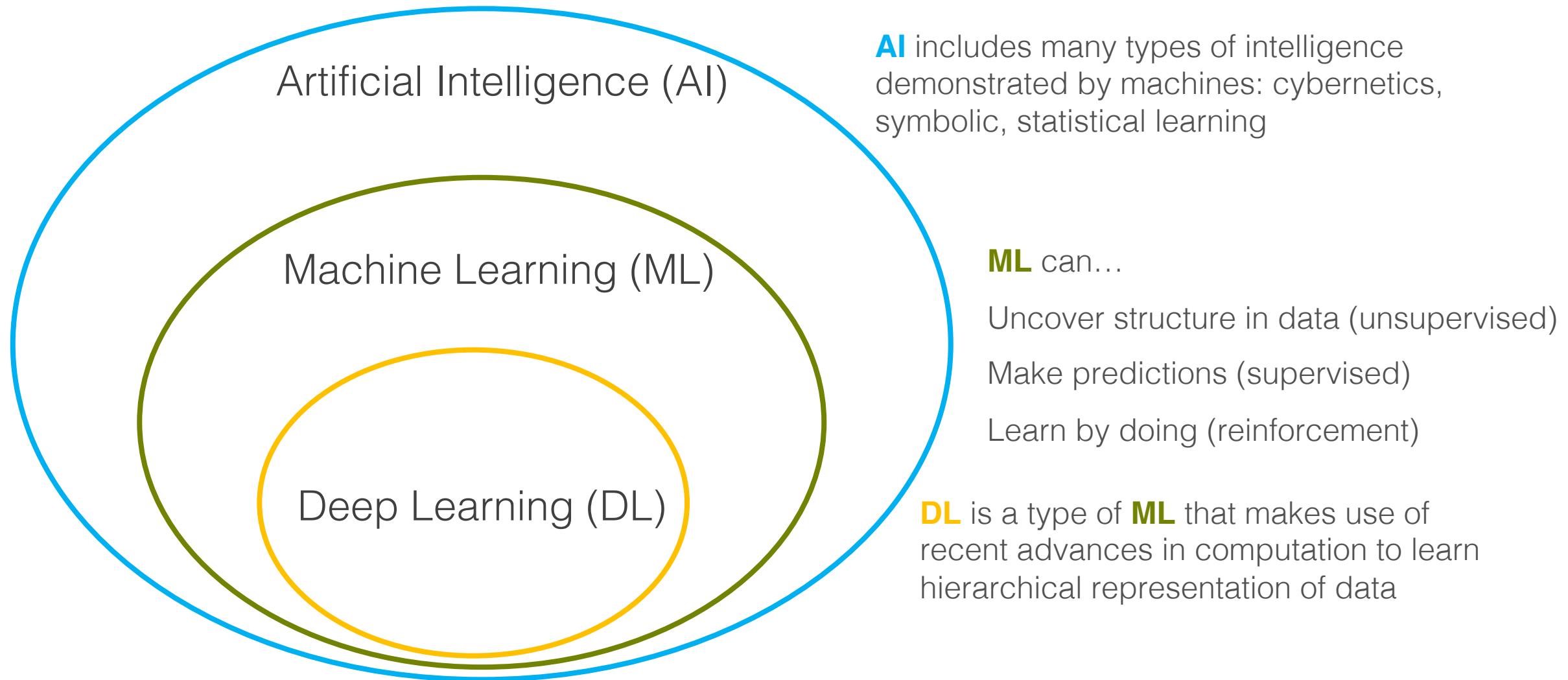


Deep Learning

Lecture 18

Hierarchy of Learning



Types of Deep Learning Tools

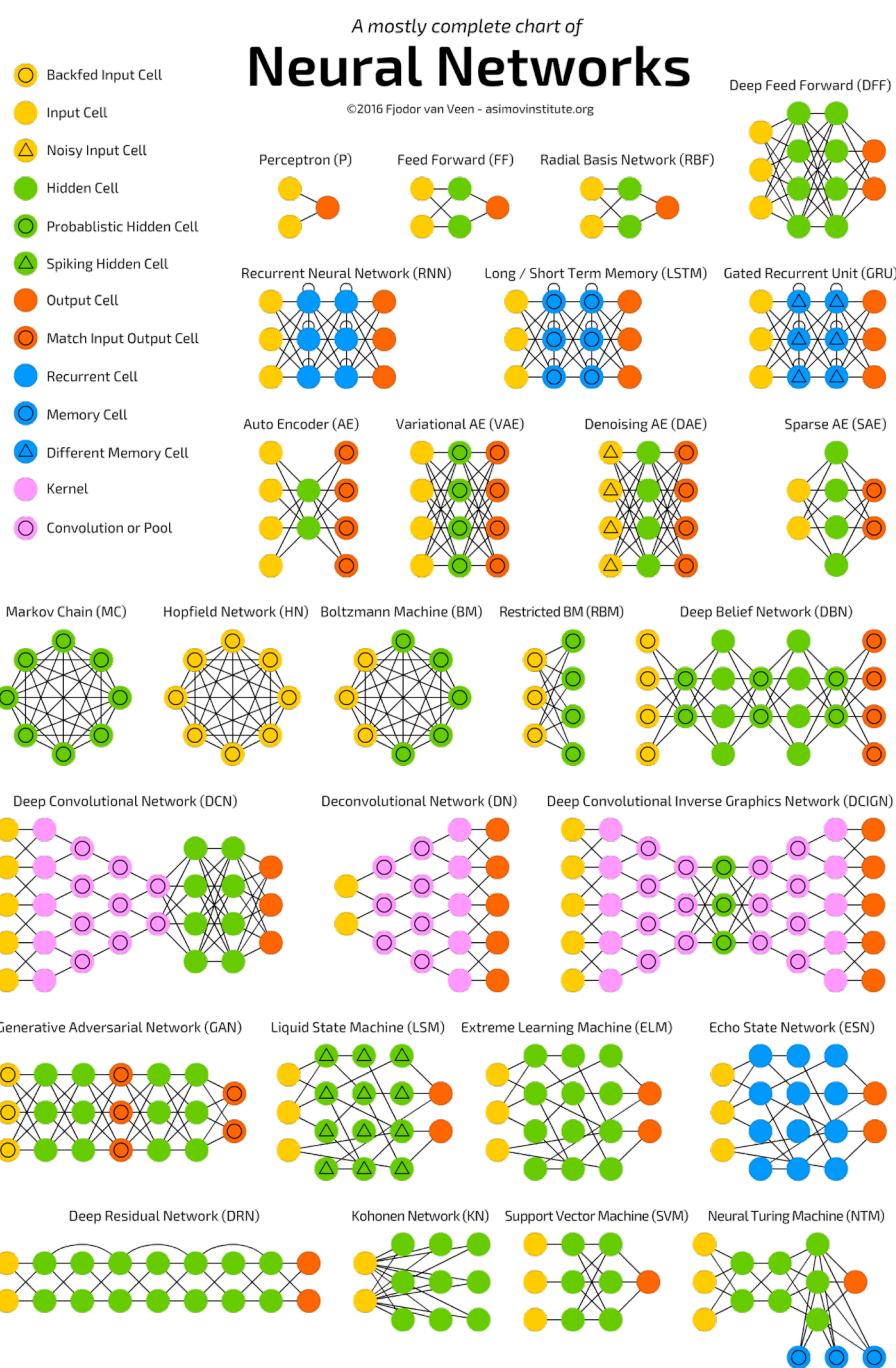
Autoencoders

Convolutional Neural Networks

Recurrent Neural Networks (including LSTMs)

Generative Adversarial Networks (GANs)

