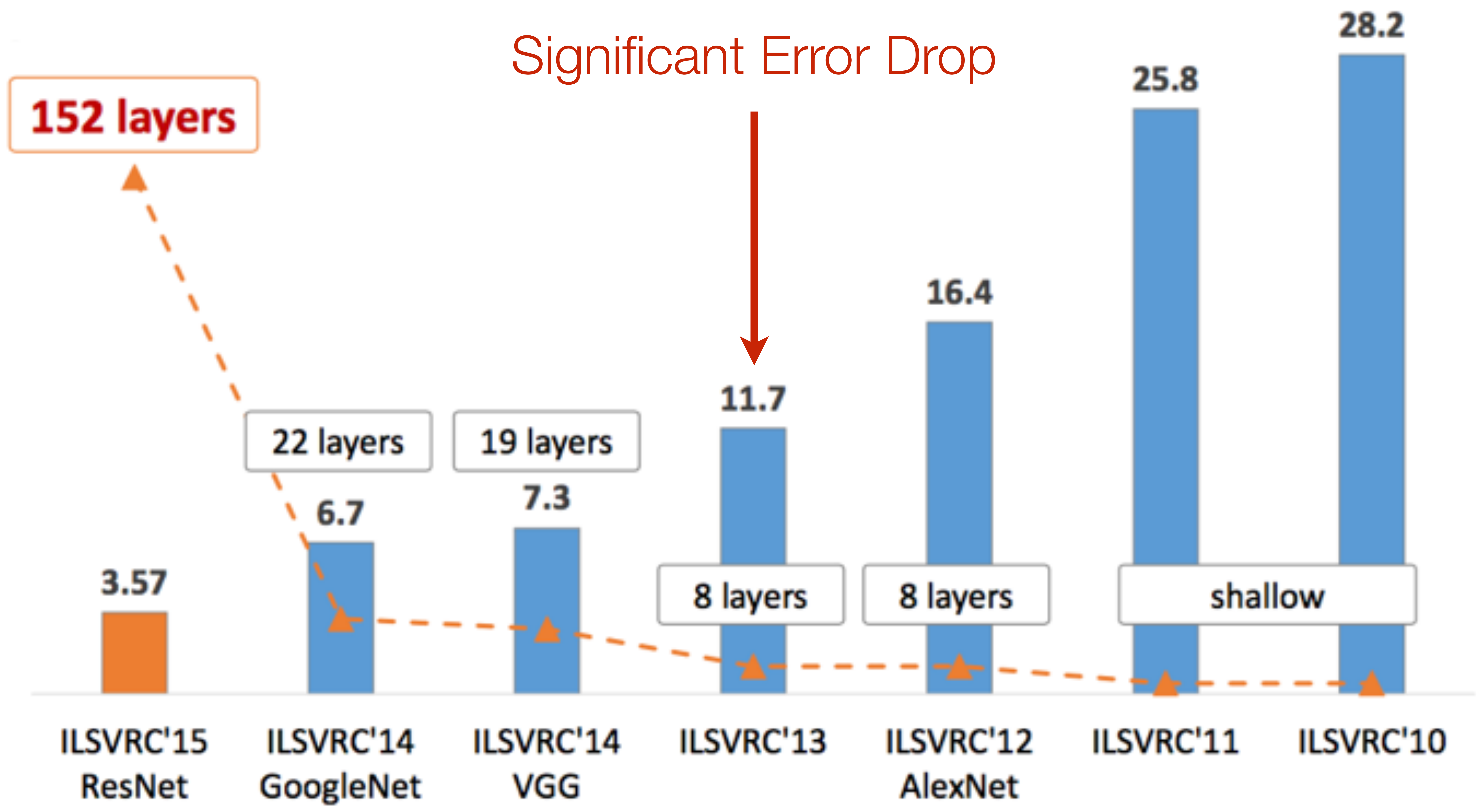
ZF Net

[Zeiler and Fergus, 2013]



AlexNet with small modifications:
— CONV1 (11 x 11 stride 4) to (7 x 7 stride 2)
— CONV3 # of filters 384 -> 512
— CONV4 # of filters 384 -> 1024
— CONV5 # of filters 256 -> 512

ILSVRC winner 2012



* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

VGG Net

[Simonyan and Zisserman, 2014]

Trend:

— smaller filters (3 x 3)

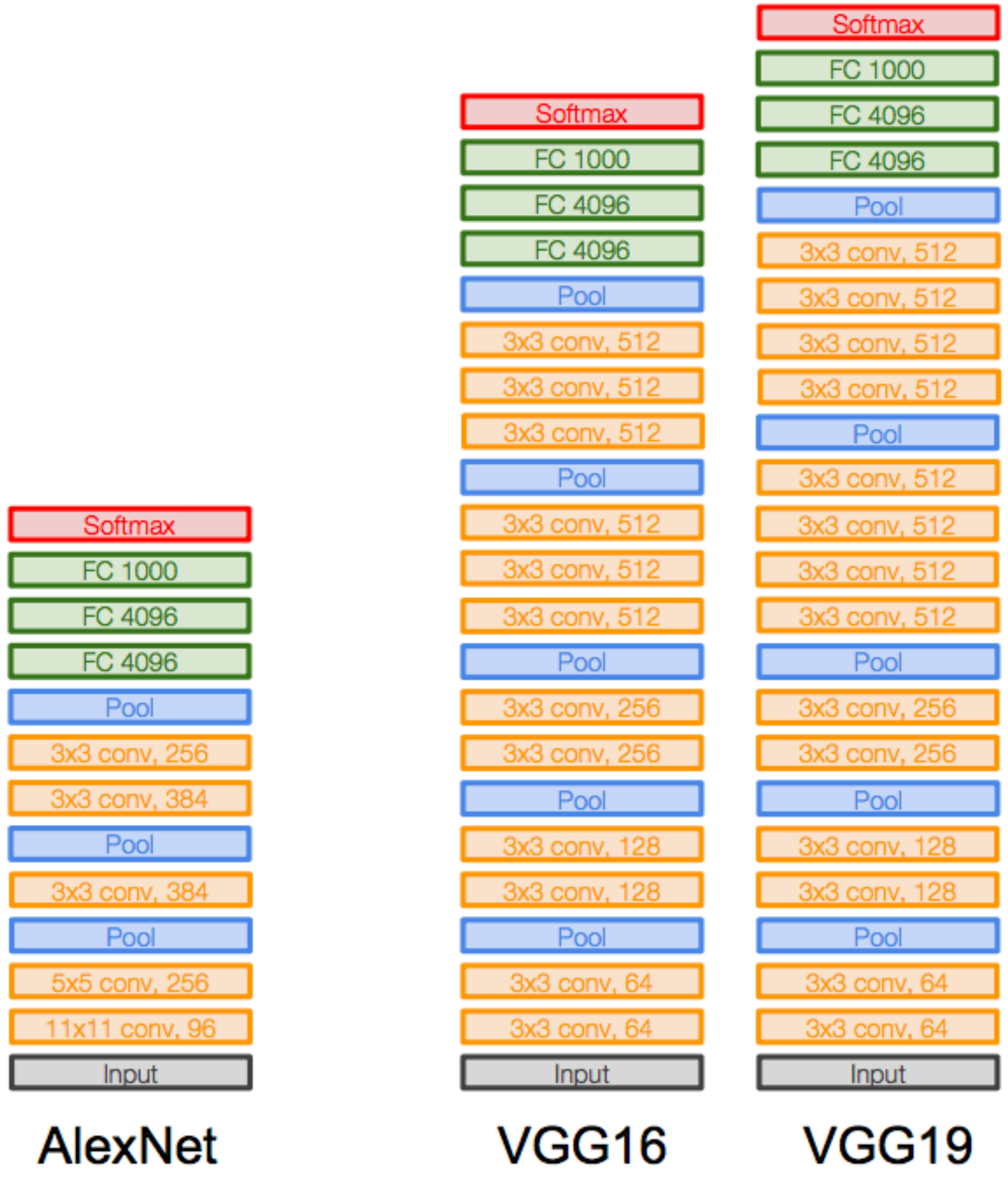
— deeper network (16 or 19 vs. 8 in AlexNet)

Why?

— **receptive field** of a 3 layer ConvNet with filter size = 3x3 is the same as 1 layer ConvNet with filter 7x7 (at stride 1)

— deeper = **more non-linearity** (so richer filters)

— **fewer parameters**

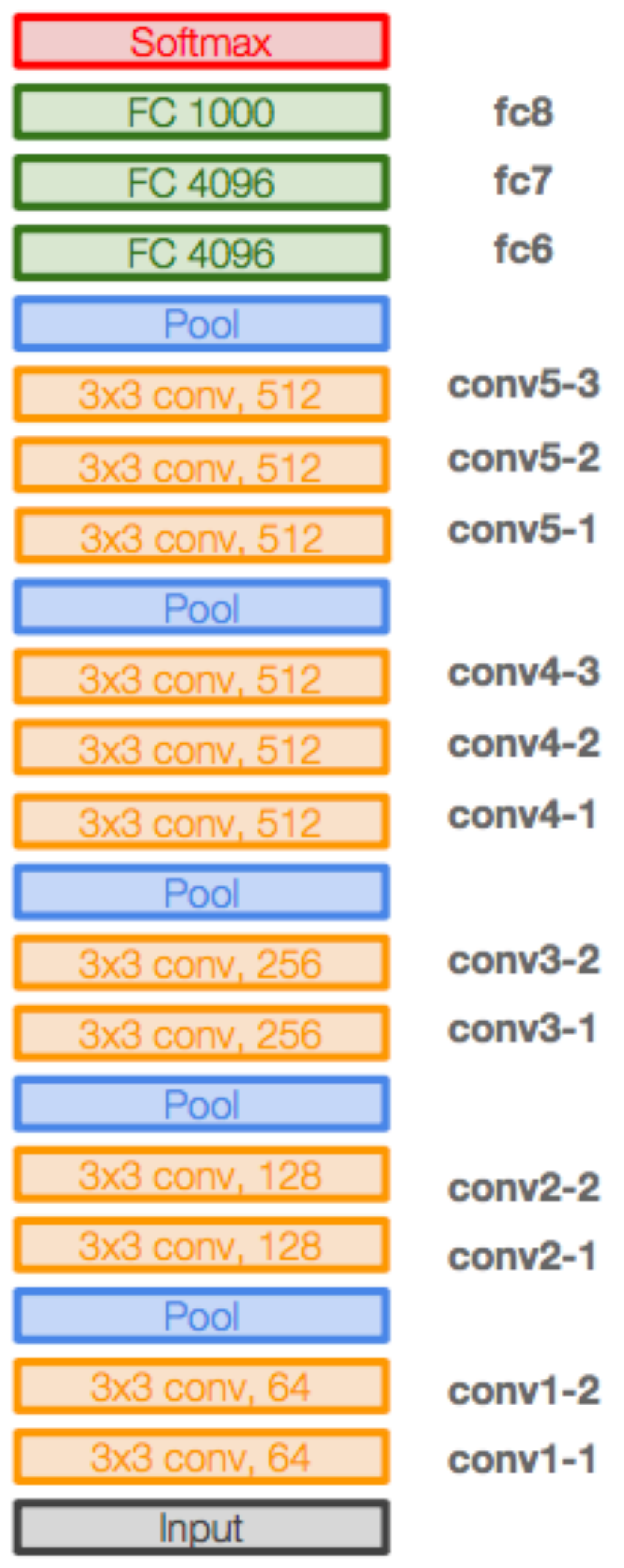


VGG Net

[Simonyan and Zisserman, 2014]

(not counting biases)

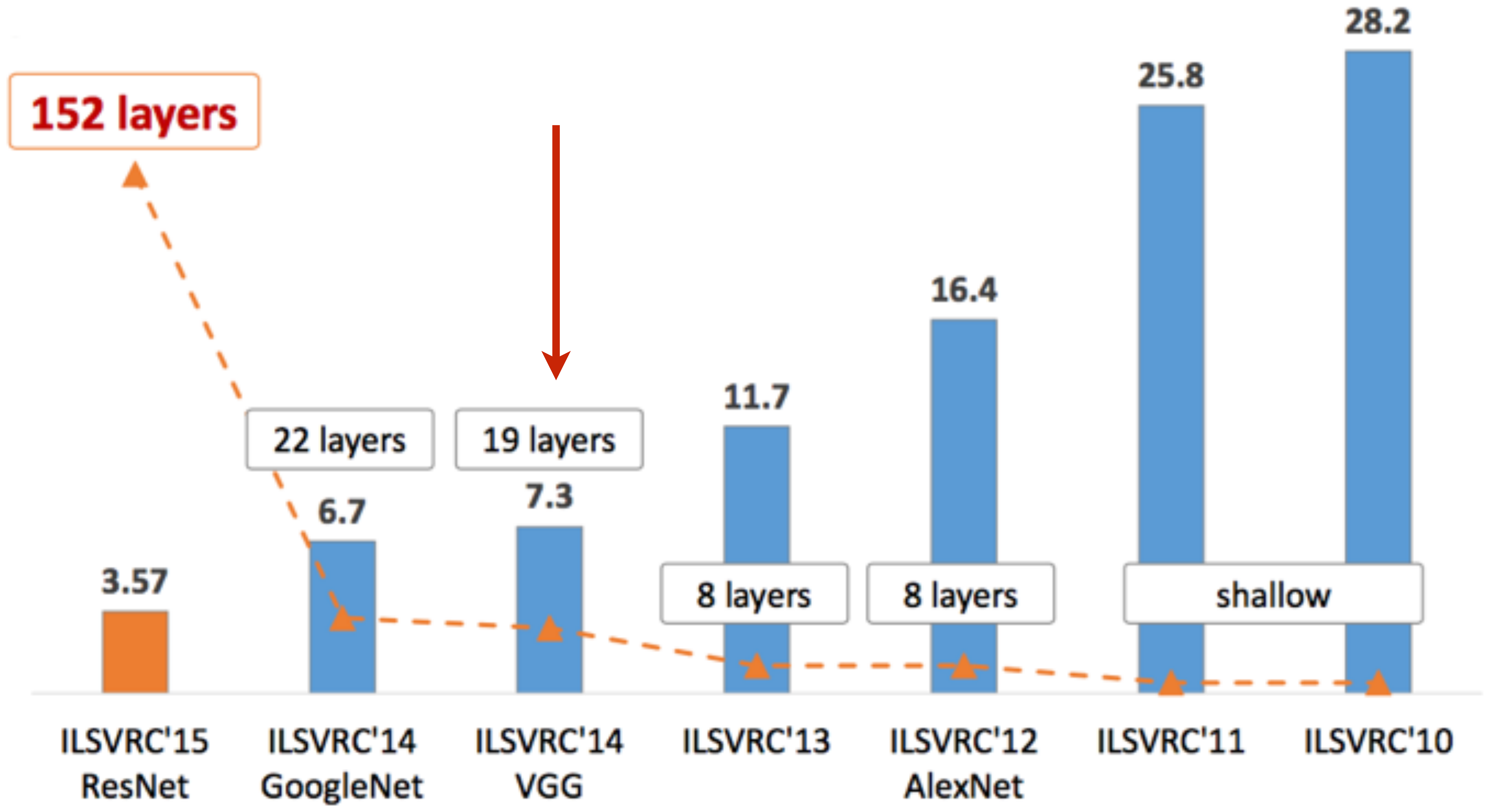
INPUT: [224x224x3] memory: 224*224*3=150K params: 0
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*3)*64 = 1,728
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*64)*64 = 36,864
POOL2: [112x112x64] memory: 112*112*64=800K params: 0
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*64)*128 = 73,728
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*128)*128 = 147,456
POOL2: [56x56x128] memory: 56*56*128=400K params: 0
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*128)*256 = 294,912
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
POOL2: [28x28x256] memory: 28*28*256=200K params: 0
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*256)*512 = 1,179,648
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
POOL2: [14x14x512] memory: 14*14*512=100K params: 0
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
POOL2: [7x7x512] memory: 7*7*512=25K params: 0
FC: [1x1x4096] memory: 4096 params: 7*7*512*4096 = 102,760,448
FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16,777,216
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000



VGG16

TOTAL memory: 24M * 4 bytes ~= 96MB / image (only forward! ~*2 for bwd)
TOTAL params: 138M parameters

