Deep Learning

Deep learning

Representation learning with a hierarchy of concepts

Those concepts are represented by layers in a neural network model

Types of Deep Learning Tools

Unsupervised models

- Autoencoders

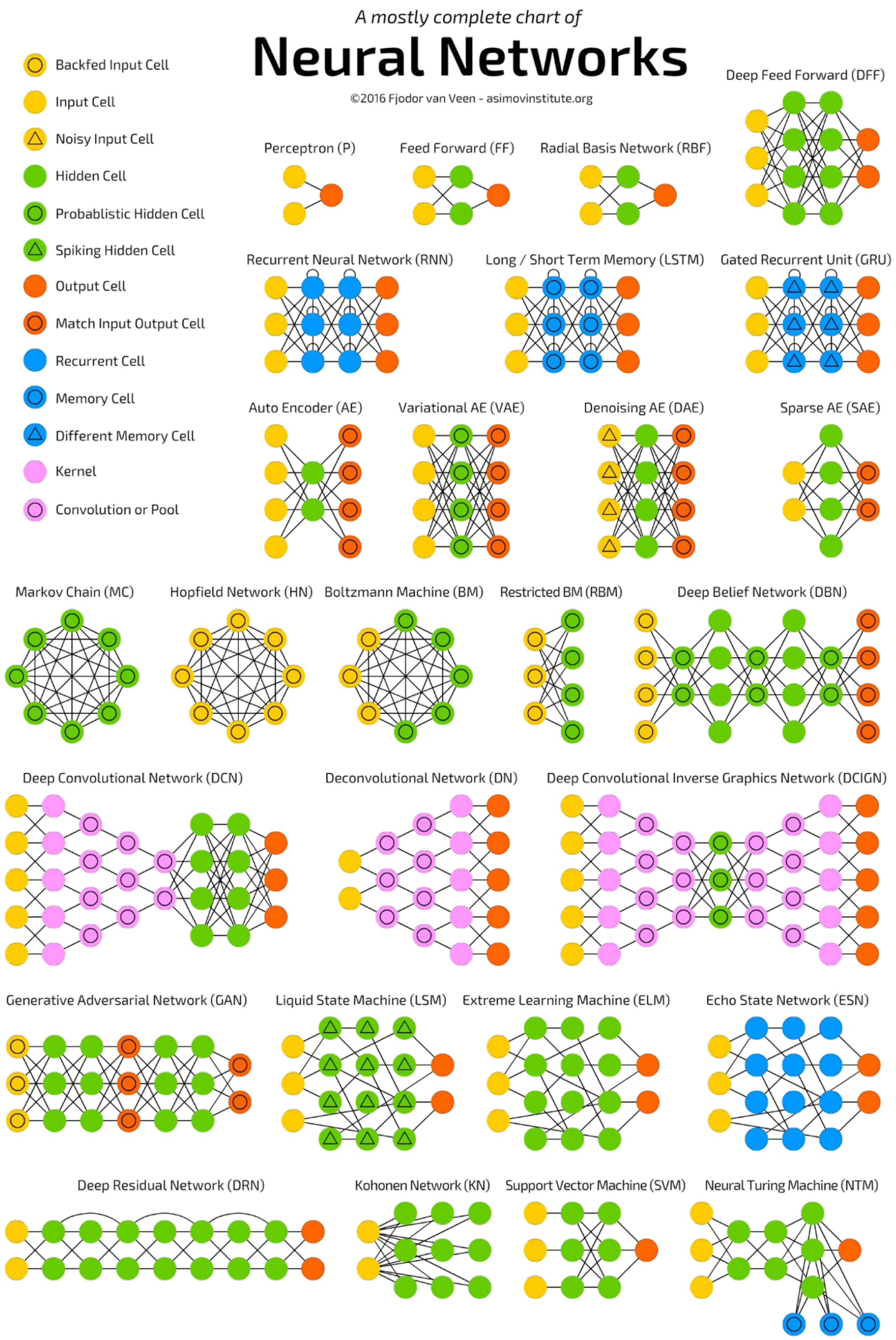
Supervised models

- Image analysis:
    - Convolutional Neural Networks
- Timeseries analysis (often NLP):
    - Recurrent Neural Networks (e.g. LSTMs)
    - Transformer models

Generative models

- Generative Adversarial Networks (GANs)
- Diffusion Models (e.g. DALL-E 2, Stable Diffusion)
- Generative Pre-trained Transformer (GPT)

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



Autoencoders

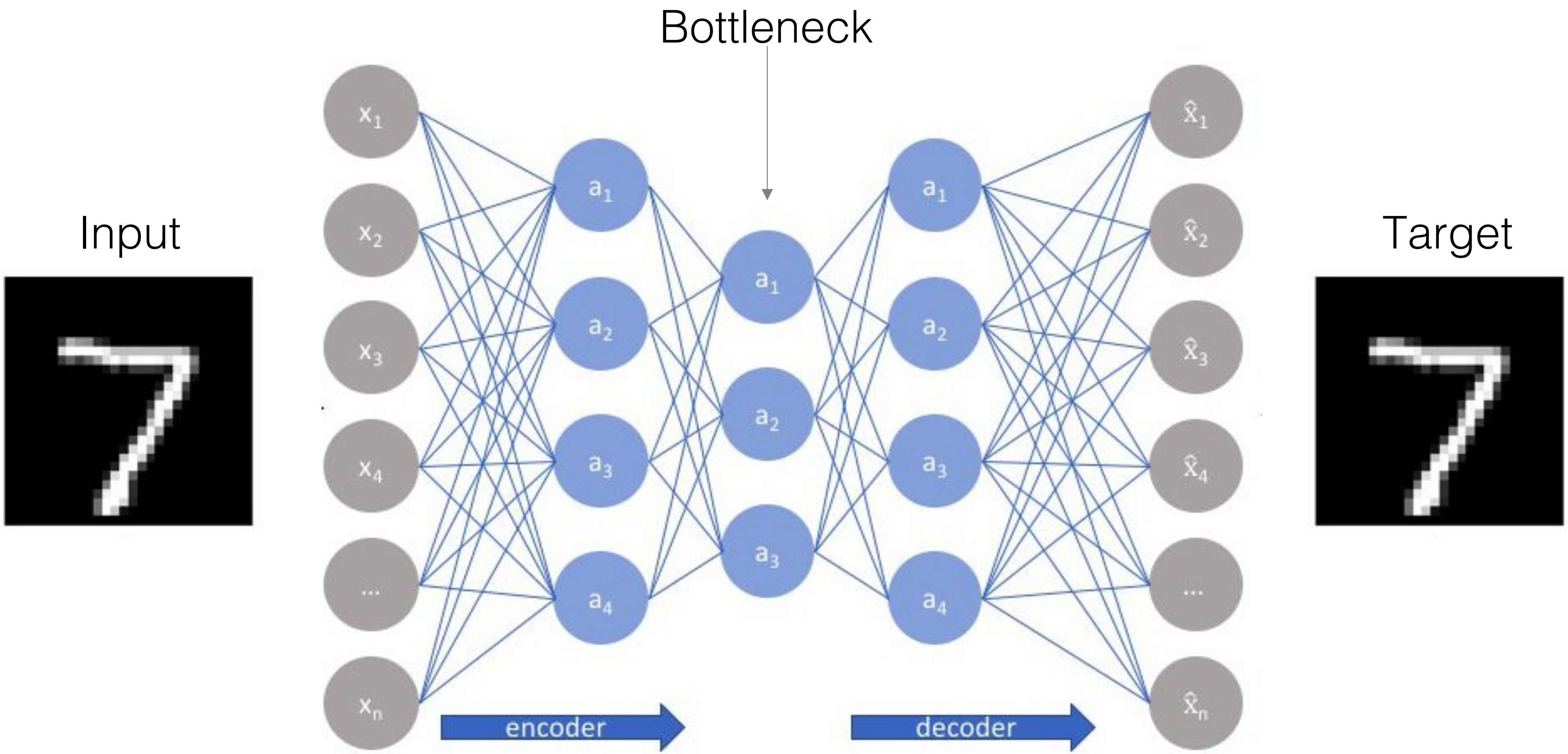
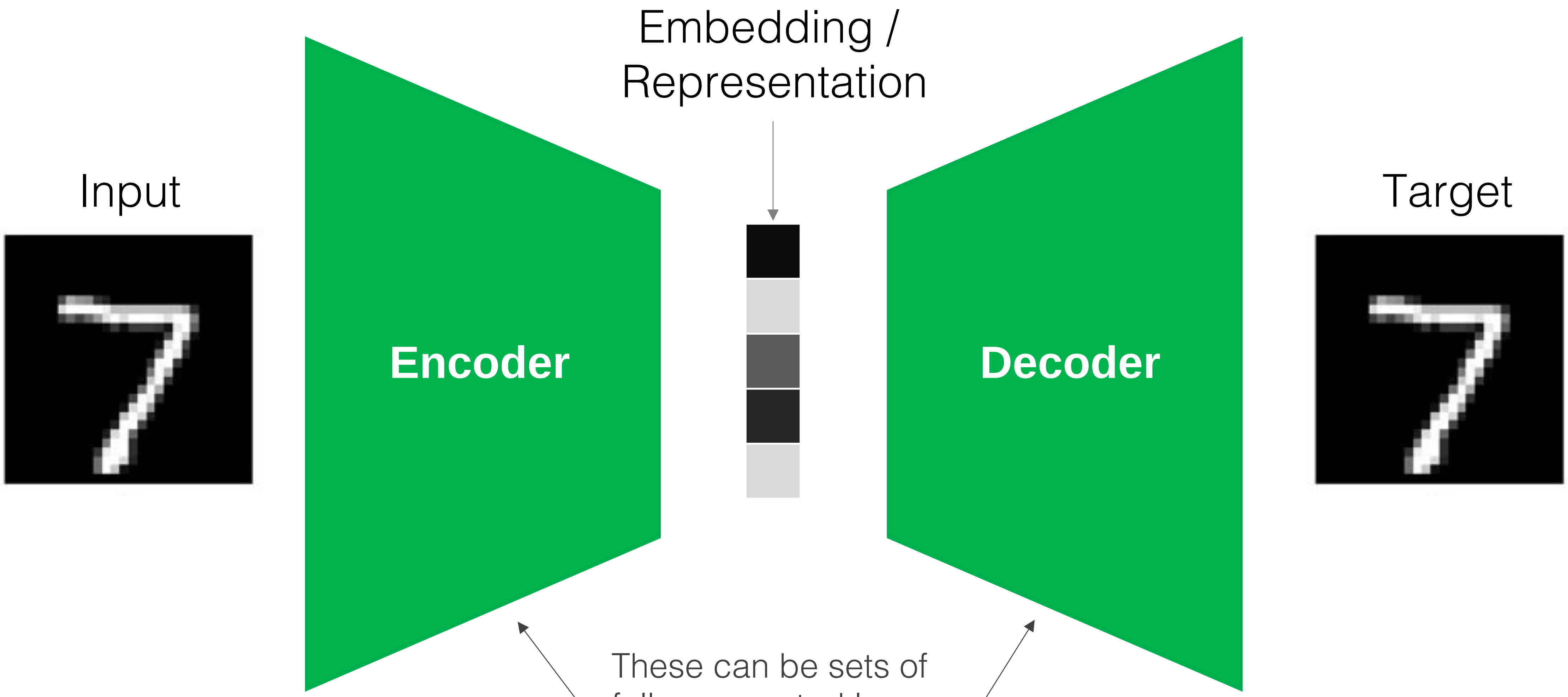