Azimov Institute: <http://www.asimovinstitute.org/neural-network-zoo/>



Autoencoders

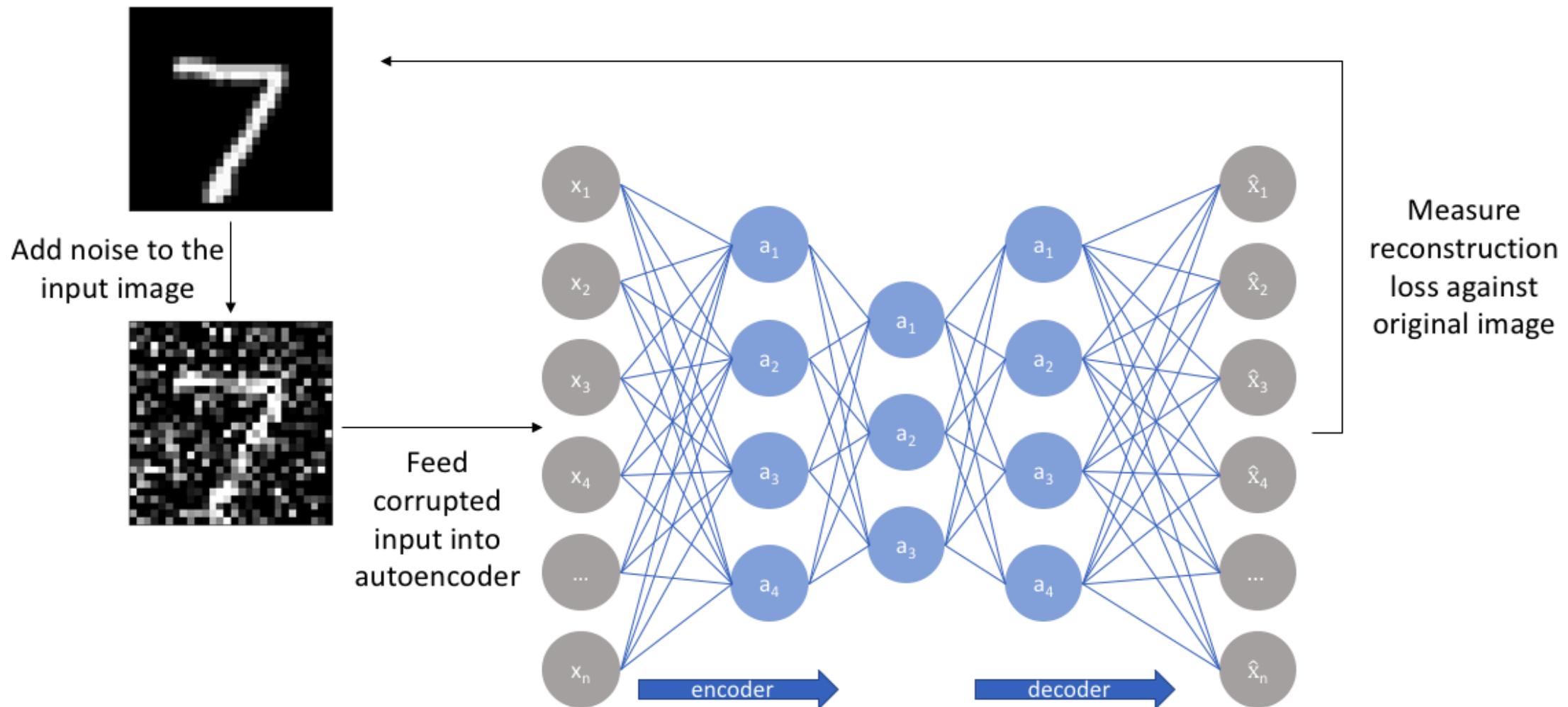
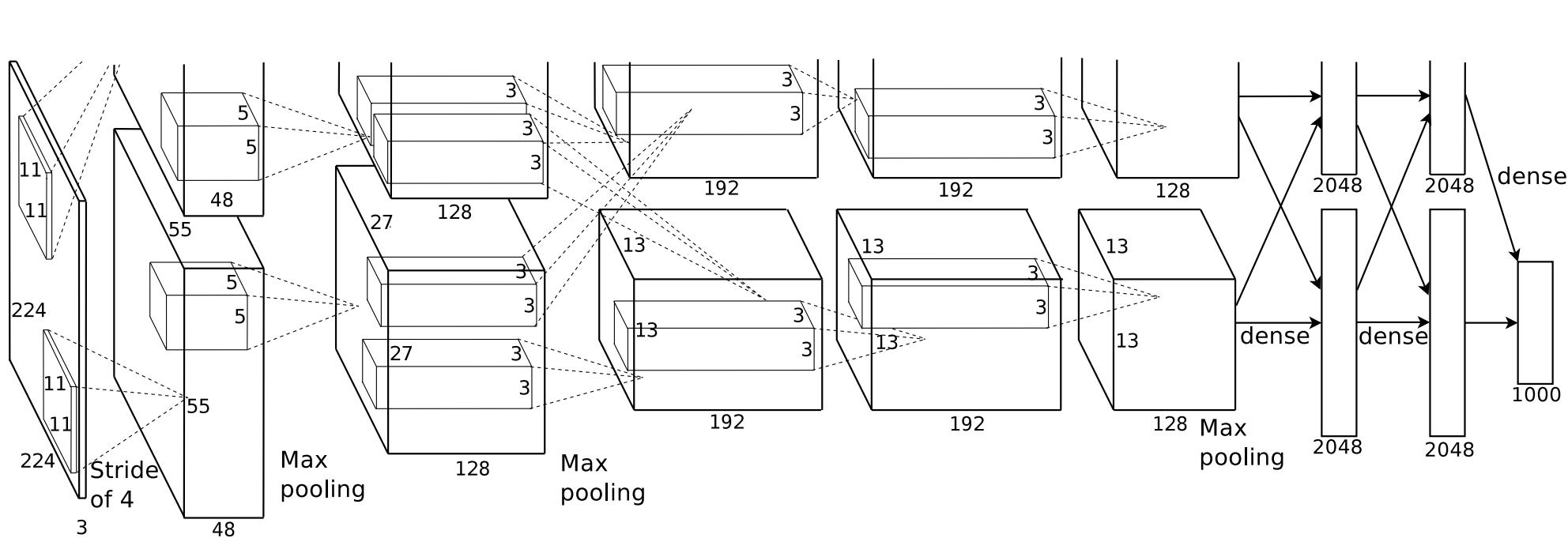


Image from: <https://www.jeremyjordan.me/autoencoders/>

Convolutional Neural Networks

AlexNet



Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "Imagenet classification with deep convolutional neural networks." Advances in neural information processing systems. 2012.

Key

Input or output layer
Convolutional Layer
Fully Connected Layer
max pooling layer

Convolutional Neural Networks

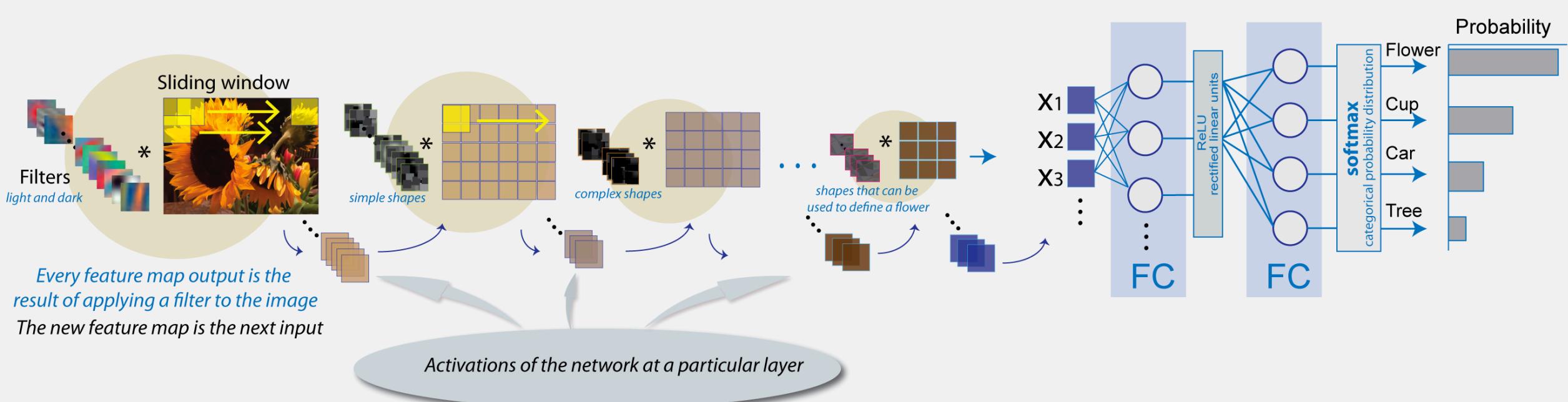
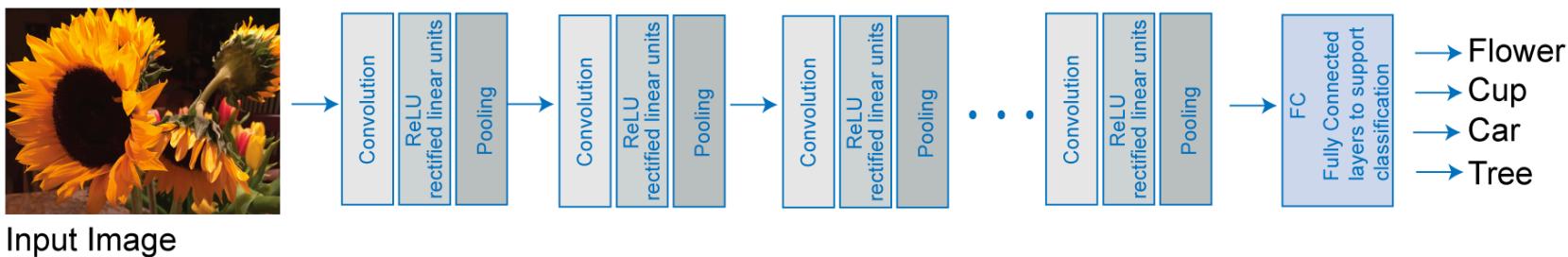


Image from the Mathworks

Data: x

1	2	5	1	4	2
0	2	3	2	0	0
4	5	5	9	8	1
6	3	4	2	3	1
0	1	9	8	7	2
2	3	5	5	5	6

Weights: w

1	1	1
0	0	0
-1	-1	-1



Output: $x * w$

=

2D Convolution

Data: x

1	2	5	1	4	2
0	2	3	2	0	0
4	5	5	9	8	1
6	3	4	2	3	1
0	1	9	8	7	2
2	3	5	5	5	6

Weights: w

1	1	1
0	0	0
-1	-1	-1

Output: $x * w$

*

=

Computing one output value:

$$1 \cdot 1 + 1 \cdot 2 + 1 \cdot 5 + \\ 0 \cdot 0 + 0 \cdot 2 + 0 \cdot 3 + \\ (-1) \cdot 4 + (-1) \cdot 5 + (-1) \cdot 5$$

2D Convolution

Data: x

1	2	5	1	4	2
0	2	3	2	0	0
4	5	5	9	8	1
6	3	4	2	3	1
0	1	9	8	7	2
2	3	5	5	5	6

Weights: w

1	1	1
0	0	0
-1	-1	-1

*

=

Output: $x * w$

-6			

Computing one output value:

$$1 \cdot 1 + 1 \cdot 2 + 1 \cdot 5 + \\ 0 \cdot 0 + 0 \cdot 2 + 0 \cdot 3 + \\ (-1) \cdot 4 + (-1) \cdot 5 + (-1) \cdot 5 = -6$$