ILSVRC winner 2012



* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

GoogleLeNet

[Szegedy et al., 2014]

even deeper network with **computational efficiency**

— 22 layers

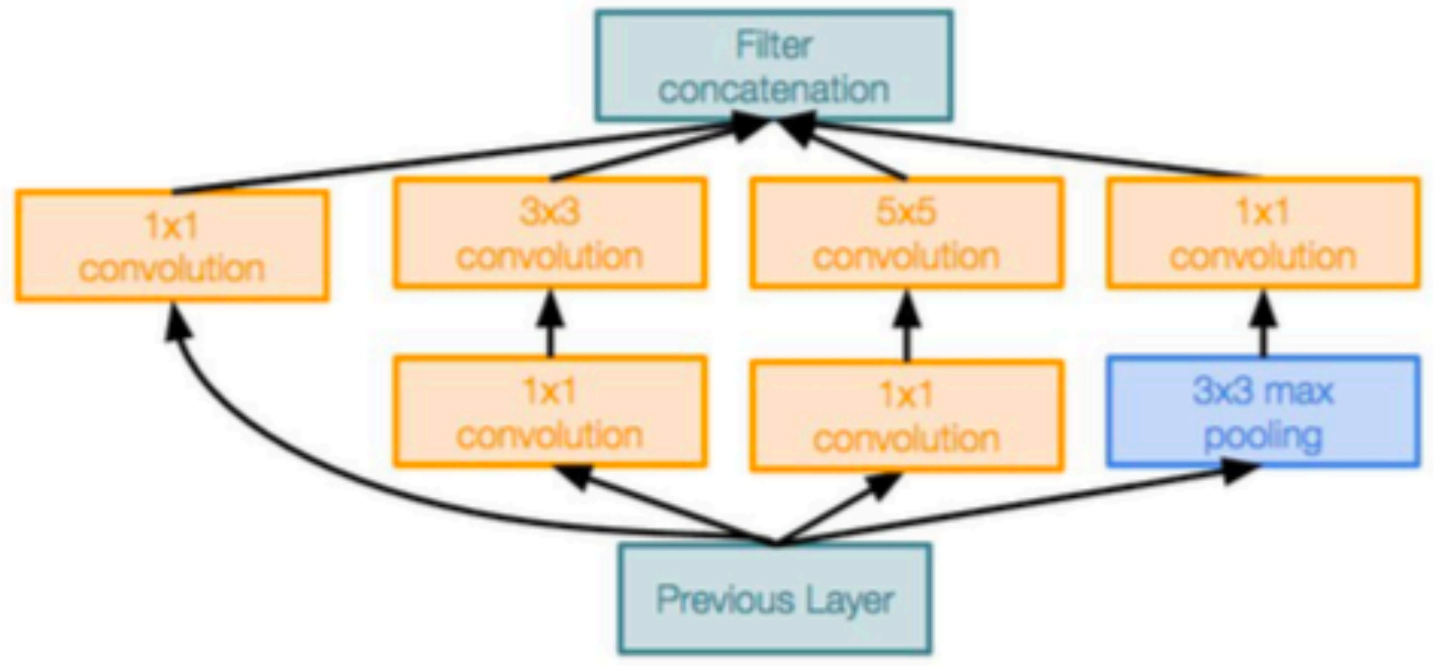
— Efficient “Inception” module

— No FC layers

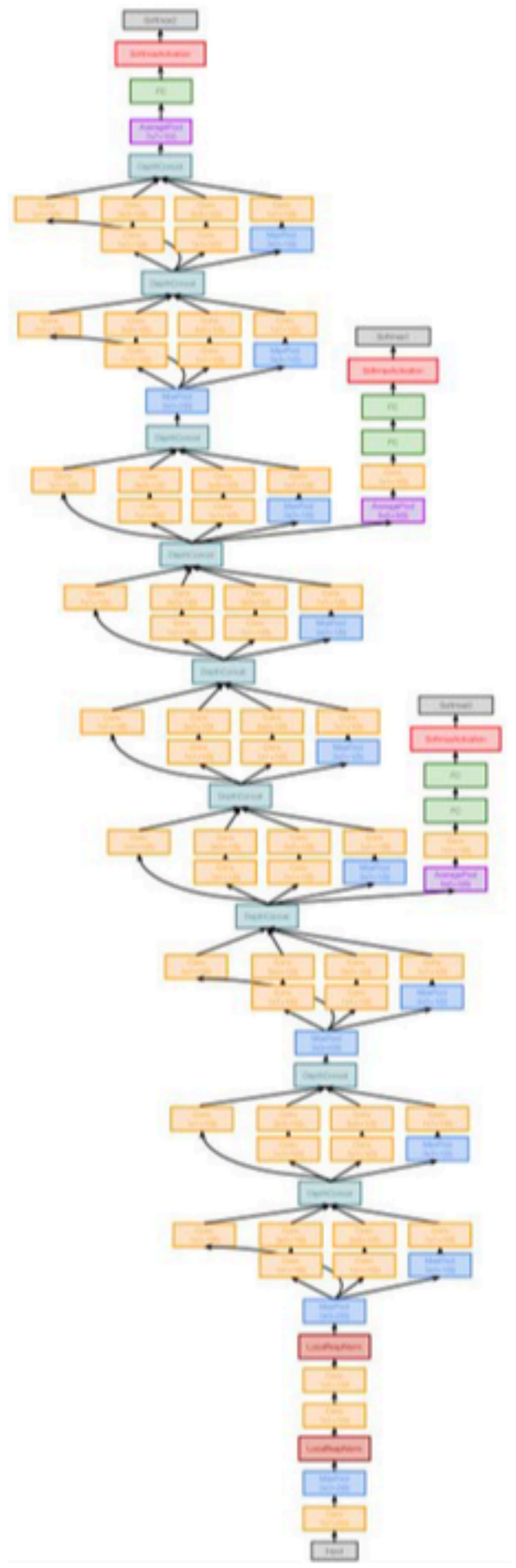
— Only 5 million parameters!

(12x less than AlexNet!)

— Better performance (@6.7 top 5 error)



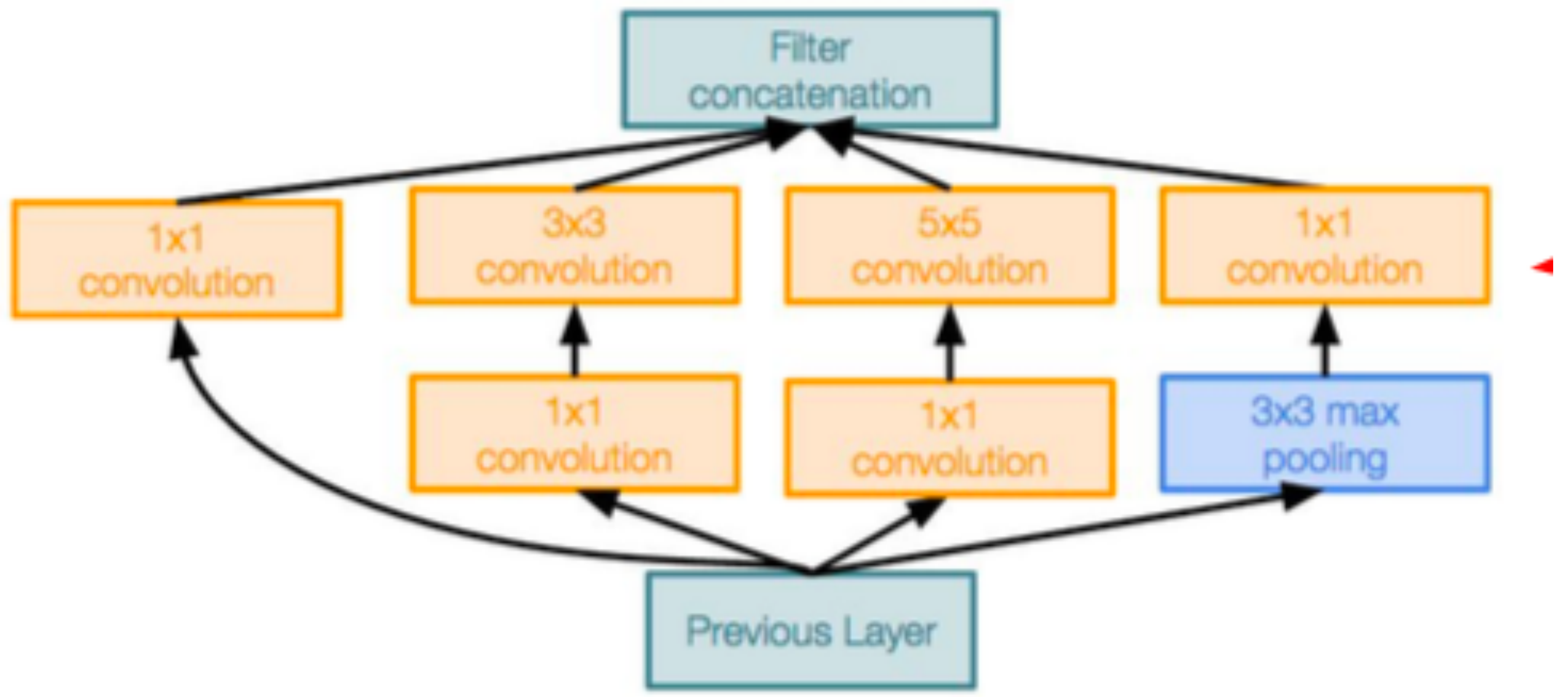
Inception module



GoogleLeNet: Inception Module

[Szegedy et al., 2014]

Idea: design good local topology ("network within network") and then stack these modules



Inception module

GoogleLeNet: Inception Module

[Szegedy et al., 2014]

Idea: design good local topology ("network within network") and then stack these modules

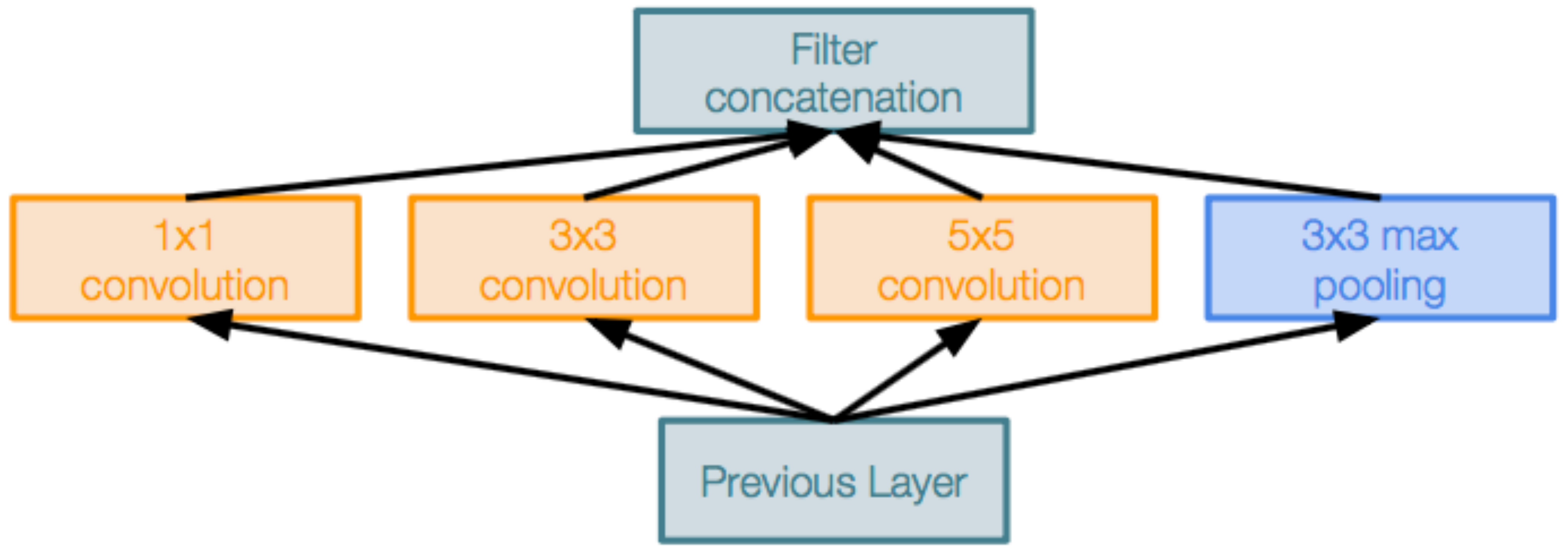
Apply **parallel filter operations** on the input from previous layer

— Multiple receptive field sizes for convolution (1x1, 3x3, 5x5)

— Pooling operation (3x3)

Concatenate all filter outputs together at output depth-wise

What's the problem?



Naive Inception module

GoogleLeNet: Inception Module

[Szegedy et al., 2014]

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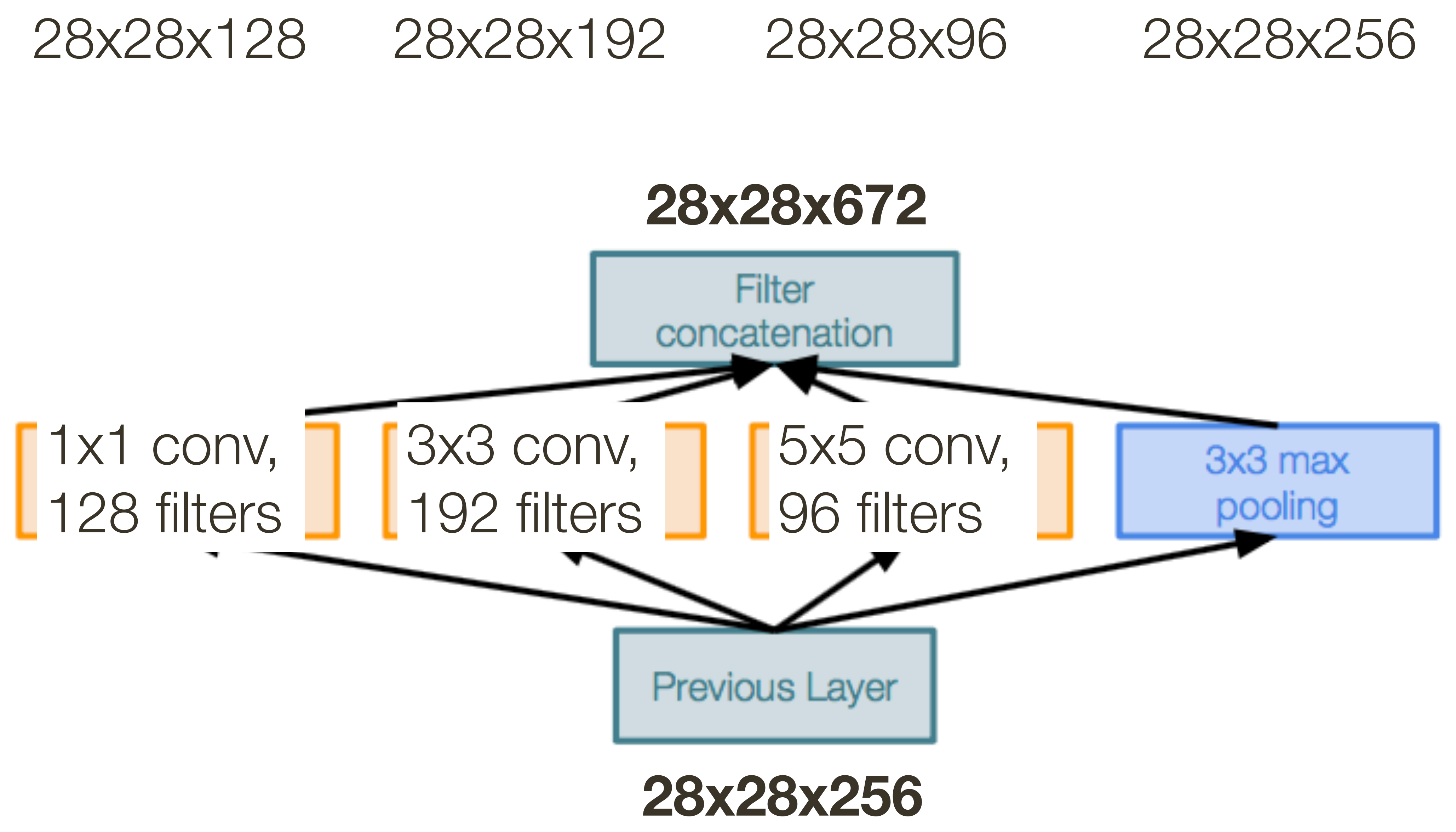
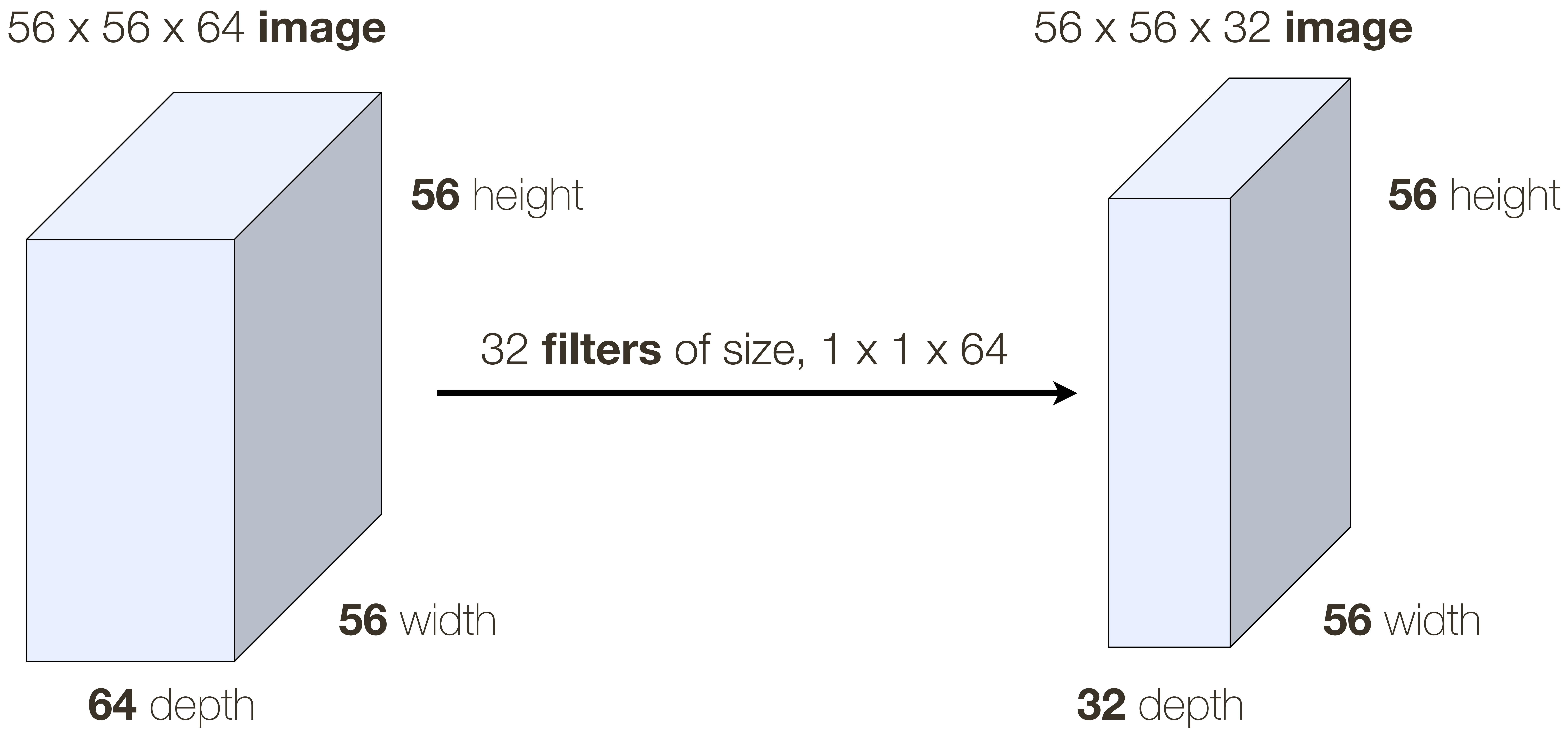


