Advanced Machine Learning For Design

Lecture 5: Machine Learning for Image Processing (part 2)

Evangelos Niforatos

18/10/2023

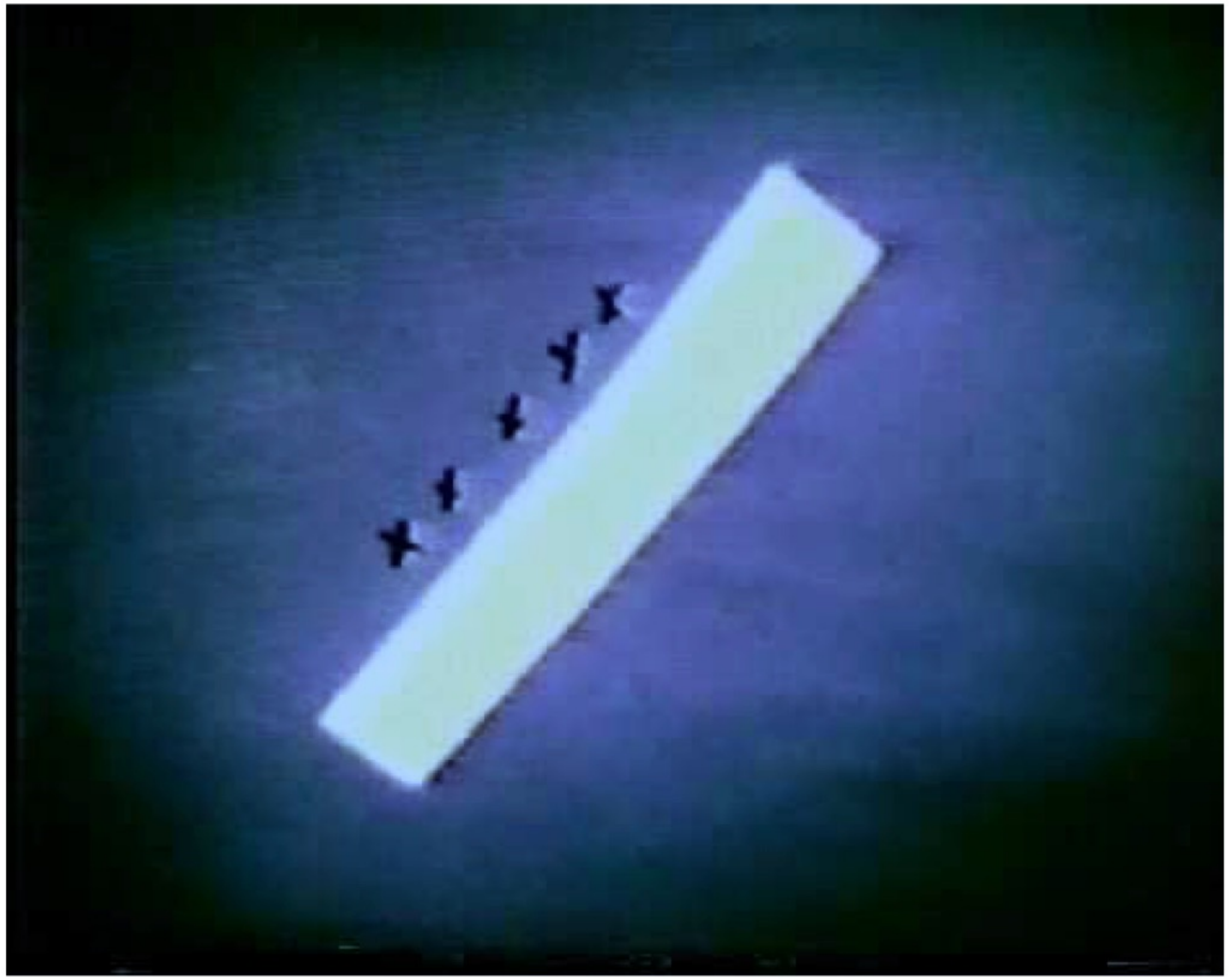
aml4d-ide@tudelft.nl
https://aml4design.github.io/

Admin

- Only 26/45 Peer Assessment forms completed for Group Assignment 1!
- We will publish Group Assignment feedback and aggregated peer assessment scores by next week.
- Preparation about the final exam
    - Content: Slides, Sources and Materials on https://aml4design.github.io/
    - Quizzes: Complete them at your own time
    - Example exam in the last week of the course
- Final Exam
    - Register for the final exam (Nov. 10 at 13:30)!
    - Registration for the final exam expires 14 calendar days before the day of the exam.
    - For more information, please check this website: https://www.tudelft.nl/en/student/education/courses-and-examinations/examinations/registration-for-exams

How do humans see?

Hubel and Wiesel, 1959



https://www.youtube.com/watch?v=IOHayh06LJ4

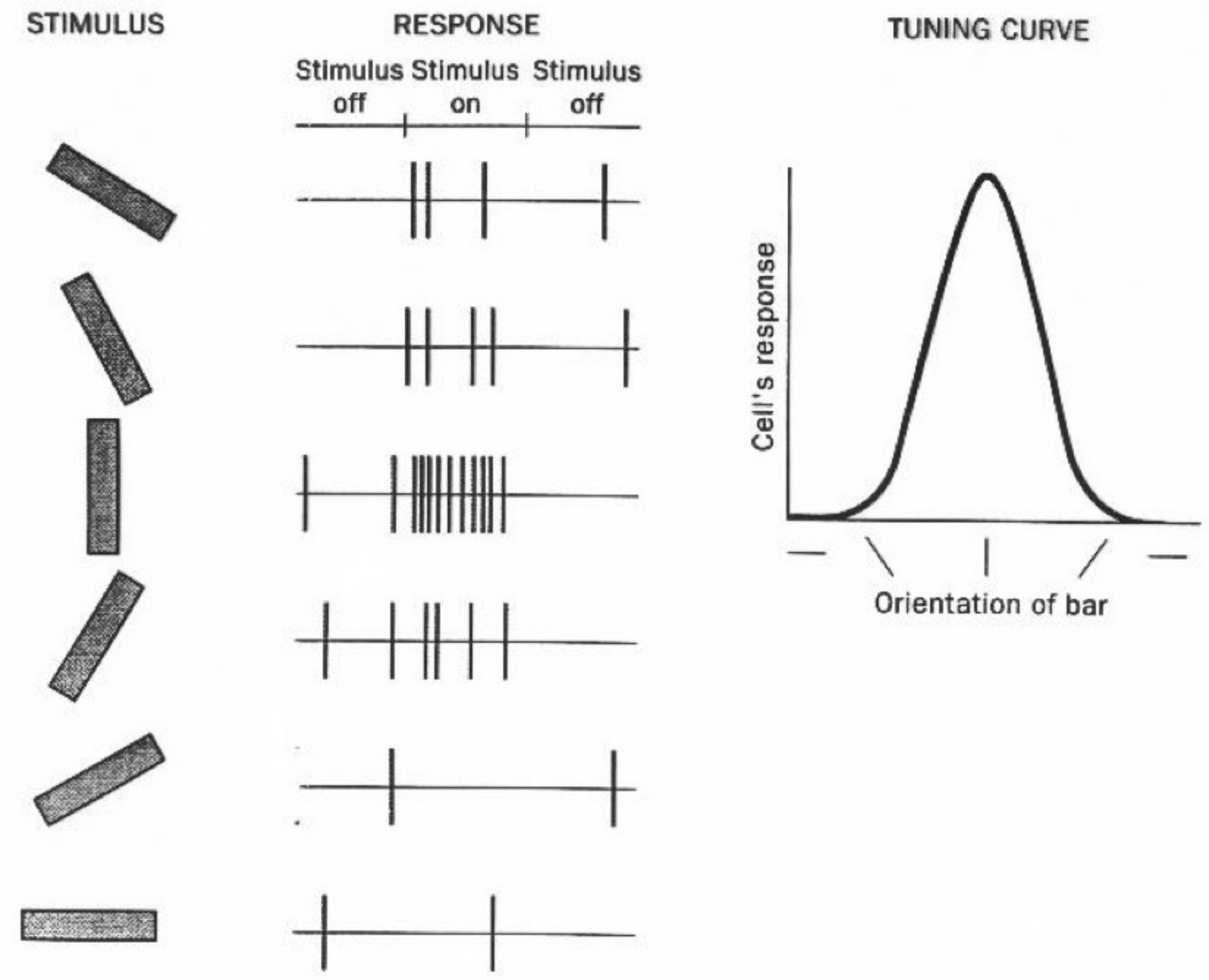
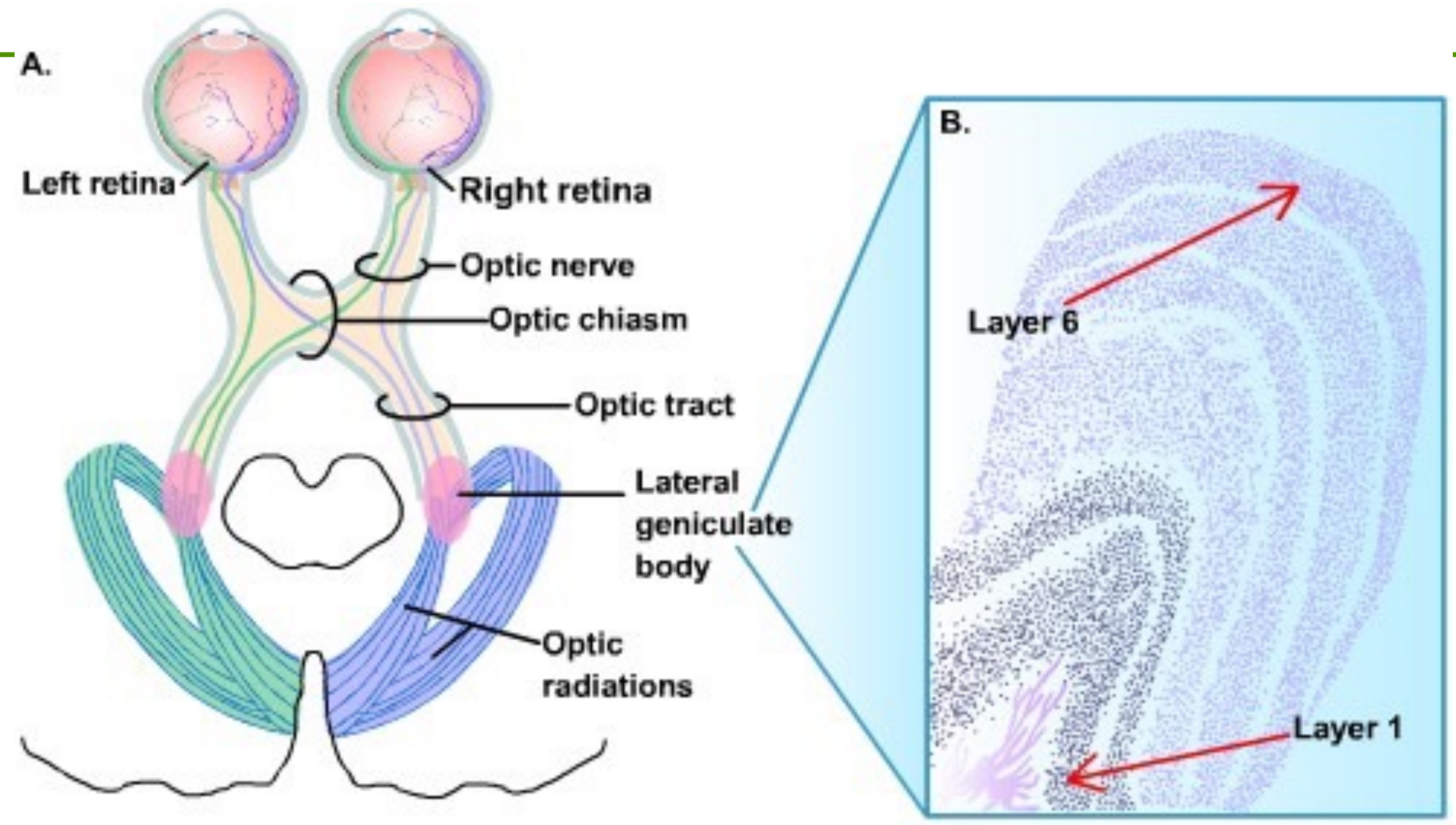


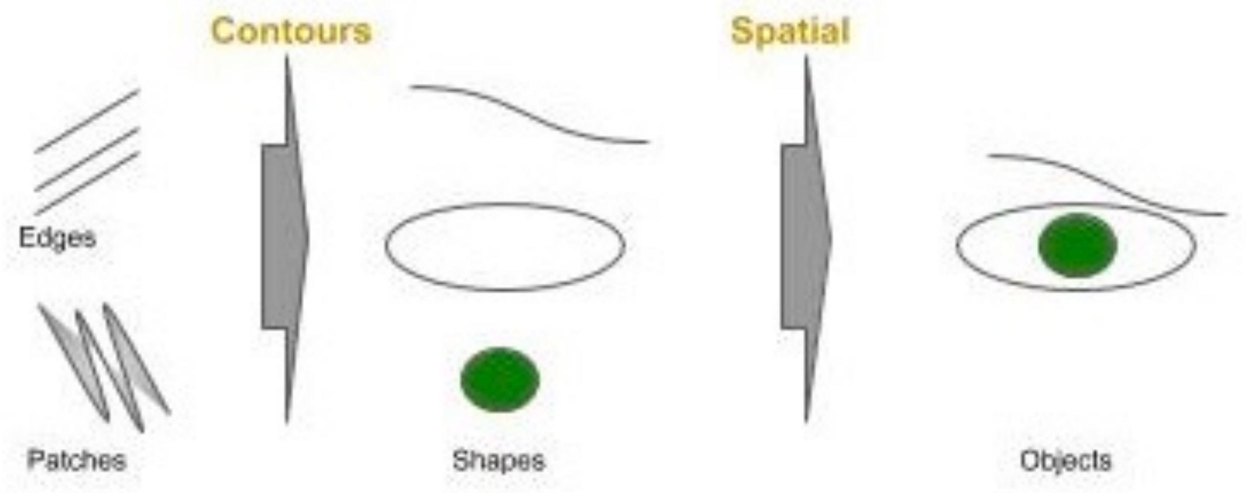
FIGURE 4.8 Response of a single cortical cell to bars presented at various orientations.