Image from: https://www.jeremyjordan.me/autoencoders/

Autoencoders

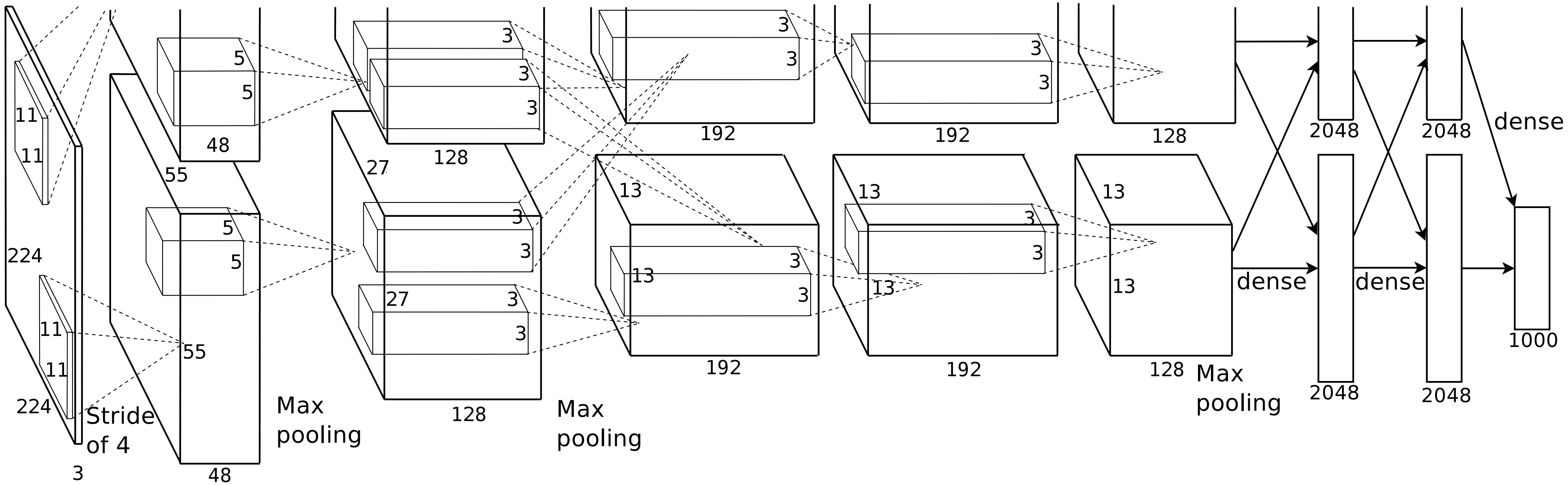
Our goal is often to develop a good **encoder** that represents our features well

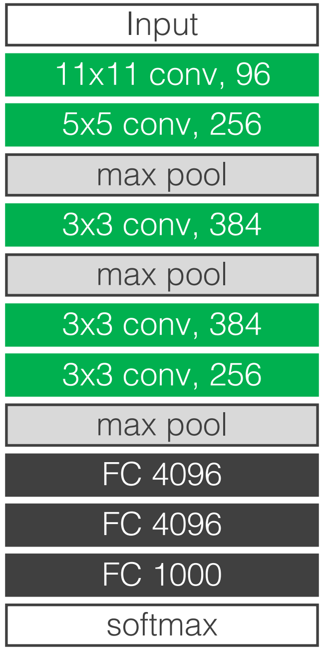


These can be sets of fully-connected layers or convolutional layers, etc.

Convolutional Neural Networks

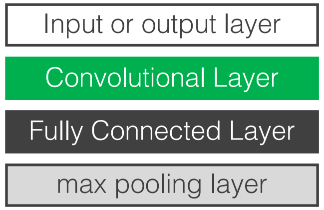
AlexNet





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

Key



Convolutional Neural Networks

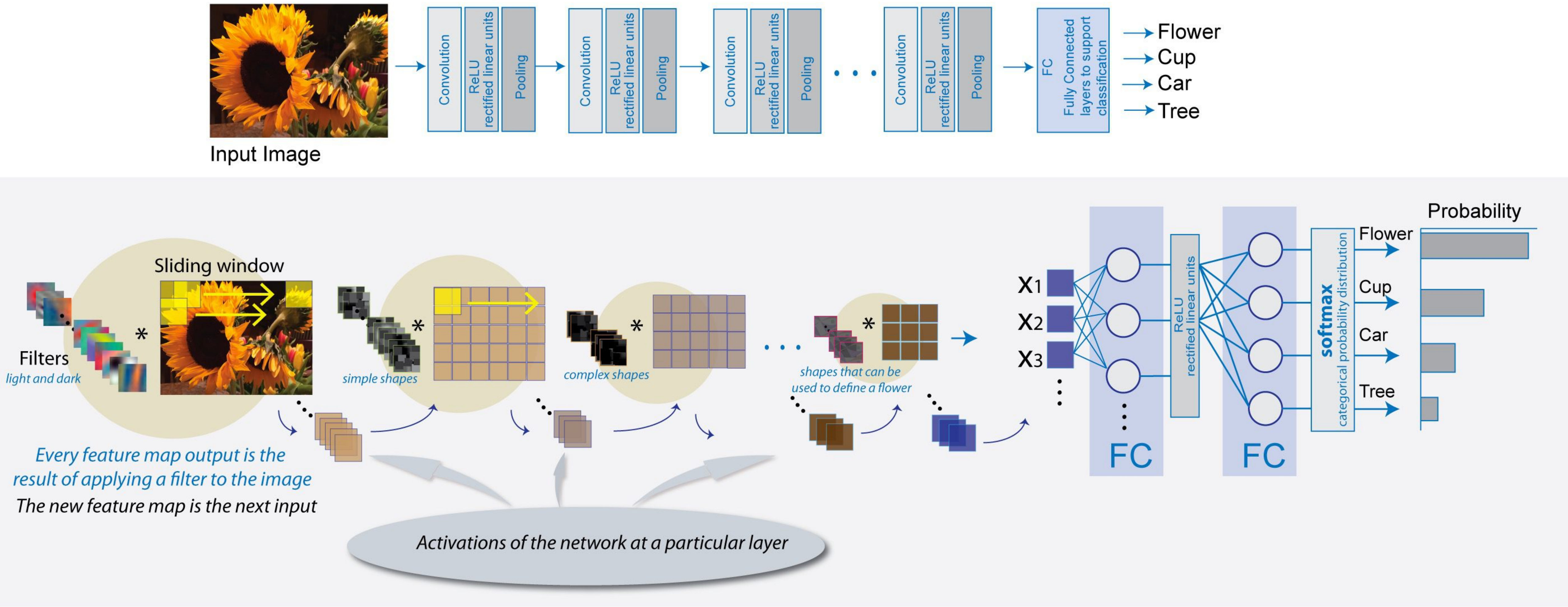


Image from the Mathworks

Data: $\boldsymbol{x}$

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: $\boldsymbol{w}$

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

$=$

Output: $\boldsymbol{x} * \boldsymbol{w}$

2D Convolution

Data: $\boldsymbol{x}$

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: $\boldsymbol{w}$

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

$=$

Output: $\boldsymbol{x} * \boldsymbol{w}$

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: $\boldsymbol{x}$

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: $\boldsymbol{w}$

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

$=$

Output: $\boldsymbol{x} * \boldsymbol{w}$

-6			

Computing one output value:

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

2D Convolution

Data: $\boldsymbol{X}$

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: $\boldsymbol{w}$

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

$=$

Output: $\boldsymbol{X} * \boldsymbol{w}$

-6	**-11**		

Computing one output value:

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

2D Convolution

2D Convolution

Data: $\boldsymbol{X}$

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: $\boldsymbol{w}$

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

$=$

Output: $\boldsymbol{X} * \boldsymbol{w}$

-6	**-11**	**-12**	

Computing one output value:

$$1\cdot5 + 1\cdot1 + 1\cdot4 +$$
$$0\cdot3 + 0\cdot2 + 0\cdot0 +$$
$$(-1)\cdot5 + (-1)\cdot9 + (-1)\cdot8 = \mathbf{-12}$$

Data: $\boldsymbol{X}$

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: $\boldsymbol{w}$

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

$=$

Output: $\boldsymbol{X} * \boldsymbol{w}$

-6	**-11**	**-12**	**-11**

Computing one output value:

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

2D Convolution

Data: $\boldsymbol{X}$

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: $\boldsymbol{w}$

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

$=$

Output: $\boldsymbol{X} * \boldsymbol{w}$

-6	**-11**	**-12**	**-11**
-7			

Computing one output value:

$$1\cdot 0 + 1\cdot 2 + 1\cdot 3 + 0\cdot 4 + 0\cdot 5 + 0\cdot 5 + (-1)\cdot 6 + (-1)\cdot 3 + (-1)\cdot 4 = \mathbf{-7}$$

2D Convolution

Data: $\boldsymbol{X}$

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 x 6

$*$

Weights: $\boldsymbol{w}$

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

3 x 3

$=$

Output: $\boldsymbol{X} * \boldsymbol{w}$

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

4 x 4

2D Convolution

What features do layers respond to?