Naive Inception module

Convolutional Layer: **1x1 convolutions**



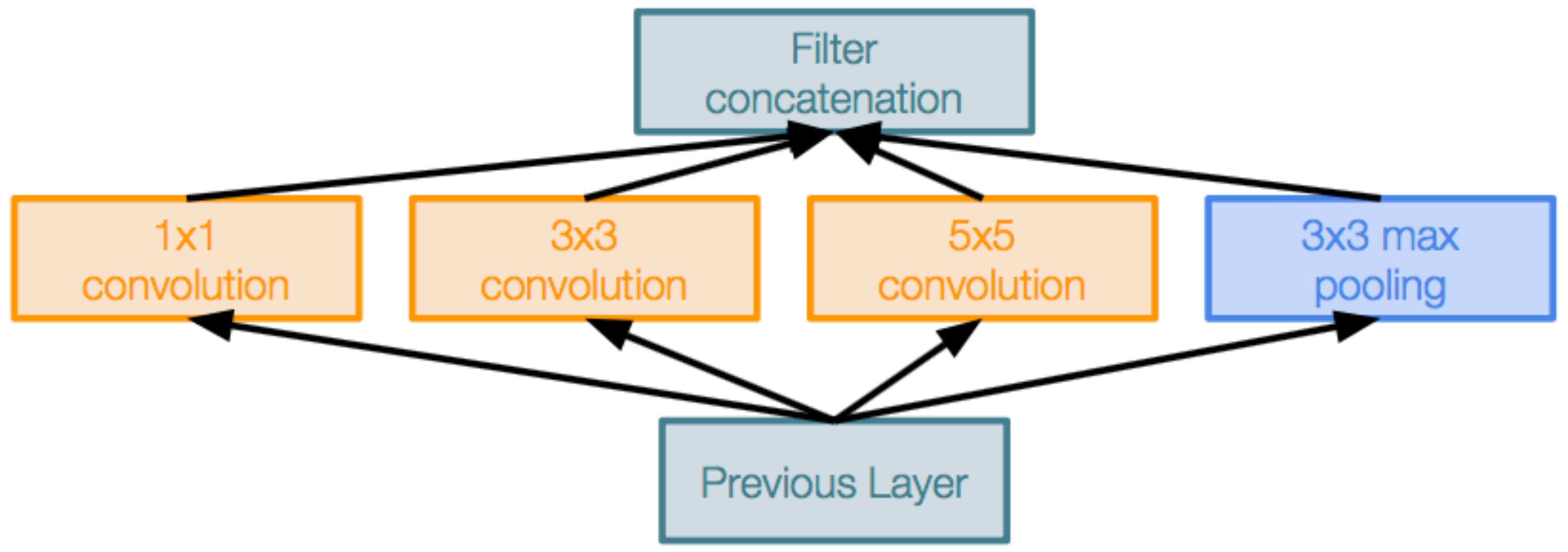
* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

GoogleLeNet: Inception Module

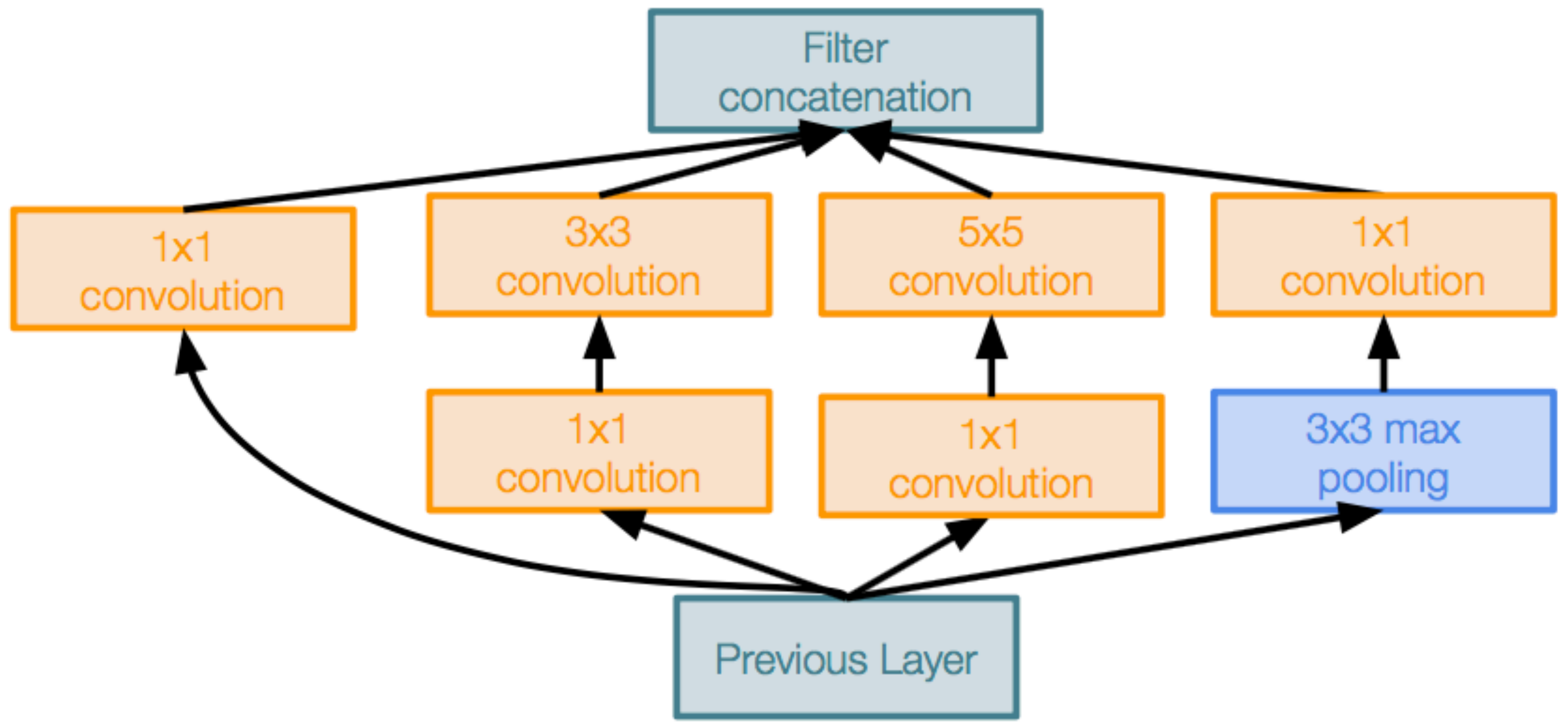
[Szegedy et al., 2014]

Idea: design good local topology ("network within network") and then stack these modules

1x1 "bottleneck" layers



Naive Inception module



Inception module with dimension reduction

saves approximately 60% of computations

GoogleLeNet

[Szegedy et al., 2014]

even deeper network with **computational efficiency**

— 22 layers

— Efficient “Inception” module

— No FC layers

— Only 5 million parameters!

(12x less than AlexNet!)

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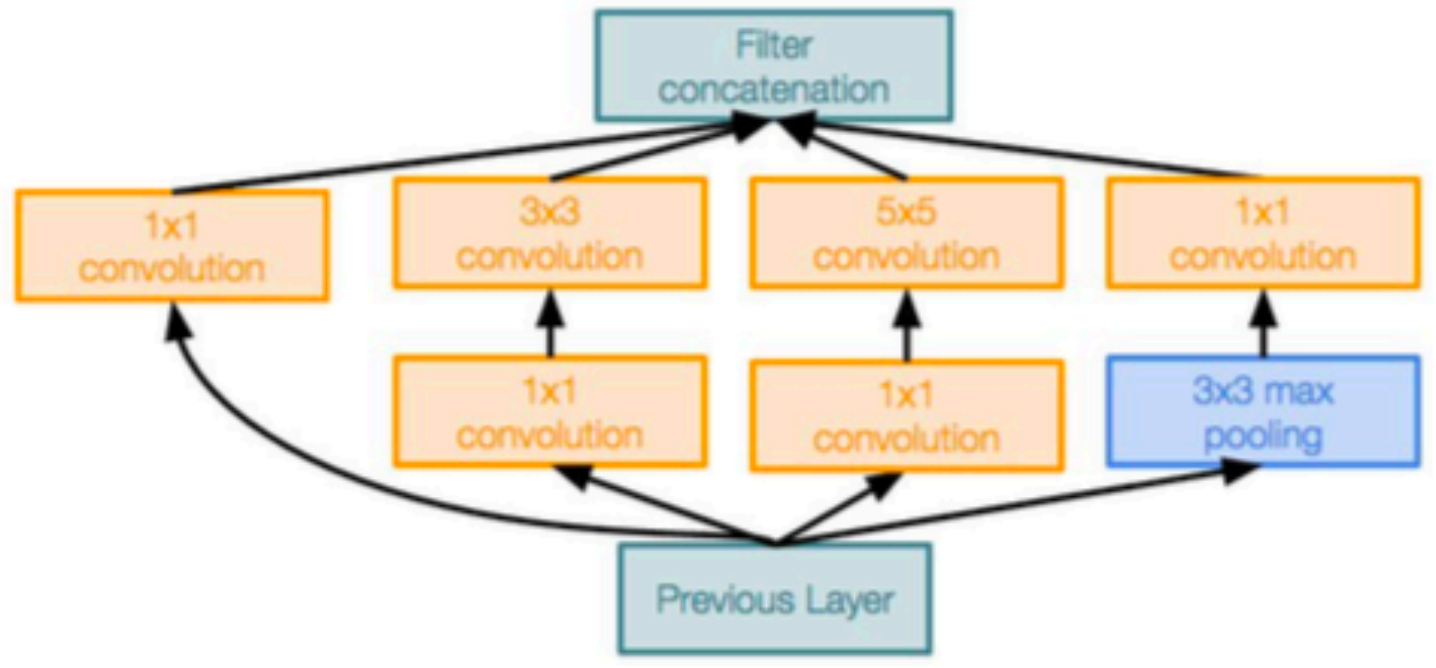
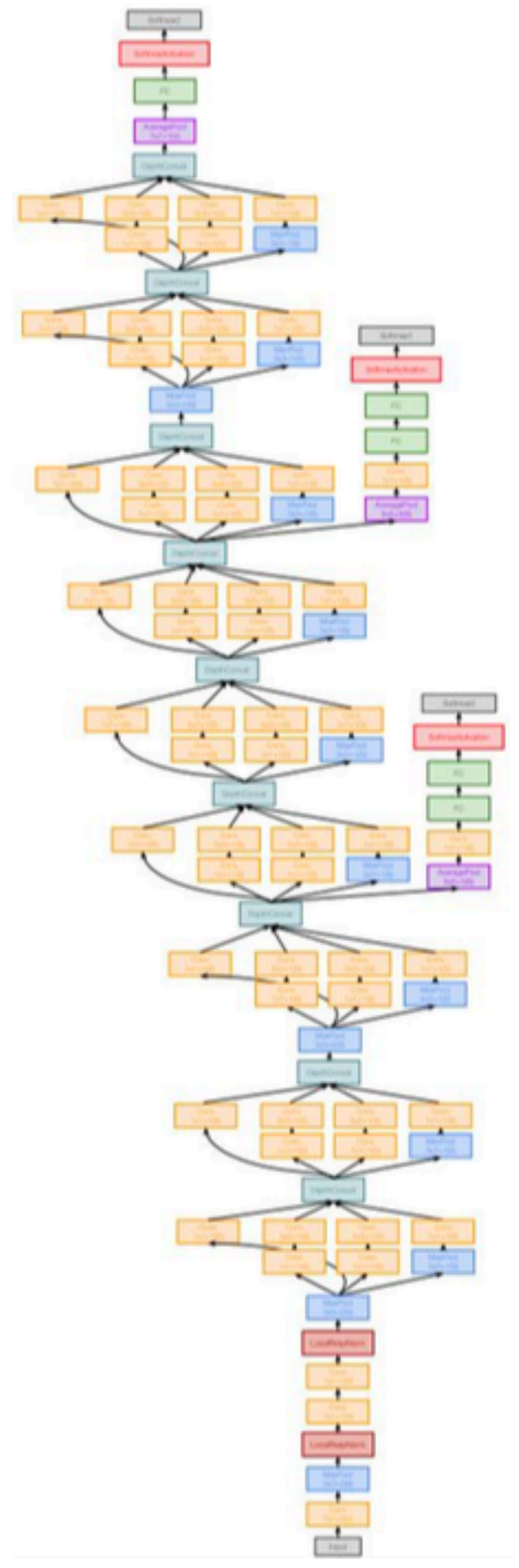


Inception module



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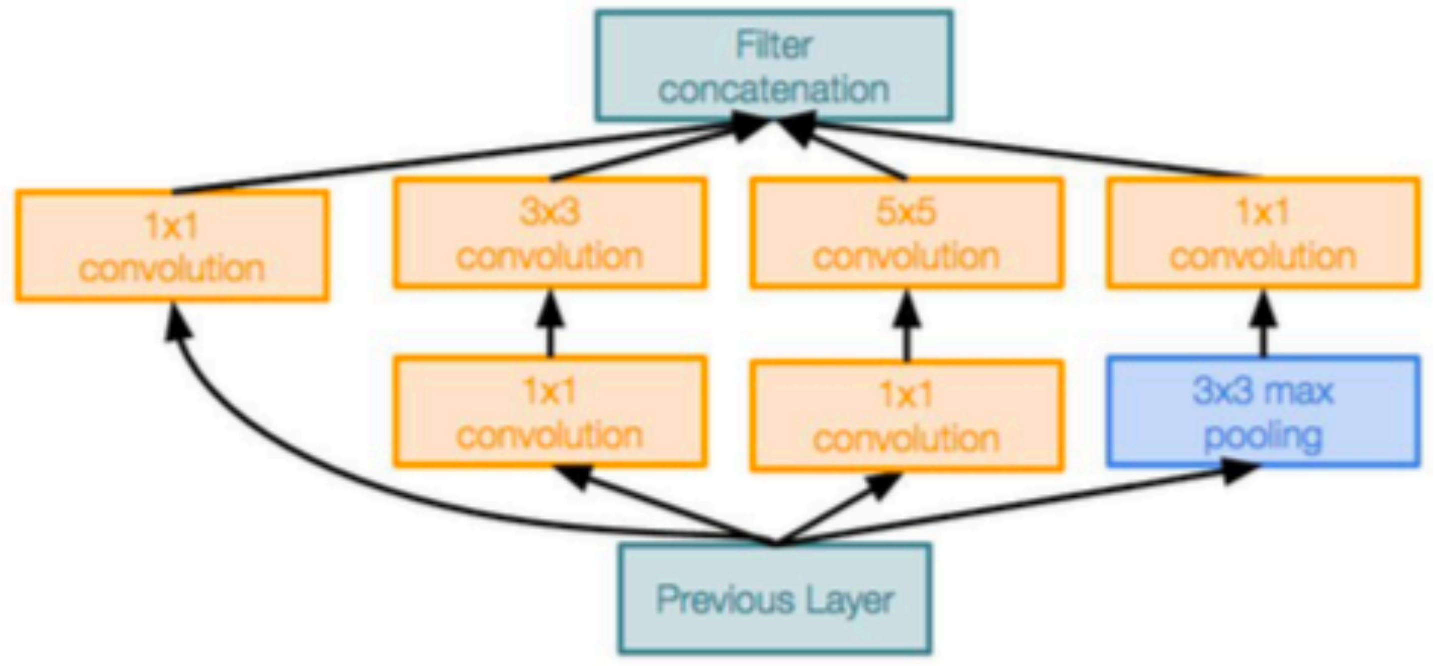
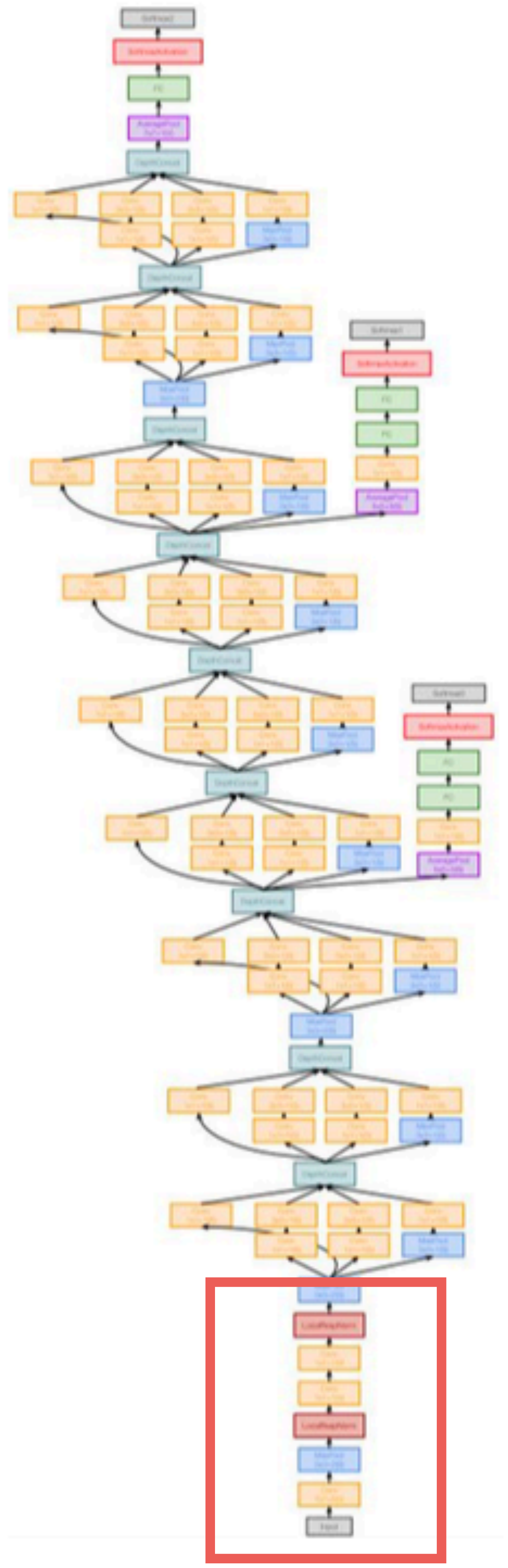