Neural Pathways



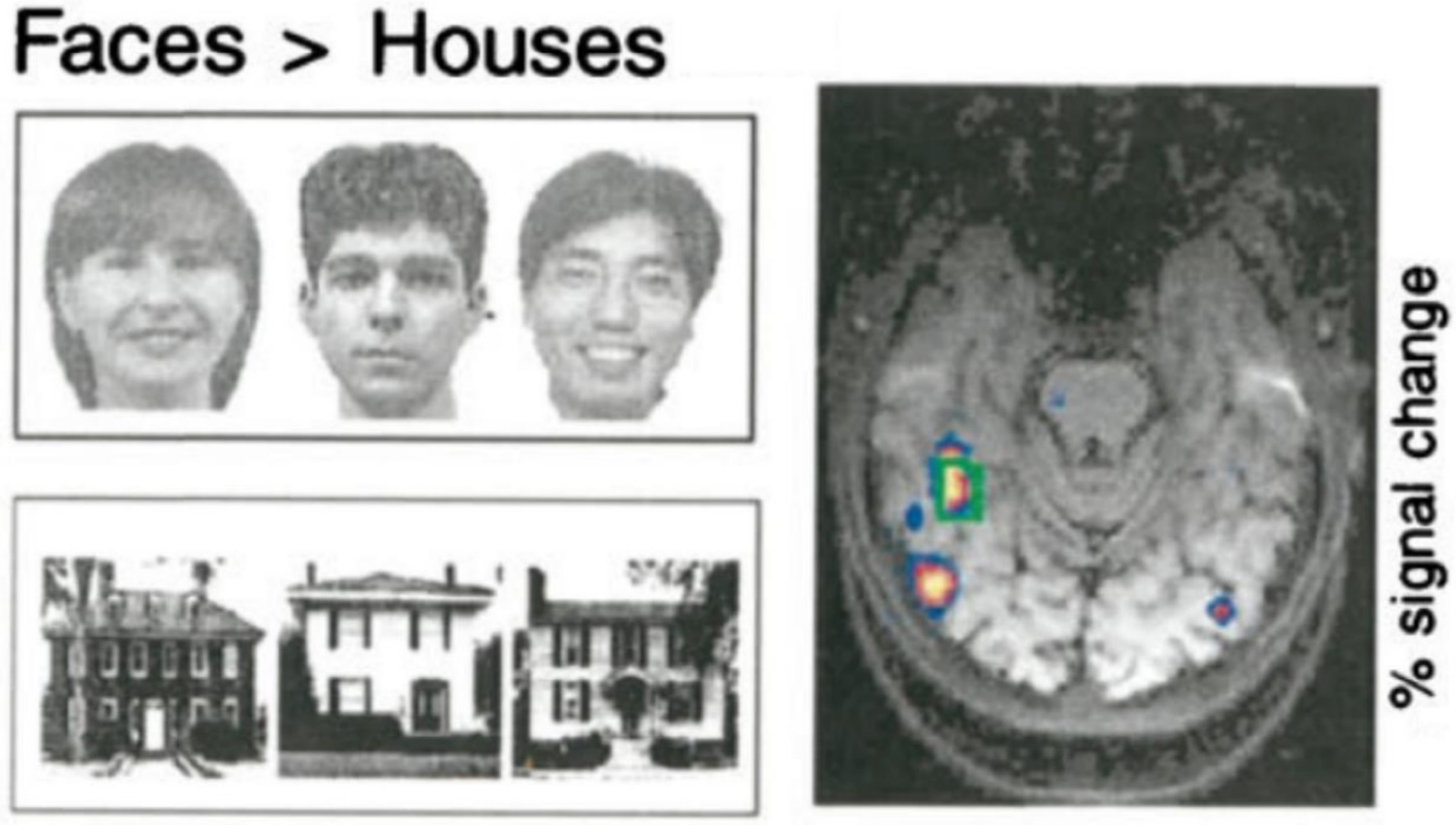
Edges → Simple Shapes → Complex Shapes → Faces and Objects

← Lower layers   Upper layers →

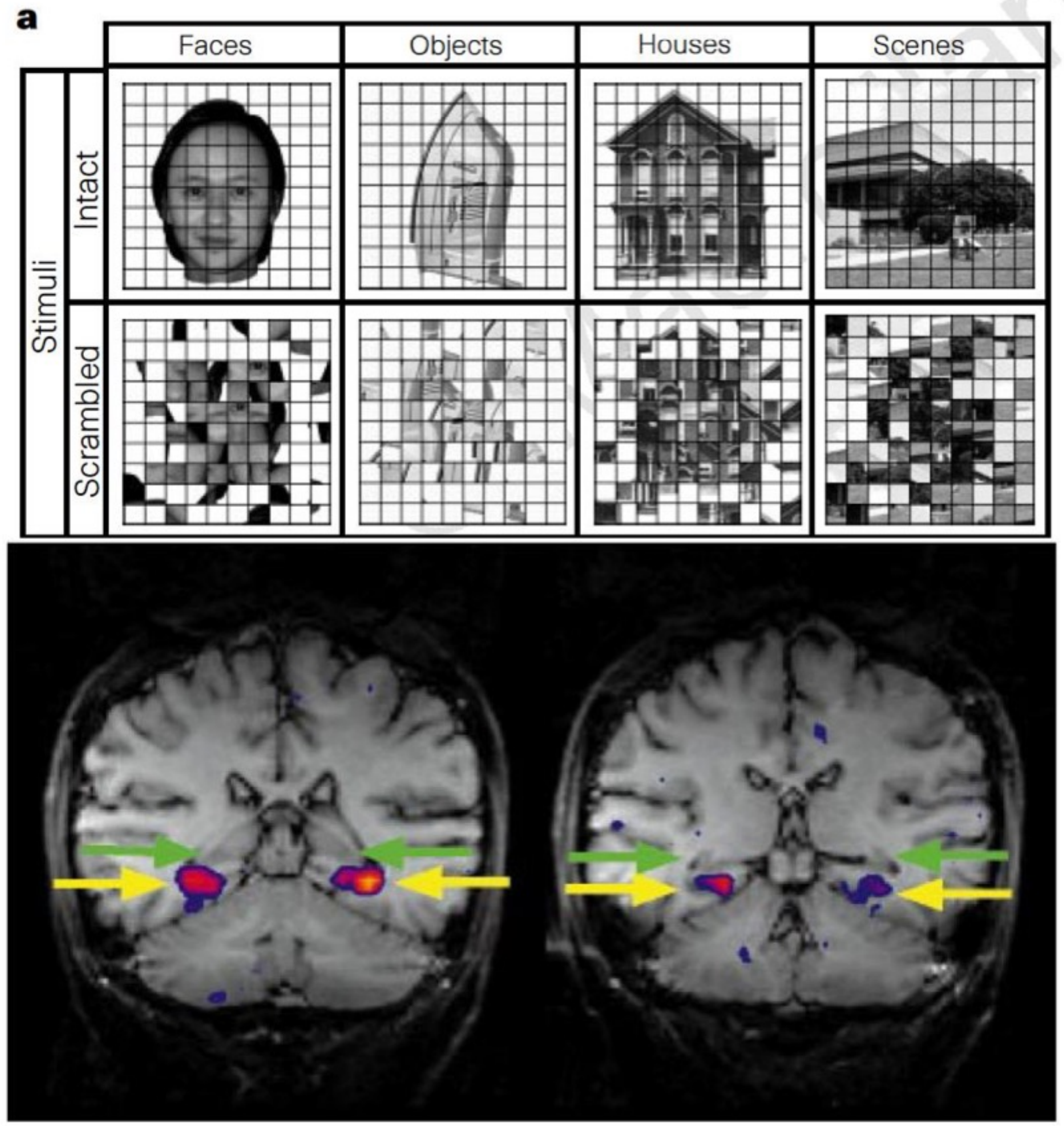


https://nba.uth.tmc.edu/neuroscience/m/s2/chapter15.html

Neural Correlation of Objects & Scene Recognition



Kanwisher et al. J. Neuro. 1997



Epstein & Kanwisher, Nature, 1998

Why is machine vision hard?

The deformable and truncated cat

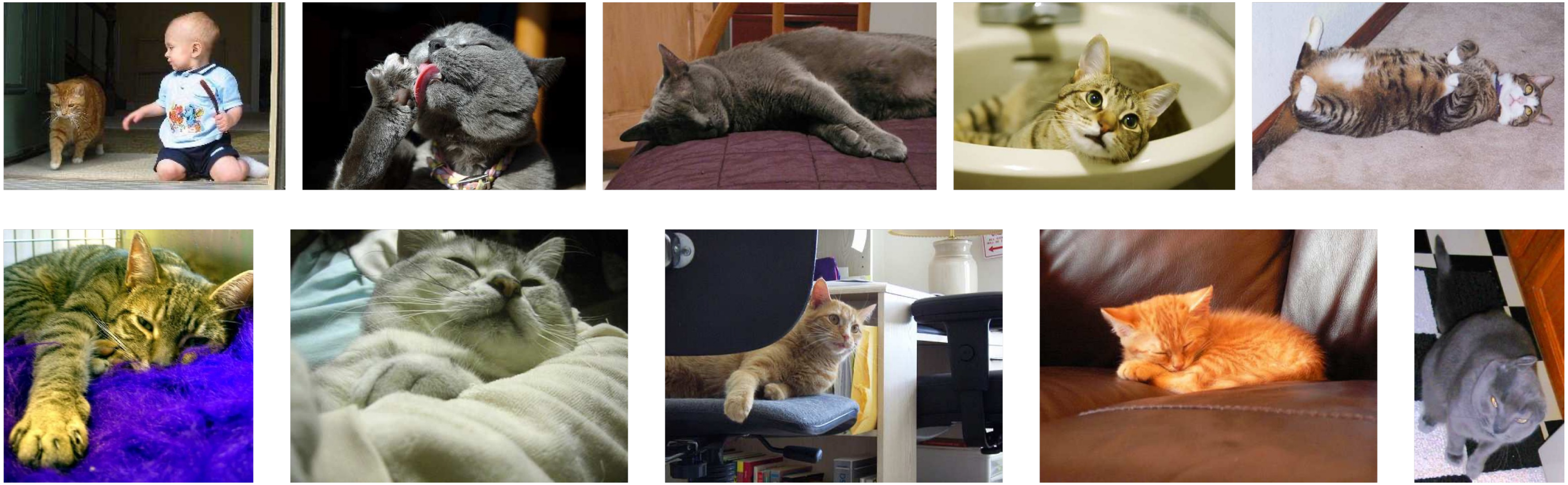
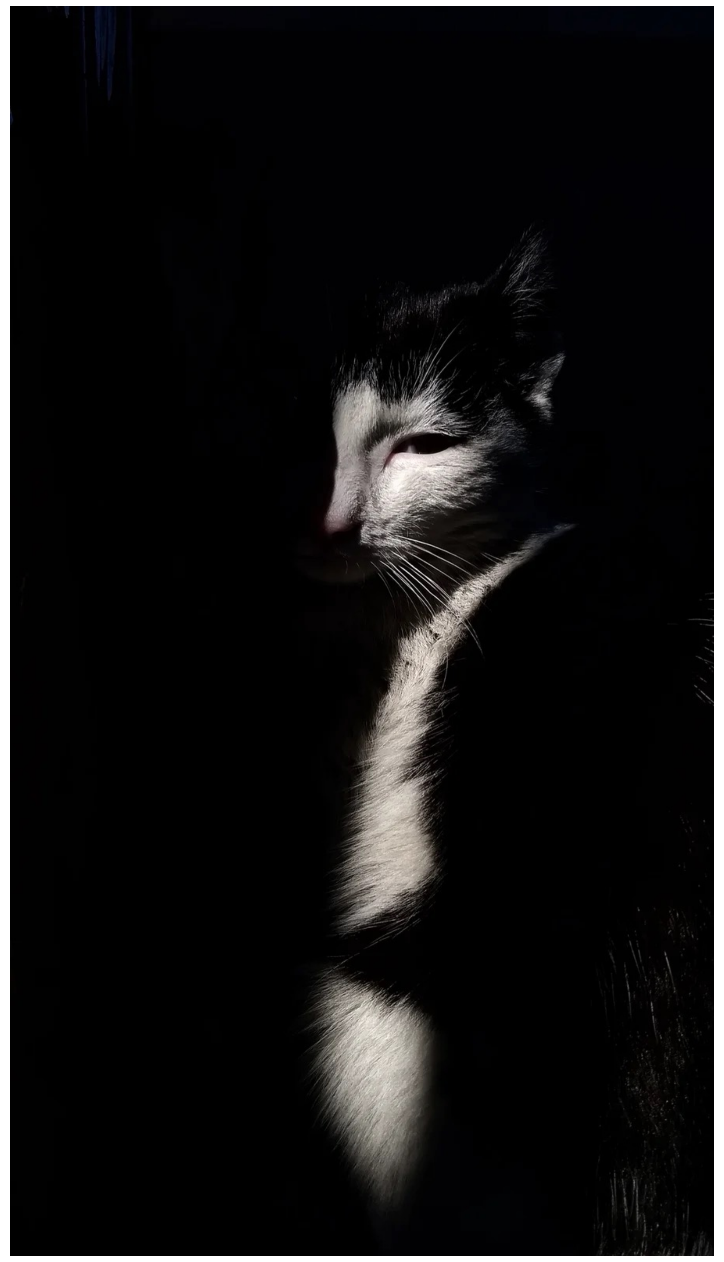
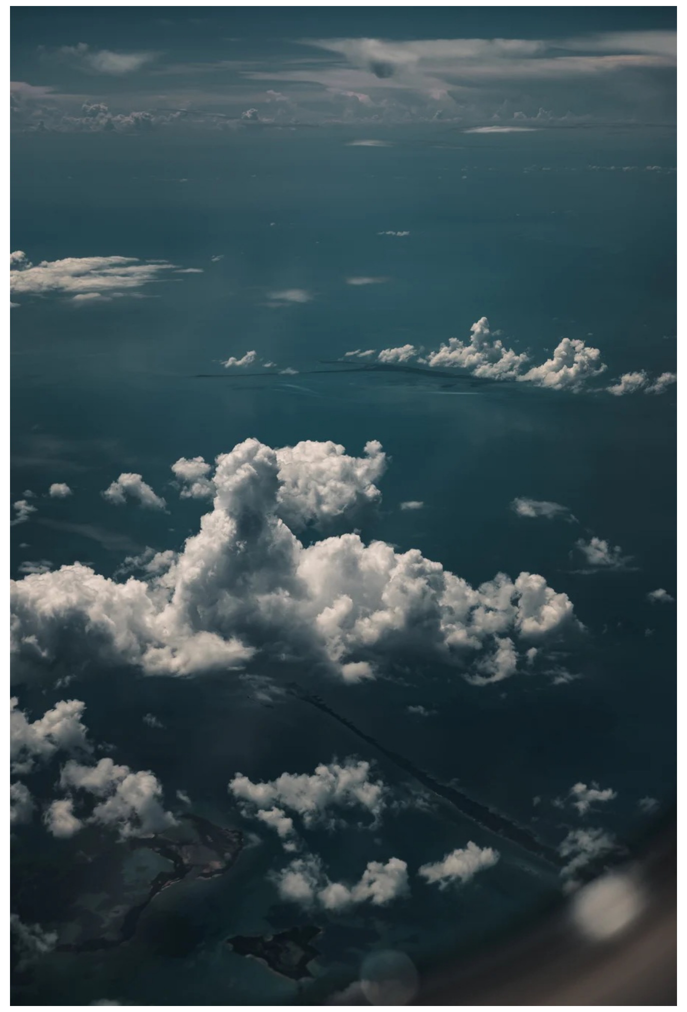
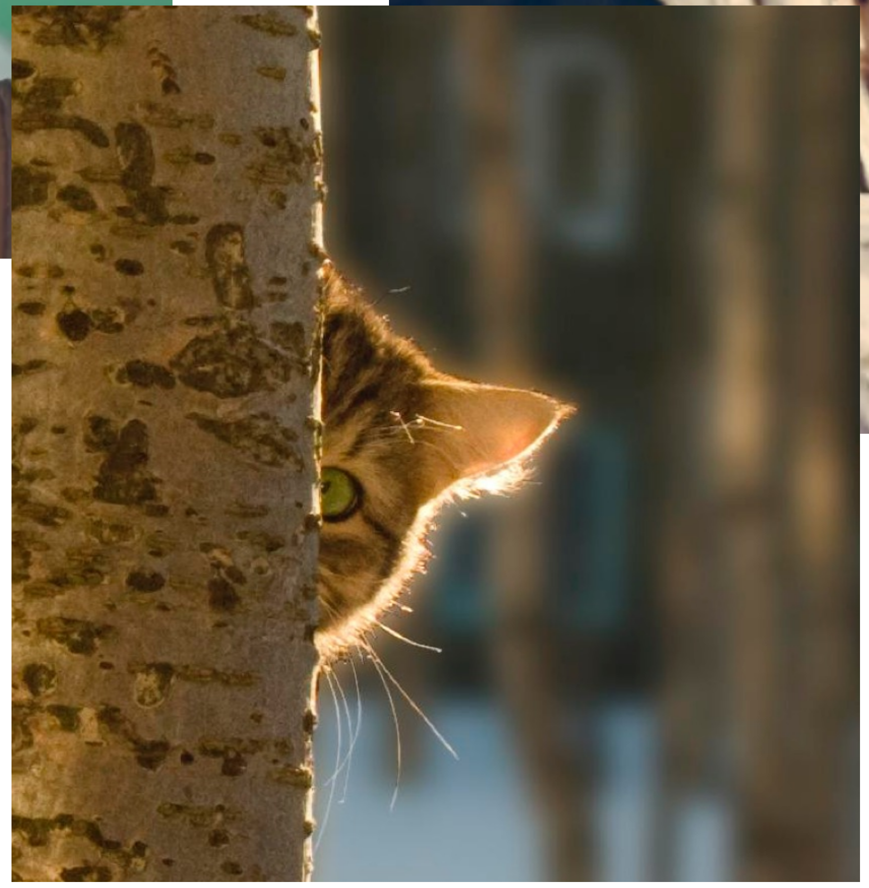


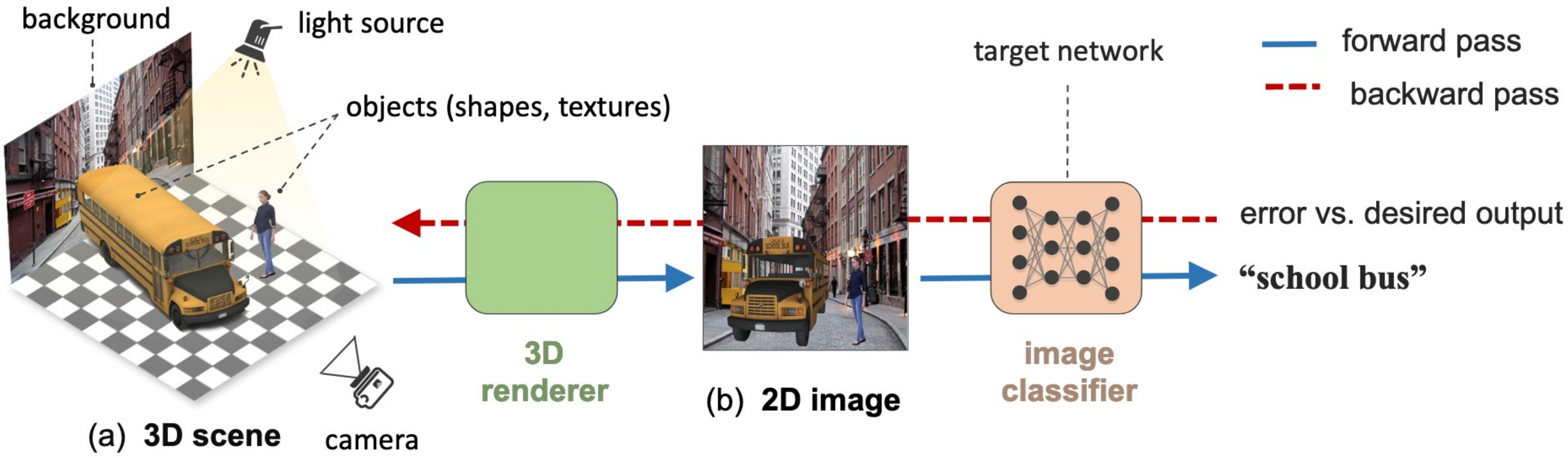
Figure 1. **The deformable and truncated cat.** Cats exhibit (almost) unconstrained variations in shape and layout.