2D Convolution

Data: X

1	2	5	1	4	2
0	2	3	2	0	0
4	5	5	9	8	1
6	3	4	2	3	1
0	1	9	8	7	2
2	3	5	5	5	6

Weights: w

1	1	1
0	0	0
-1	-1	-1

*

=

Output: $X * w$

-6	-11		

Computing one output value:

$$1 \cdot 2 + 1 \cdot 5 + 1 \cdot 1 + \\ 0 \cdot 2 + 0 \cdot 3 + 0 \cdot 2 + \\ (-1) \cdot 5 + (-1) \cdot 5 + (-1) \cdot 9 = -11$$

2D Convolution

Data: X

1	2	5	1	4	2
0	2	3	2	0	0
4	5	5	9	8	1
6	3	4	2	3	1
0	1	9	8	7	2
2	3	5	5	5	6

Weights: w

1	1	1
0	0	0
-1	-1	-1

*

=

Output: $X * w$

-6	-11	-12	

Computing one output value:

$$\begin{aligned} & 1 \cdot 5 + 1 \cdot 1 + 1 \cdot 4 + \\ & 0 \cdot 3 + 0 \cdot 2 + 0 \cdot 0 + \\ & (-1) \cdot 5 + (-1) \cdot 9 + (-1) \cdot 8 = -12 \end{aligned}$$

2D Convolution

Data: X

1	2	5	1	4	2
0	2	3	2	0	0
4	5	5	9	8	1
6	3	4	2	3	1
0	1	9	8	7	2
2	3	5	5	5	6

Weights: w

1	1	1
0	0	0
-1	-1	-1

*

=

Output: $X * w$

-6	-11	-12	-11

Computing one output value:

$$1 \cdot 1 + 1 \cdot 4 + 1 \cdot 2 + \\ 0 \cdot 2 + 0 \cdot 0 + 0 \cdot 0 + \\ (-1) \cdot 9 + (-1) \cdot 8 + (-1) \cdot 1 = -11$$

2D Convolution

Data: X

1	2	5	1	4	2
0	2	3	2	0	0
4	5	5	9	8	1
6	3	4	2	3	1
0	1	9	8	7	2
2	3	5	5	5	6

Weights: w

1	1	1
0	0	0
-1	-1	-1

*

=

-6	-11	-12	-11
-7			

Computing one output value:

$$1 \cdot 0 + 1 \cdot 2 + 1 \cdot 3 + \\ 0 \cdot 4 + 0 \cdot 5 + 0 \cdot 5 +$$

$$(-1) \cdot 6 + (-1) \cdot 3 + (-1) \cdot 4 = -7$$

2D Convolution

Data: X

1	2	5	1	4	2
0	2	3	2	0	0
4	5	5	9	8	1
6	3	4	2	3	1
0	1	9	8	7	2
2	3	5	5	5	6

6×6

Weights: w

1	1	1
0	0	0
-1	-1	-1

*

3×3

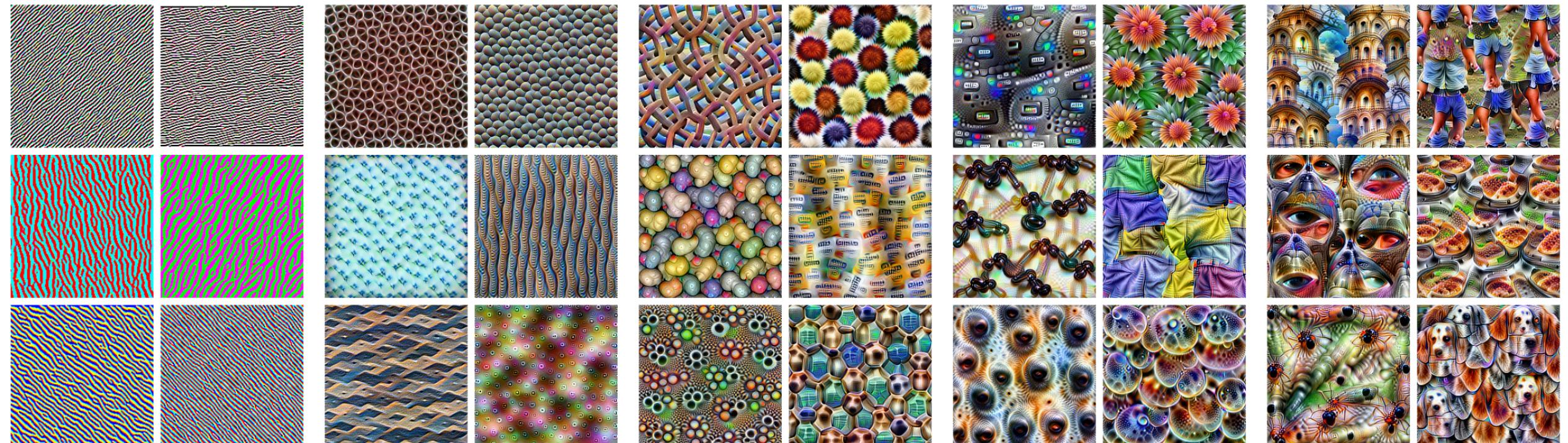
Output: $X * w$

-6	-11	-12	-11
-7	-2	-2	-4
4	1	-2	1
3	-4	-6	-10

4×4

2D Convolution

Features



Edges (layer conv2d0)

Textures (layer mixed3a)

Patterns (layer mixed4a)

Parts (layers mixed4b & mixed4c)

Objects (layers mixed4d & mixed4e)

Olah et al, 2017: <https://distill.pub/2017/feature-visualization/>

Features

Dataset Examples show us what neurons respond to in practice



Optimization isolates the causes of behavior from mere correlations. A neuron may not be detecting what you initially thought.



Baseball—or stripes?
mixed4a, Unit 6

Animal faces—or snouts?
mixed4a, Unit 240

Clouds—or fluffiness?
mixed4a, Unit 453

Buildings—or sky?
mixed4a, Unit 492

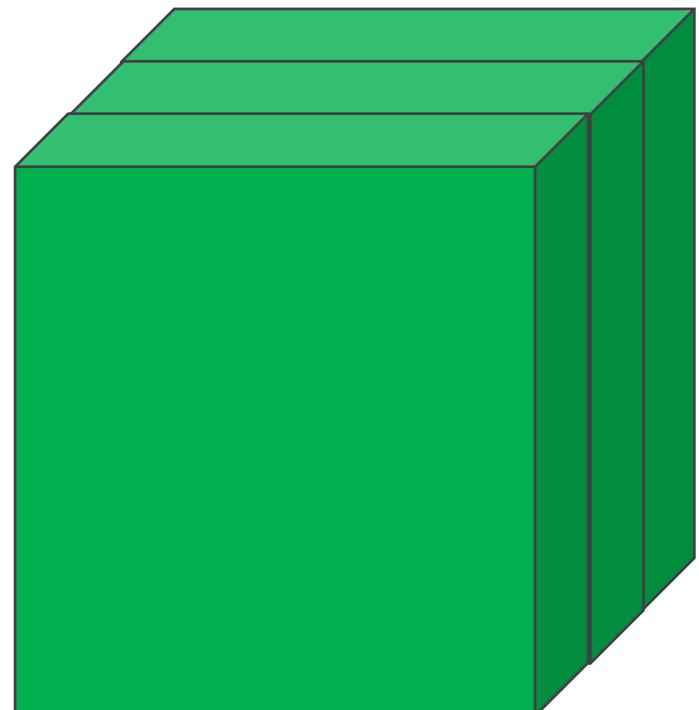
Resources on Visualization of Features

Feature visualization: <https://distill.pub/2017/feature-visualization/>

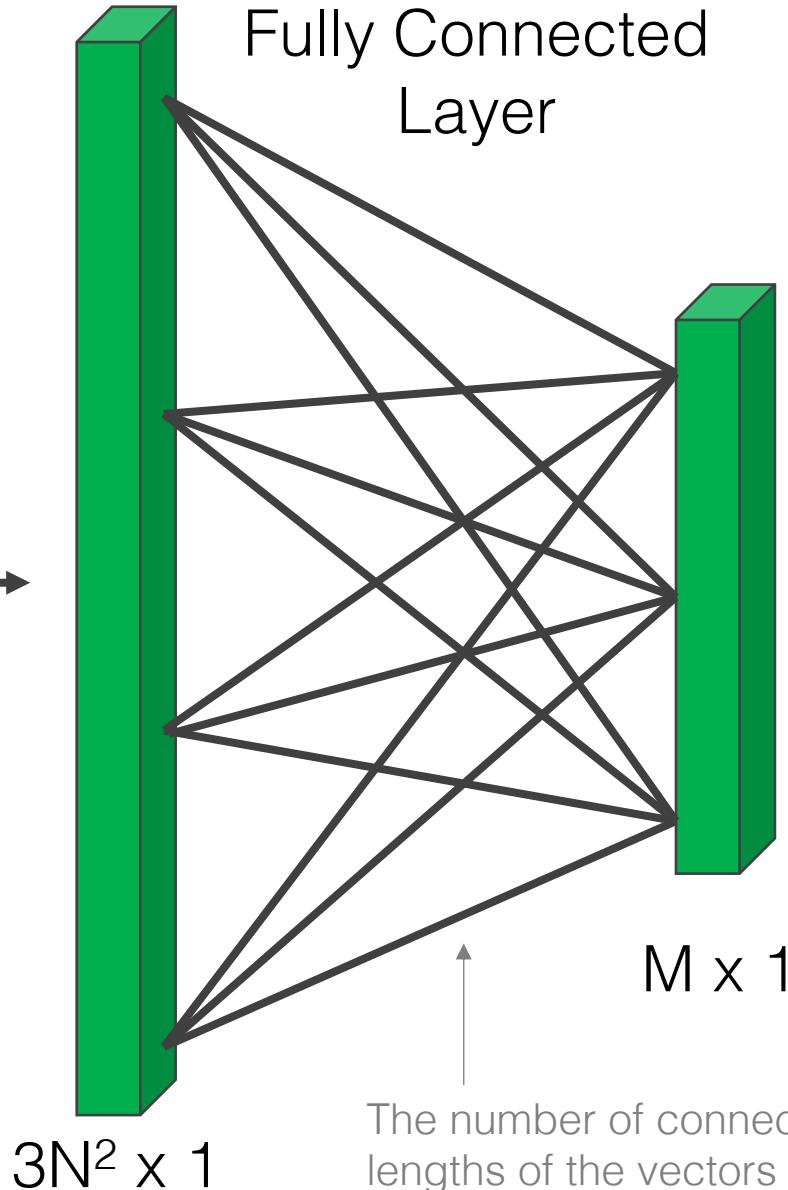
Building blocks of interpretability: <https://distill.pub/2018/building-blocks/>