Inception module



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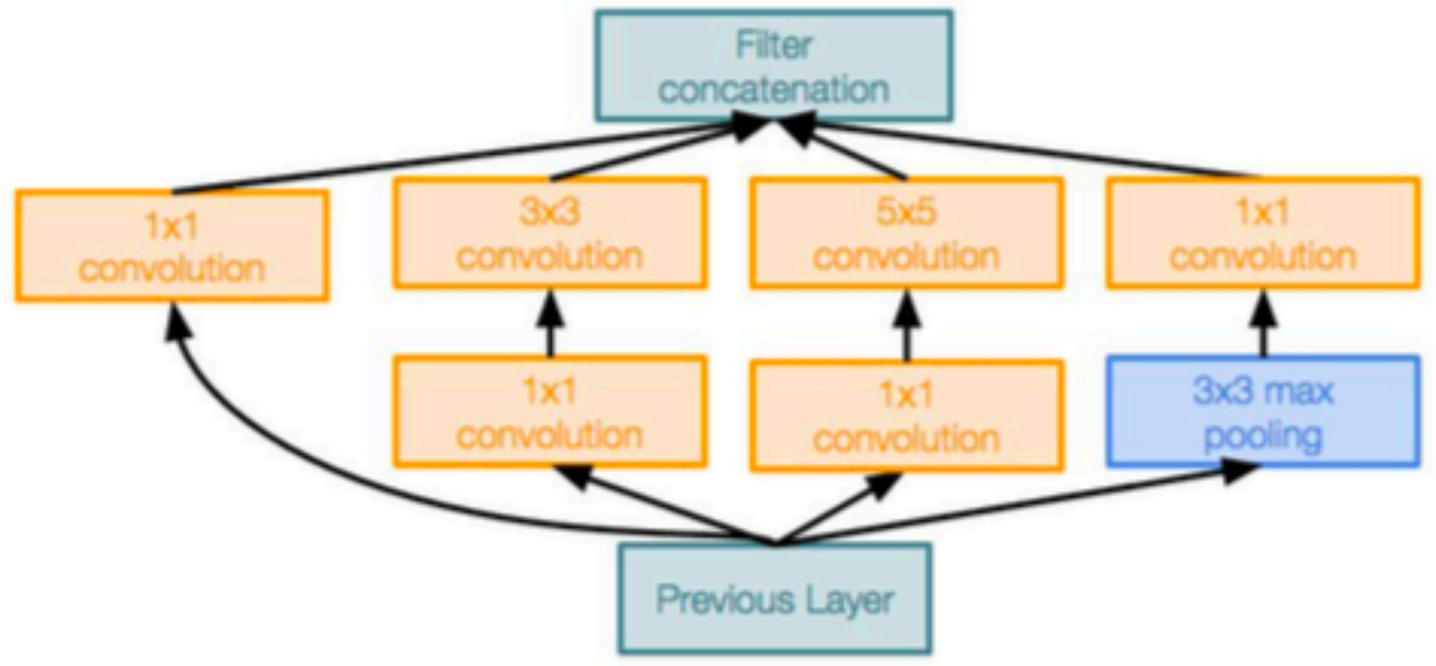

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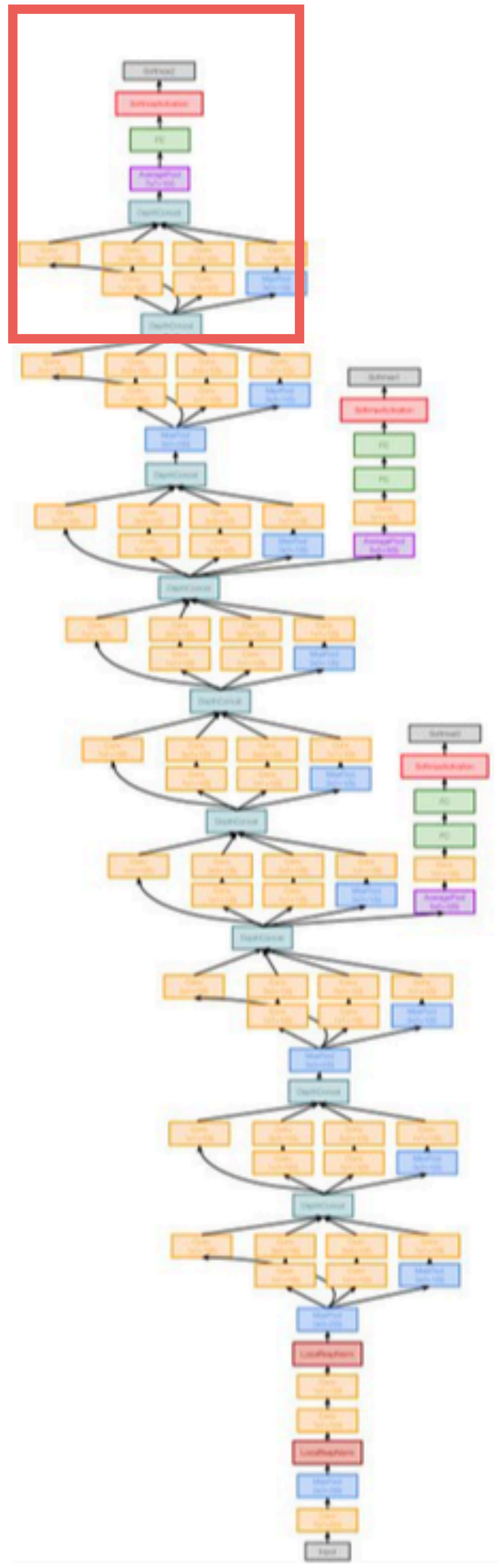

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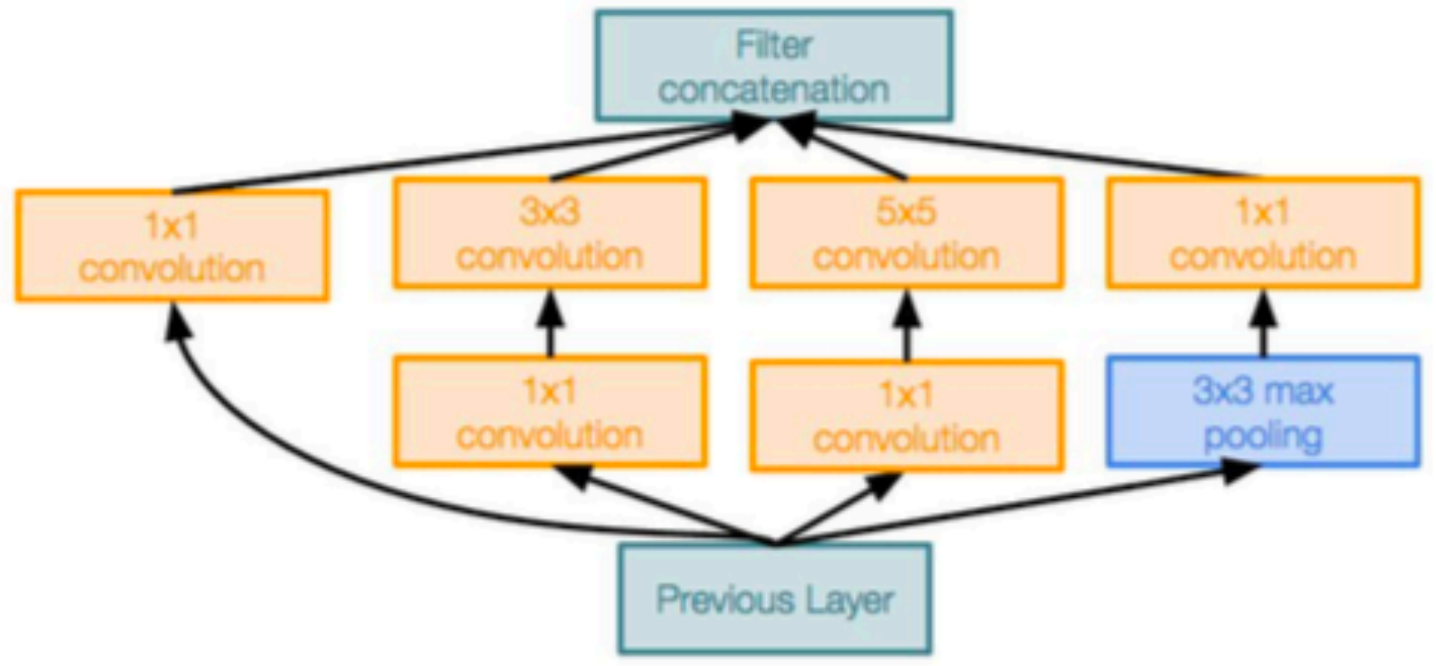
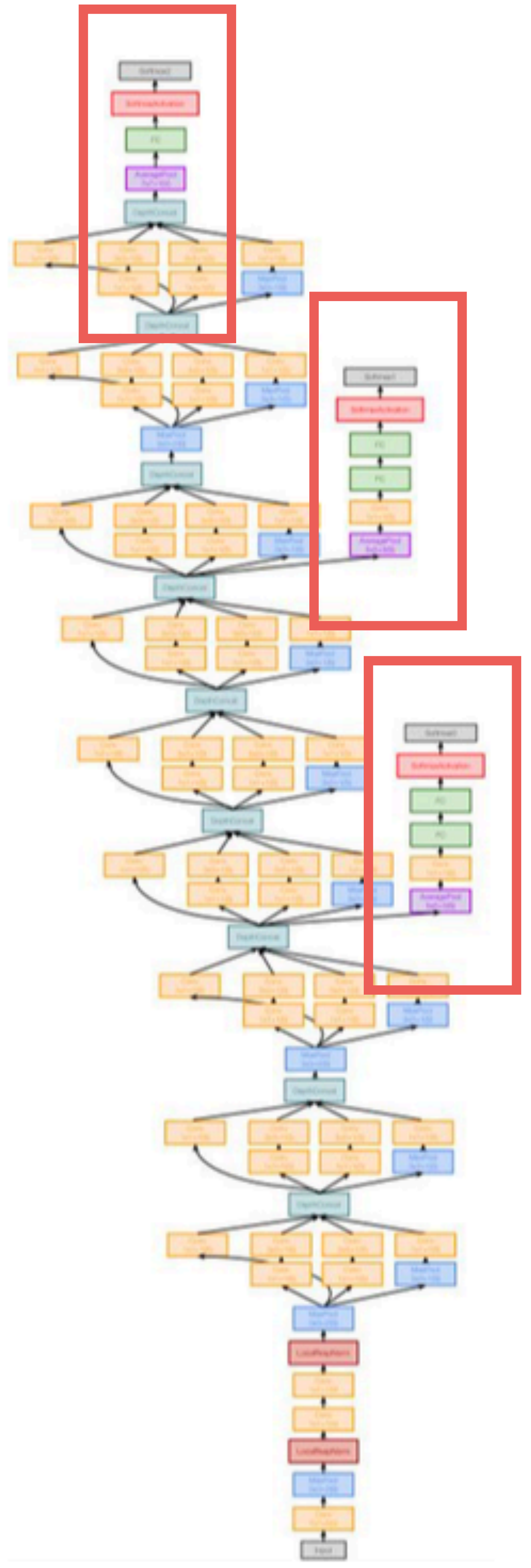
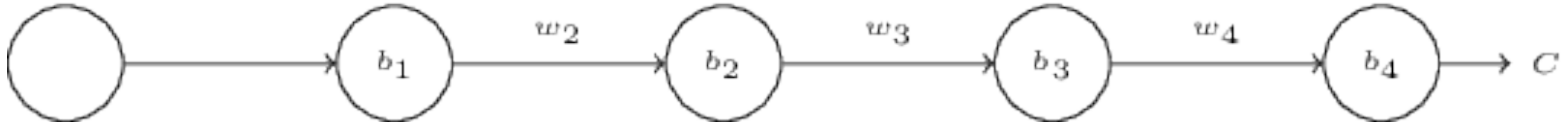


Inception module



Optimizing **Deep** Neural Networks

Consider multi-layer neural network with sigmoid activations and loss C



Source: http://neuralnetworksanddeeplearning.com/chap5.html

Optimizing **Deep** Neural Networks

$$\frac{\partial C}{\partial b_1} = \sigma'(z_1) \times w_2 \times \sigma'(z_2) \times w_3 \times \sigma'(z_3) \times w_4 \times \sigma'(z_4) \times \frac{\partial C}{\partial a_4}$$

$$\begin{tikzcd} \bigcirc \arrow[r] & b_1 \arrow[r, "w_2"] & b_2 \arrow[r, "w_3"] & b_3 \arrow[r, "w_4"] & b_4 \arrow[r] & C \end{tikzcd}$$

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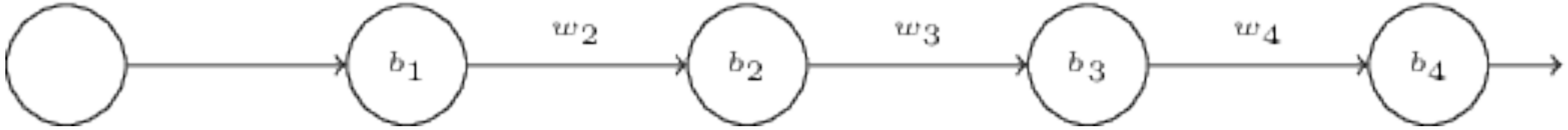


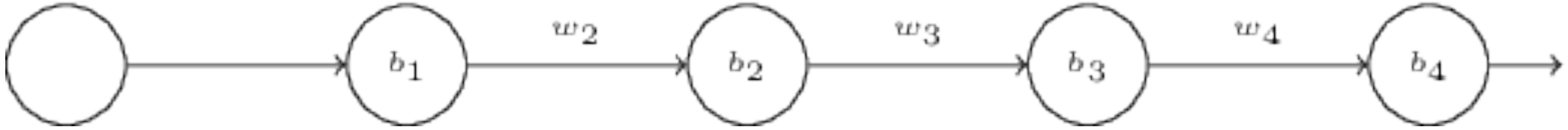
Expression for **gradient** of bias in **Layer 1**: $\frac{\partial C}{\partial b_1} = \sigma'(z_1)\, w_2\sigma'(z_2)\, w_3\sigma'(z_3)\, w_4\sigma'(z_4)\frac{\partial C}{\partial a_4}$

Expression for **gradient** of bias in **Layer 3**: $\frac{\partial C}{\partial b_3} = \sigma'(z_3)\, w_4\sigma'(z_4)\frac{\partial C}{\partial a_4}$

Source: http://neuralnetworksanddeeplearning.com/chap5.html

Optimizing **Deep** Neural Networks

$$\frac{\partial C}{\partial b_1} = \sigma'(z_1) \times w_2 \times \sigma'(z_2) \times w_3 \times \sigma'(z_3) \times w_4 \times \sigma'(z_4) \times \frac{\partial C}{\partial a_4}$$



Expression for **gradient** of bias in **Layer 1**: $\frac{\partial C}{\partial b_1} = \sigma'(z_1)\, w_2\sigma'(z_2)\, w_3\sigma'(z_3)\, \underbrace{w_4\sigma'(z_4)\frac{\partial C}{\partial a_4}}$

$\updownarrow$ common terms

Expression for **gradient** of bias in **Layer 3**: $\frac{\partial C}{\partial b_3} = \sigma'(z_3)\, \overbrace{w_4\sigma'(z_4)\frac{\partial C}{\partial a_4}}$