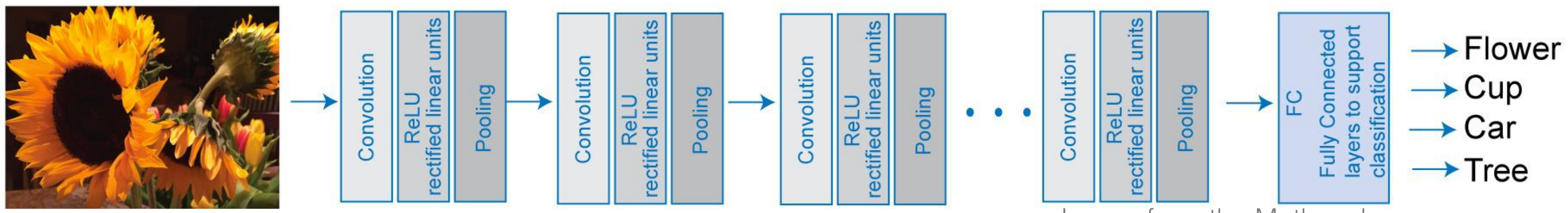
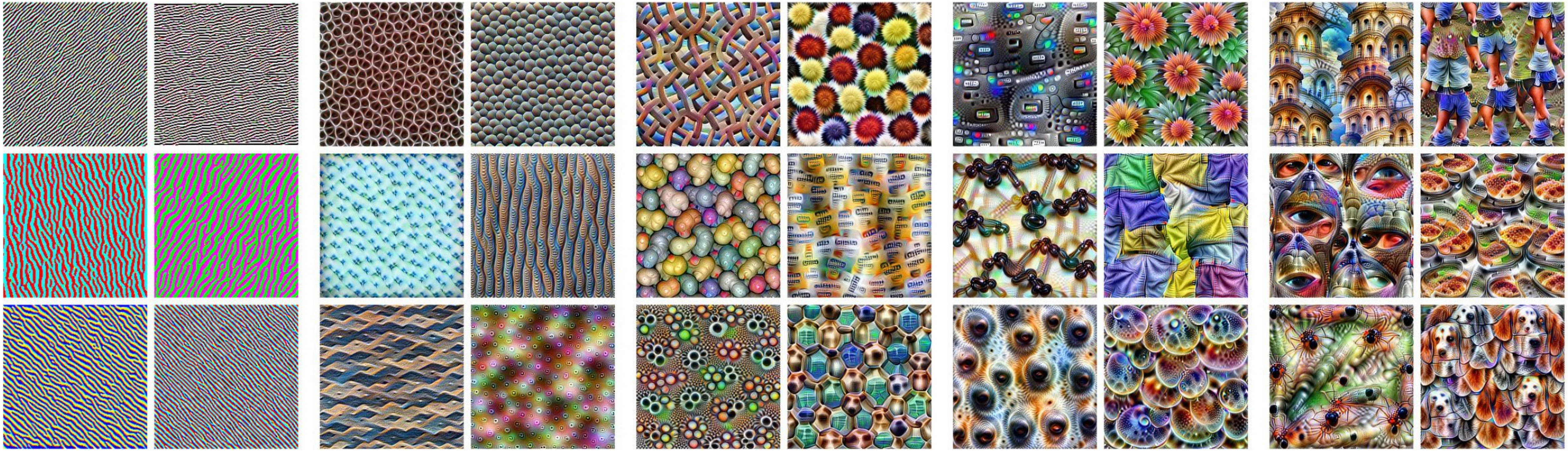


Image from the Mathworks



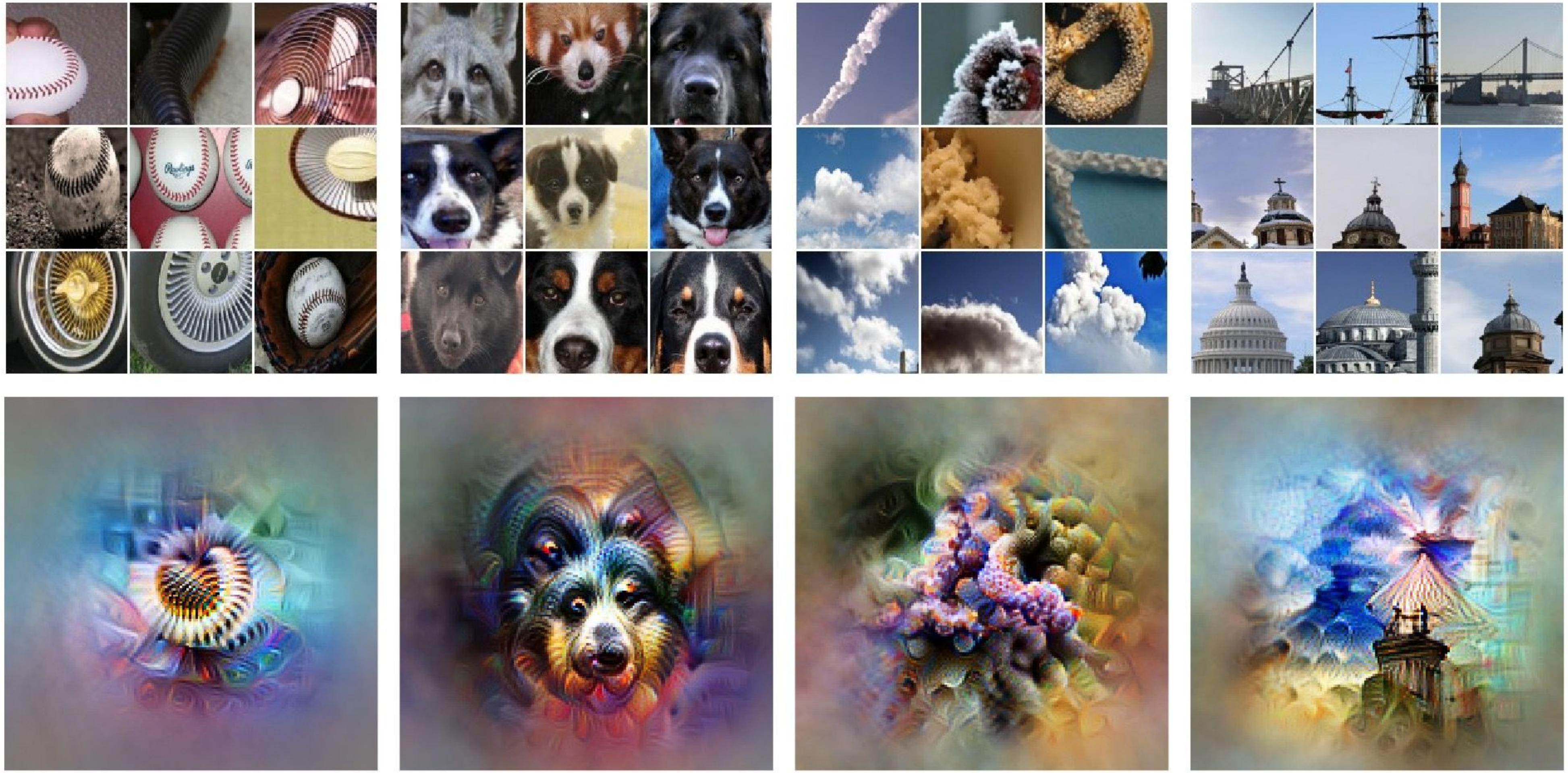
Edges (layer conv2d0) **Textures** (layer mixed3a) **Patterns** (layer mixed4a) **Parts** (layers mixed4b & mixed4c) **Objects** (layers mixed4d & mixed4e)