Activation Atlases: <https://distill.pub/2019/activation-atlas/>

Fully Connected Layer

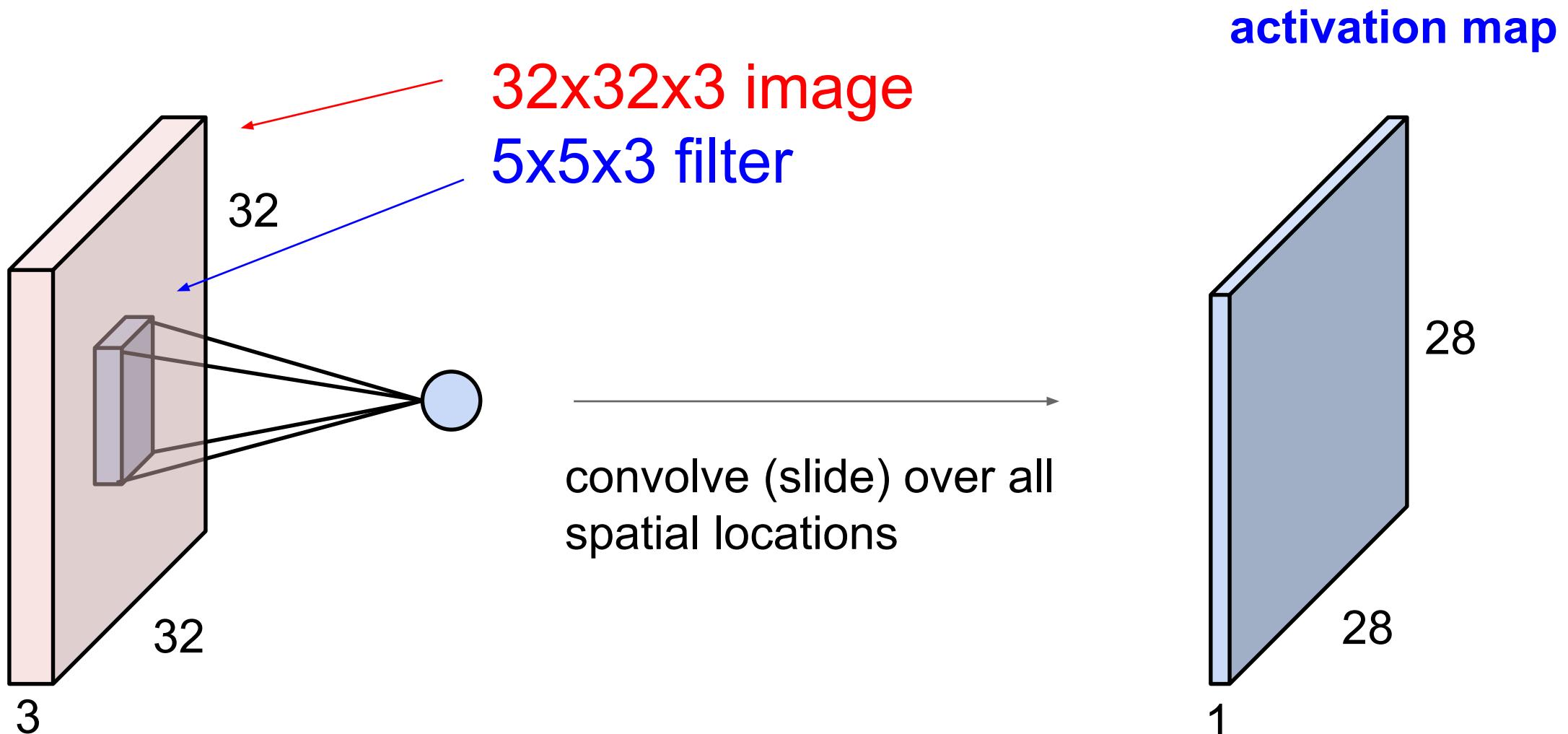


Flatten
(reshape)