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Optimizing **Deep** Neural Networks

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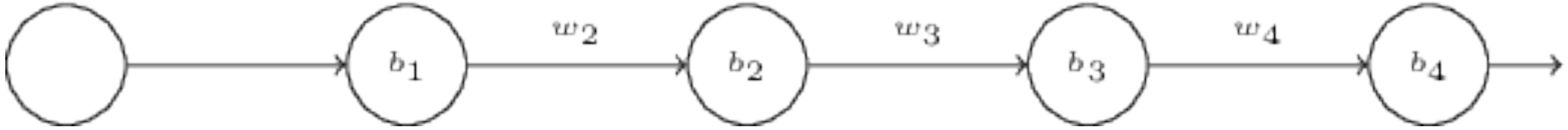


$$\frac{\partial C}{\partial b_1} = \sigma'(z_1)\, w_2\sigma'(z_2)\, w_3\sigma'(z_3)\, \underbrace{w_4\sigma'(z_4)\frac{\partial C}{\partial a_4}}$$

$$\updownarrow \text{ common terms}$$

$$\frac{\partial C}{\partial b_3} = \sigma'(z_3)\, \overbrace{w_4\sigma'(z_4)\frac{\partial C}{\partial a_4}}$$

Observations:

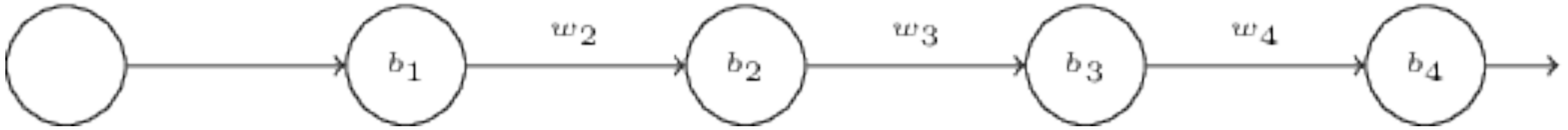
|weight| < 1 (due to initialization)

max of derivative of sigmoid = 1/4 @ 0

Source: http://neuralnetworksanddeeplearning.com/chap5.html

Optimizing **Deep** Neural Networks

$$\frac{\partial C}{\partial b_1} = \sigma'(z_1) \times w_2 \times \sigma'(z_2) \times w_3 \times \sigma'(z_3) \times w_4 \times \sigma'(z_4) \times \frac{\partial C}{\partial a_4}$$



$$\frac{\partial C}{\partial b_1} = \sigma'(z_1)\overbrace{w_2\sigma'(z_2)}^{<\frac{1}{4}}\overbrace{w_3\sigma'(z_3)}^{<\frac{1}{4}}\underbrace{w_4\sigma'(z_4)\frac{\partial C}{\partial a_4}}$$

common terms

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Observations:
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Optimizing **Deep** Neural Networks

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$$\begin{tikzcd}
\bigcirc \arrow[r] & b_1 \arrow[r, "w_2"] & b_2 \arrow[r, "w_3"] & b_3 \arrow[r, "w_4"] & b_4 \arrow[r] & C
\end{tikzcd}$$

$$\frac{\partial C}{\partial b_1} = \sigma'(z_1) \overbrace{w_2\sigma'(z_2)}^{<\frac{1}{4}} \overbrace{w_3\sigma'(z_3)}^{<\frac{1}{4}} \underbrace{w_4\sigma'(z_4)\frac{\partial C}{\partial a_4}}$$

common terms

$$\frac{\partial C}{\partial b_3} = \sigma'(z_3) \overbrace{w_4\sigma'(z_4)\frac{\partial C}{\partial a_4}}$$

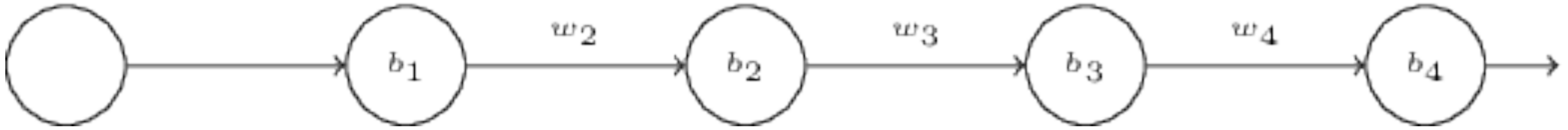
This is called **vanishing gradient** problem

— makes deep networks hard to train
— later layers learn faster than earlier ones

Source: http://neuralnetworksanddeeplearning.com/chap5.html

Optimizing **Deep** Neural Networks

$$\frac{\partial C}{\partial b_1} = \sigma'(z_1) \times w_2 \times \sigma'(z_2) \times w_3 \times \sigma'(z_3) \times w_4 \times \sigma'(z_4) \times \frac{\partial C}{\partial a_4}$$



$$\frac{\partial C}{\partial b_1} = \sigma'(z_1)\overbrace{w_2\sigma'(z_2)}^{>1}\overbrace{w_3\sigma'(z_3)}^{>1}\underbrace{w_4\sigma'(z_4)\frac{\partial C}{\partial a_4}}$$

$$\updownarrow \text{ common terms}$$

$$\frac{\partial C}{\partial b_3} = \sigma'(z_3)\overbrace{w_4\sigma'(z_4)\frac{\partial C}{\partial a_4}}$$

Exploding gradient problem

— makes weights large (e.g., 100)
— make bias such that pre-activation = 0

Source: http://neuralnetworksanddeeplearning.com/chap5.html

GoogleLeNet

[Szegedy et al., 2014]

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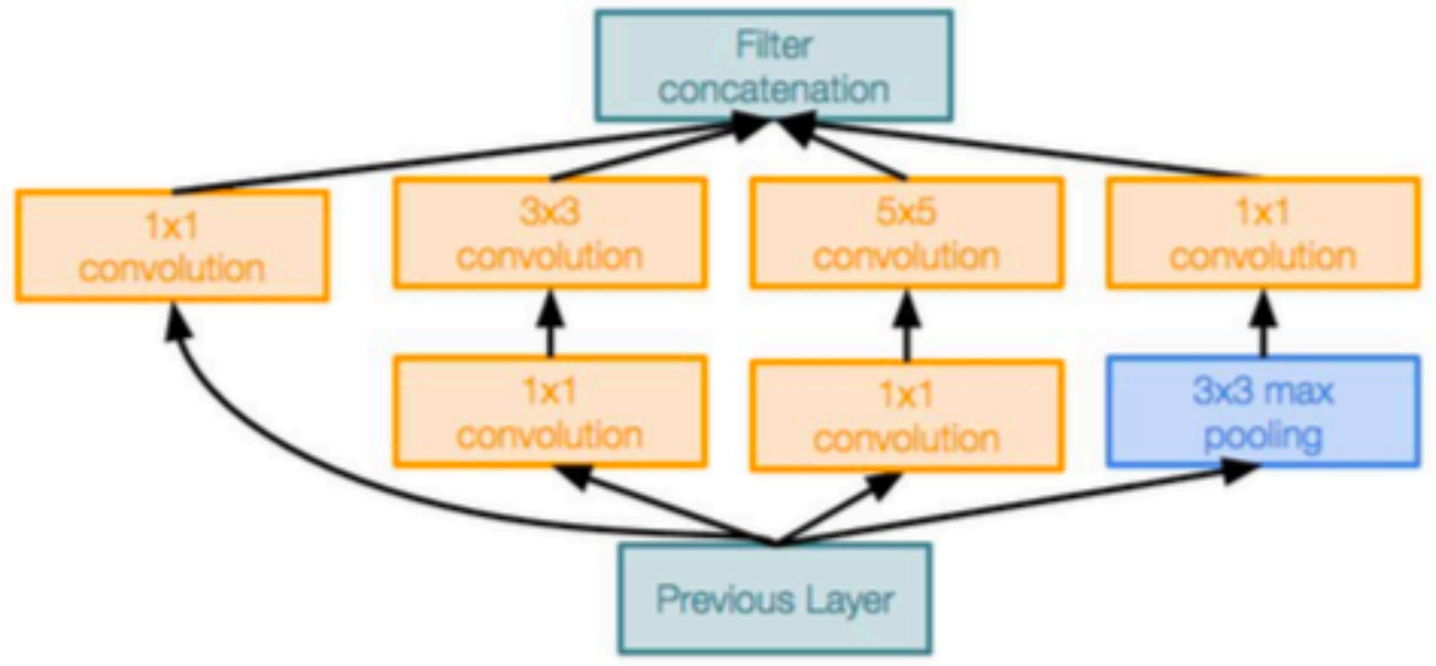
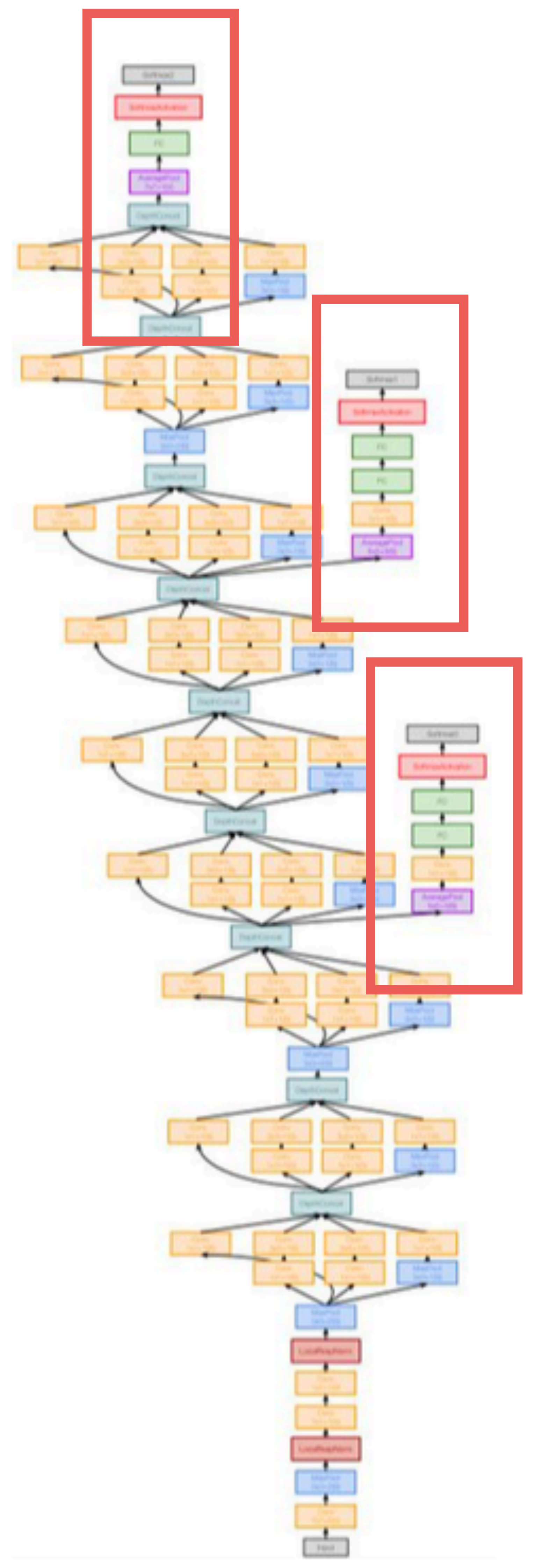
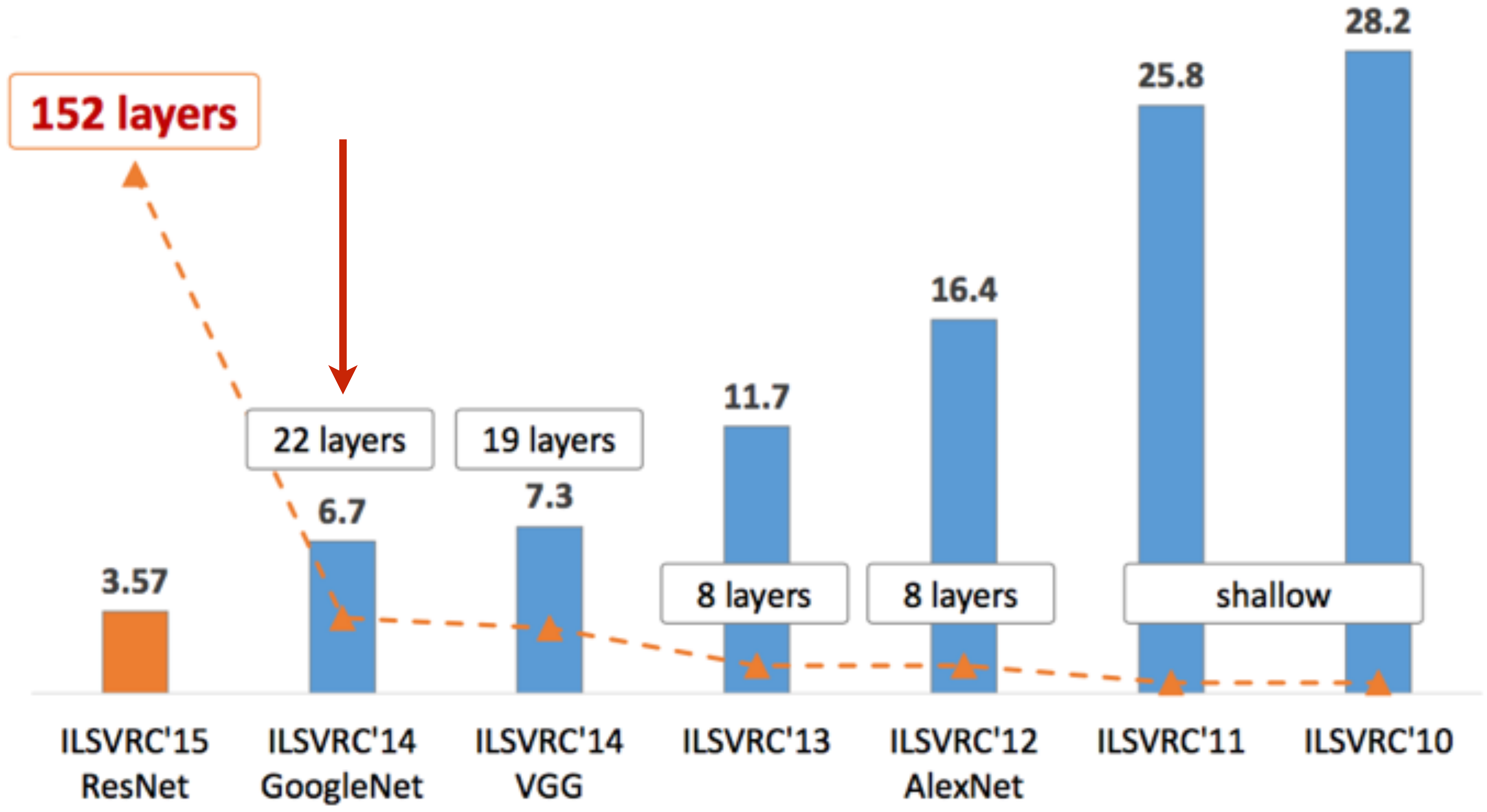