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*

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

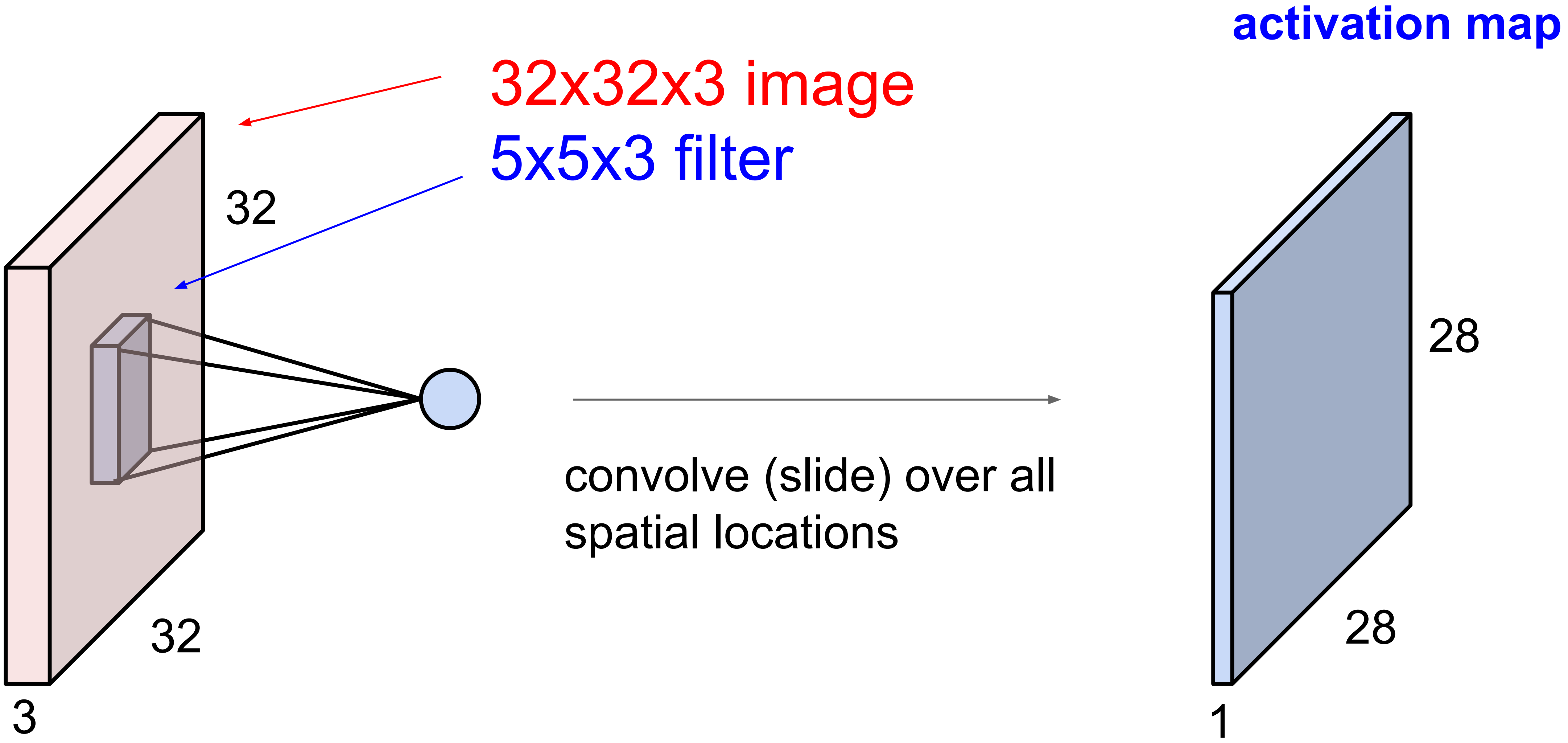
Resources on Visualization of Features

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

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

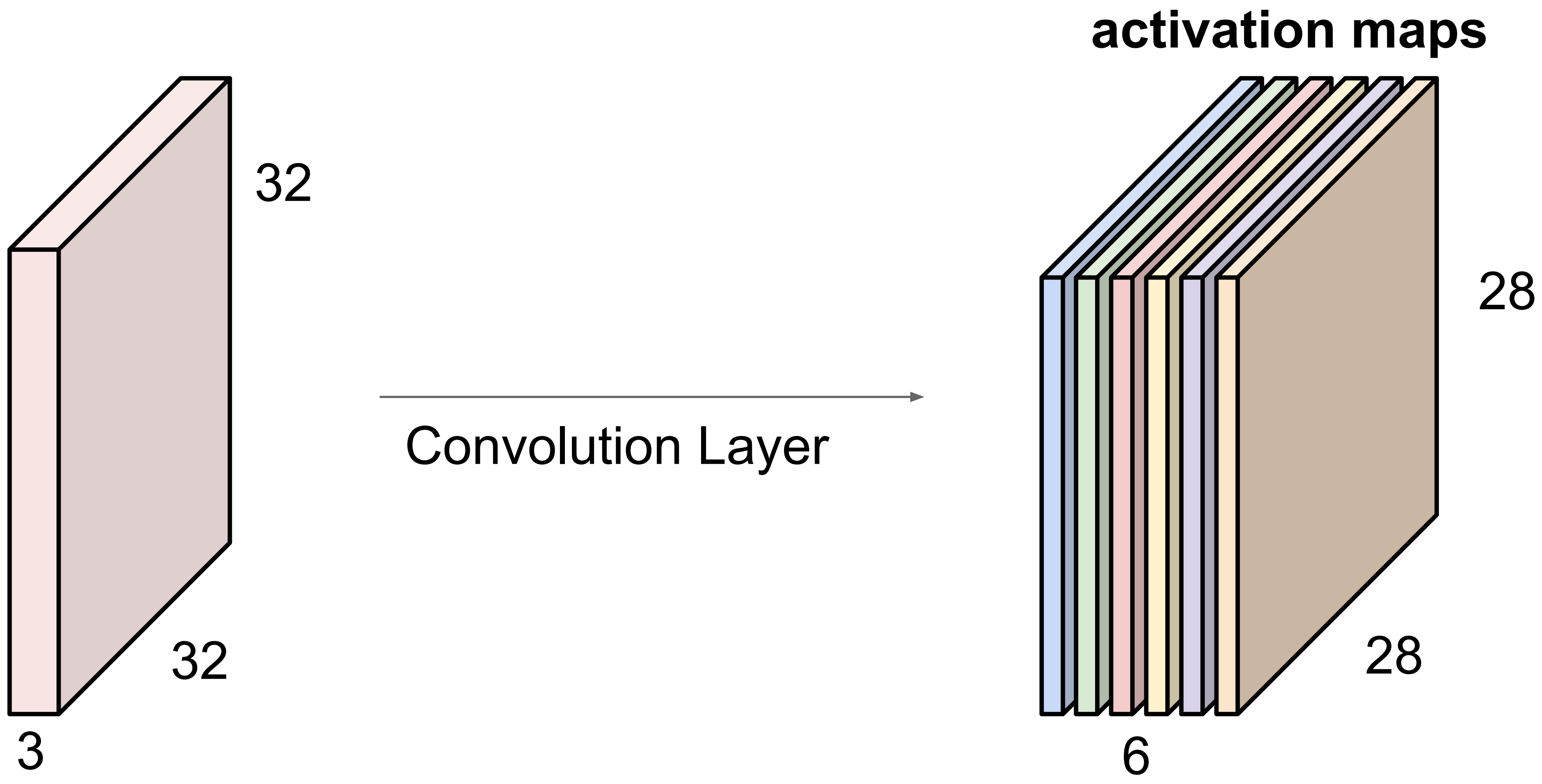
Activation Activation Atlases: https://distill.pub/2019/activation-atlas/

Convolution Layer



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

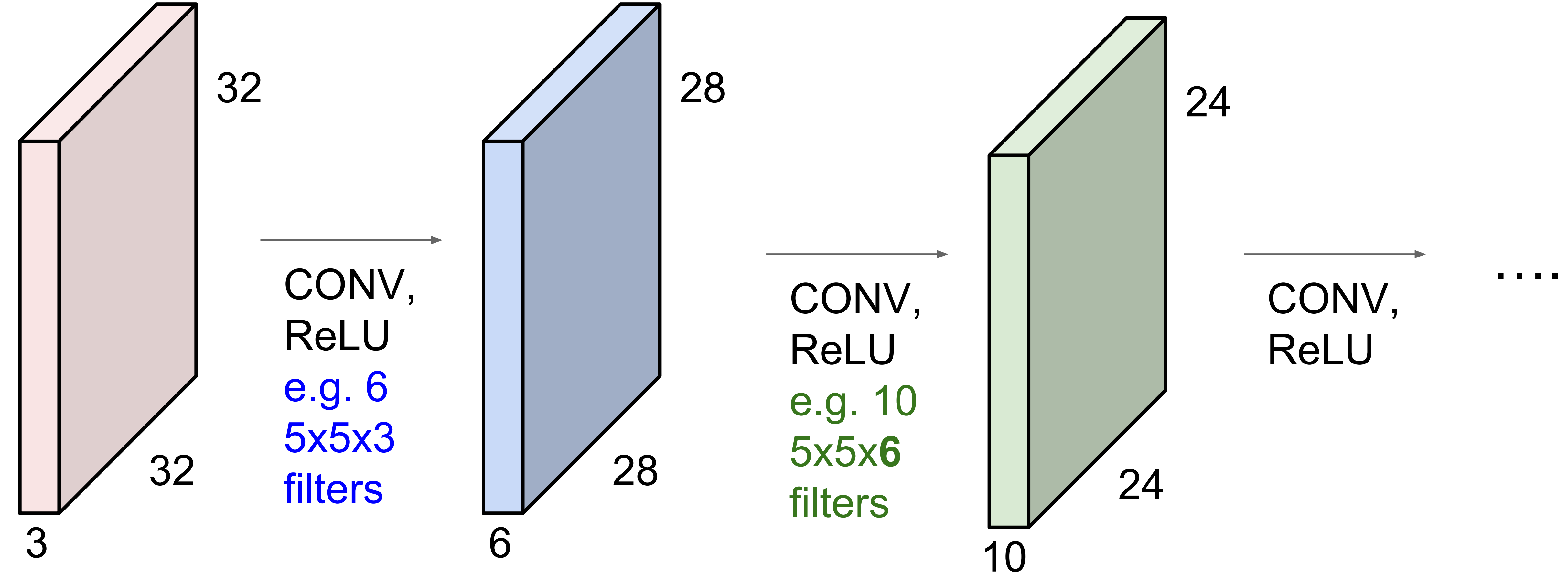
For example, if we had 6 5x5 filters, we'll get 6 separate activation maps:



We stack these up to get a "new image" of size 28x28x6!