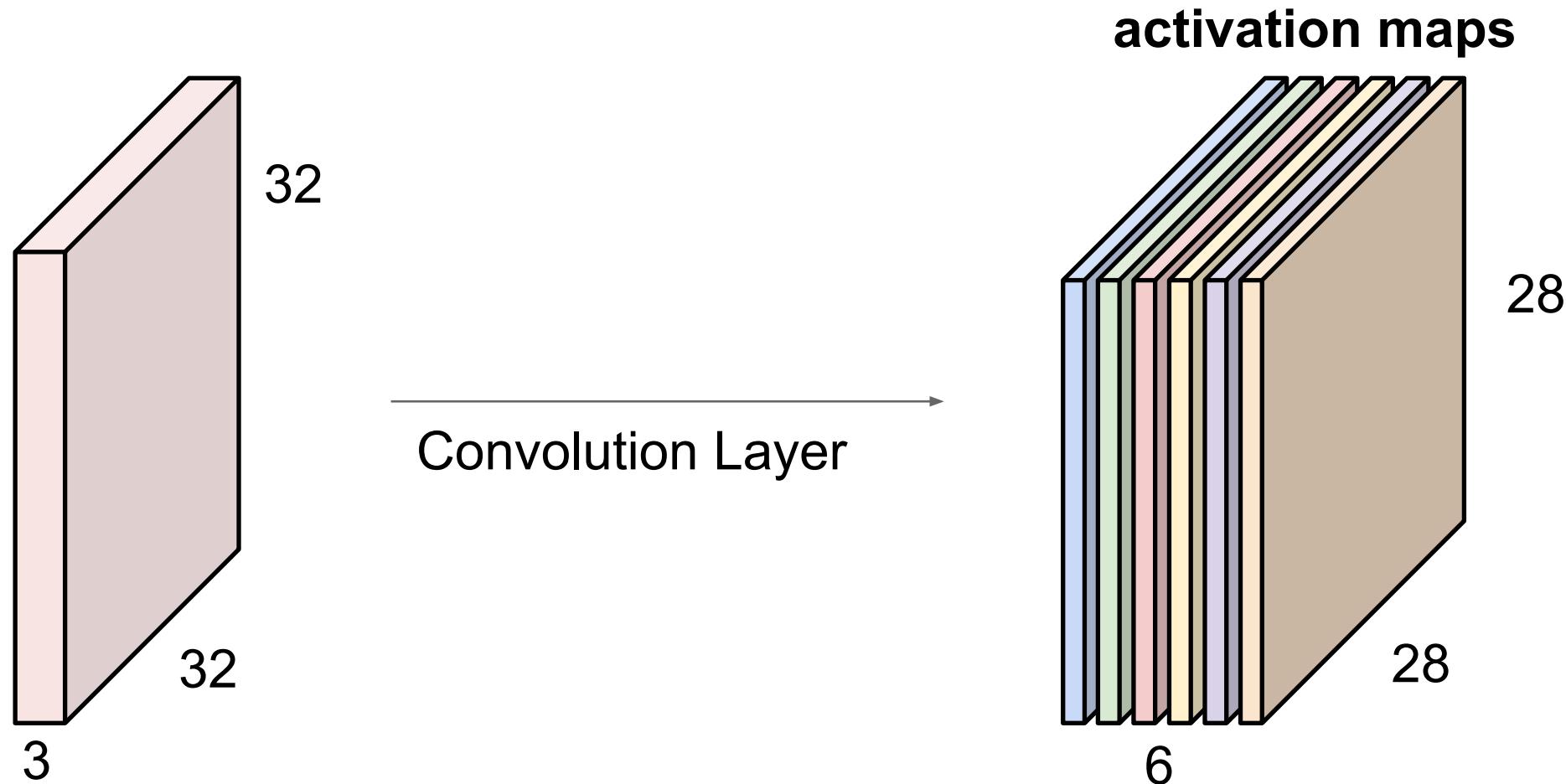
$N \times N \times 3$

Convolution Layer



From Fei-Fei Li, Justin Johnson, and Serena Young. CS231n, 2018

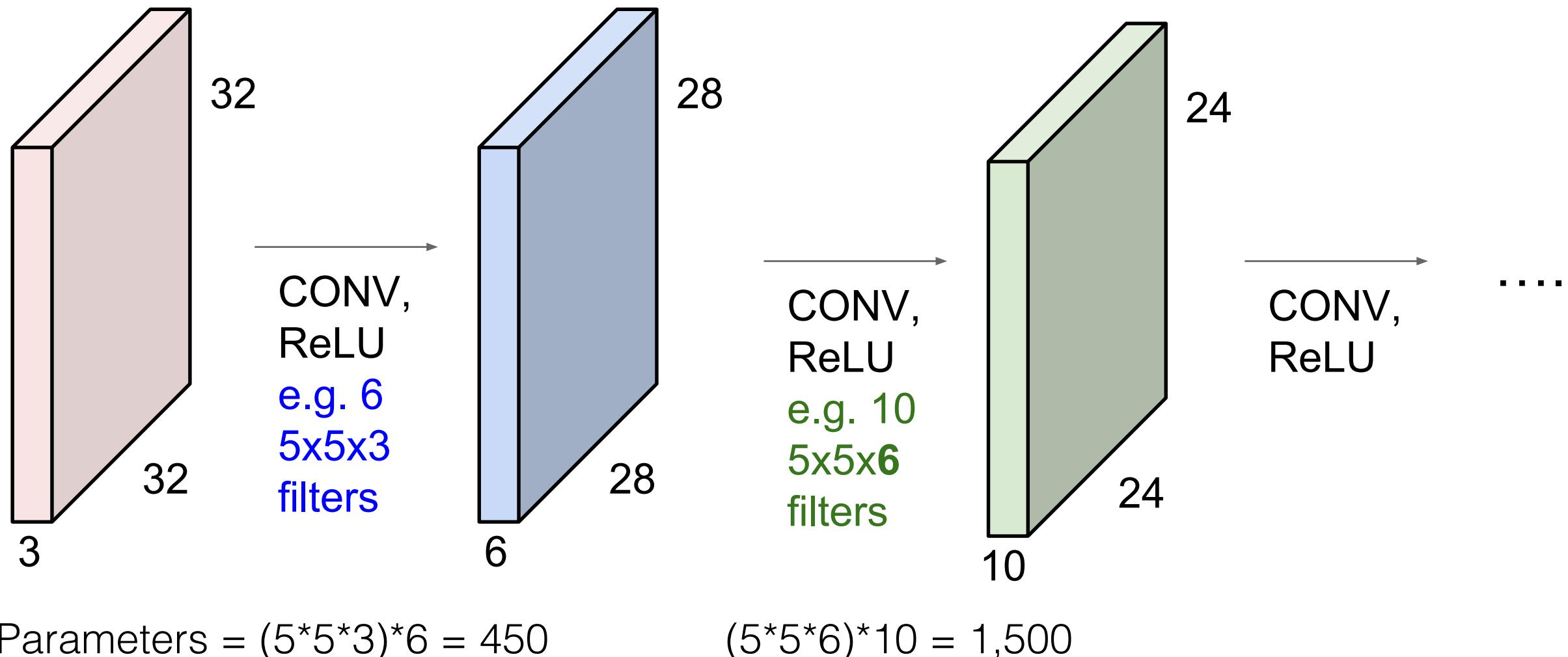
For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:



We stack these up to get a “new image” of size $28 \times 28 \times 6$!

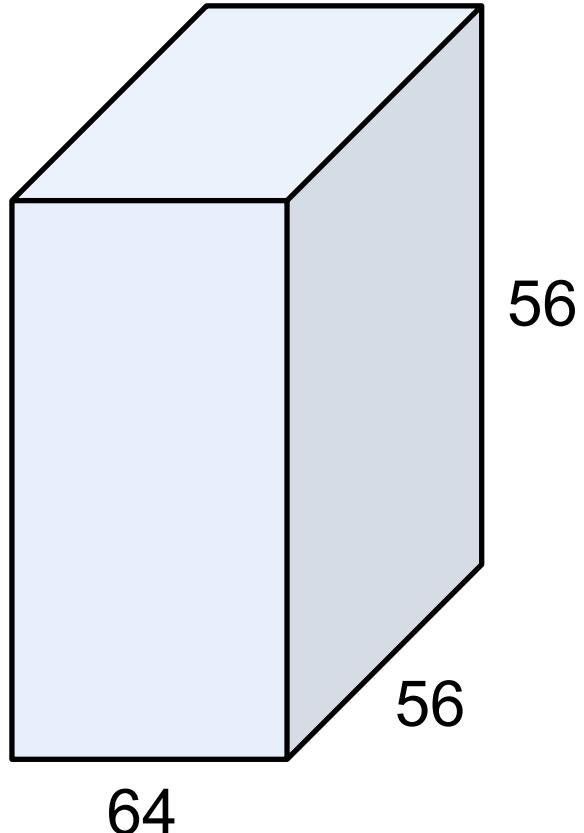
From Fei-Fei Li, Justin Johnson, and Serena Young. CS231n, 2018

Preview: ConvNet is a sequence of Convolution Layers, interspersed with activation functions



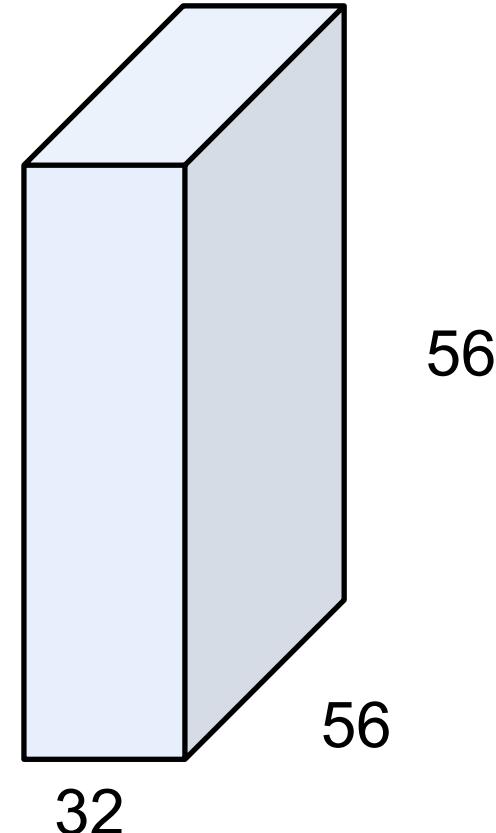
From Fei-Fei Li, Justin Johnson, and Serena Young. CS231n, 2018

1×1 Convolution Explained



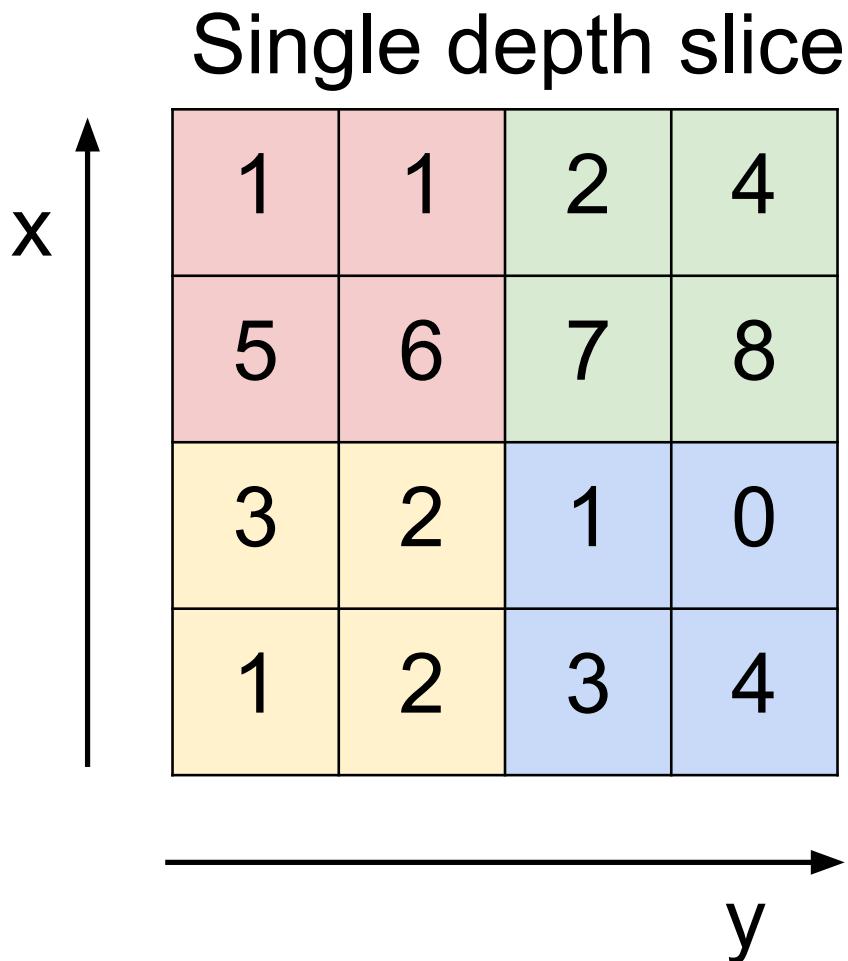
1×1 CONV
with 32 filters

(each filter has size
 $1 \times 1 \times 64$, and performs a
64-dimensional dot
product)