Inception module



* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

ILSVRC winner 2012



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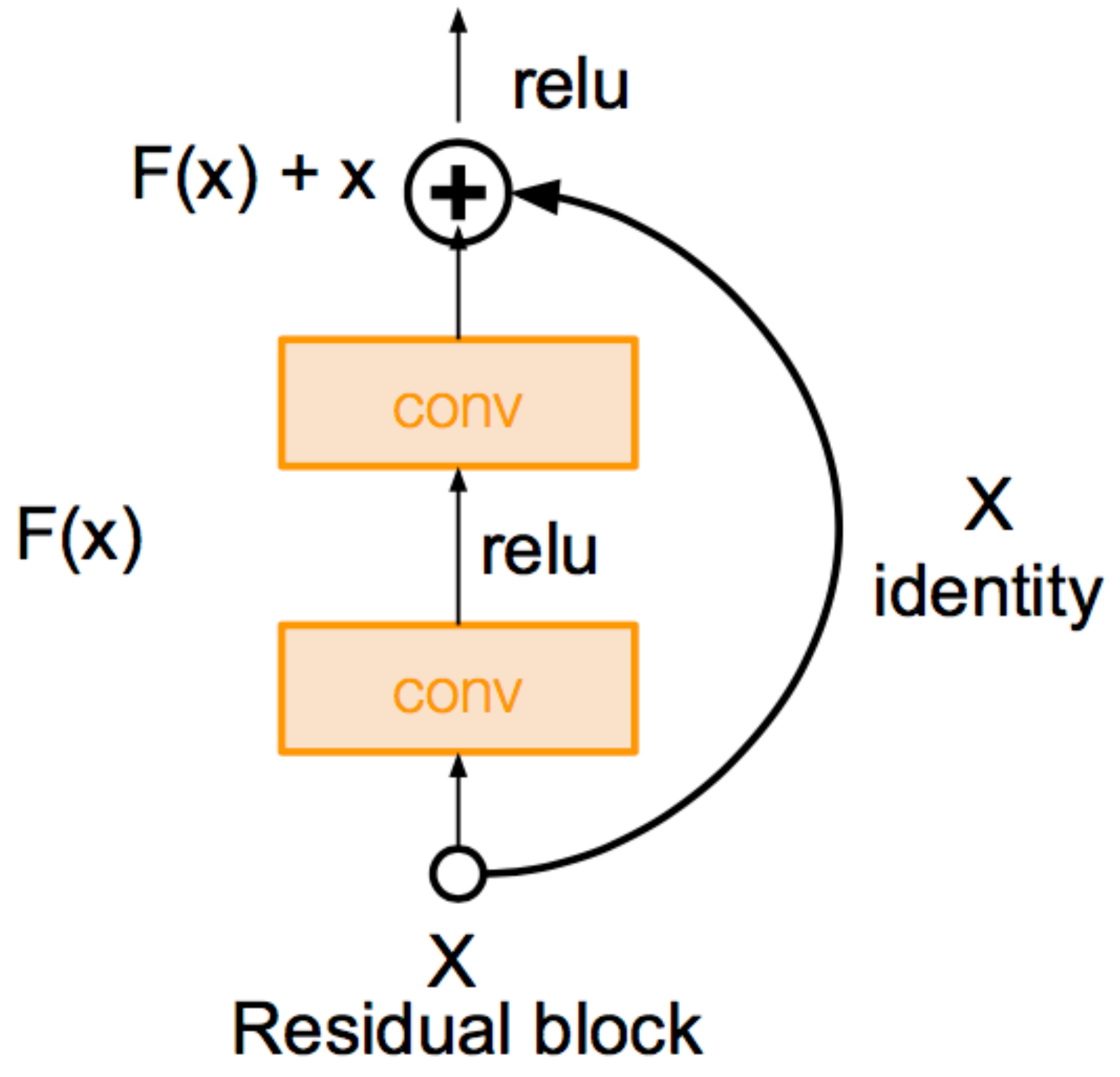
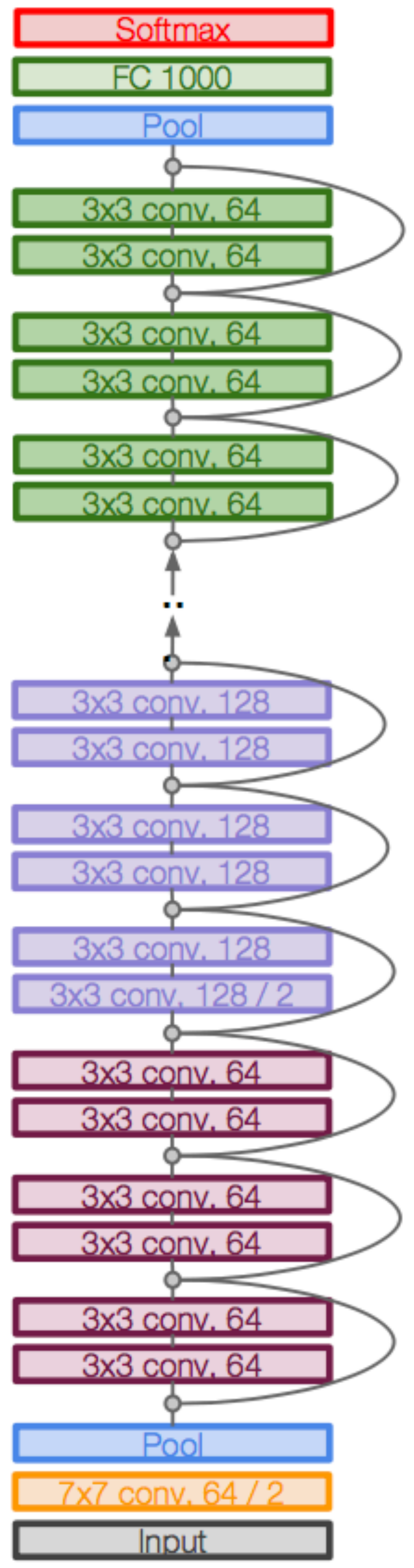
ResNet

[He et al., 2015]

even deeper — **152 layers**!

using residual connections

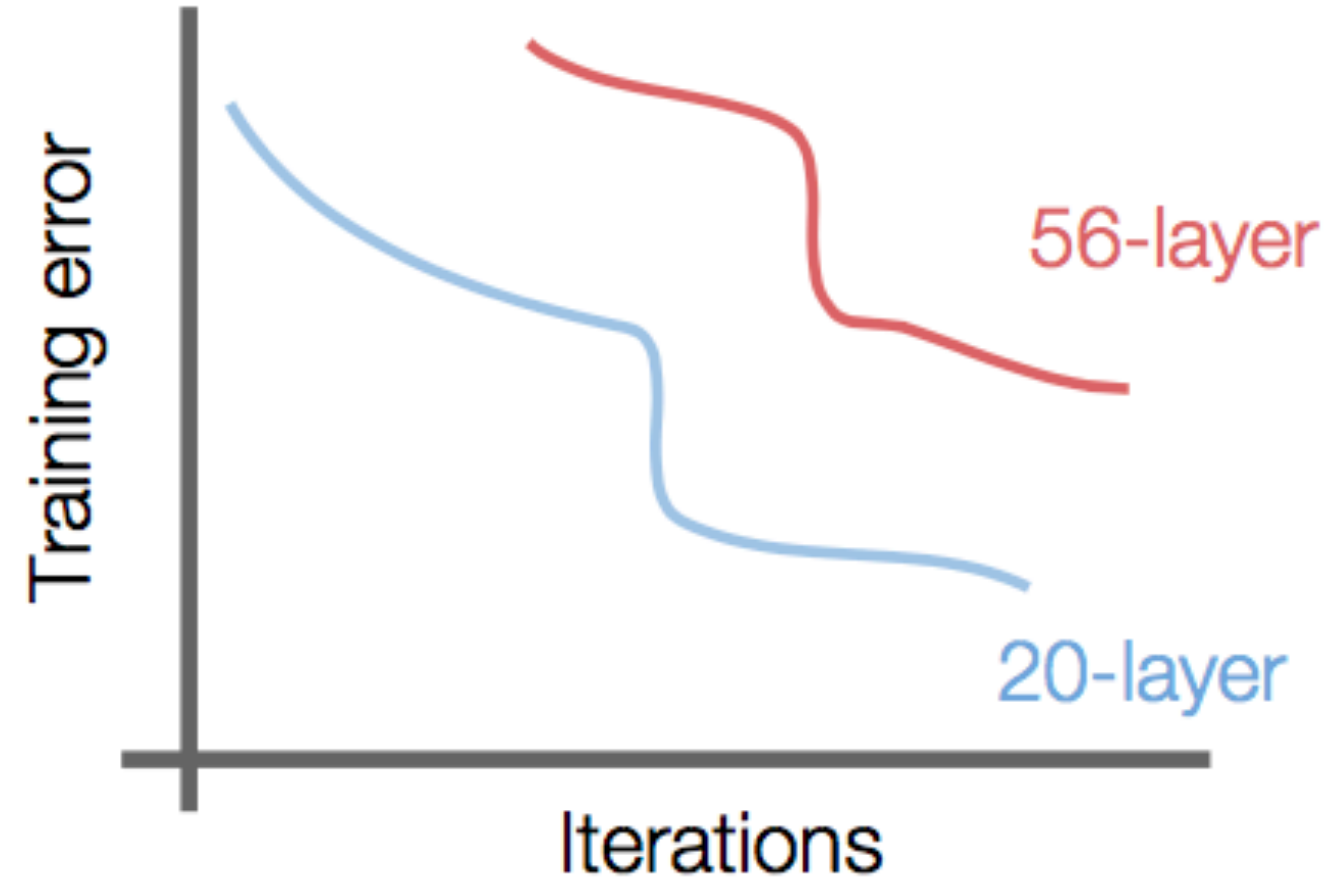


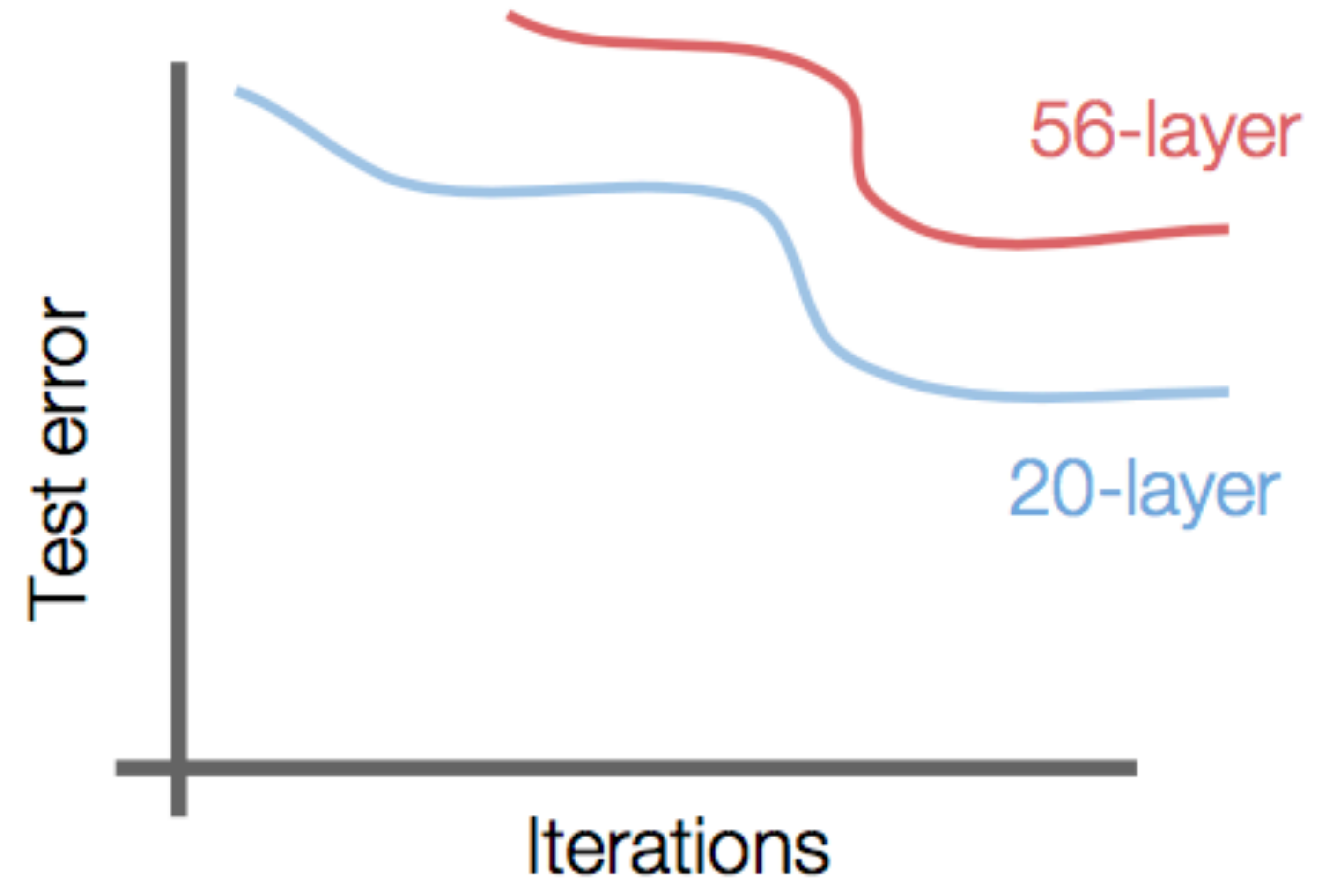


ResNet: Motivation

[He et al., 2015]

What happens when we continue to stacking deeper layers on a “plain” CNN





Whats the **problem**?

ResNet: Motivation

[He et al., 2015]

Hypothesis: deeper models are harder to optimize (optimization problem)

Observation: the deeper model should (conceptually) perform just as well (e.g., take shallower model and use identity for all remaining layers)

How do we implement this idea in practice

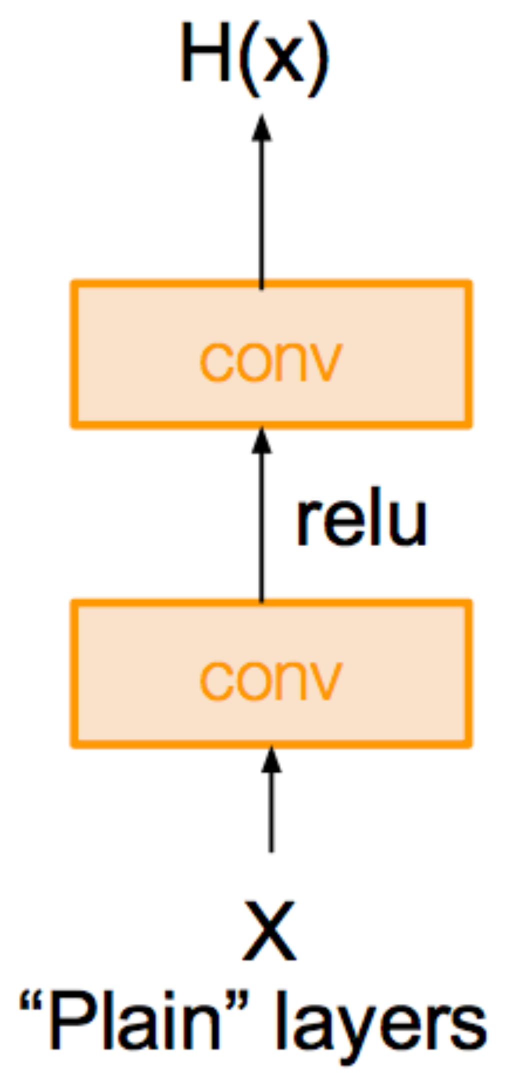
ResNet

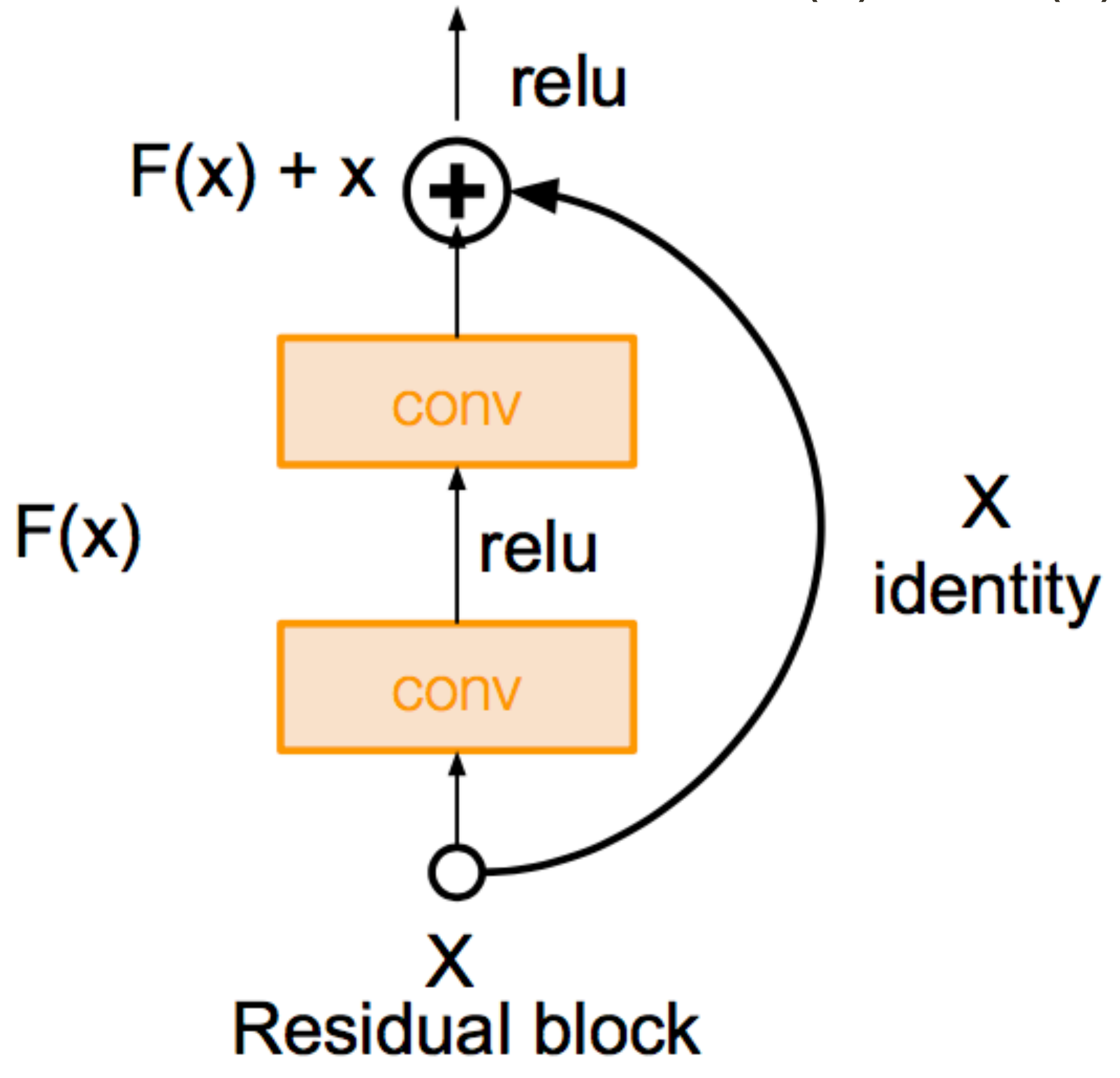
[He et al., 2015]

Solution: use network to fit residual mapping instead of directly trying to fit a desired underlying mapping

$$H(x) = F(x) + X$$

Use layers to fit **residual** F(x) = H(x) - X instead of H(x) directly





* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

ResNet

[He et al., 2015]