Parkhi et al. *The truth about cats and dogs*. 2011





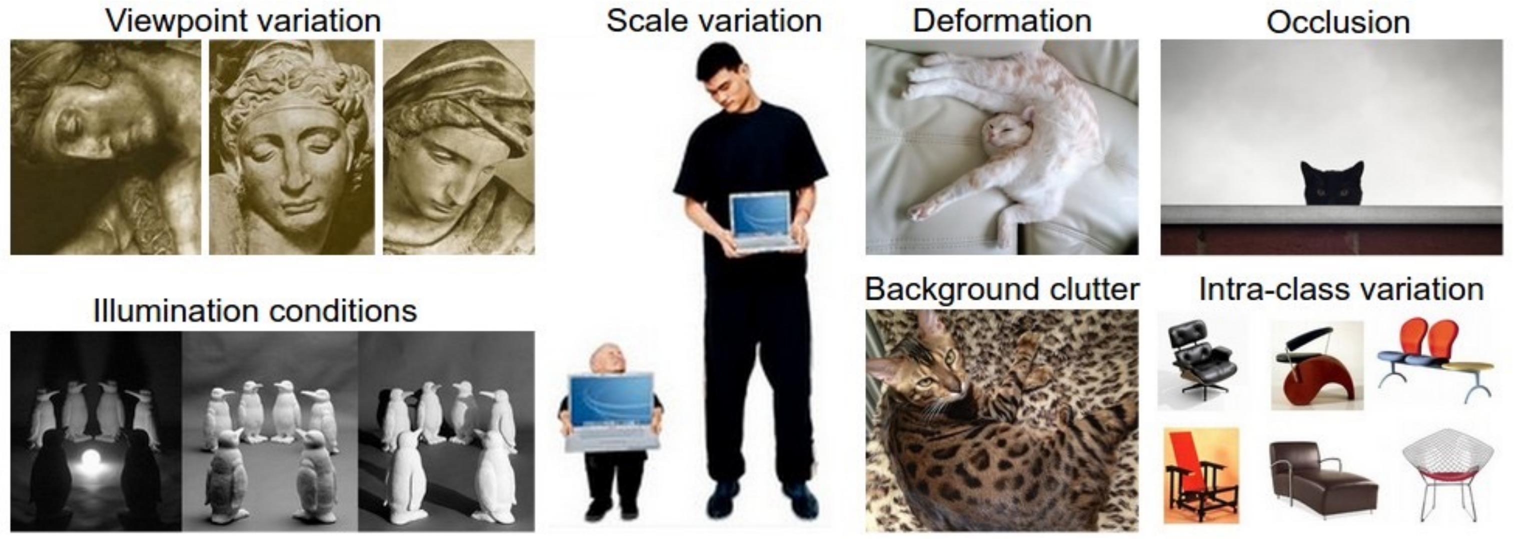



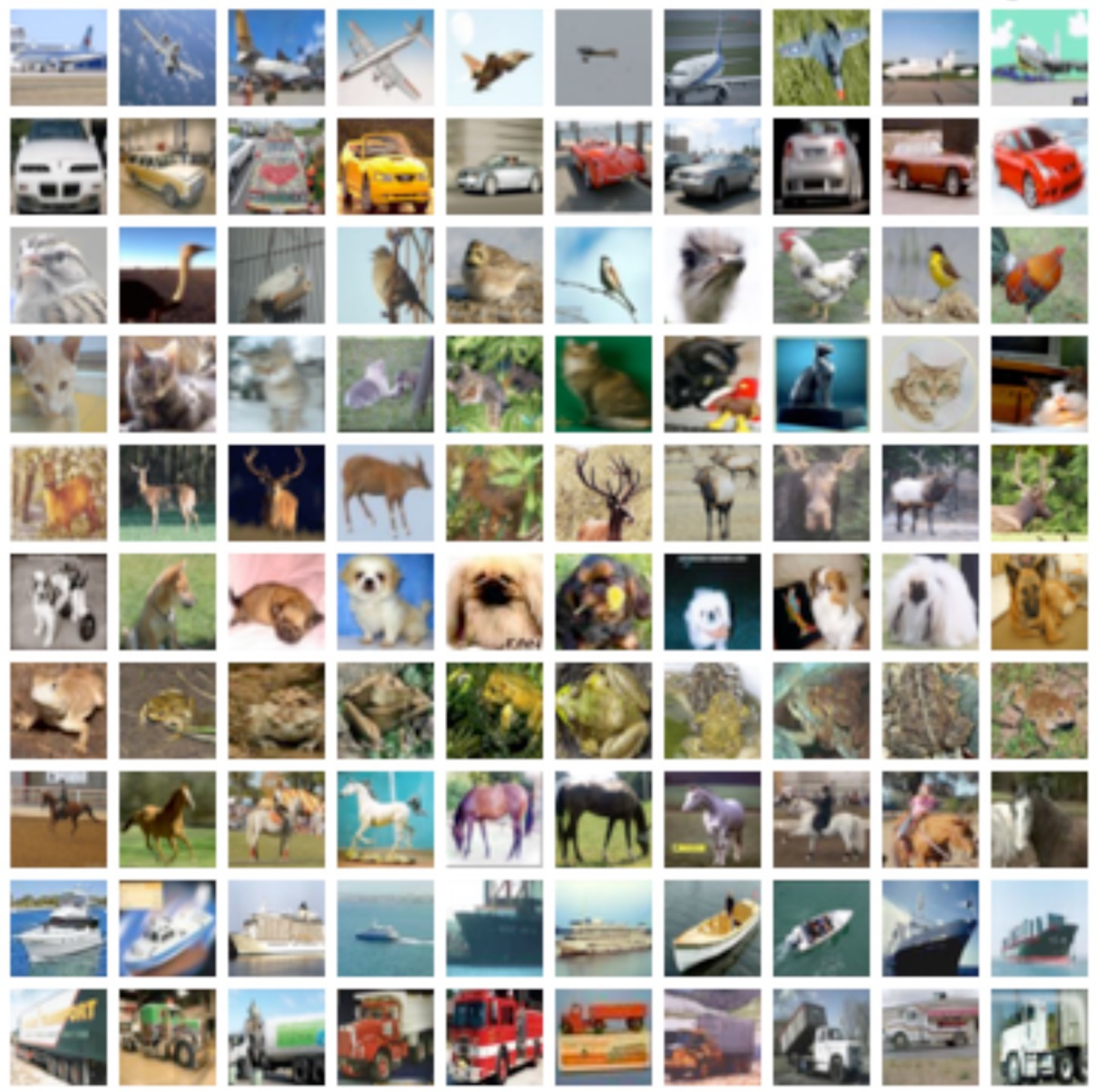
Strike (with) a Pose: Neural Networks Are Easily Fooled by Strange Poses of Familiar Objects. Alcorn et al. 2019

https://arxiv.org/pdf/1811.11553.pdf

Computer Vision Challenges

- **Viewpoint Variation**
  - A single instance of an object can be oriented in many ways with respect to the camera
- **Scale variation**
  - Visual classes often exhibit variation in their size (size in the real world, not only in terms of their extent in the image)
- **Deformation**
  - Many objects of interest are not rigid bodies and can be deformed in extreme ways
- **Occlusion**
  - The objects of interest can be occluded. Sometimes only a small portion of an object (as little as few pixels) could be visible
- **Illumination Condition**
  - The effects of illumination are drastic on the pixel level
- **Background clutter**
  - The objects of interest may blend into their environment, making them hard to identify
- **Intra-class variation**
  - The classes of interest can often be relatively broad, such as chair. There are many different types of these objects, each with their own appearance



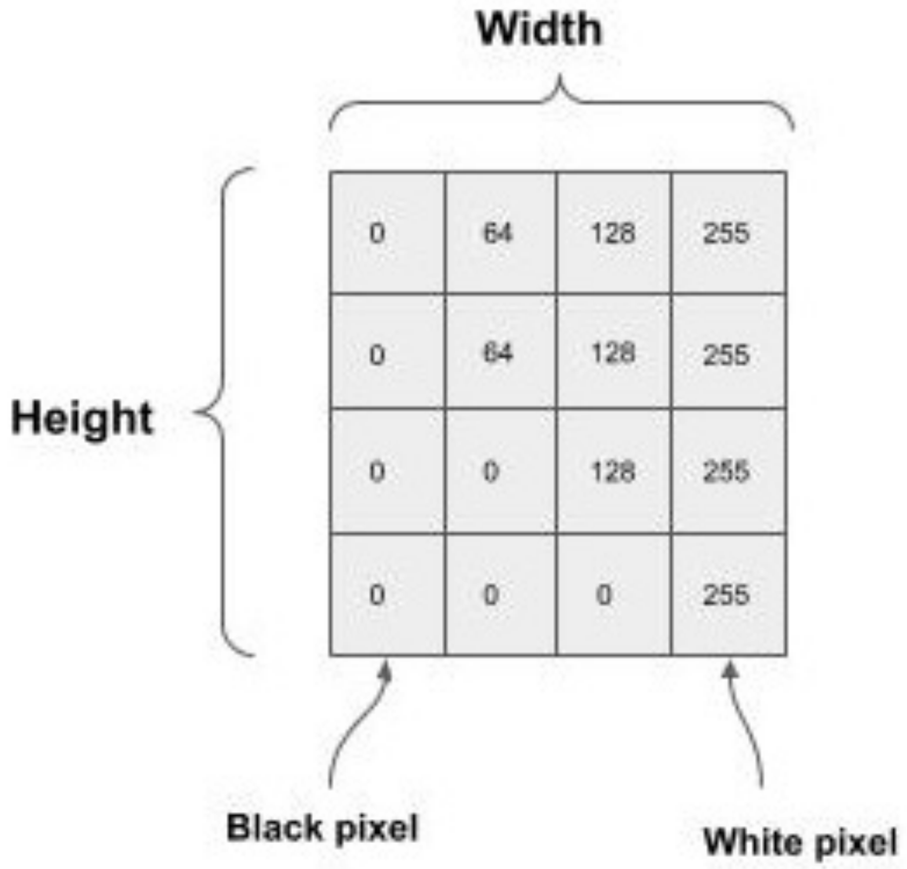


Let's see this in practice: Real-time Object Detection Demo

Model: [YOLOv5 in PyTorch] when / where does the model fail?
Find code on: https://aml4design.github.io/code/

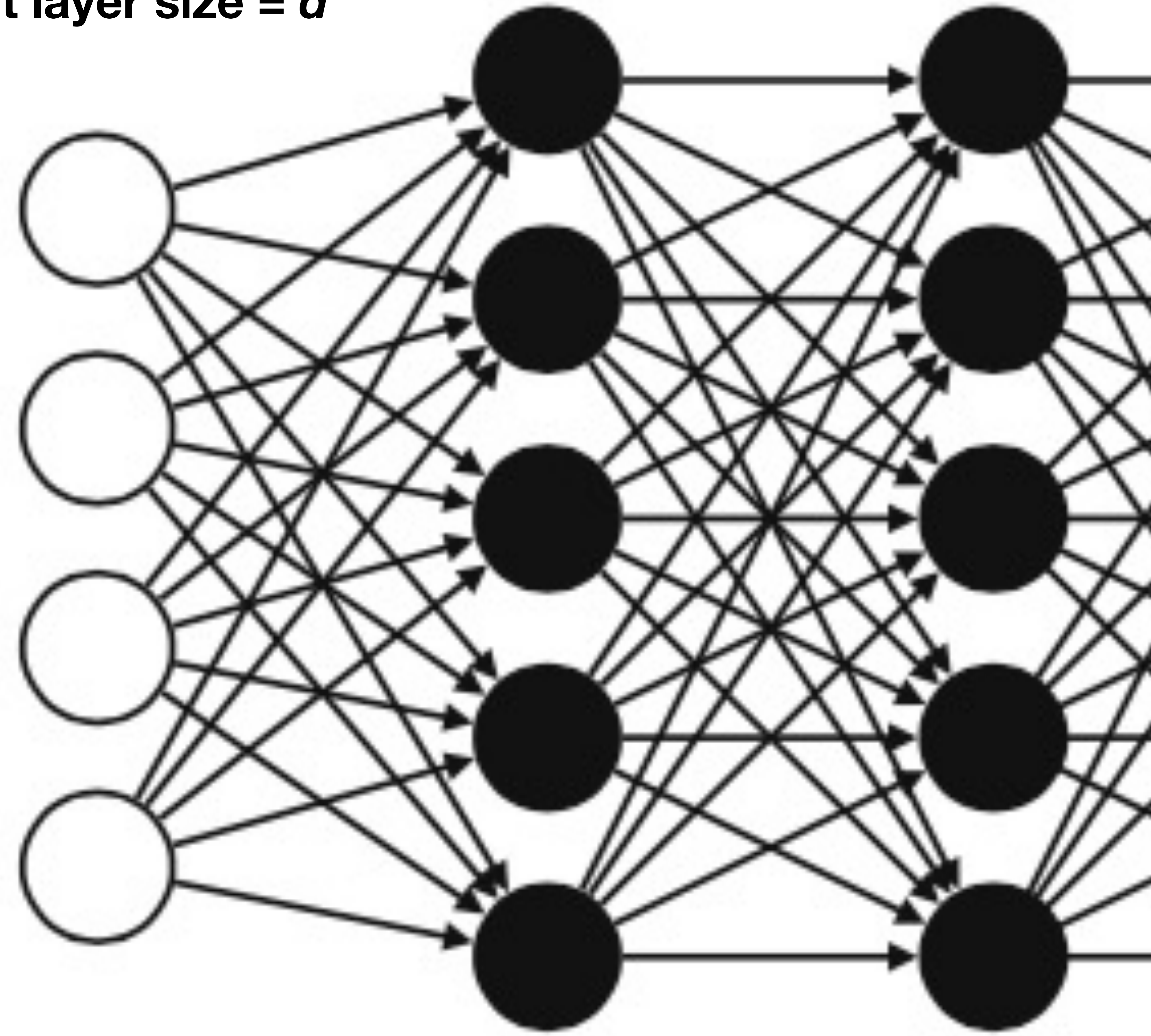
How CV models work?