From Fei-Fei Li, Justin Johnson, and Serena Young. CS231n, 2018

Max Pooling



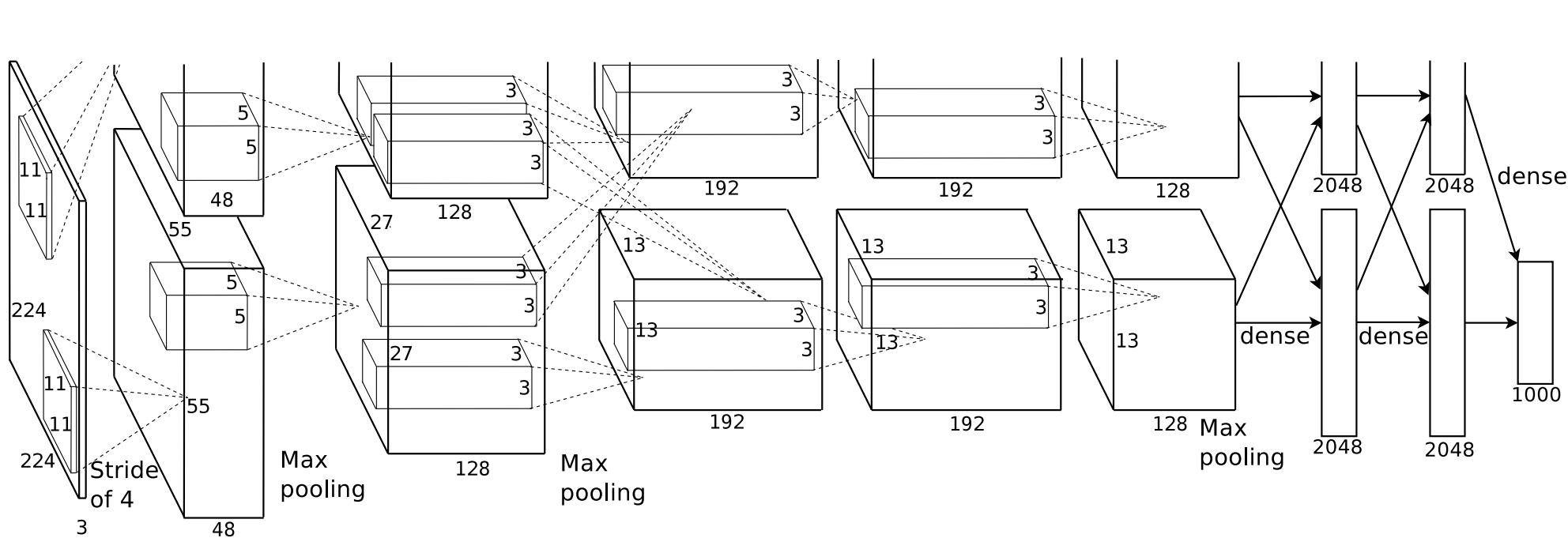
max pool with 2x2 filters
and stride 2



6	8
3	4

From Fei-Fei Li, Justin Johnson, and Serena Young. CS231n, 2018

AlexNet



Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "Imagenet classification with deep convolutional neural networks." Advances in neural information processing systems. 2012.

Key

Input or output layer
Convolutional Layer
Fully Connected Layer
max pooling layer

AlexNet
(2012)

Input
11x11 conv, 96
5x5 conv, 256
max pool
3x3 conv, 384
max pool
3x3 conv, 384
3x3 conv, 256
max pool
FC 4096
FC 4096
FC 1000
softmax

Note: an activation function is applied to the output of each layer

VGG16
(2014)

Input
3x3 conv, 64
3x3 conv, 64
max pool
3x3 conv, 128
3x3 conv, 128
max pool
3x3 conv, 256
3x3 conv, 256
3x3 conv, 256
max pool
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
max pool
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
max pool
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
max pool
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
max pool
FC 4096
FC 4096
FC 1000
softmax

Fewer layers,
larger filters

VGG19
(2014)

Input
3x3 conv, 64
3x3 conv, 64
max pool
3x3 conv, 128
3x3 conv, 128
max pool
3x3 conv, 256
max pool
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
max pool
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
max pool
3x3 conv, 512
3x3 conv, 512
3x3 conv, 512
max pool
FC 4096
FC 4096
FC 1000
softmax

Key

Input or output layer
Convolutional Layer
Fully Connected Layer
max pooling layer

CNN Architectures

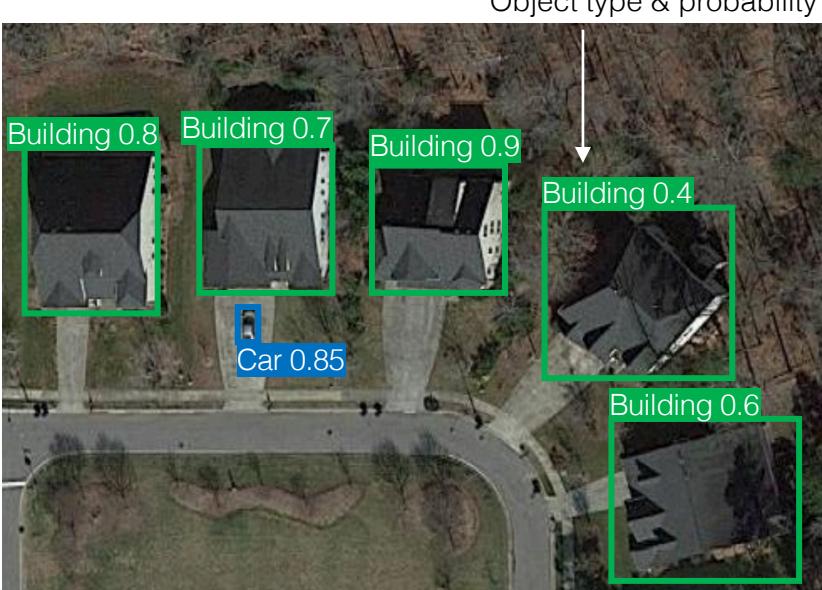
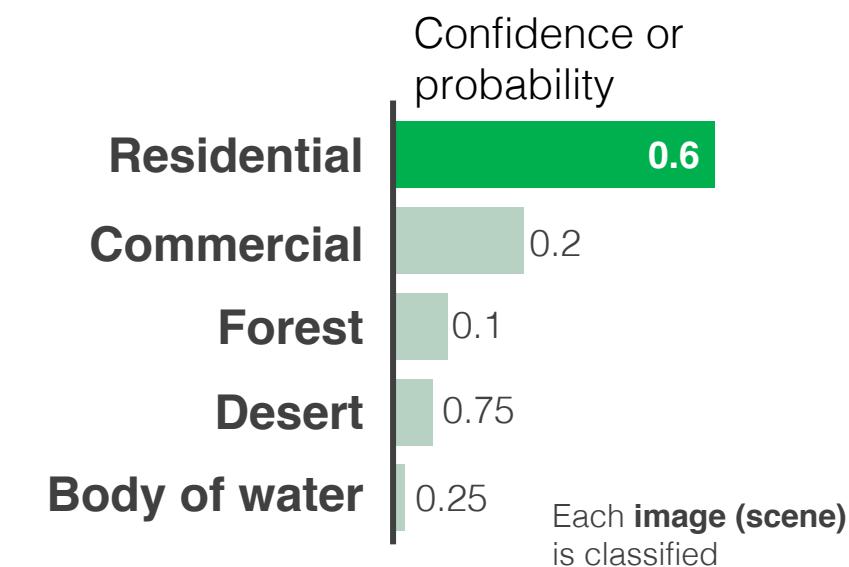
Adapted from Fei-Fei Li, Justin Johnson, and Serena Young. CS231n, 2018