Full details

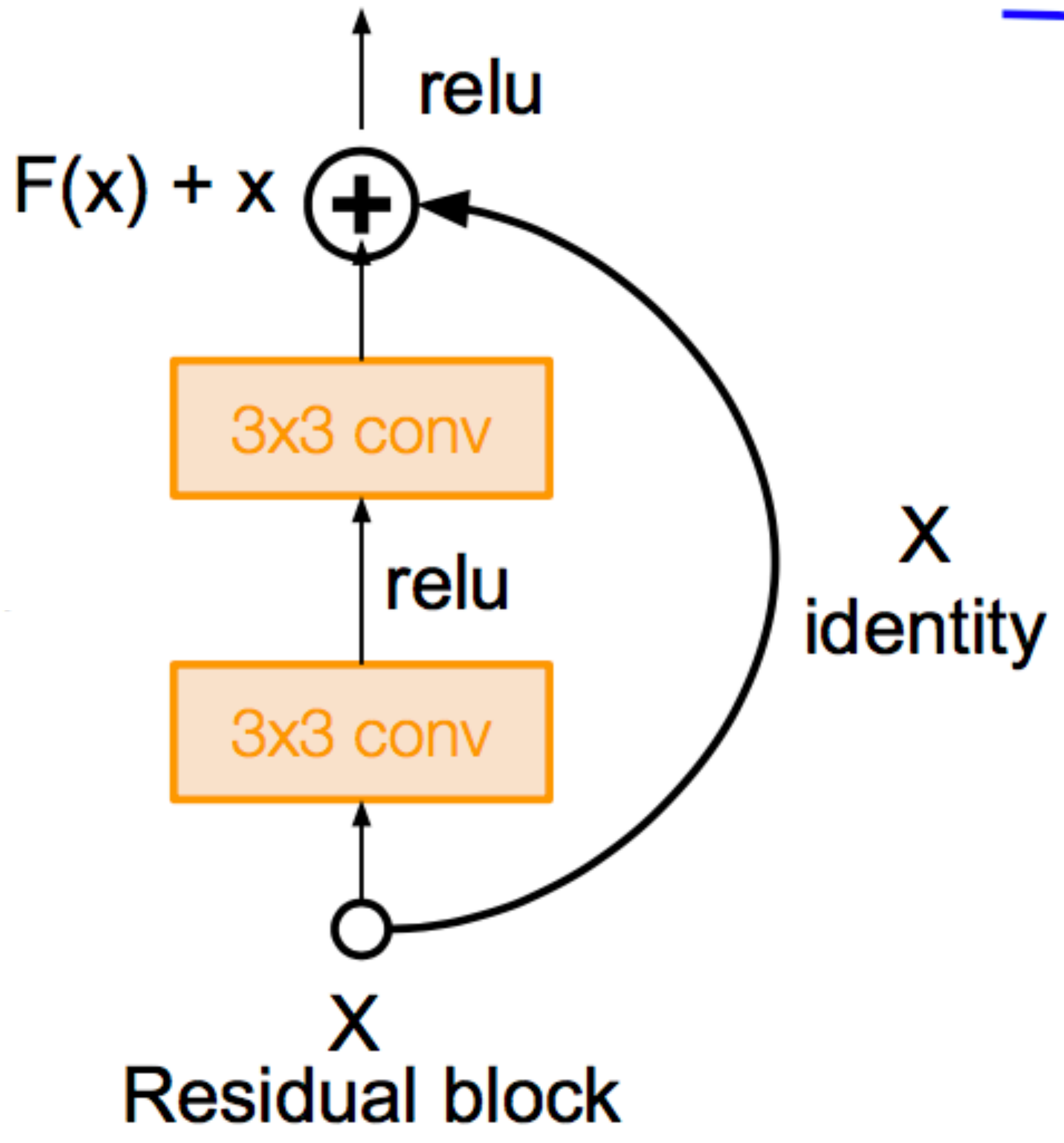
— Stacked **residual blocks**

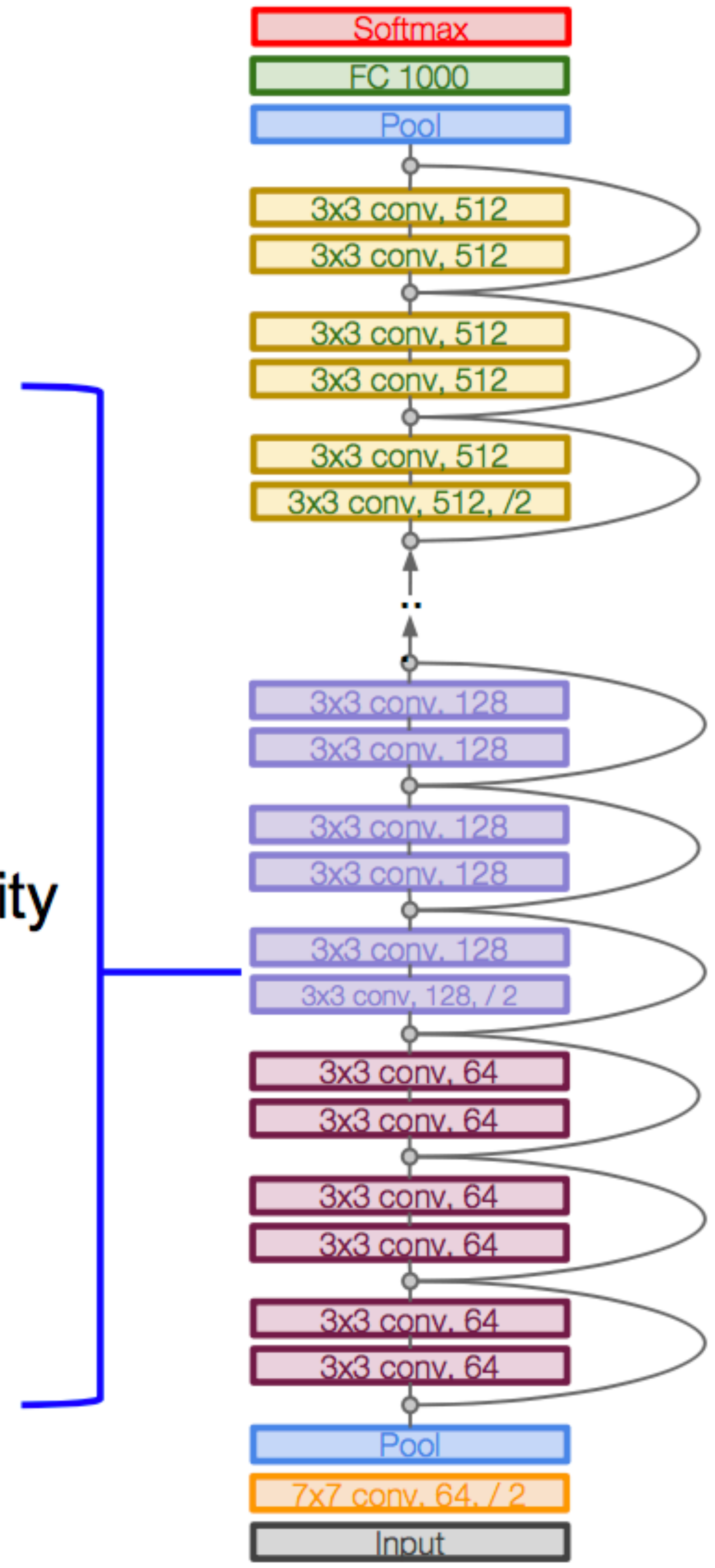
— Every residual block consists of **two 3x3 filters**

— Periodically double # of filters and downsample spatially using stride of 2

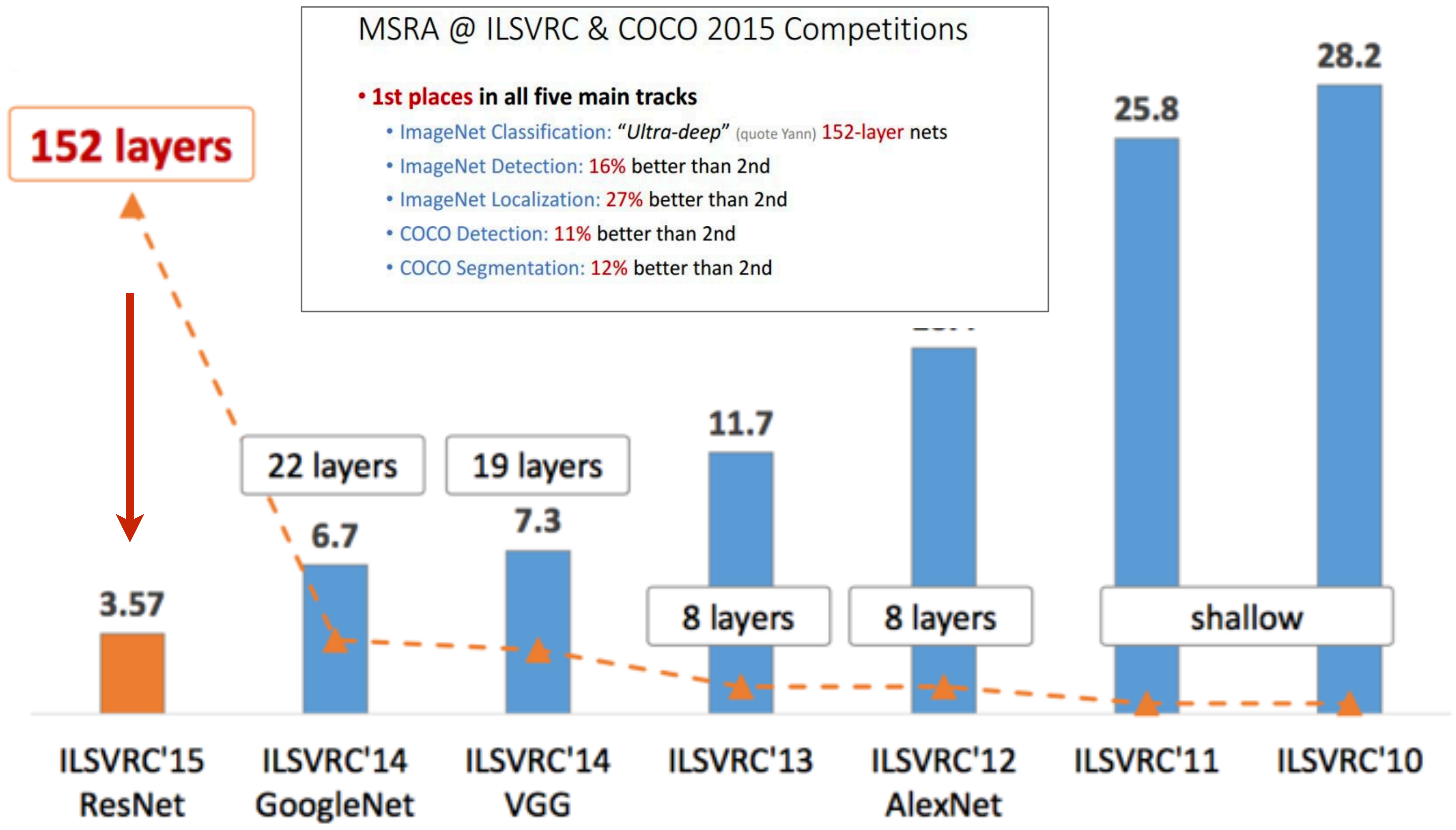
— Additional convolutional layer in the beginning

— **No FC layers** at the end (only FC to output 1000 classes)





ILSVRC winner 2012



MSRA @ ILSVRC & COCO 2015 Competitions

- **1st places in all five main tracks**
  - ImageNet Classification: *"Ultra-deep"* (quote Yann) 152-layer nets
  - ImageNet Detection: 16% better than 2nd
  - ImageNet Localization: 27% better than 2nd
  - COCO Detection: 11% better than 2nd
  - COCO Segmentation: 12% better than 2nd

* slide from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

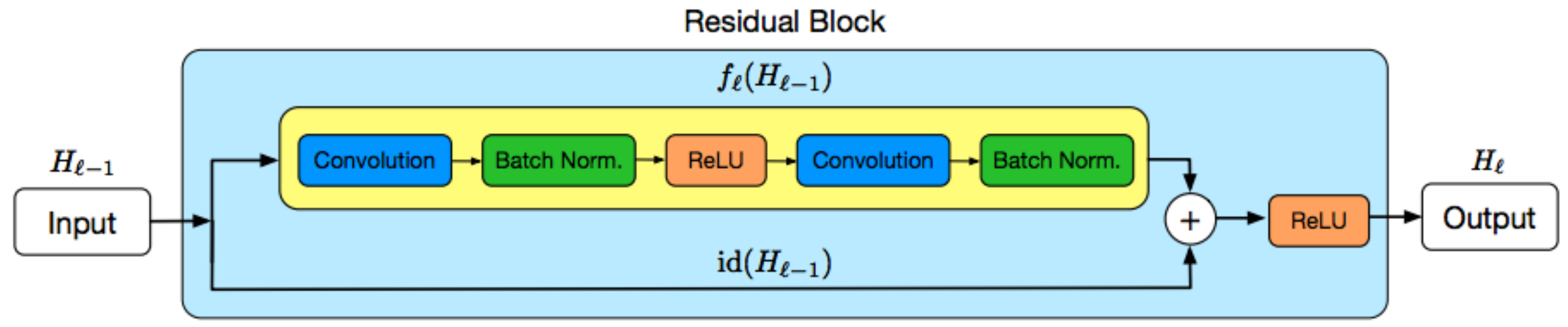
Regularization: Stochastic Depth

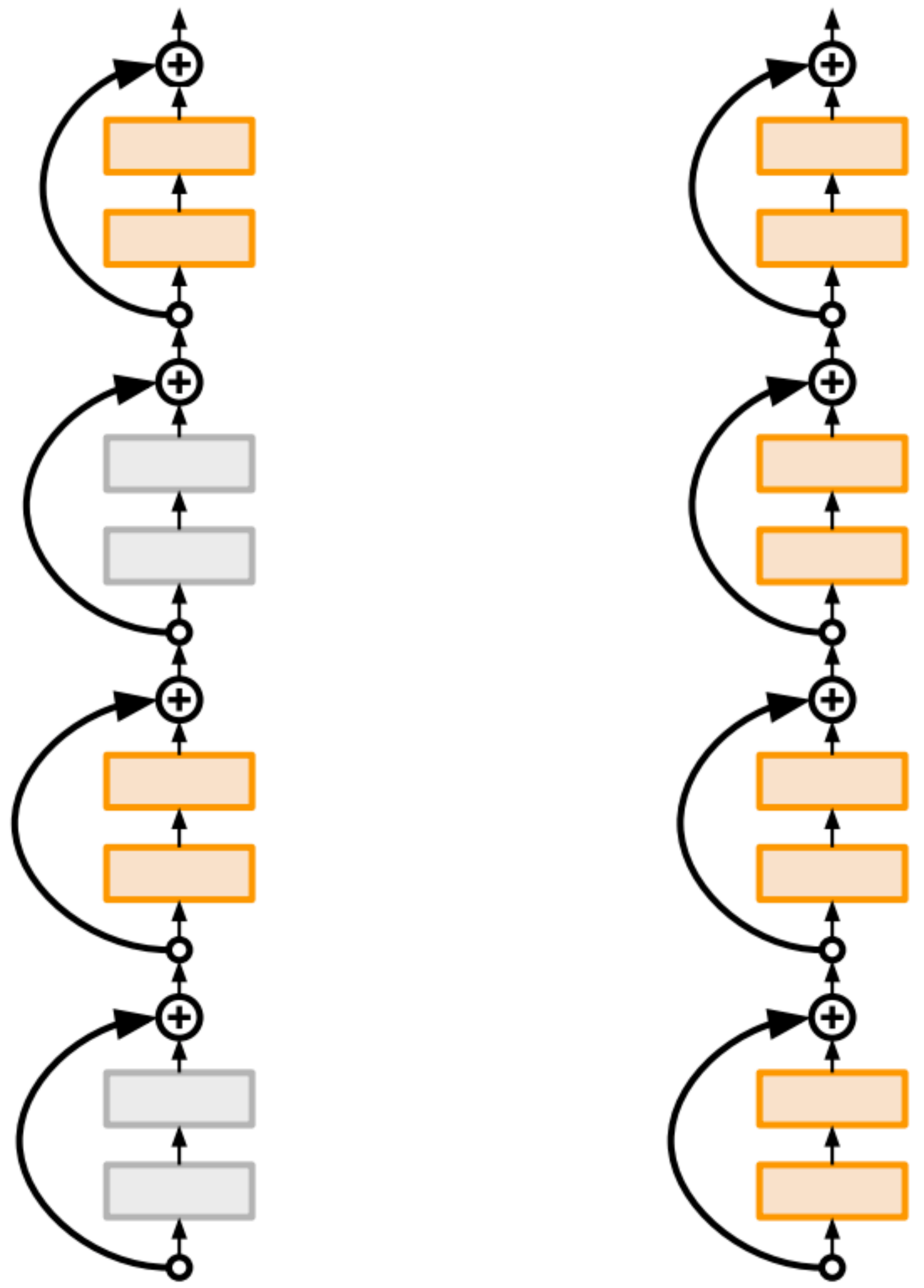
[Huang et al., ECCV 2016]

Effectively "dropout" but for layers

Stochastically with some probability **turn off some layer** (for each batch)