Flattening



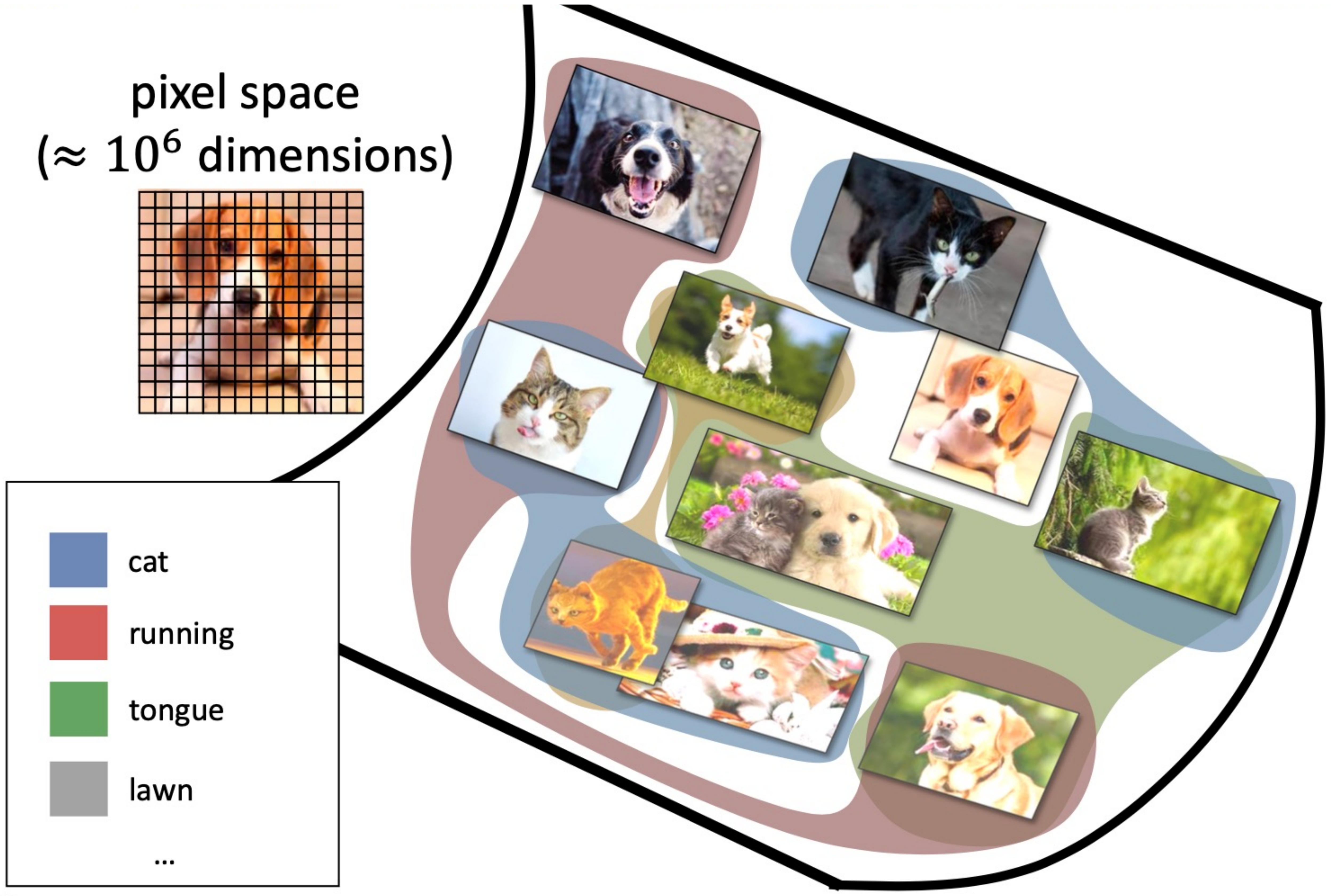
d = width x height

Input layer size = *d*

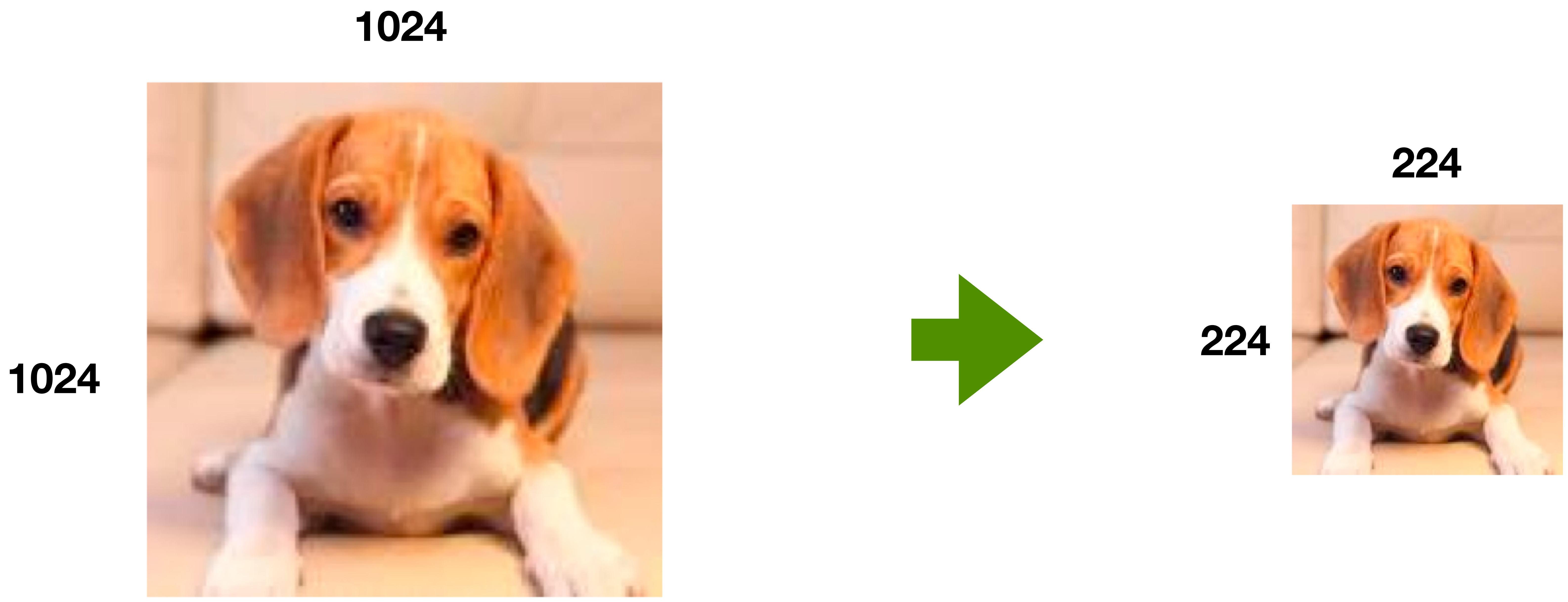


Curse of dimensionality

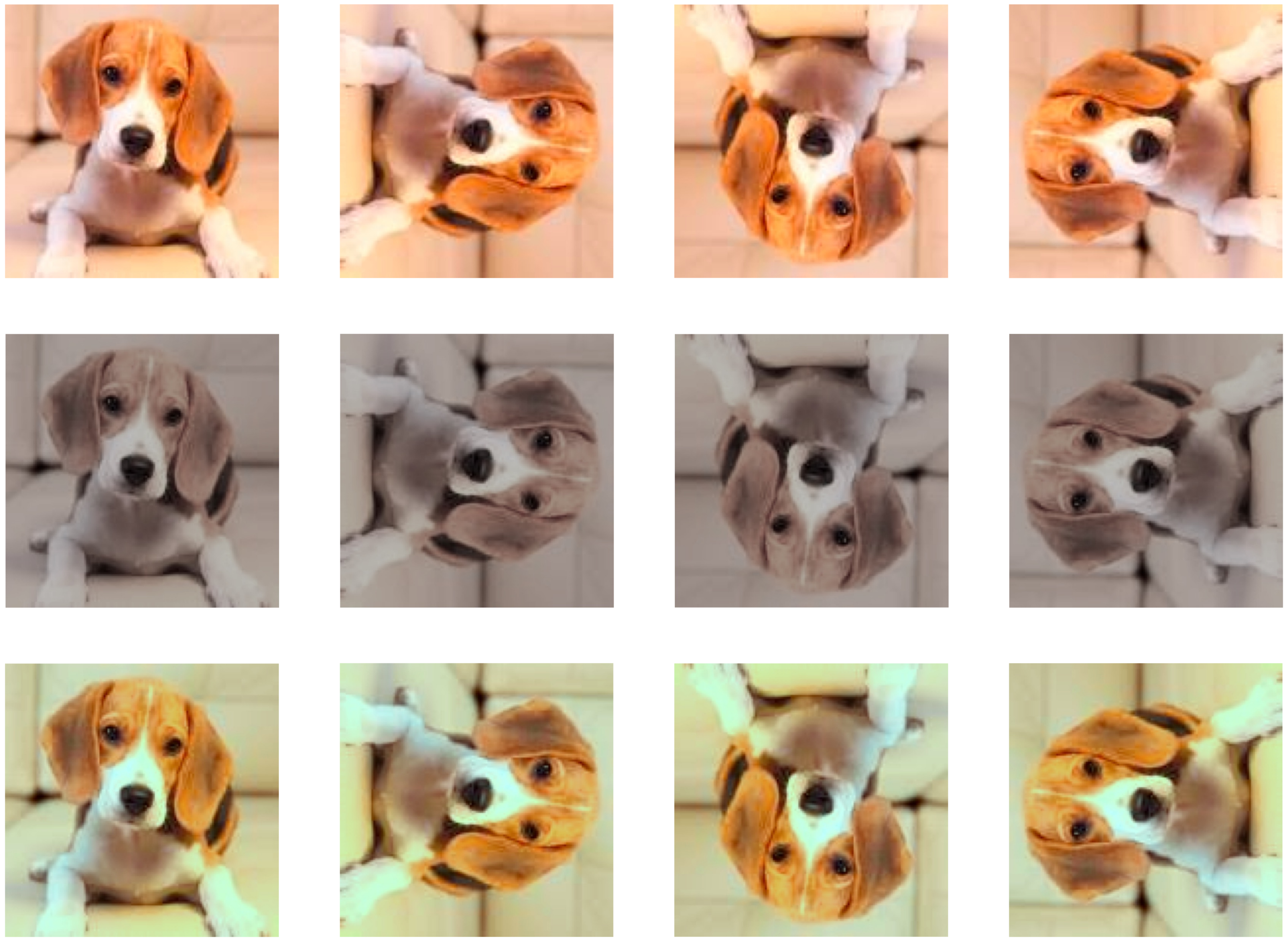
- High dimensionality
  - A 1024×768 image has *d = 786432*!
  - A tiny 32×32 image has *d = 1024*
- Decision boundaries in pixel space are extremely complex
- We will need "big" ML models with lots of parameters
  - For example, linear regressors need *d* parameters



Downsampling

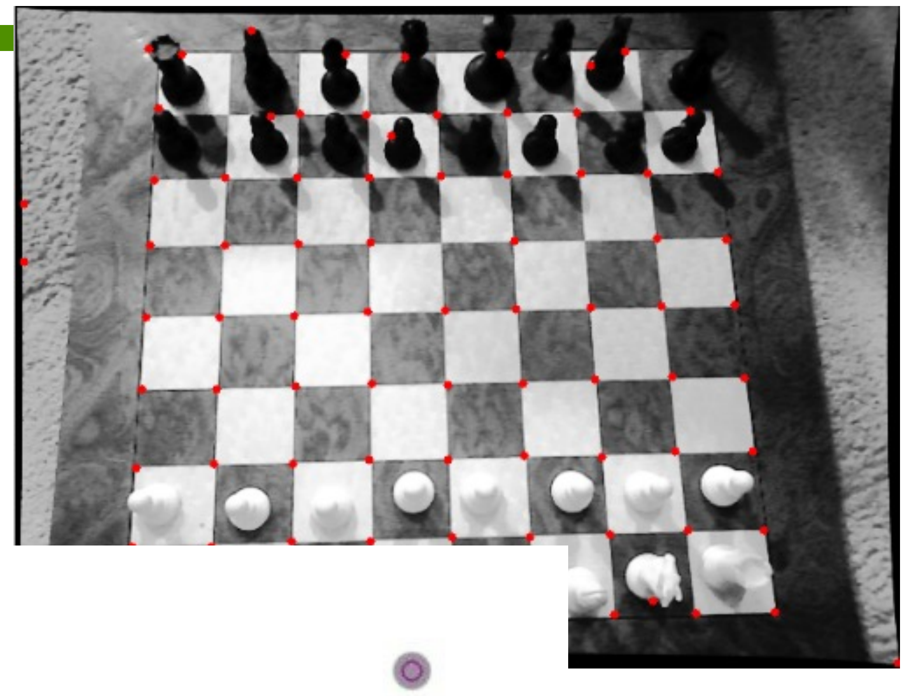


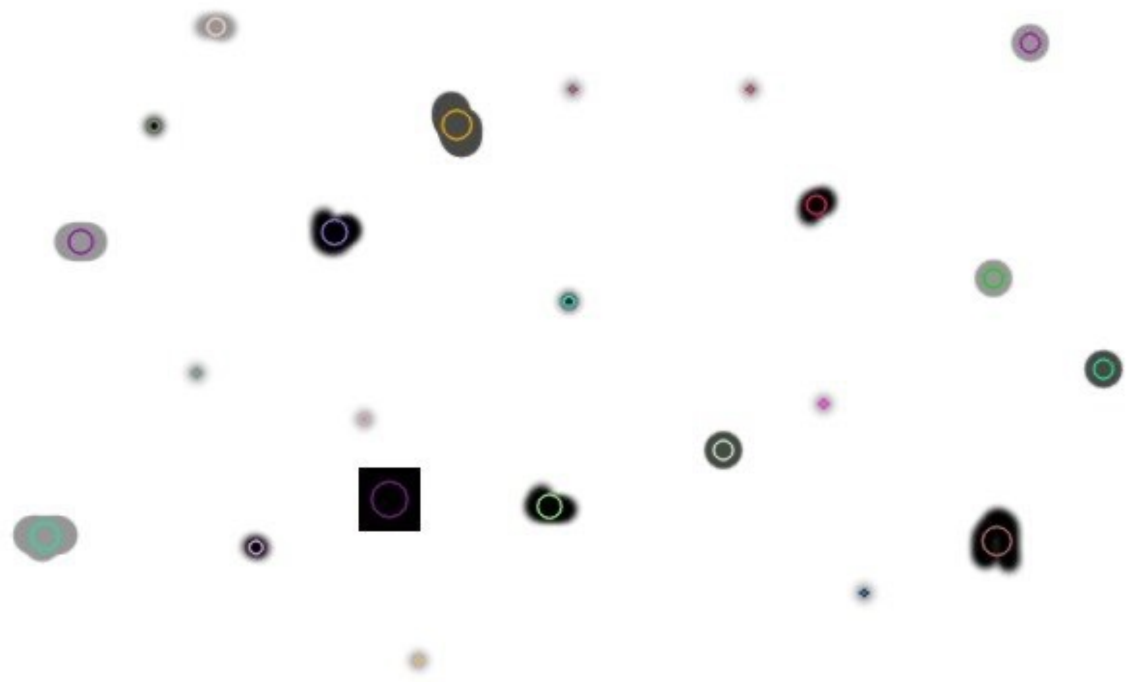
What about generalisation?