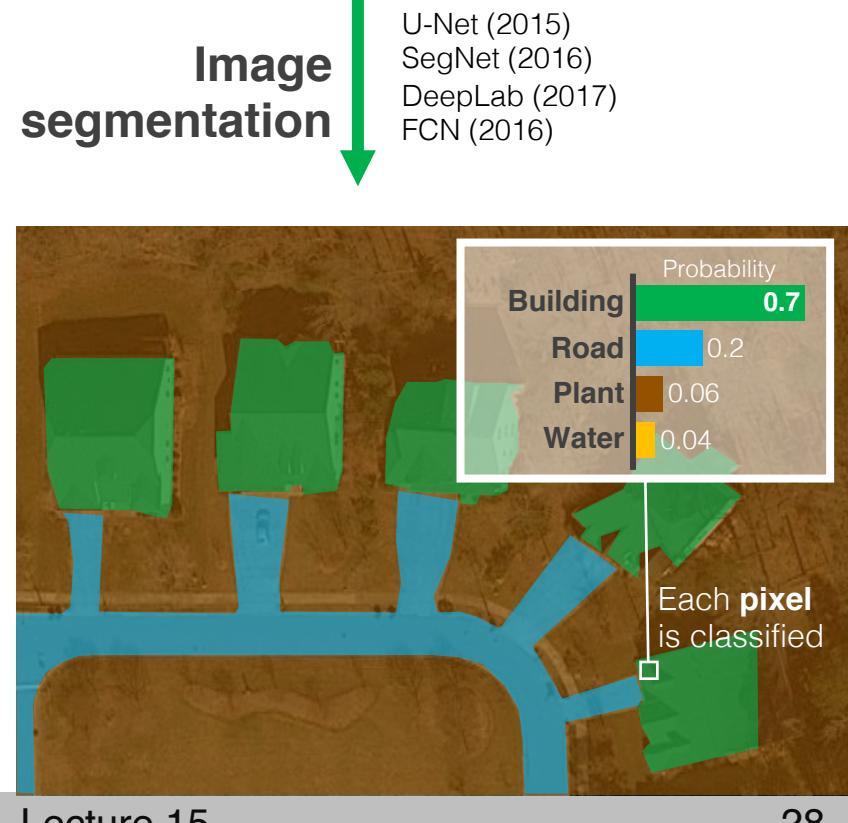
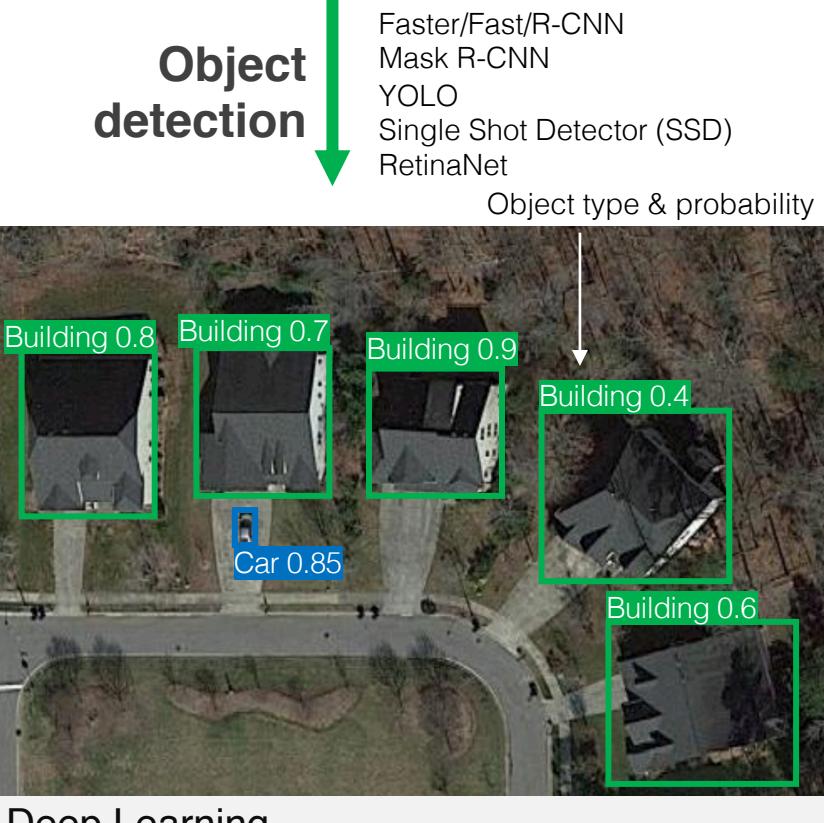
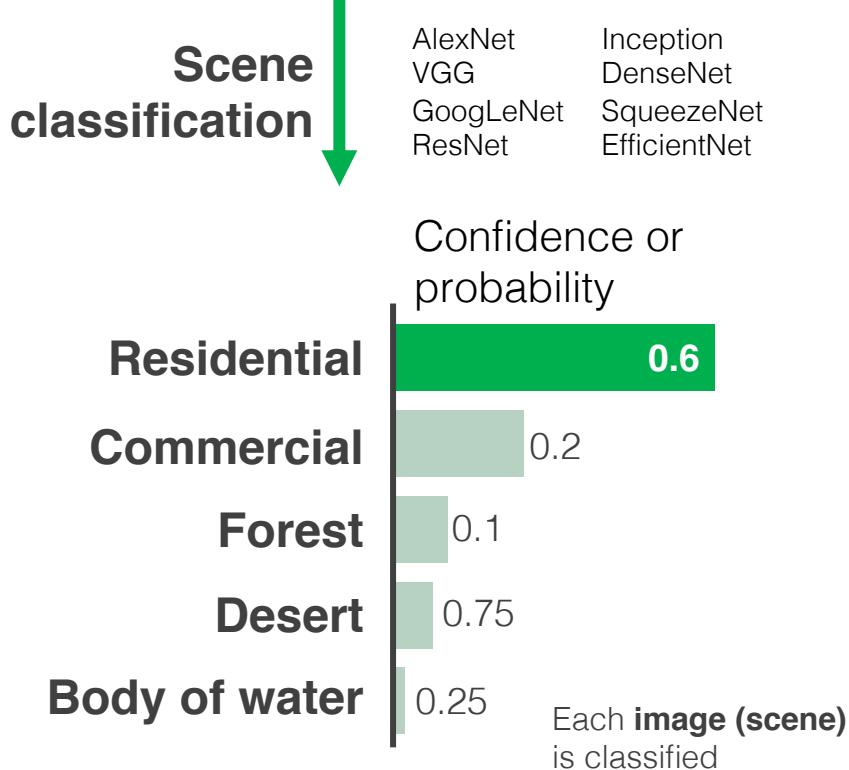