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

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

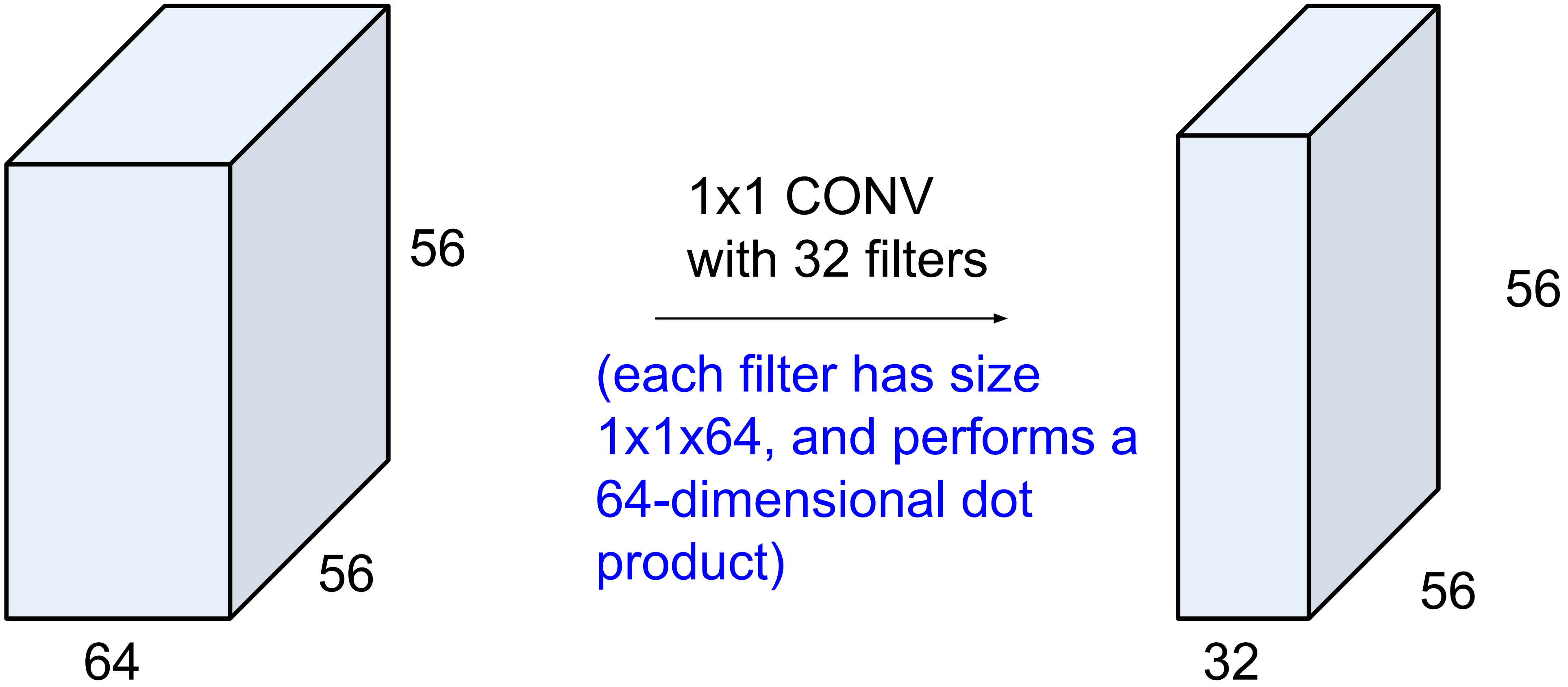


Parameters = (5*5*3)*6 = 450

(5*5*6)*10 = 1,500

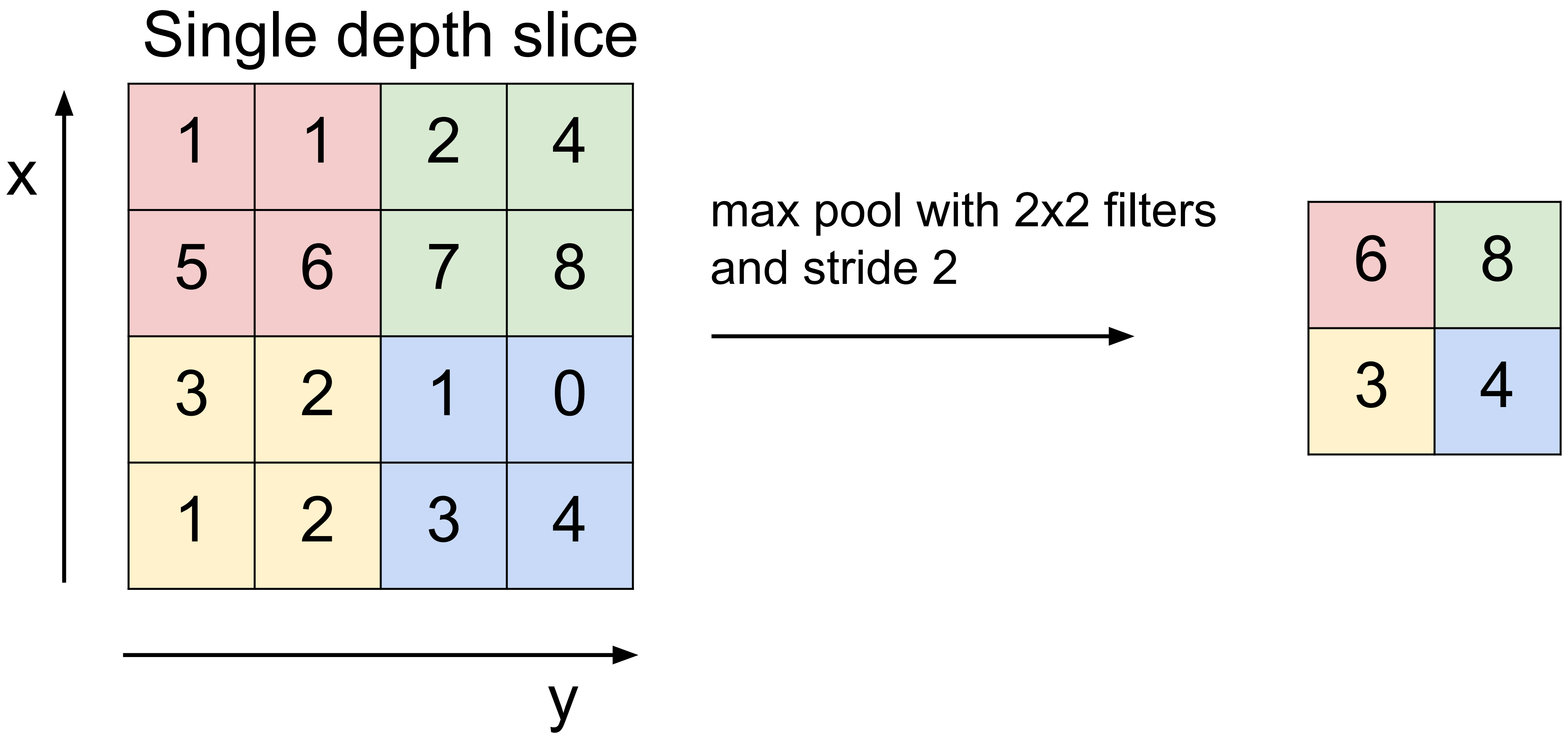
From Fei-Fei Li, Justin Johnson, and Serena Young. CS231n, 2018

1 x 1 Convolution Explained



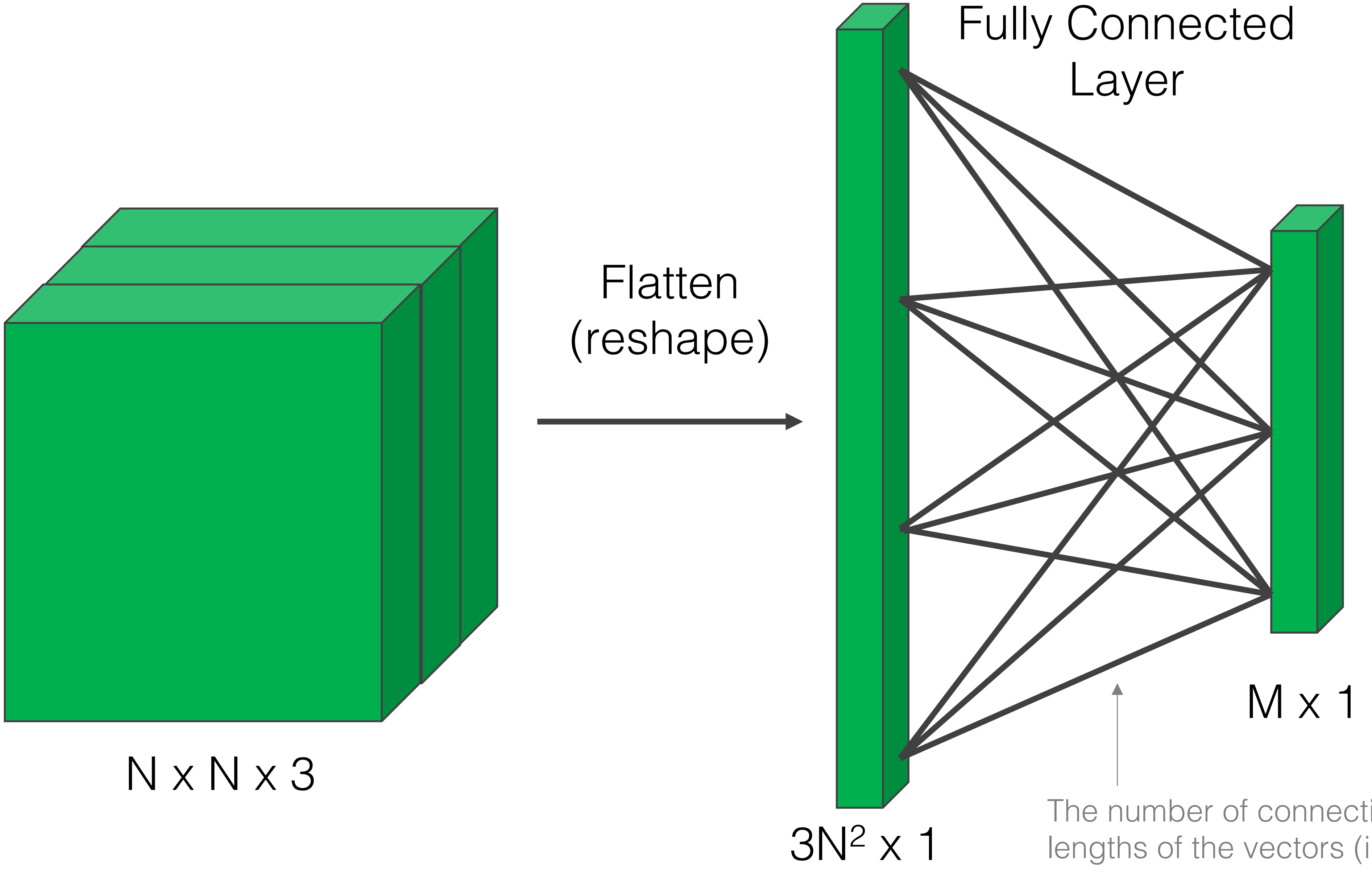
From Fei-Fei Li, Justin Johnson, and Serena Young. CS231n, 2018

Max Pooling



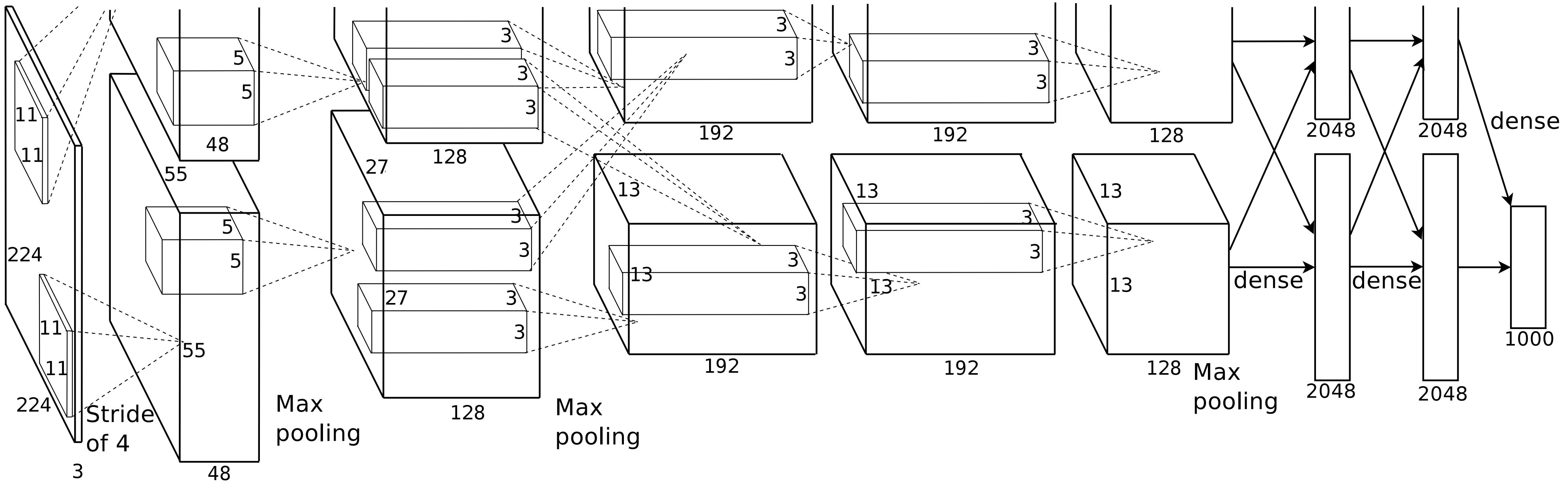
From Fei-Fei Li, Justin Johnson, and Serena Young. CS231n, 2018