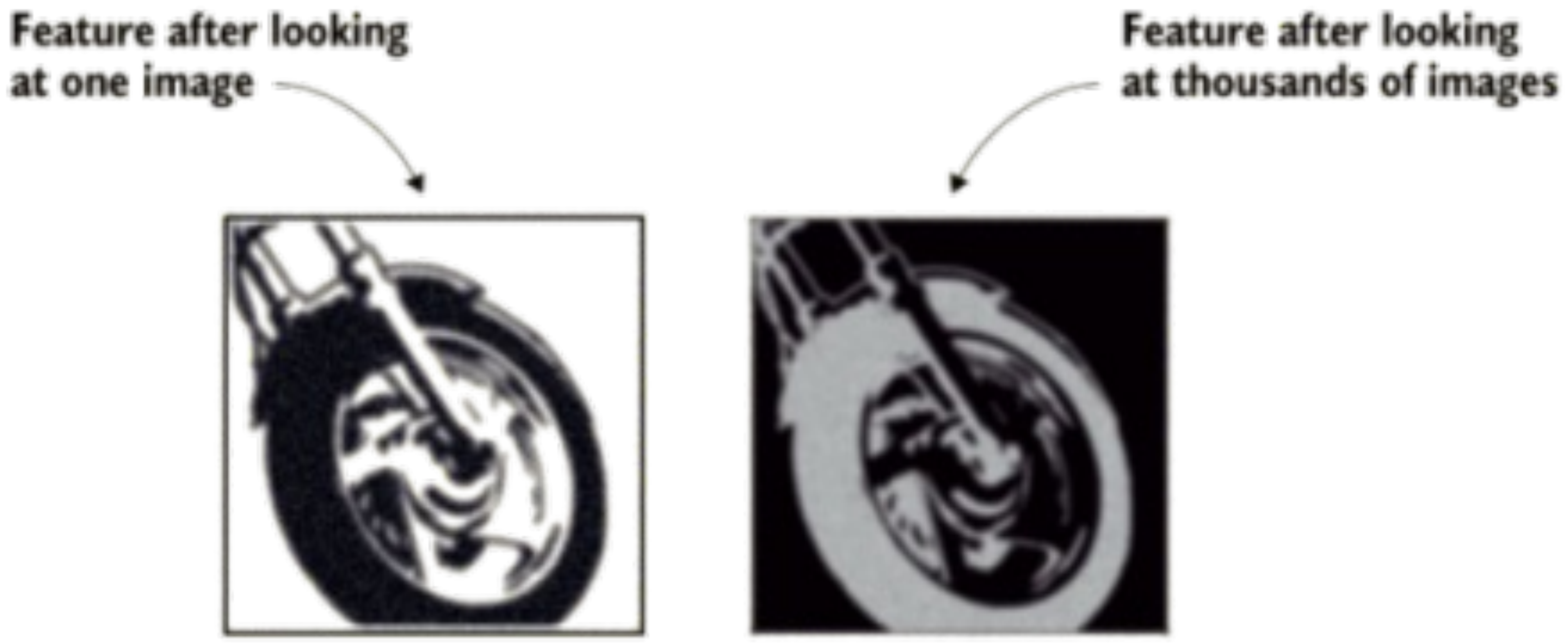
The "old days:" Feature Extraction

- **Feature**
  - A relevant piece of information about the content of an image
    - e.g., edges, corners, blobs (regions), ridges





- A good feature:
    - is repeatable
    - identifiable
    - can be easily tracked and compared
    - is consistent across different scales, lighting conditions, and viewing angles
    - is still visible in noisy images or when only part of an object is visible
    - can distinguish objects from one another

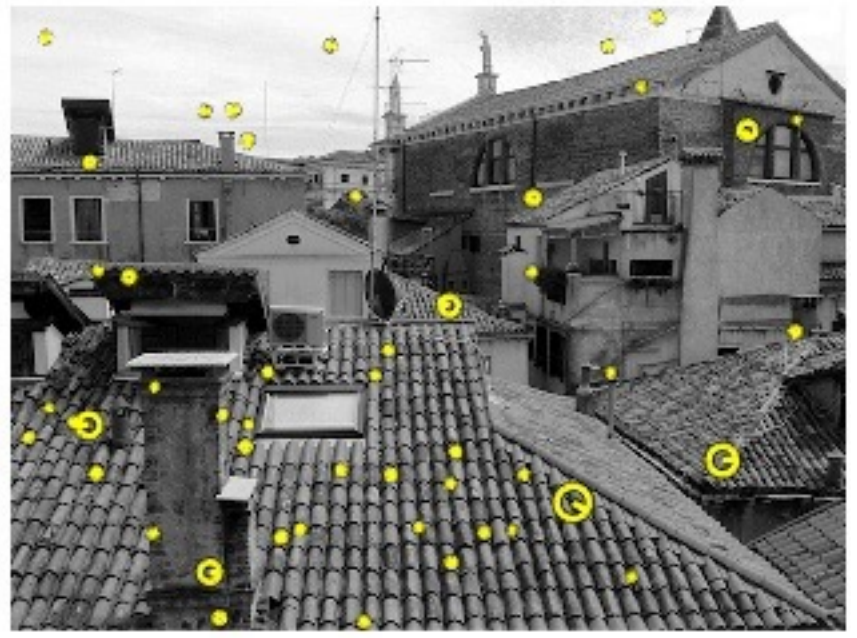


Feature Extraction Techniques

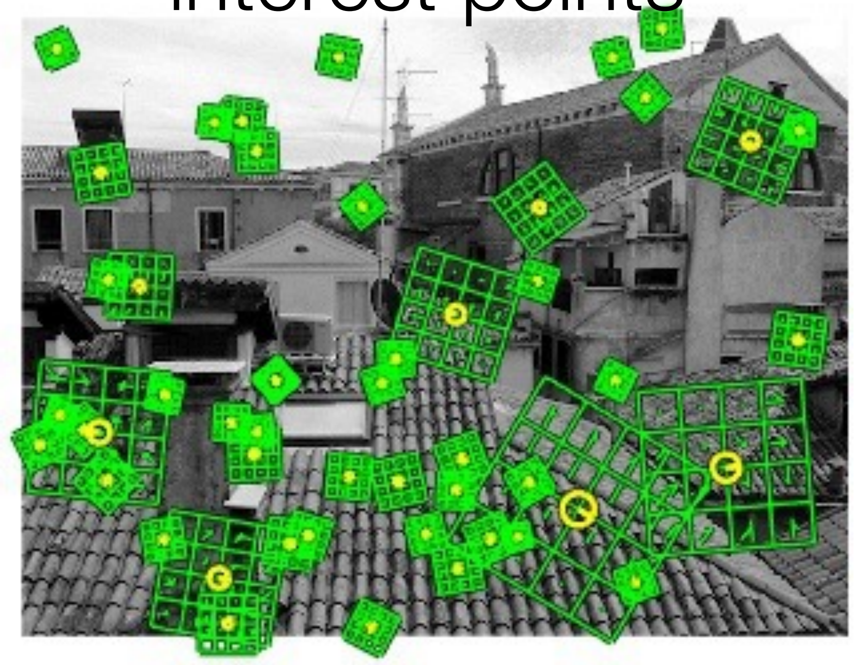
https://www.vlfeat.org

Scale-Invariant Feature Transform (SIFT)

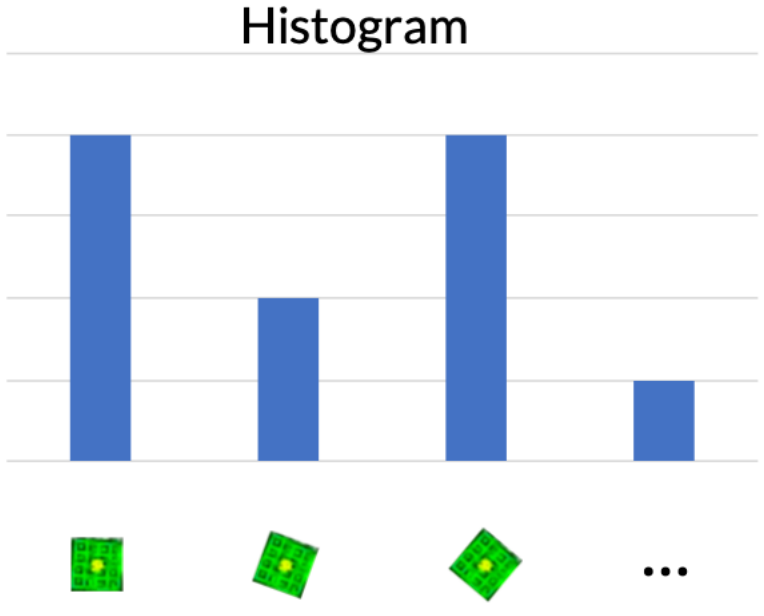
Find “interest points”
in the scene



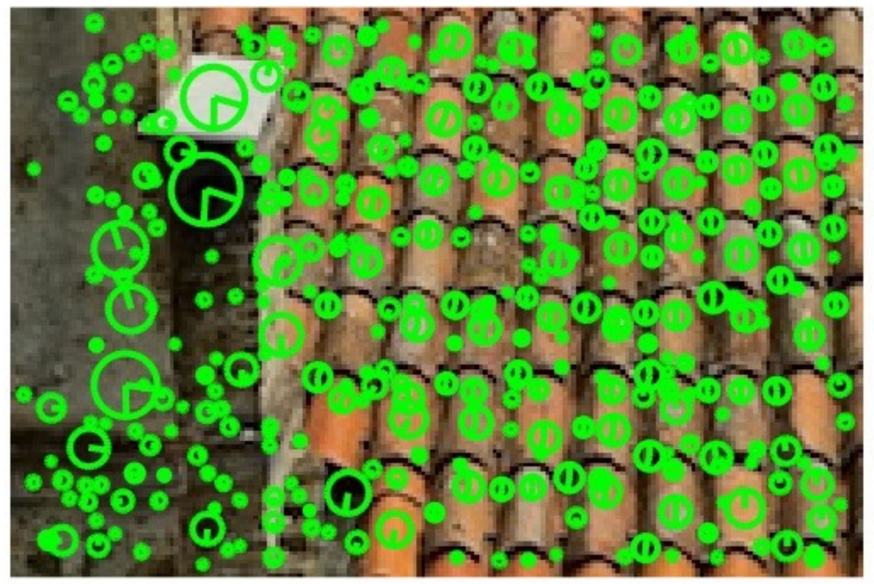
Compute features at
interest points



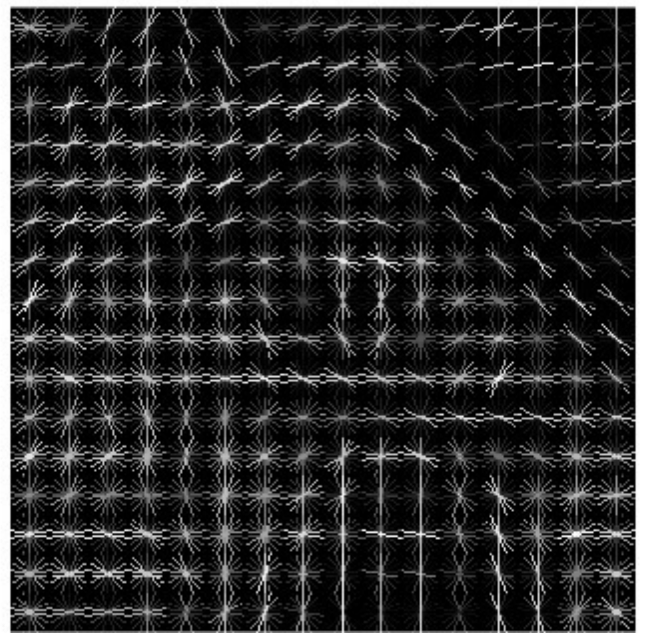
Convert to fixed-dimensional
feature vector



Co-variant feature detector

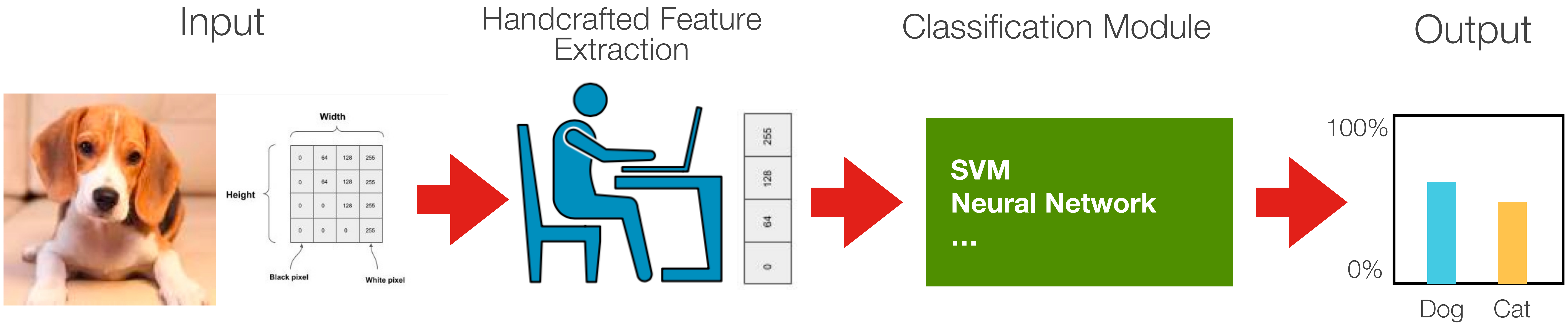


Histogram and oriented gradients



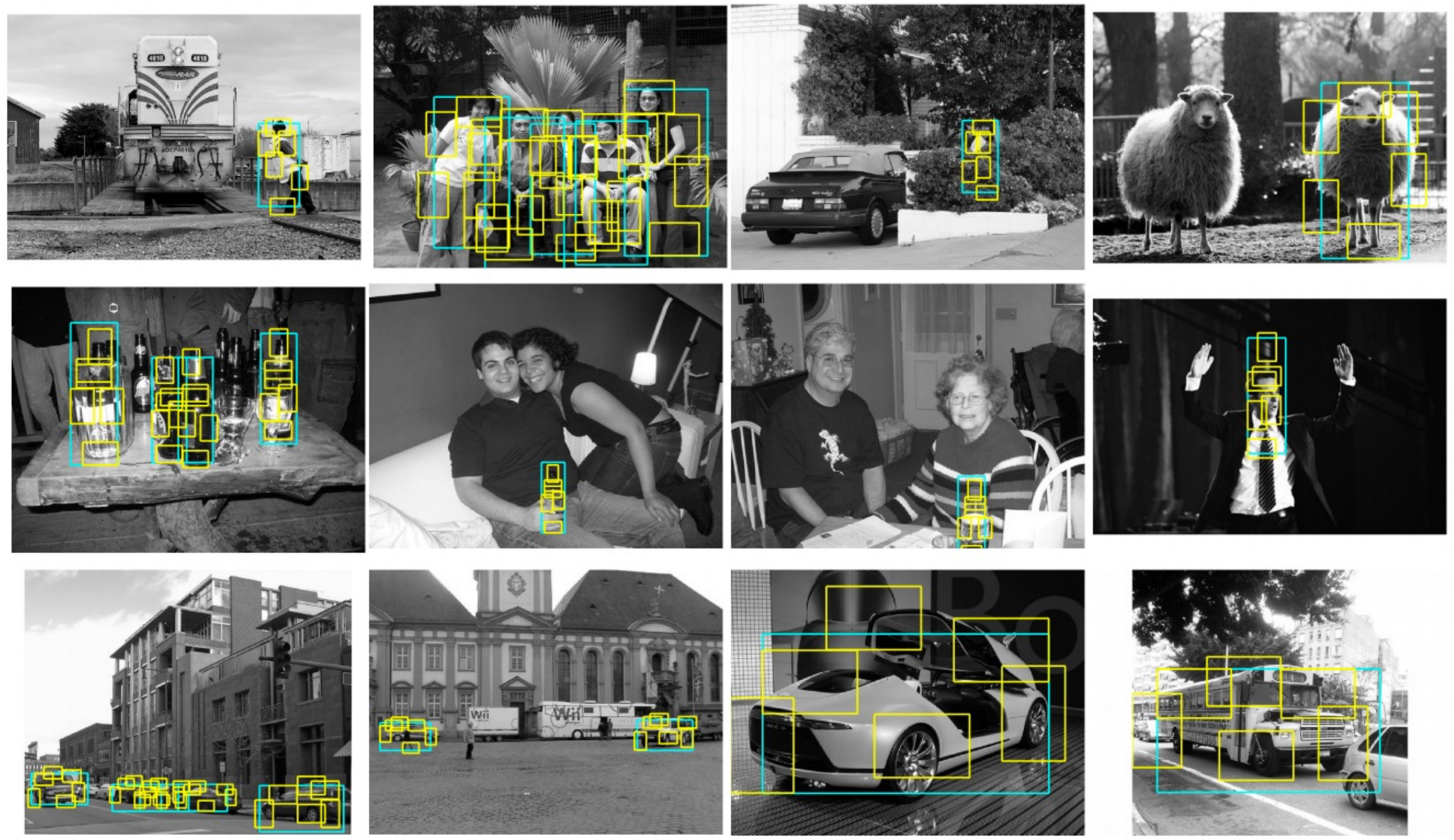
The “old days:” Feature Engineering

- Machine learning models are only as good as the features you provide them with
- To figure out which features you should use for a specific problem
  - rely on domain knowledge (or partner with domain experts)
  - experiment to create features that make machine learning algorithms work better