Scene classification

Object detection

Image segmentation

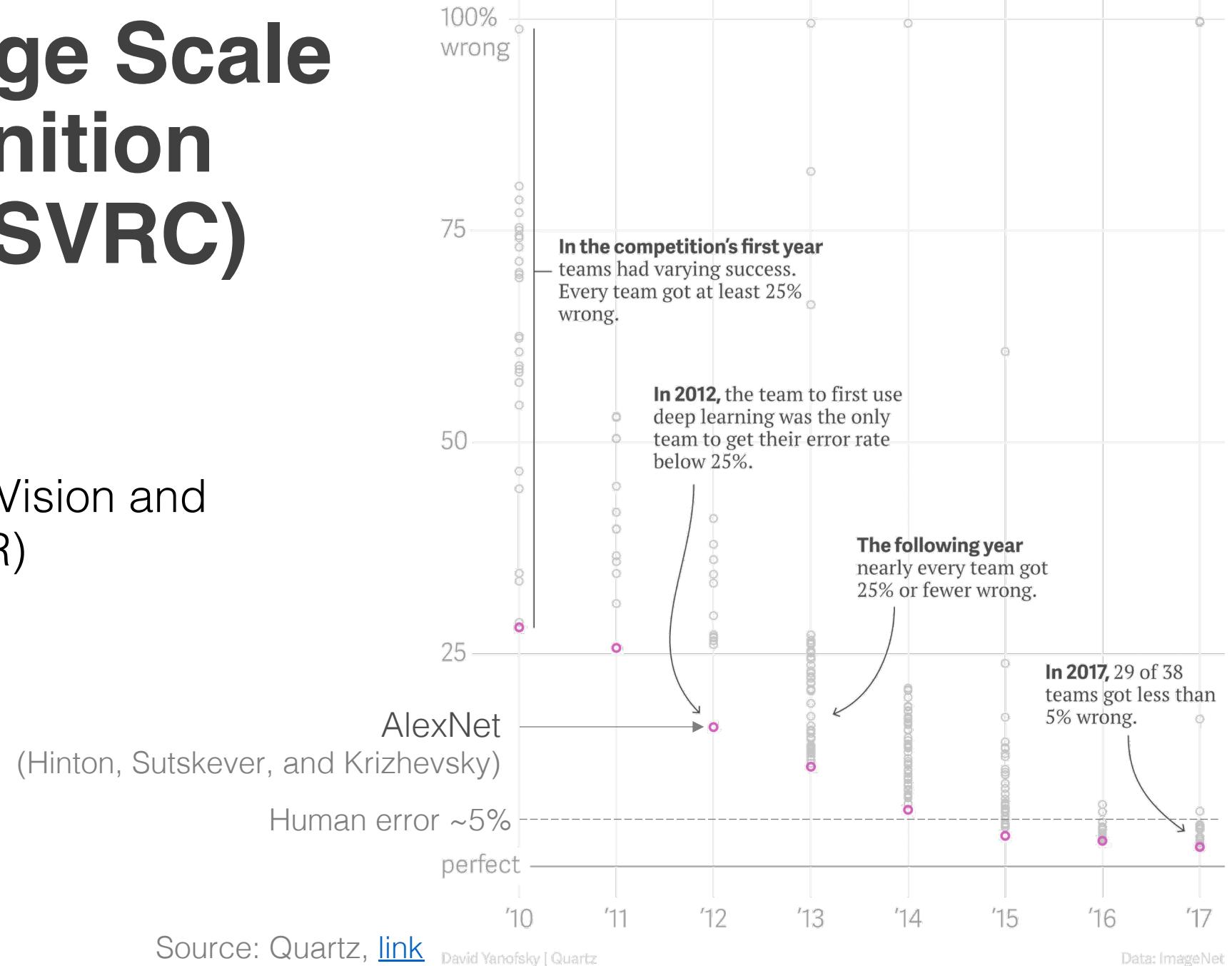




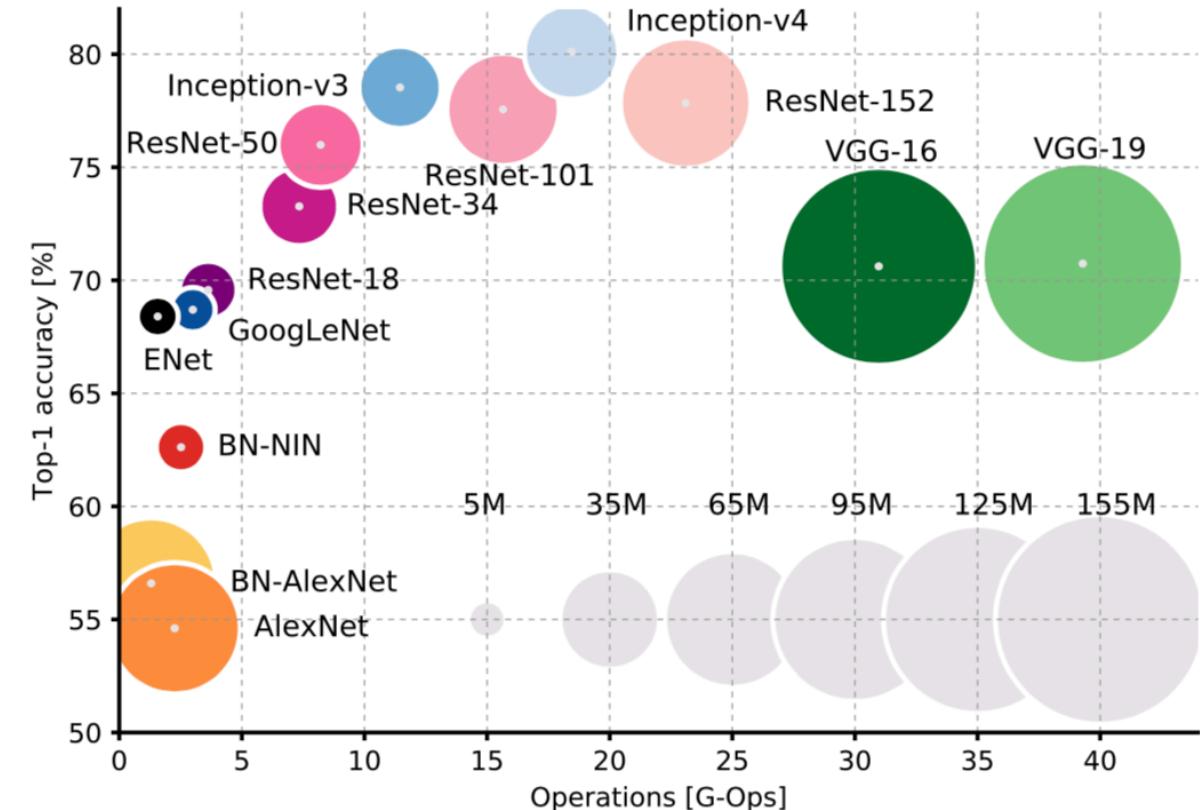
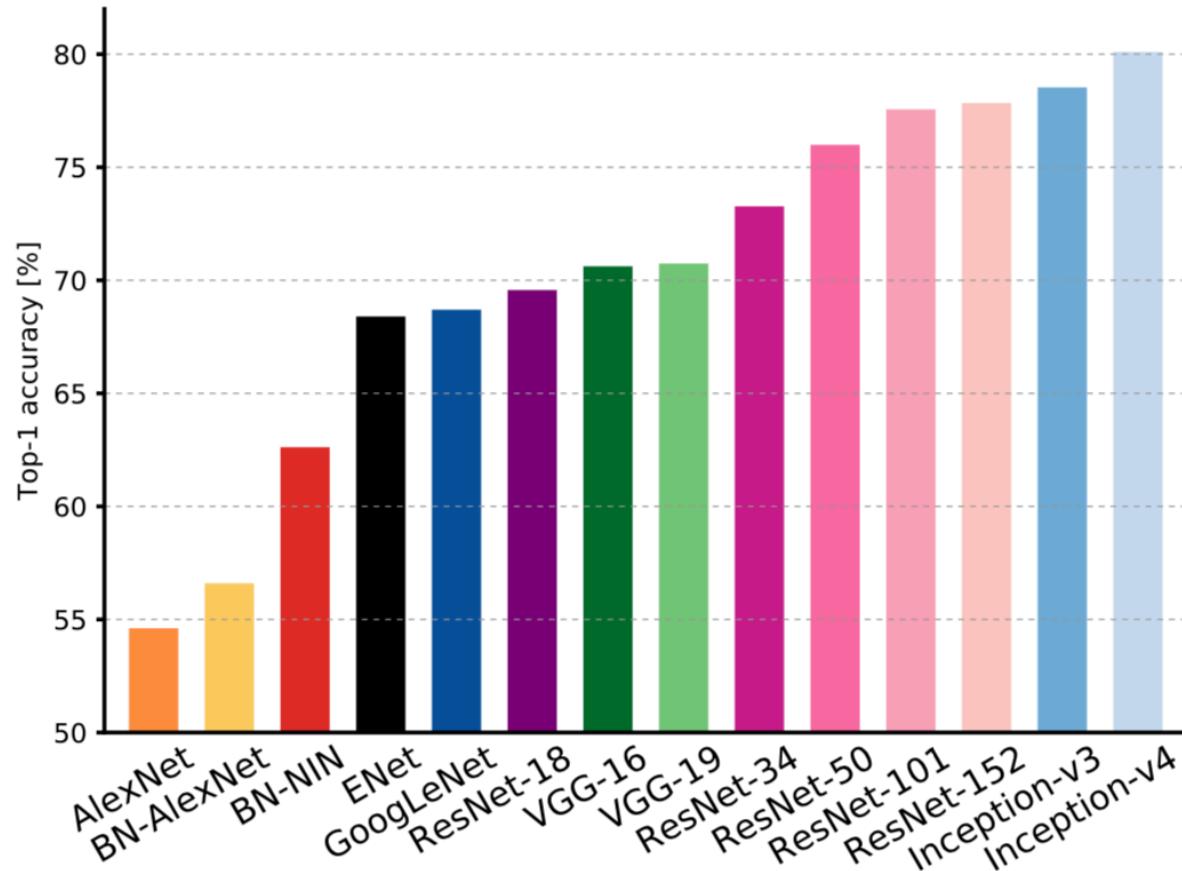
ImageNet Large Scale Visual Recognition Challenge (ILSVRC)

Fei-Fei Li et al. 2010 ([link](#))

Competition at:
Conference on Computer Vision and
Pattern Recognition (CVPR)



Deep Learning Models Compared



Models compared for ImageNet
Many of these models are available through Keras ([link](#))

A. Canziani, E. Culurciello and A. Paszke, "Evaluation of neural network architectures for embedded systems," *2017 IEEE International Symposium on Circuits and Systems (ISCAS)*, Baltimore, MD, 2017, pp. 1-4.

Deep learning frameworks

Tensorflow ([link](#))

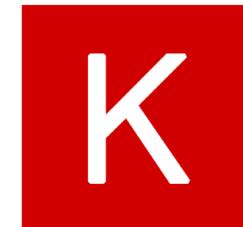
Framework for implementing graphical models, such as neural networks



TensorFlow

Keras ([link](#))

Wrapper for Tensorflow to make coding easier: higher level and excellent API



Keras

PyTorch ([link](#))

Framework for implementing graphical models, such as neural networks



KERAS DEMO

Generative Adversarial Networks

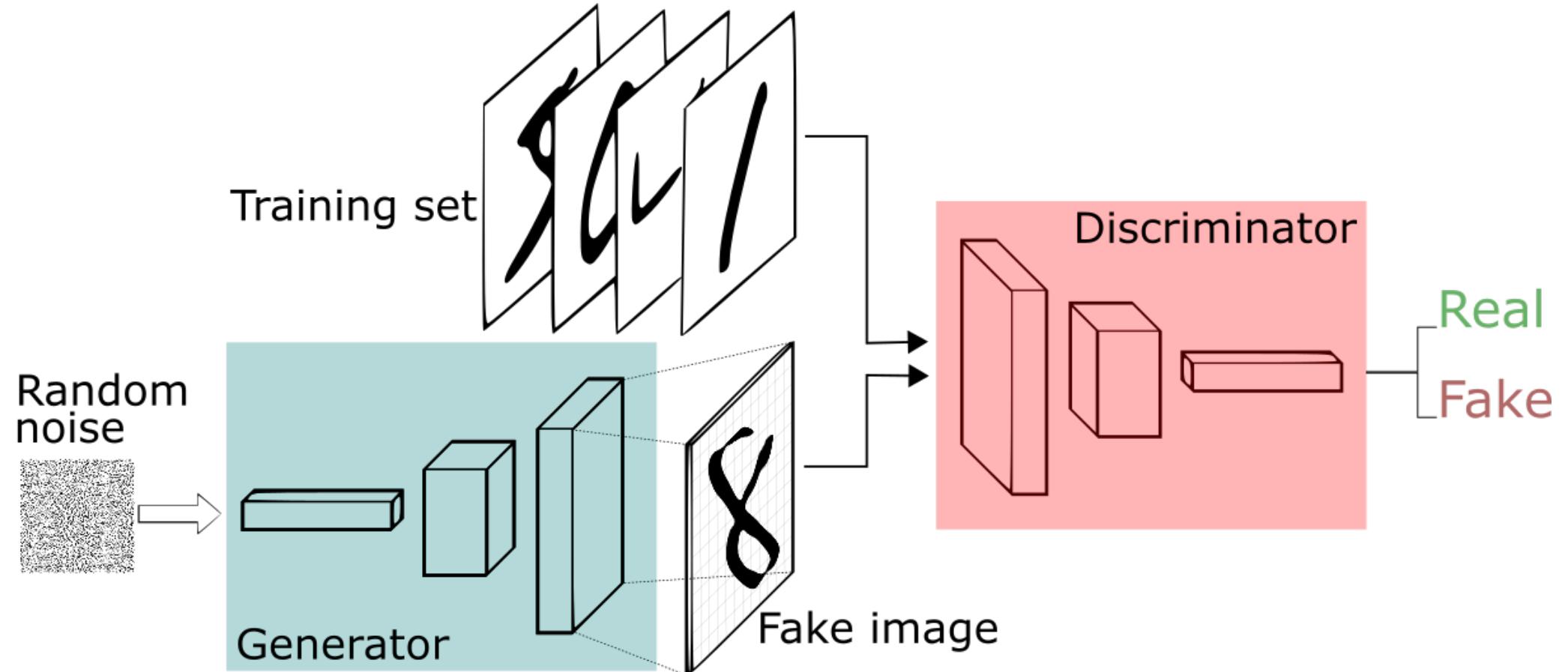


Image from: <https://skymind.ai/wiki/generative-adversarial-network-gan>