Fully Connected Layer



The number of connections is the product of the lengths of the vectors (in this case $3N^2M$)

AlexNet



- 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

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

CNN Architectures

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

Fewer layers, larger filters

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
- FC 4096
- FC 4096
- FC 1000
- softmax

VGG19 (2014)

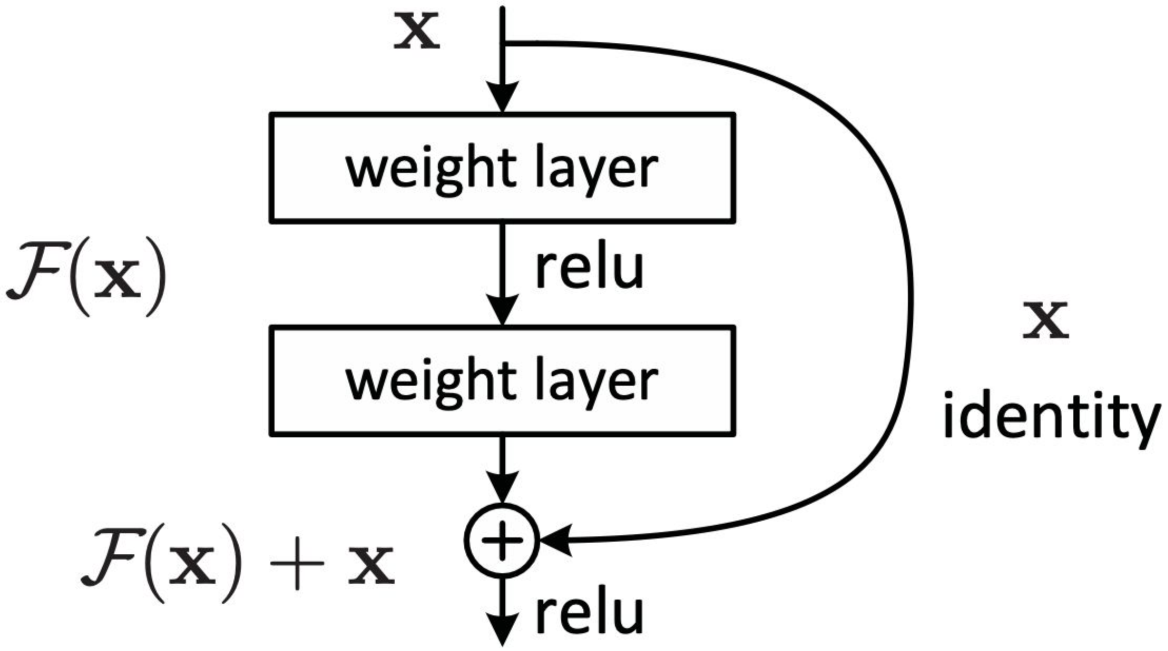
- Input
- 3x3 conv, 64
- 3x3 conv, 64
- max pool
- 3x3 conv, 128
- 3x3 conv, 128
- max pool
- 3x3 conv, 256
- 3x3 conv, 256
- 3x3 conv, 256
- 3x3 conv, 256
- max pool
- 3x3 conv, 512
- 3x3 conv, 512
- 3x3 conv, 512
- 3x3 conv, 512
- max pool
- 3x3 conv, 512
- 3x3 conv, 512
- 3x3 conv, 512
- 3x3 conv,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

Key

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

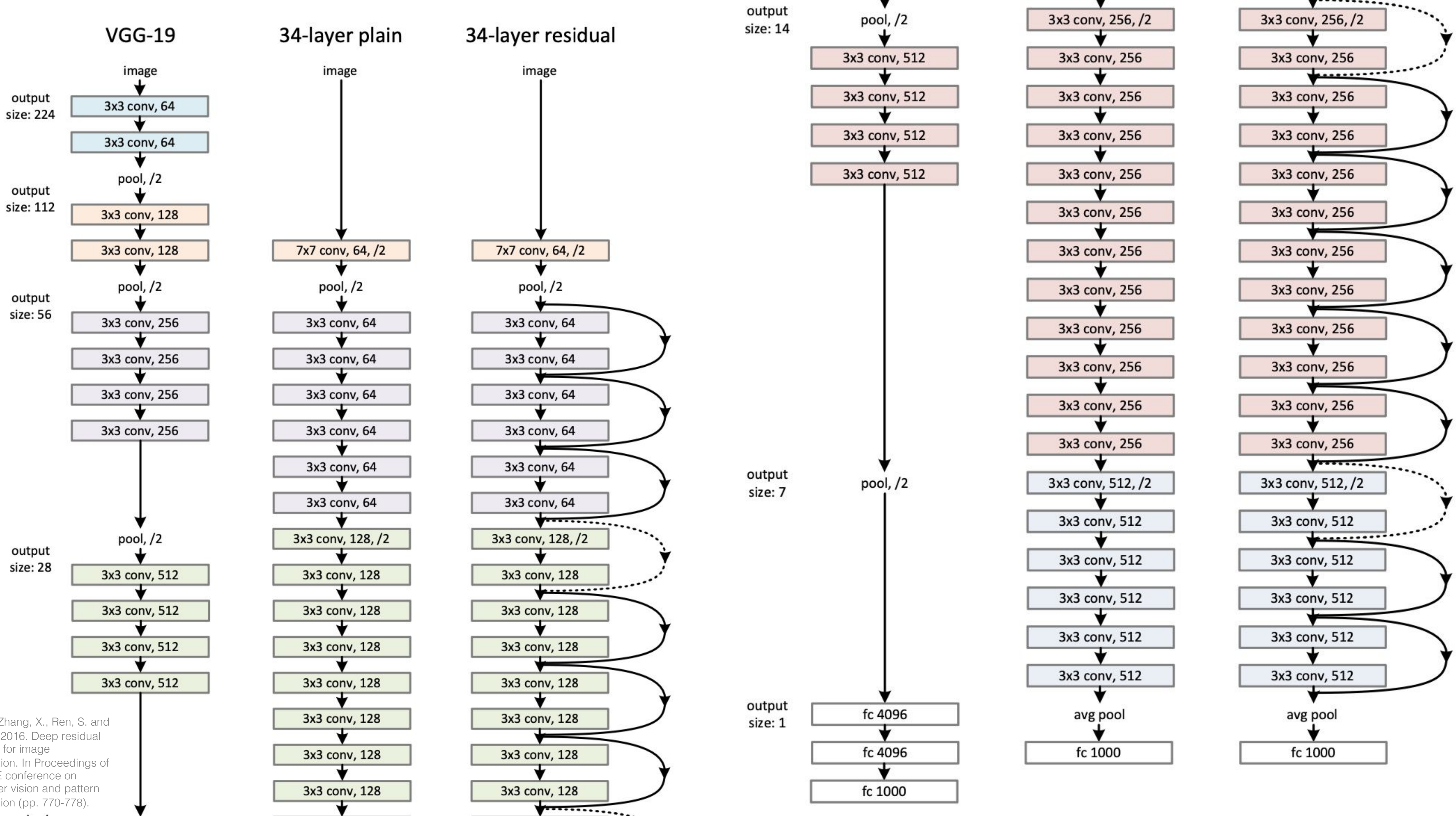
Adapted from Fei-Fei Li, Justin Johnson, and Serena Young. CS231n, 2018

Residual Networks (ResNet)



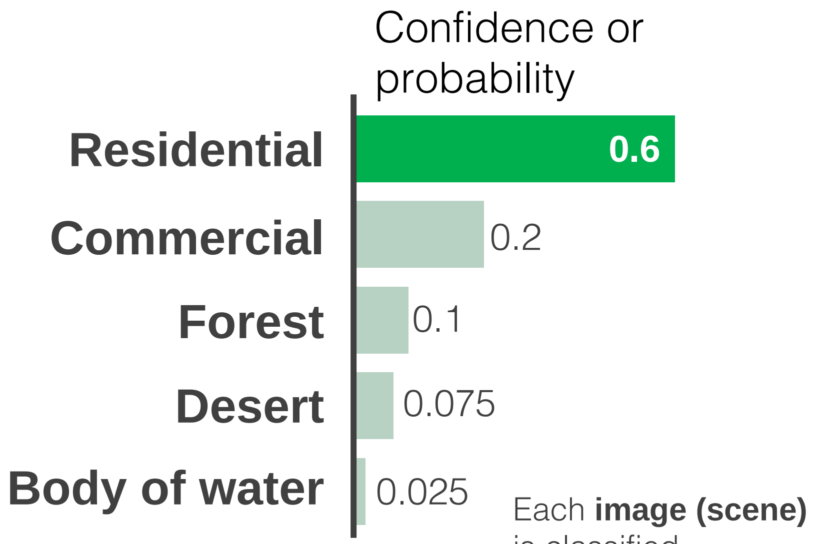
Skip Connection enable faster convergence, more effectively backpropate the error signal (avoiding vanishing gradients)

He, K., Zhang, X., Ren, S. and Sun, J., 2016. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).



He, K., Zhang, X., Ren, S. and Sun, J., 2016. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).