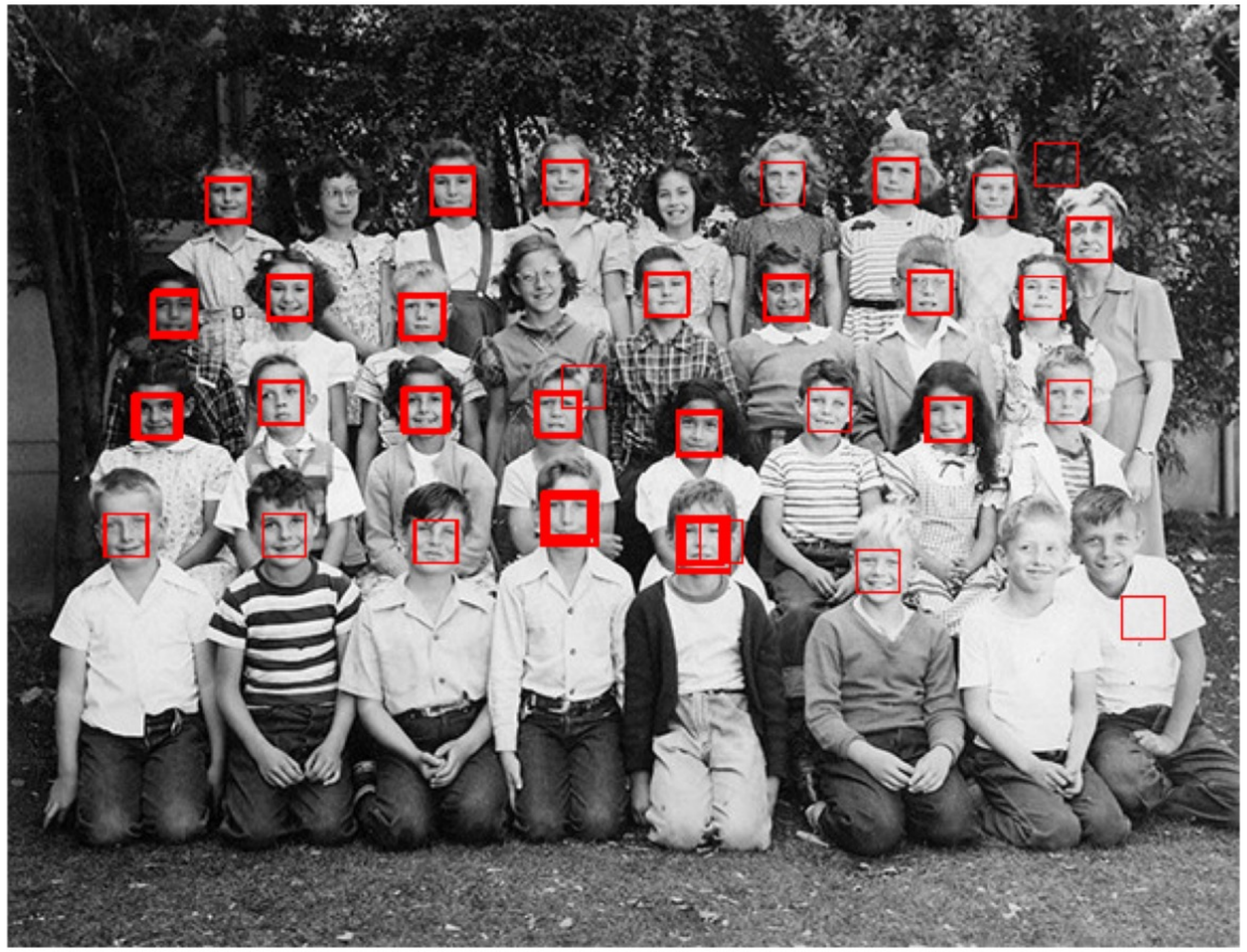
Performance

Object Detection (~2007)



Felzenszwalb, Ramanan, McAllester. A Discriminatively Trained, Multiscale, Deformable Part Model. CVPR 2008 (DPM v1)

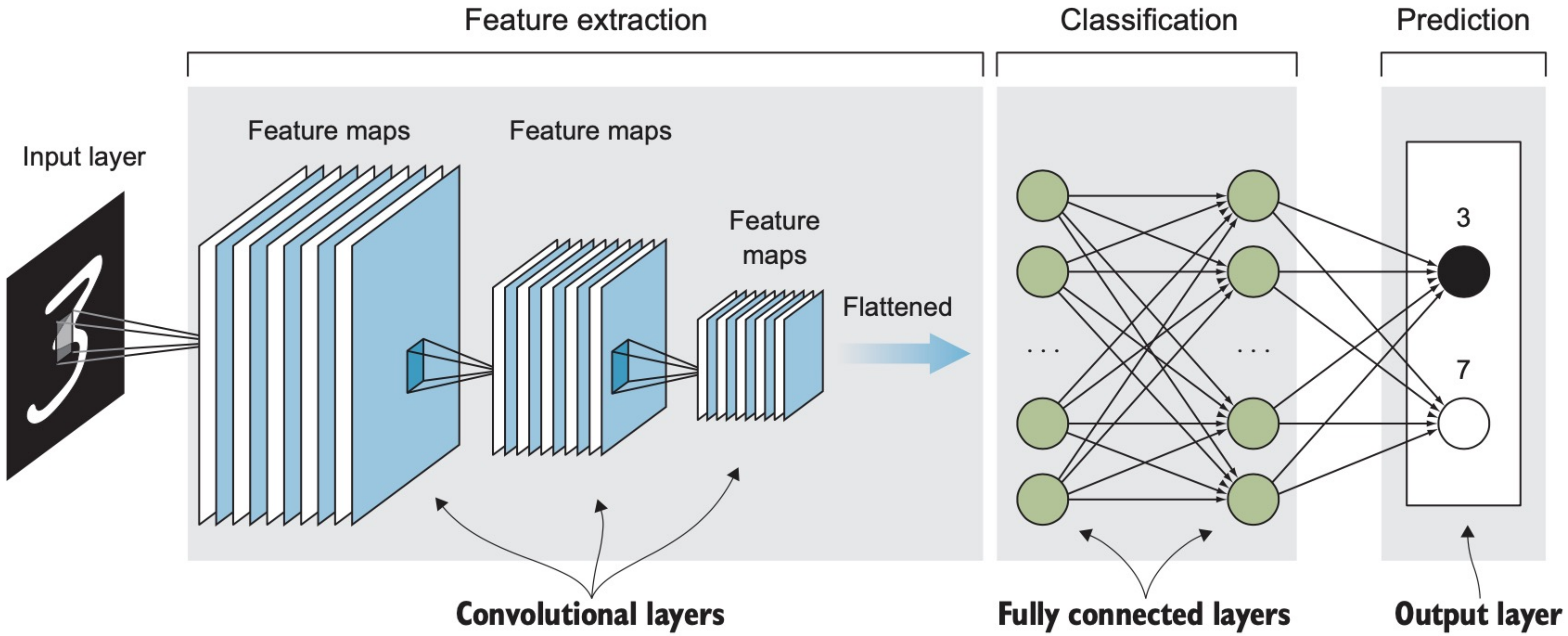
Face Detection (~2013)



https://github.com/alexdemartos/ViolaAndJones

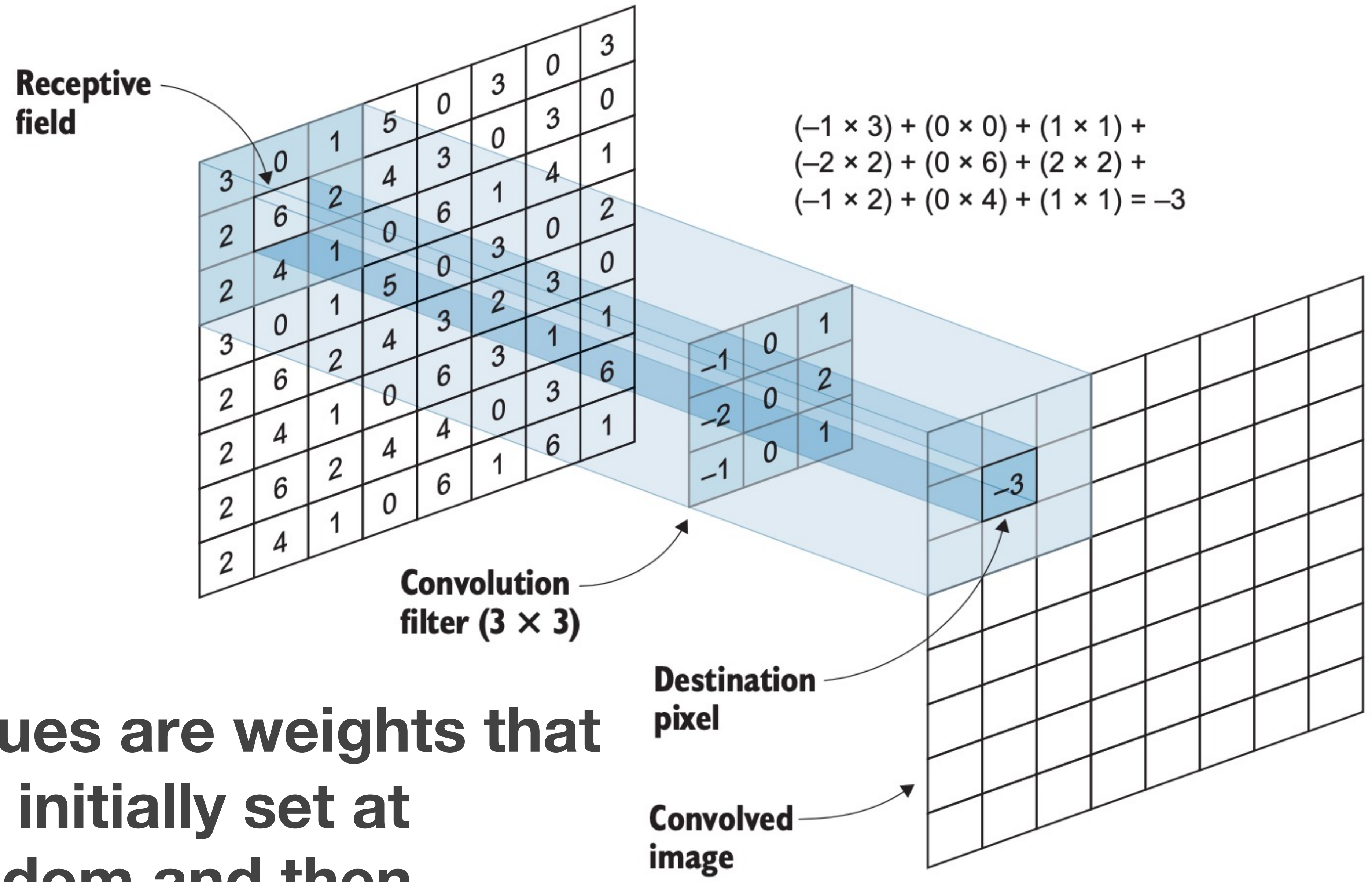
Credits: Ross Girshick (Facebook AI Research)

Convolutional Neural Networks

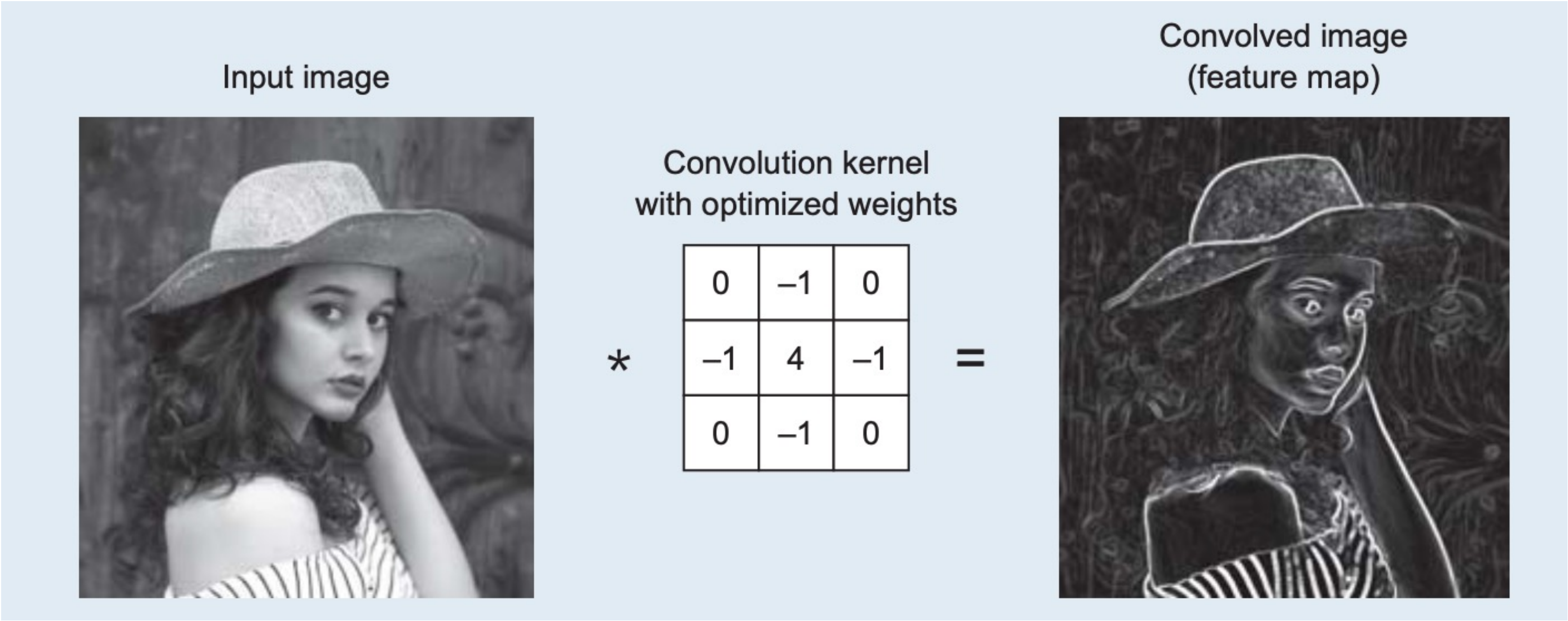


- CNNs exploit image properties to drastically reduce the number of model parameters
- Feature maps
  - **Automatically** extracted hierarchical
  - Retain spatial association between pixels
- **Translation invariance**
  - a dog is a dog even if its image is shifted by a few pixels
- Local interactions
  - all processing happens within very small image windows
  - within each layer, far-away pixels cannot influence nearby pixels