Effectively trains a collection of neural networks

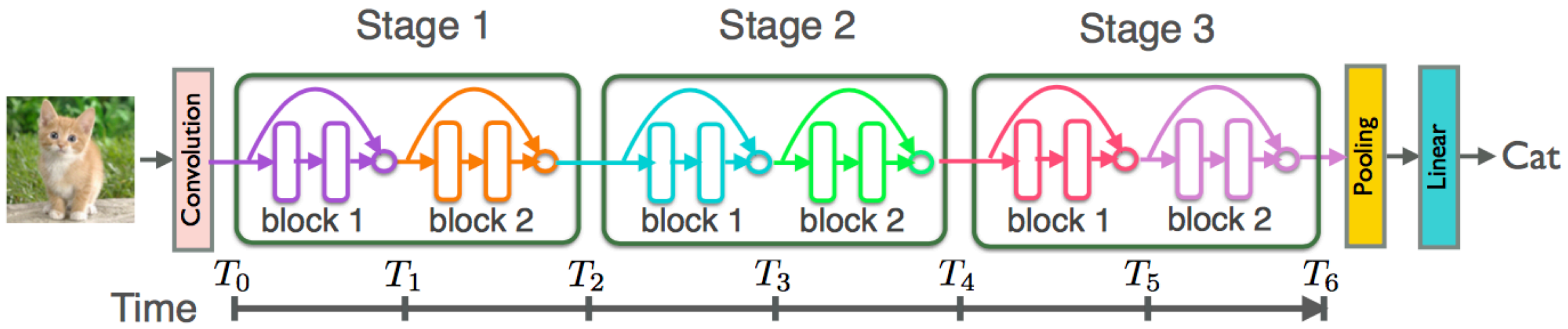




* adopted from Fei-Dei Li, Justin Johnson, Serena Yeung, **cs231n Stanford**

ResNet: A little theory

One can view a sequence of outputs from residual layers as a **Dynamical System**



[Cheng et al., ICLR 2018]

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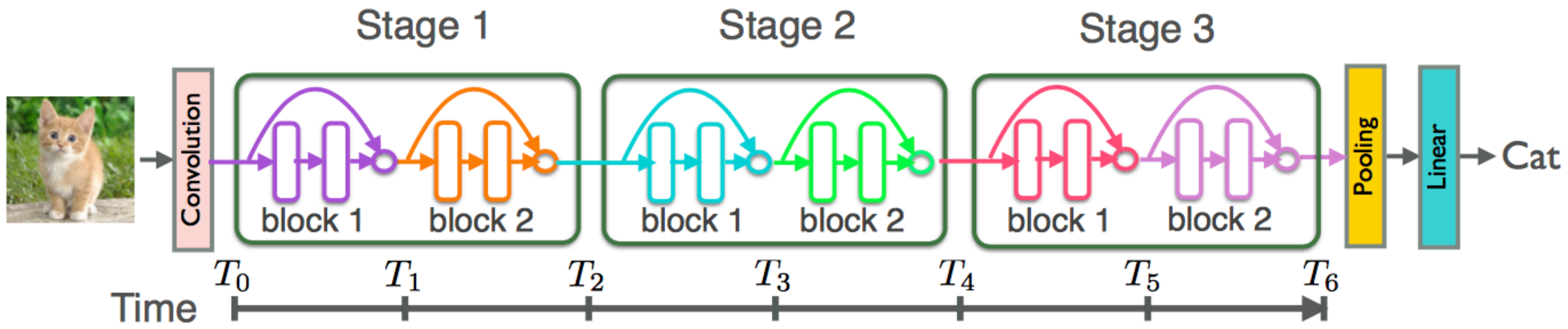
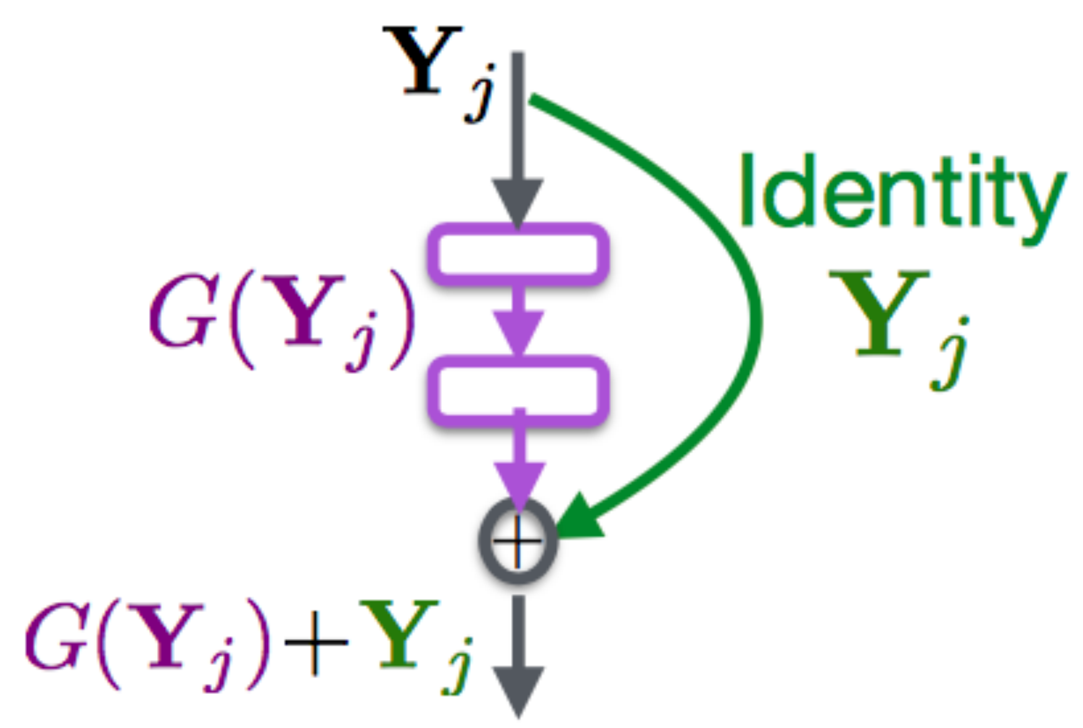


$$\mathbf{Y}_{j+1} = \mathbf{Y}_j + G(\mathbf{Y}_j, \boldsymbol{\theta}_j)$$



[Cheng et al., ICLR 2018]

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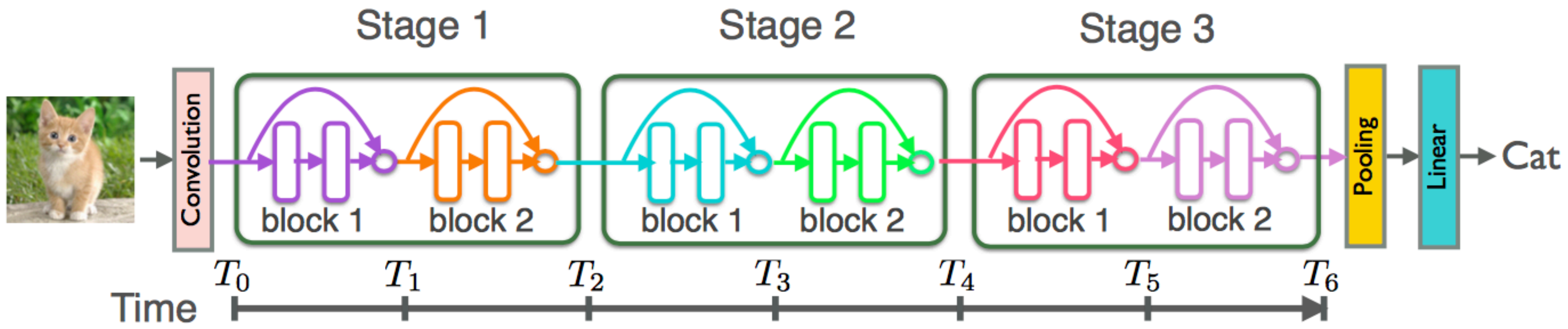

What happens if you take more layers and take smaller steps?

[Chen et al., NIPS 2018 **best paper**]

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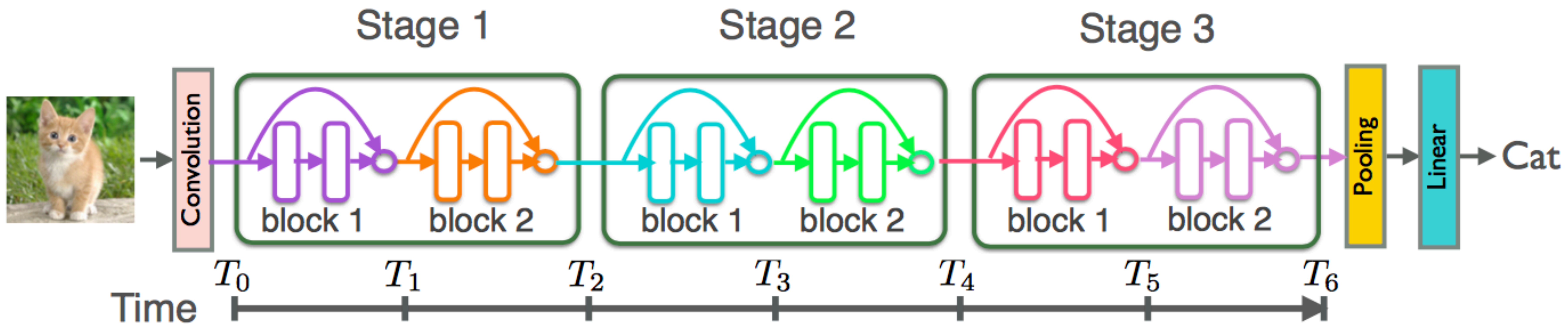
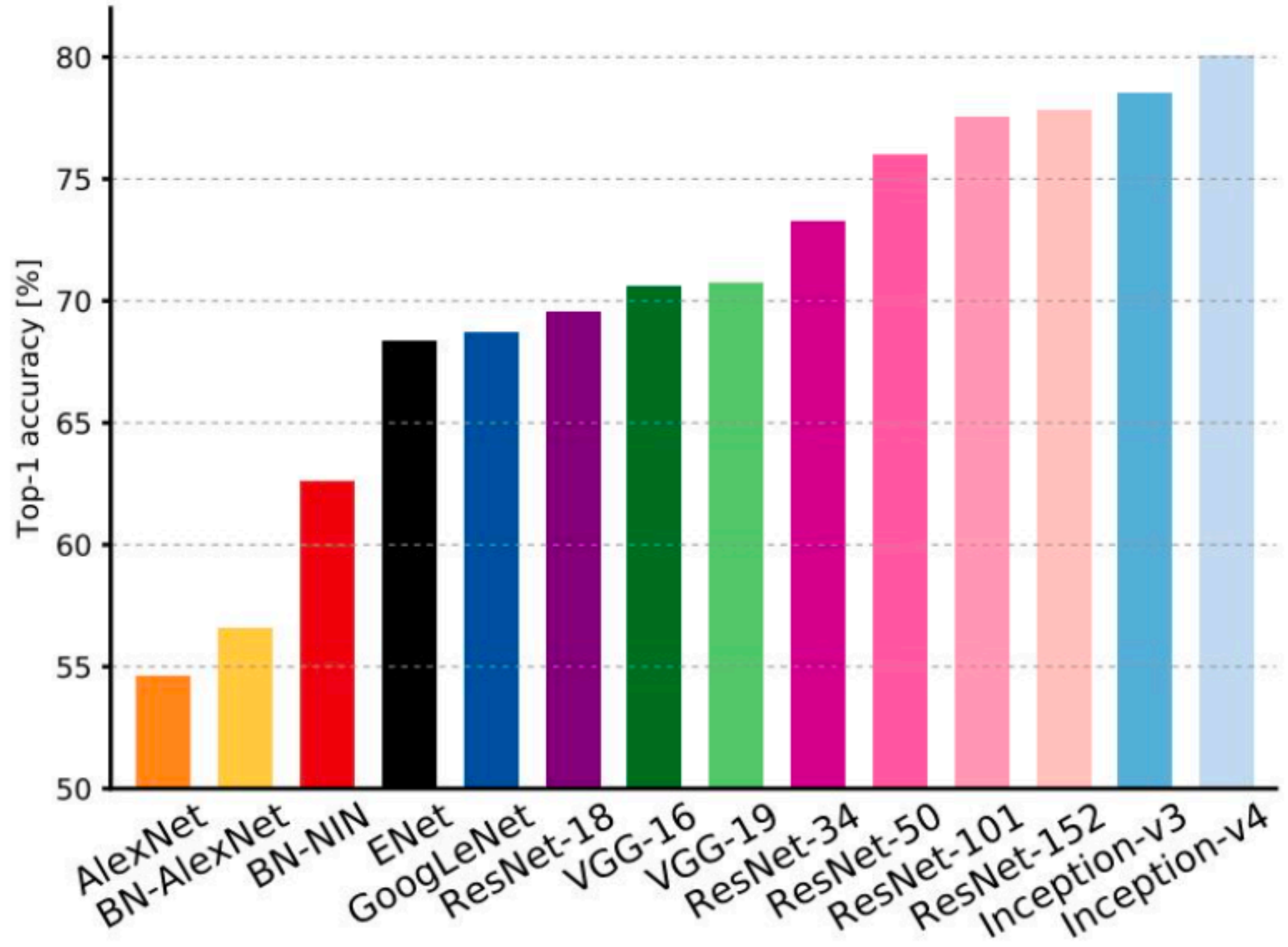


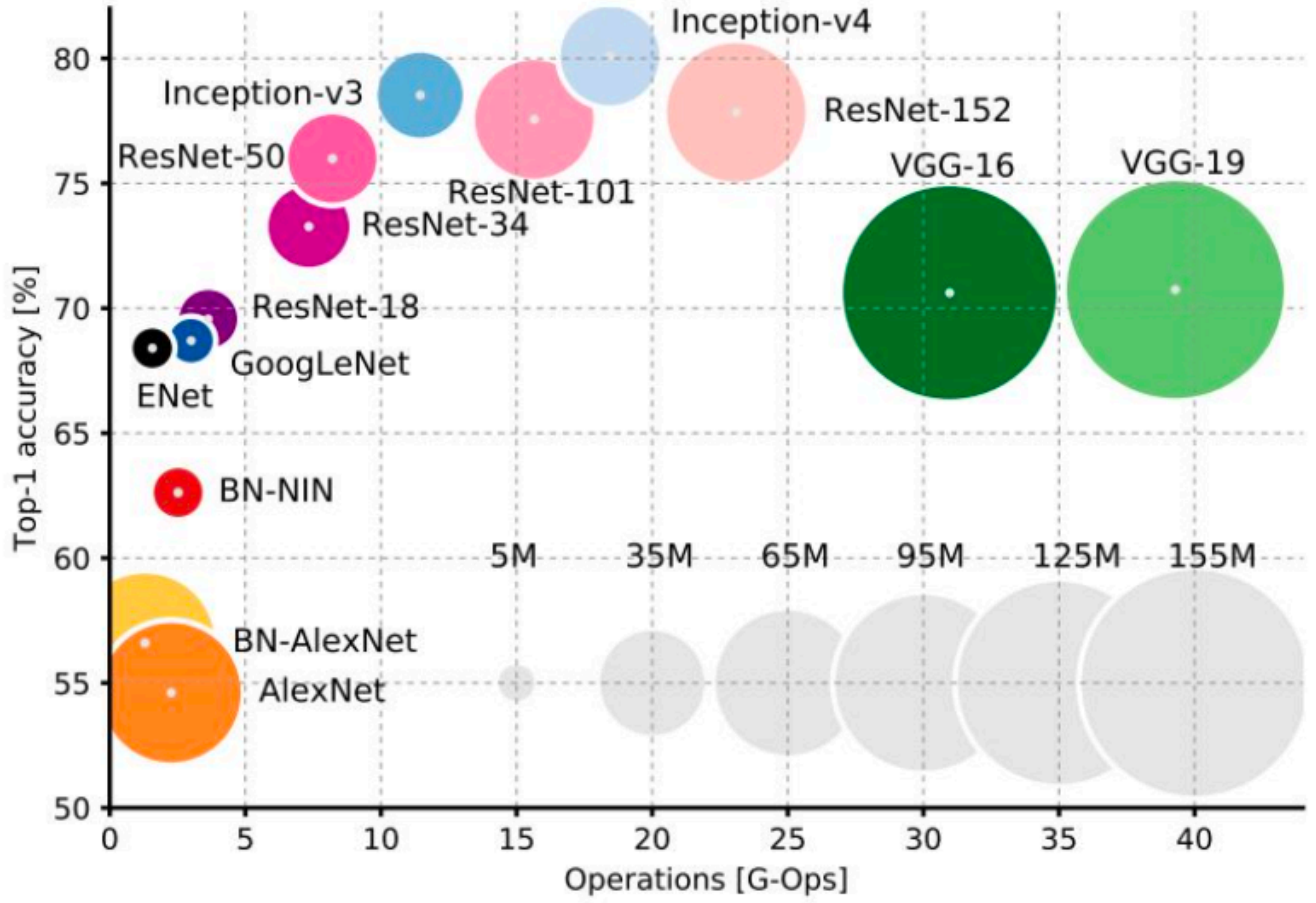
What happens if you take more layers and take smaller steps?

You can actually treat a neural network as an **ODE**: $$\frac{d\mathbf{h}(t)}{dt} = f(\mathbf{h}(t), t, \theta)$$

[Chen et al., NIPS 2018 **best paper**]

Comparing **Complexity**





An Analysis of Deep Neural Network Models for Practical Applications, 2017.