Scene classification



Each **image (scene)** is classified

Object detection

Object type & probability

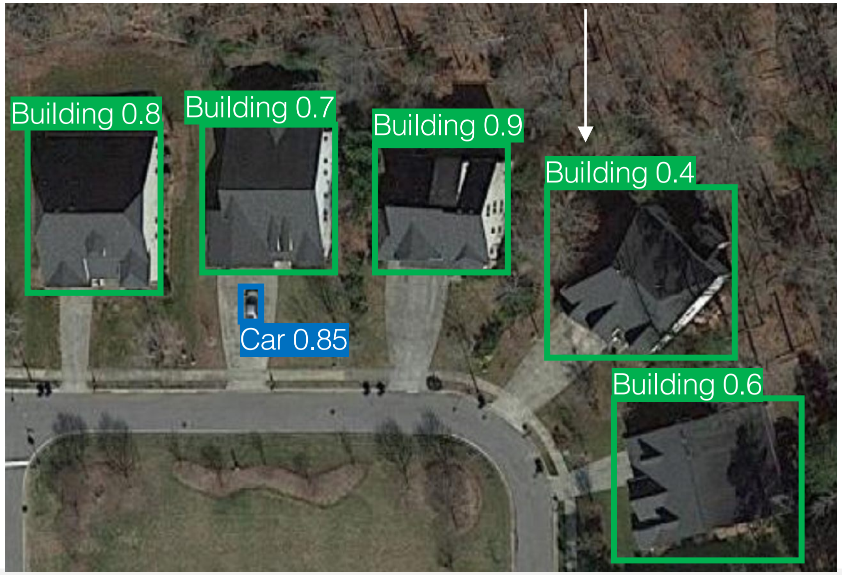
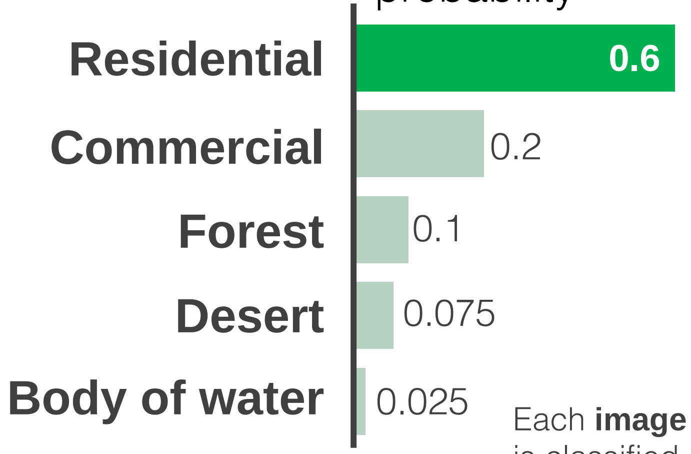


Image segmentation

Scene classification

AlexNet
VGG
GoogLeNet
ResNet
Inception
DenseNet
SqueezeNet
EfficientNet

Confidence or probability



Each **image (scene)** is classified

Object detection

Faster/Fast/R-CNN
Mask R-CNN
YOLO
Single Shot Detector (SSD)
RetinaNet

Object type & probability

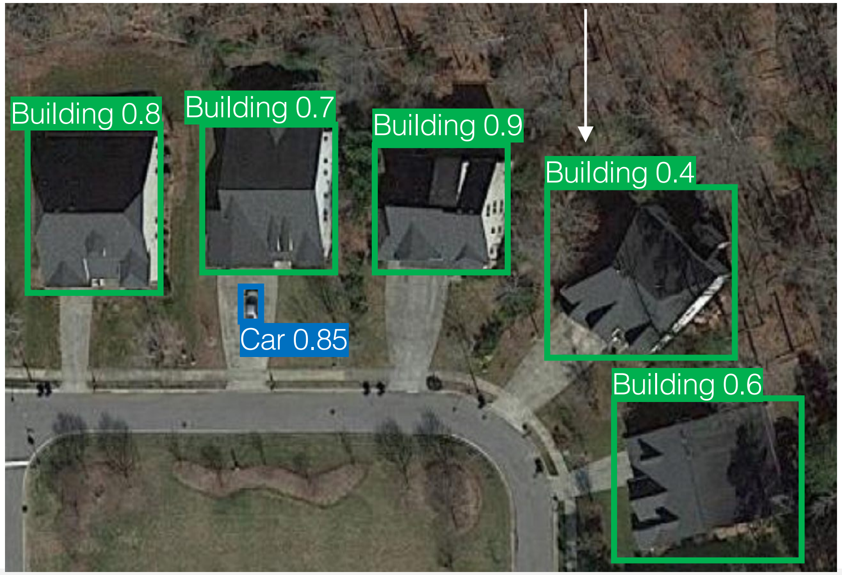


Image segmentation

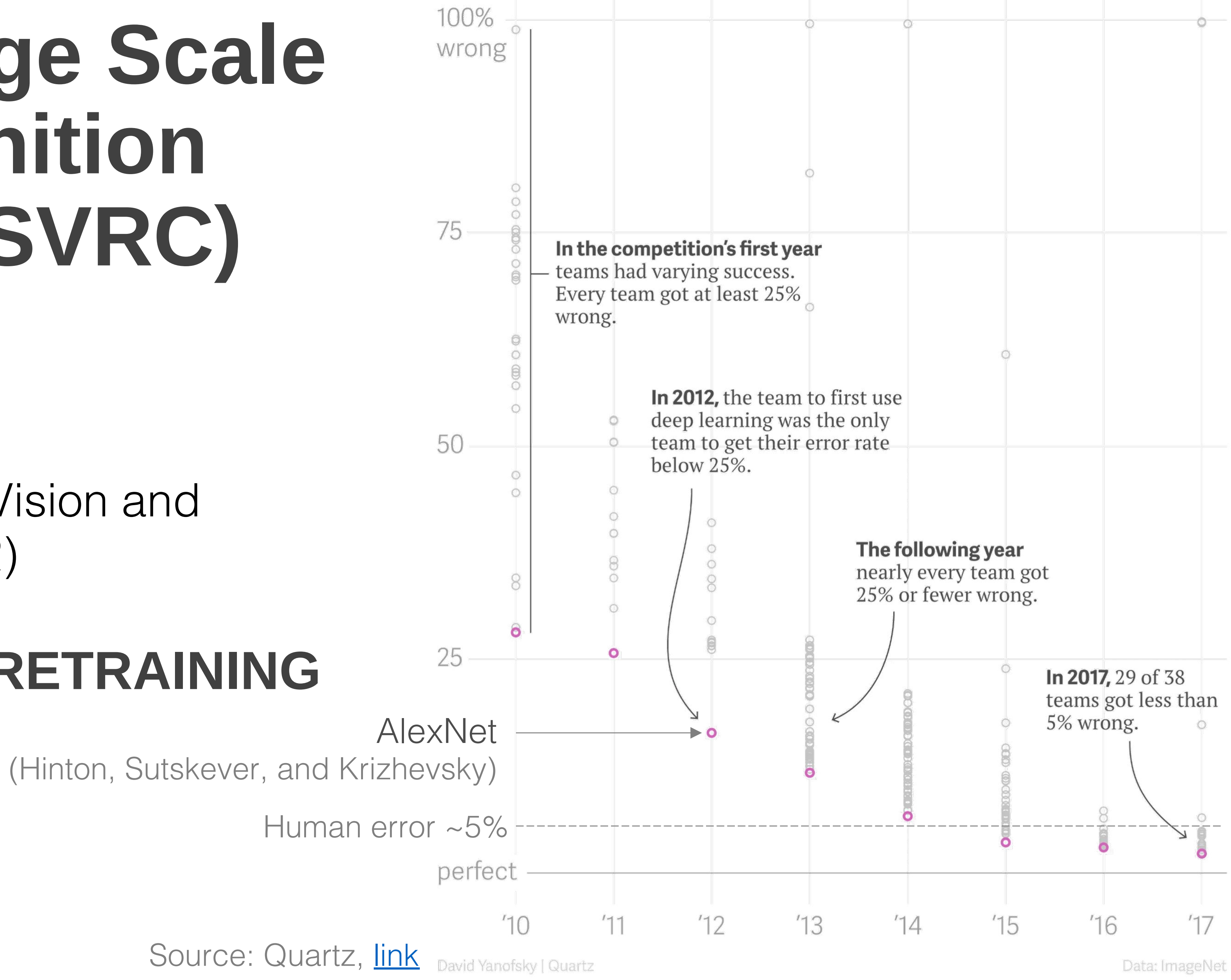
U-Net (2015)
SegNet (2016)
DeepLab (2017)
FCN (2016)

ImageNet Large Scale Visual Recognition Challenge (ILSVRC)

Fei-Fei Li et al. 2010 (link)

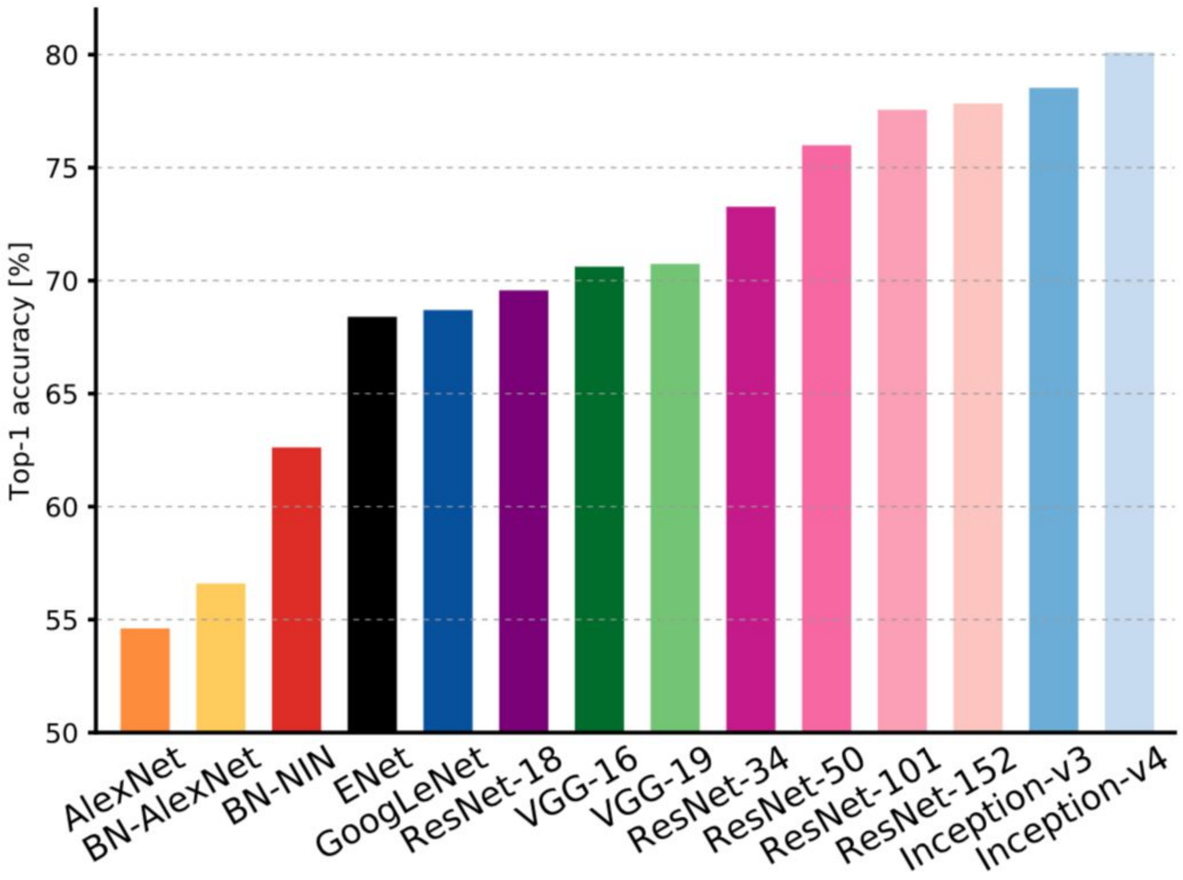
Competition at:
Conference on Computer Vision and Pattern Recognition (CVPR)