Convolution & Feature Maps



Values are weights that are initially set at random and then learned

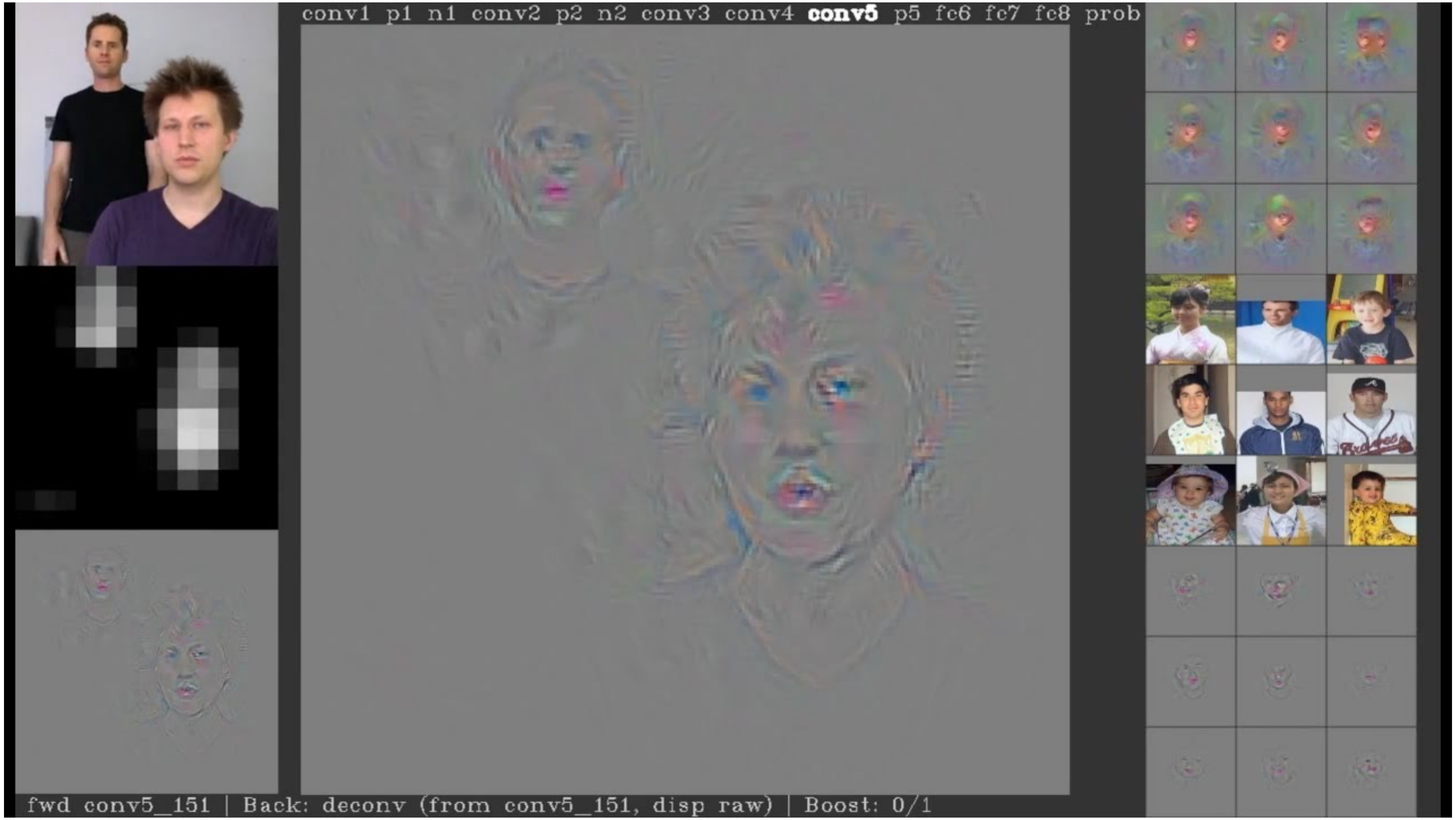


- Try this

https://cs.stanford.edu/people/karpathy/convnetjs/demo/mnist.html

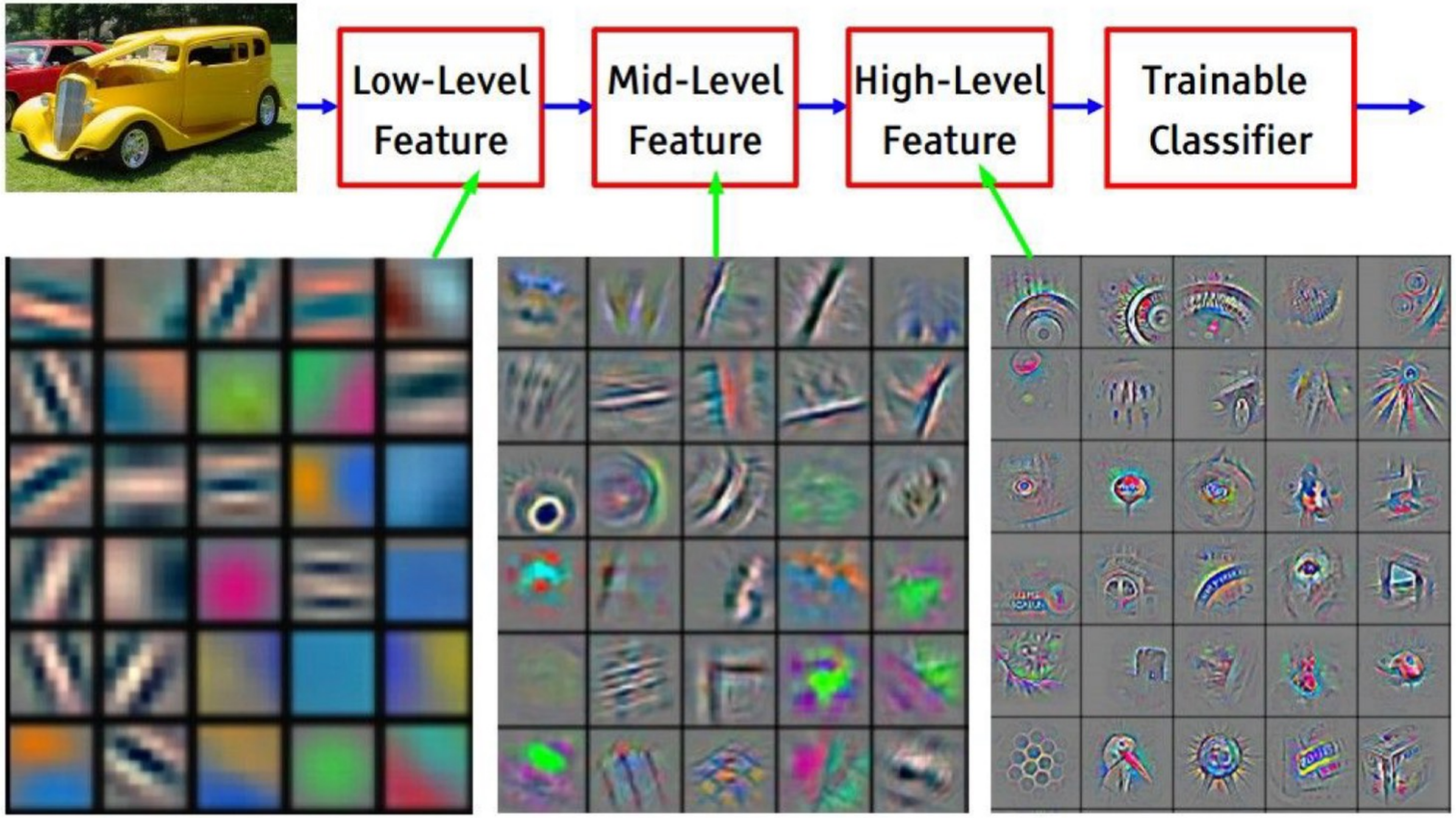
Deep Learning for Vision Systems. Mohamed Elgendy. Manning, 2020

What do CNN learn?

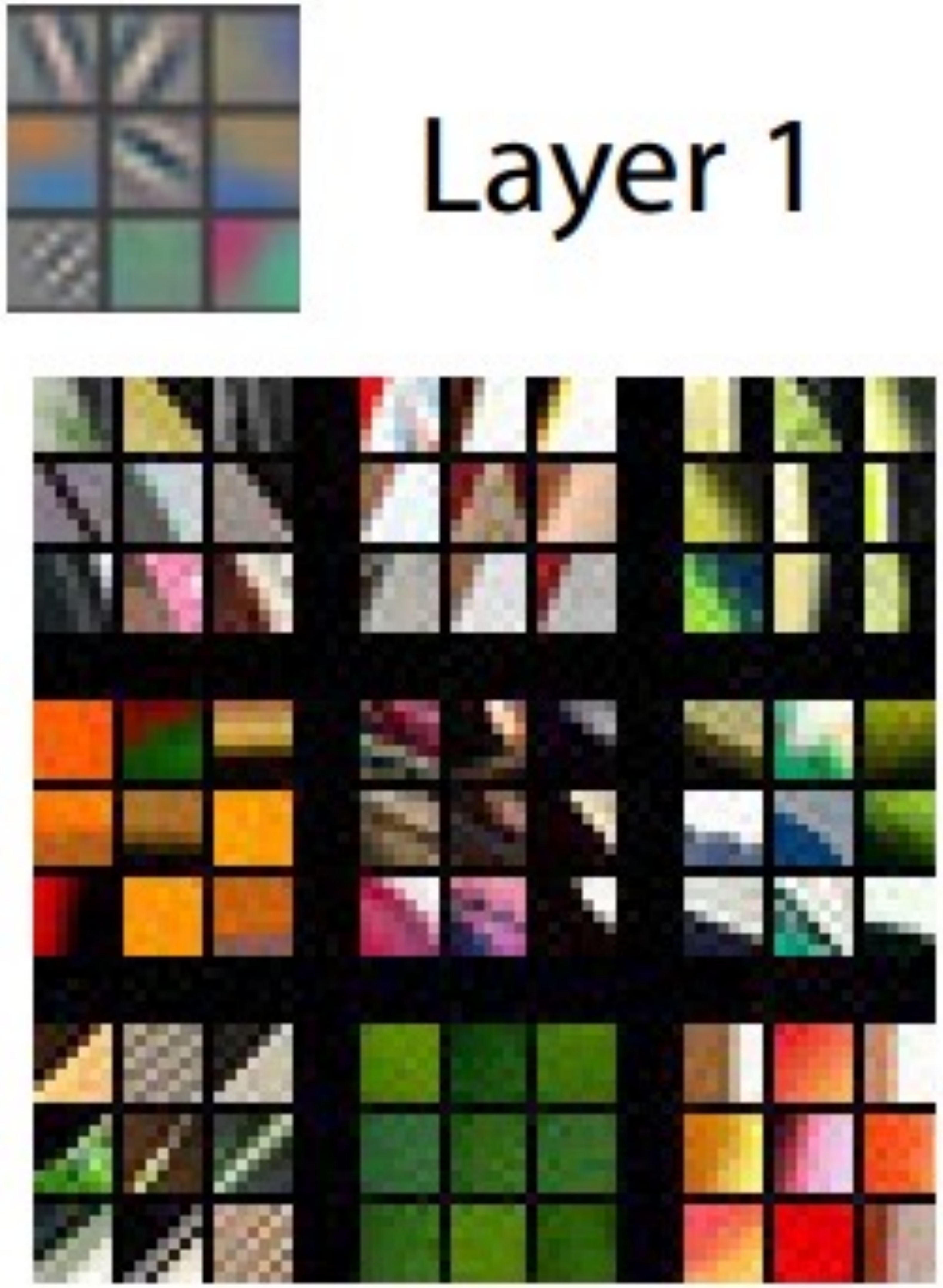


https://youtu.be/AgkfIQ4IGaM https://yosinski.com/deepvis

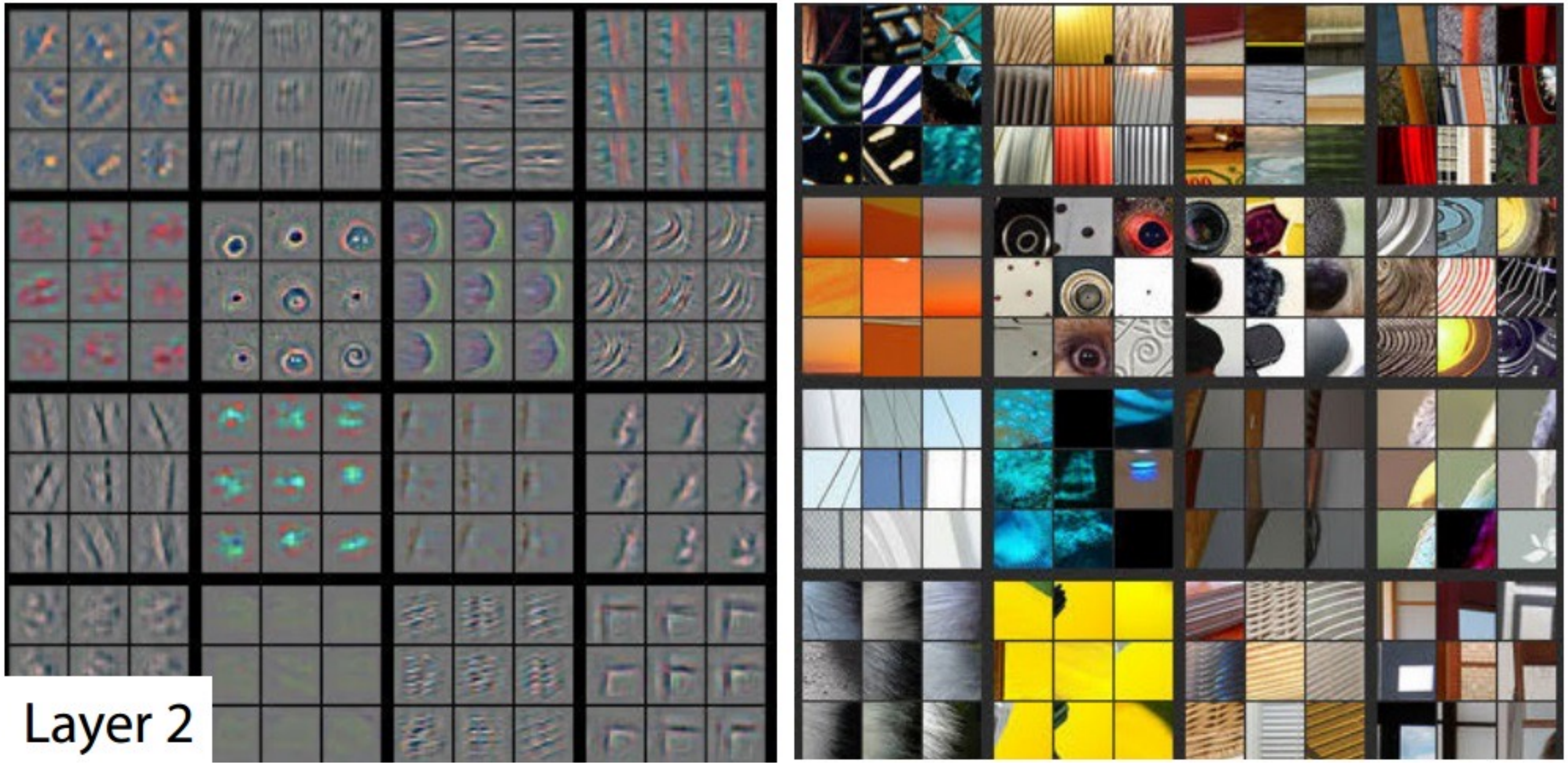
Feature Visualisation



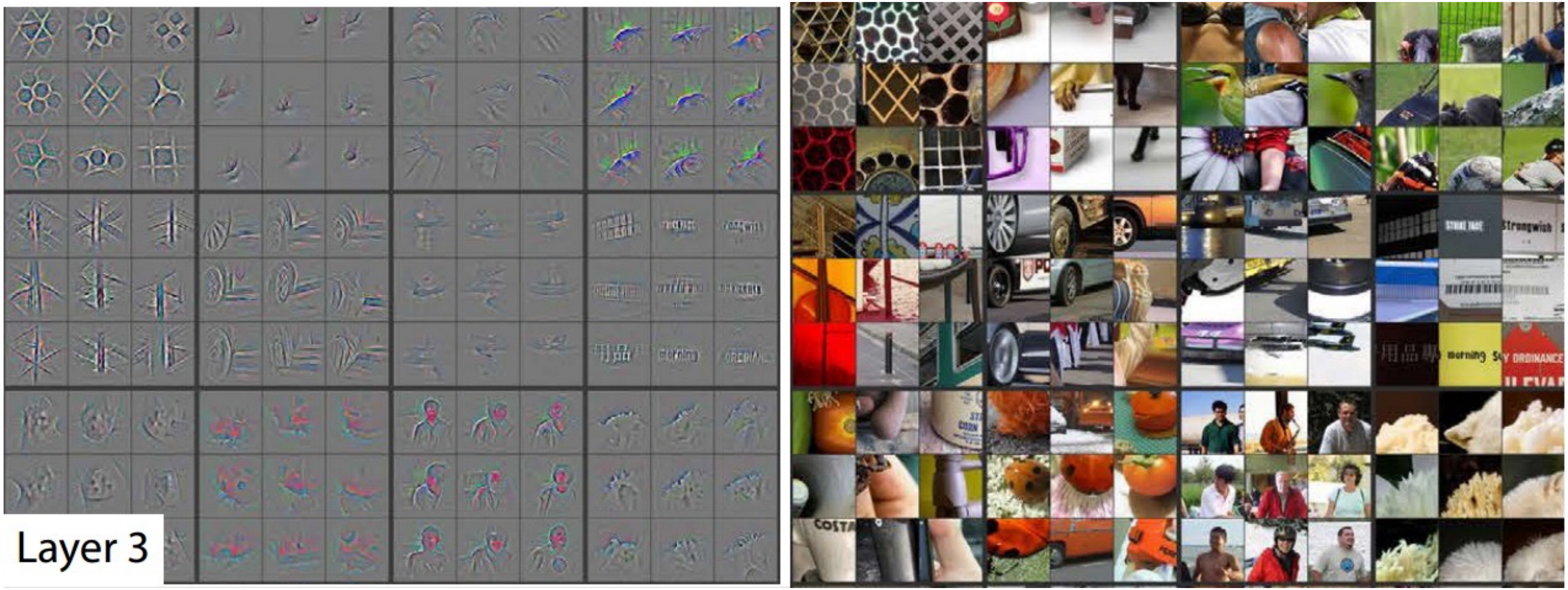
Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]