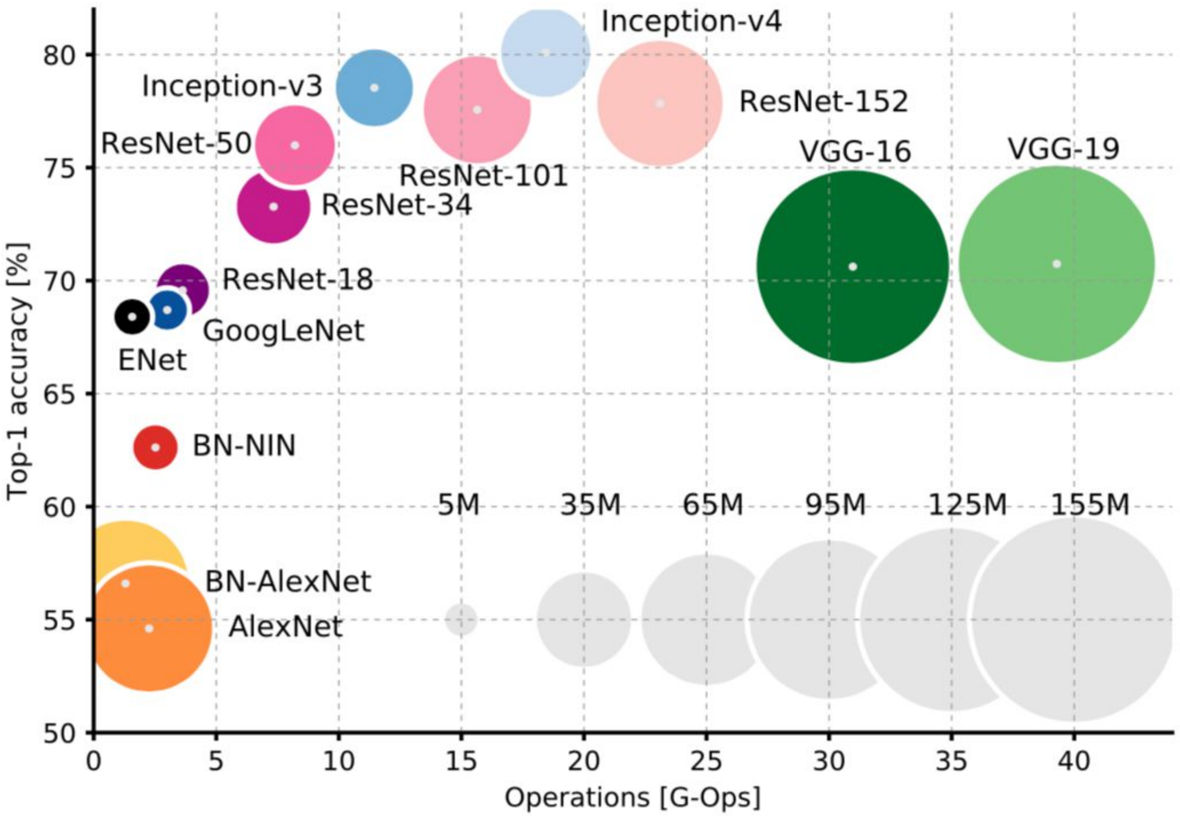
USED FOR MODEL PRETRAINING



Source: Quartz, link

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

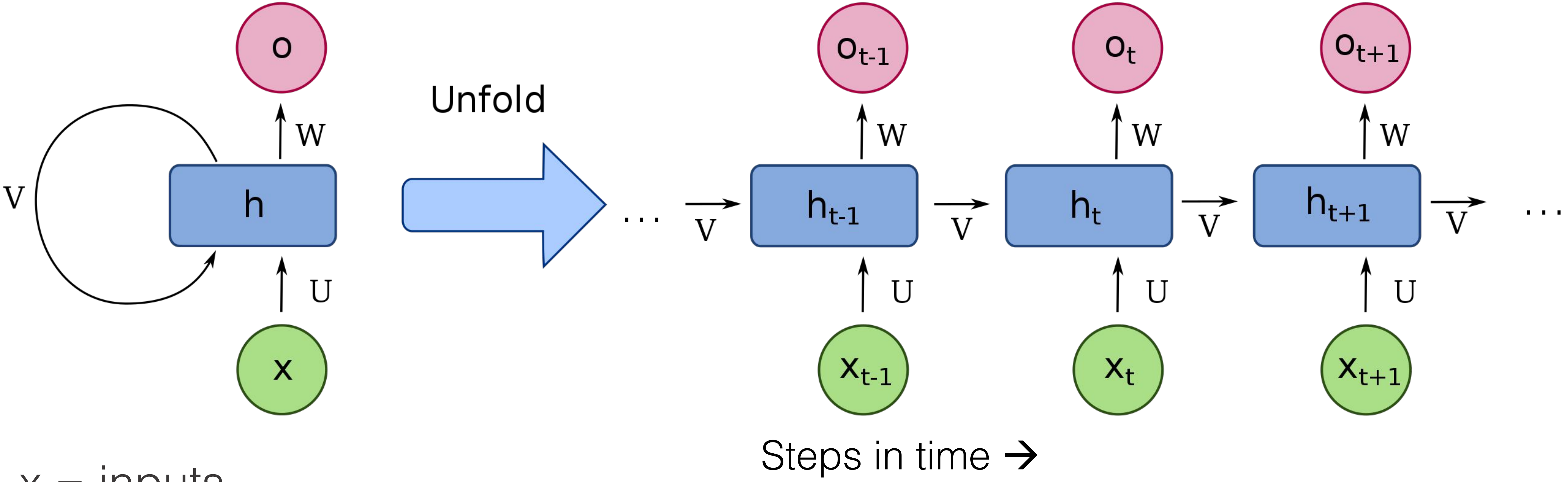
Tensorflow (link)
Framework for implementing graphical models, such as neural networks

Keras (link)
Wrapper for Tensorflow to make coding easier: higher level and excellent API

PyTorch (link)
Framework for implementing graphical models, such as neural networks

KERAS DEMO

Recurrent Neural Networks



x = inputs

o = outputs

h = hidden layers

U,V,W = model weights

Image from https://en.wikipedia.org/wiki/Recurrent_neural_network

Generative Adversarial Networks

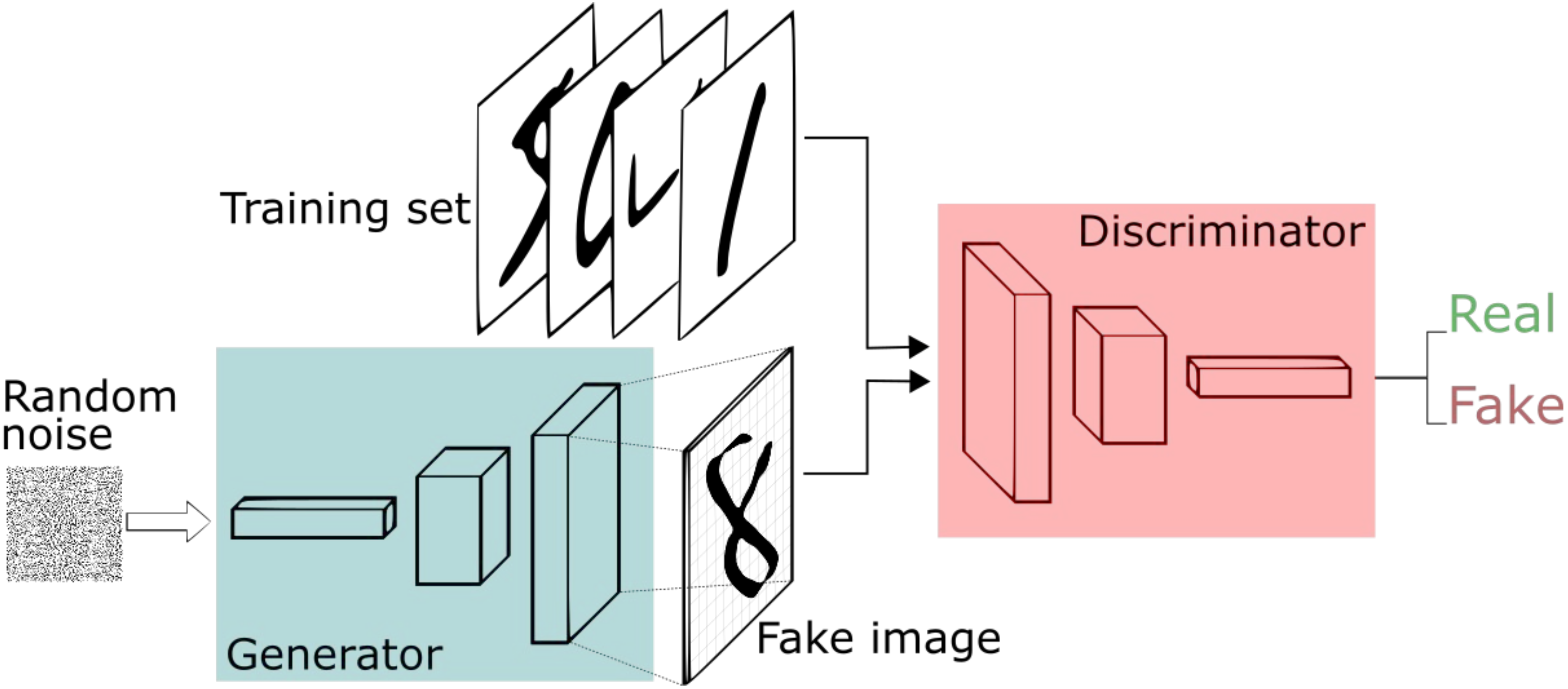


Image from: https://skymind.ai/wiki/generative-adversarial-network-gan

Supervised Learning Techniques

Covered so far

- Linear Regression
- K-Nearest Neighbors
- Perceptron
- Logistic Regression
- Linear Discriminant Analysis
- Quadratic Discriminant Analysis
- Naïve Bayes
- Support Vector Machines
- Decision Trees and Random Forests
- Ensemble methods (bagging, boosting, stacking)
- Neural Networks

Can be used with many machine learning techniques

Appropriate for:
- Classification
- Regression