Visualizing and Understanding Convolutional Network. Zeiler and Fergus, ECCV 2014

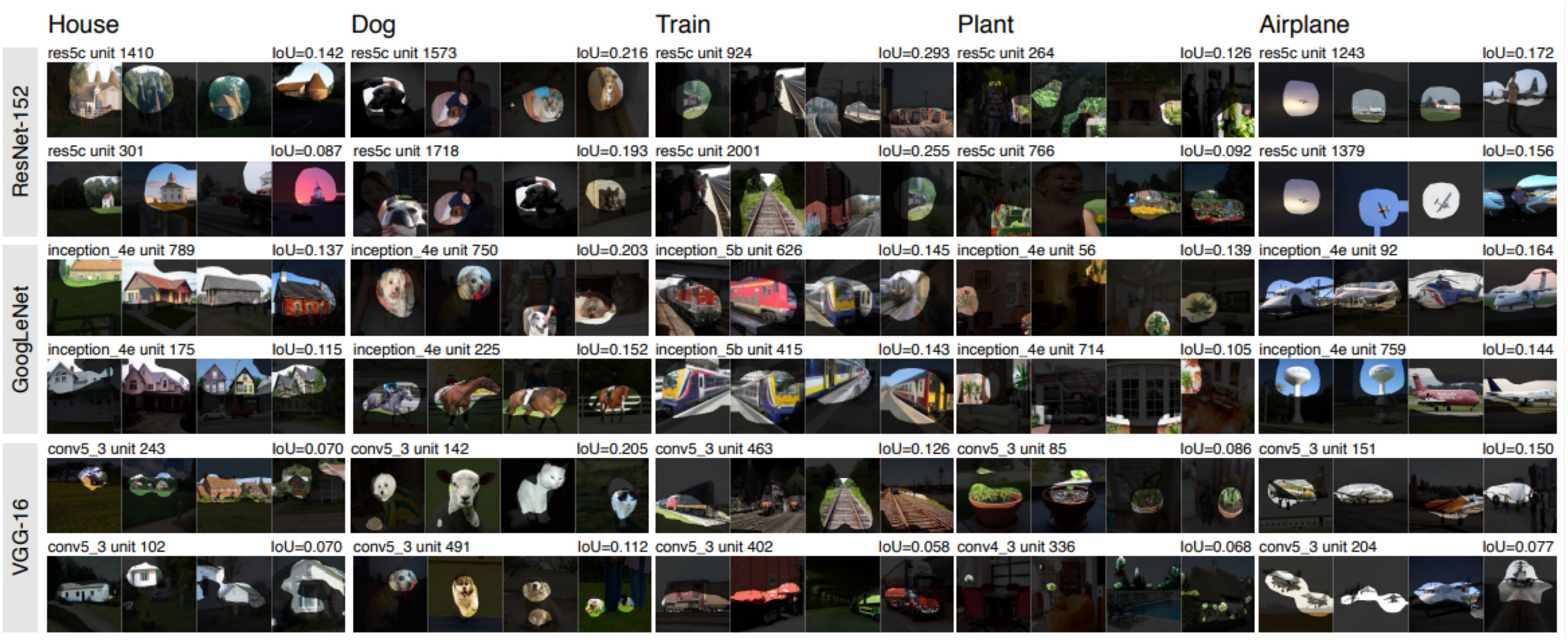


Visualizing and Understanding
Convolutional Network.
Zeiler and Fergus, ECCV 2014



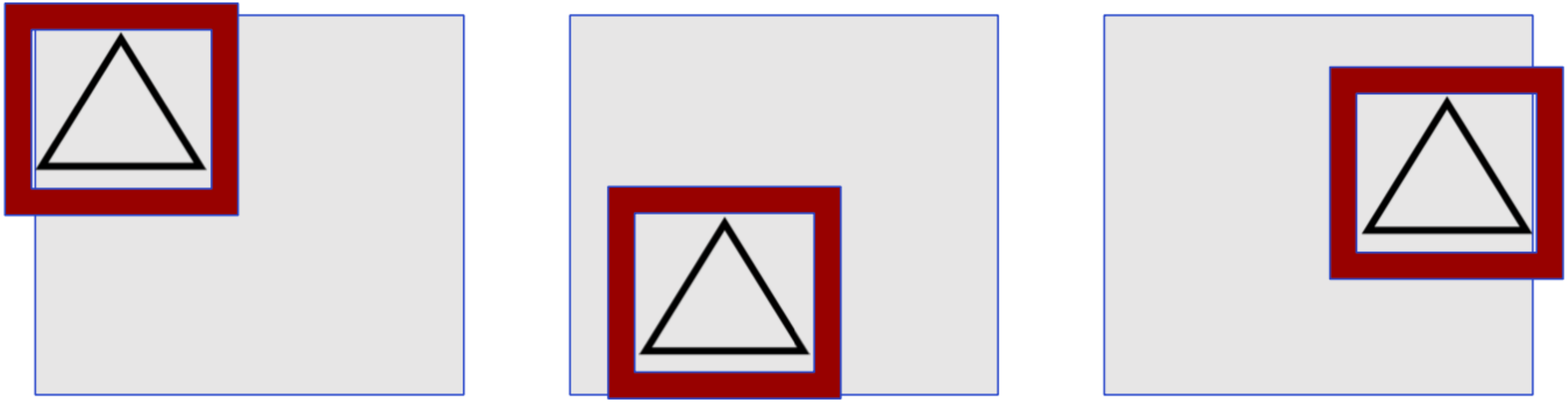
Visualizing and Understanding
Convolutional Network.
Zeiler and Fergus, ECCV 2014

Network dissection



http://netdissect.csail.mit.edu

Translation Invariance

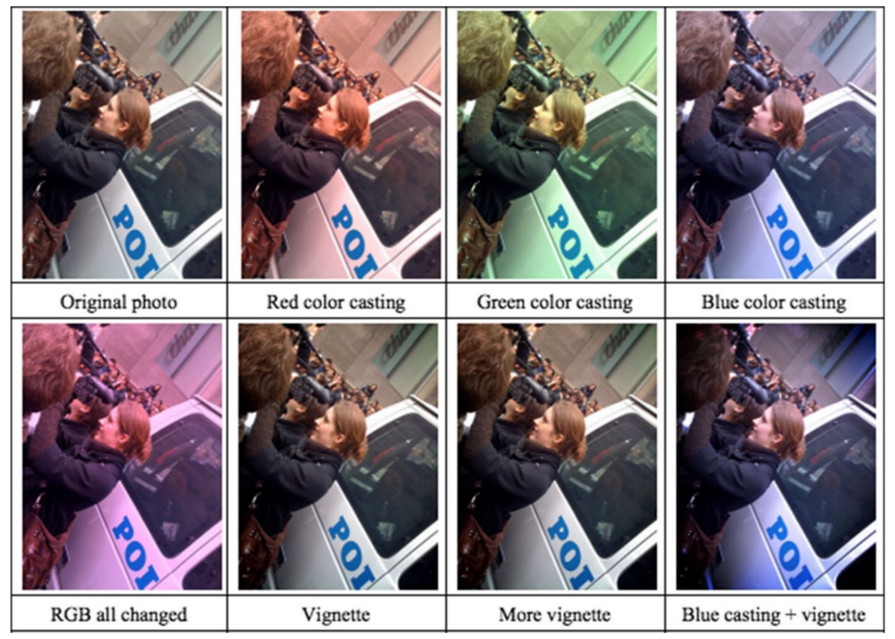


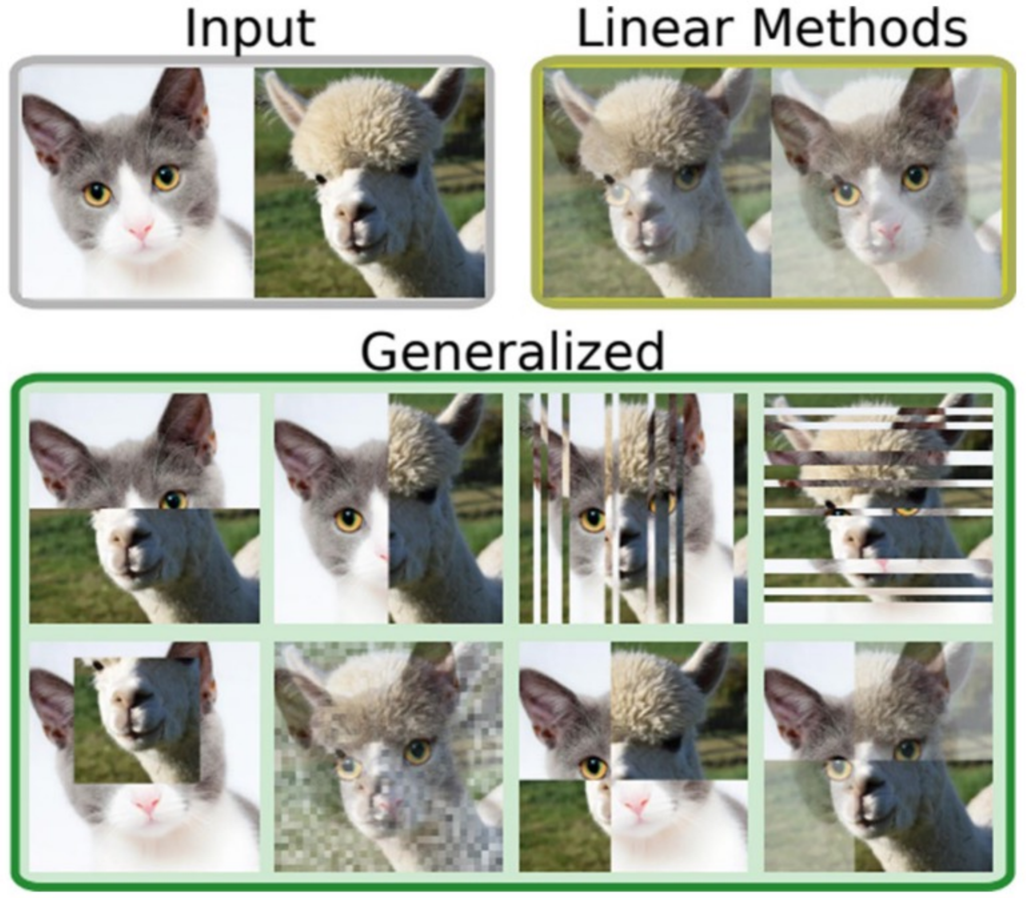
- But not rotation and scaling invariance!

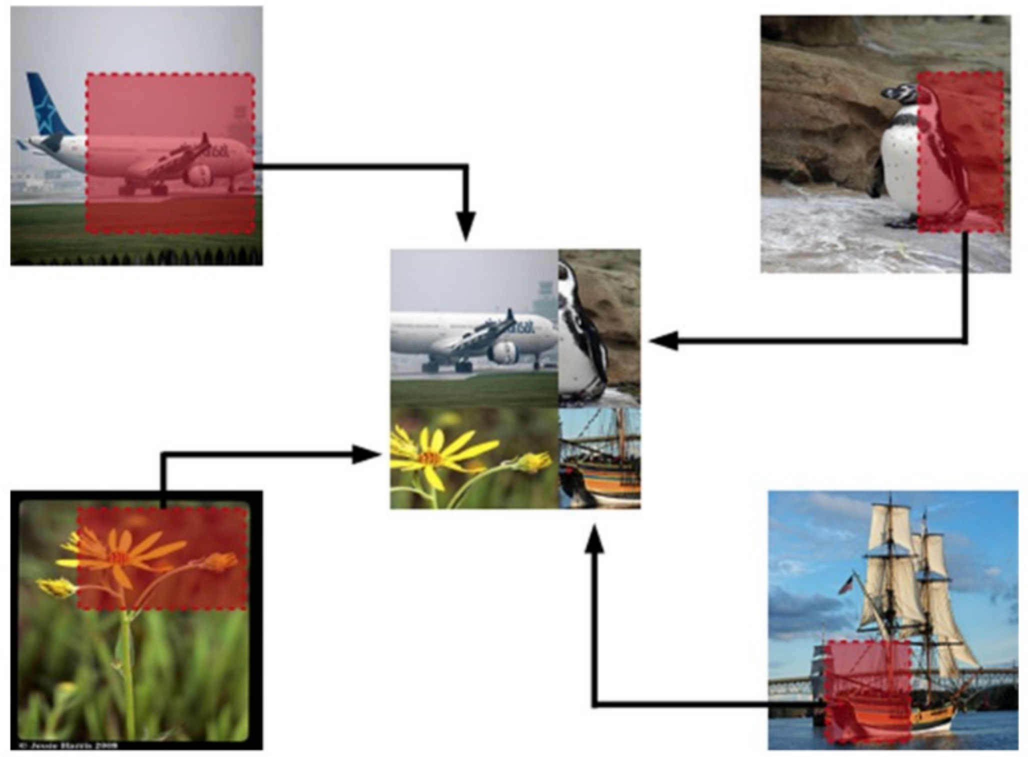
Data Augmentation

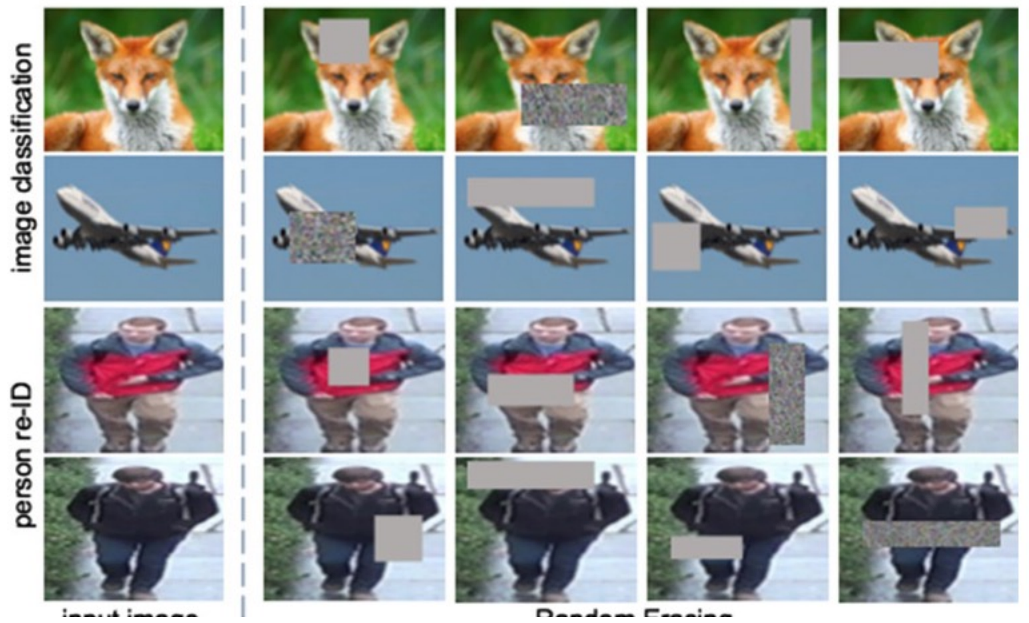
- Generate variations of the input data, to improve generalisability (out of distribution inputs)
  - Improve invariance (rotation, scaling, distortion)

- Geometric
  - Flipping
  - Color space
  - Cropping
  - Rotation
  - Translation
  - Noise Injection
- Color space transformation
- Mixing Images
- Random erasing
- Adversarial training
- GAN-based image generation



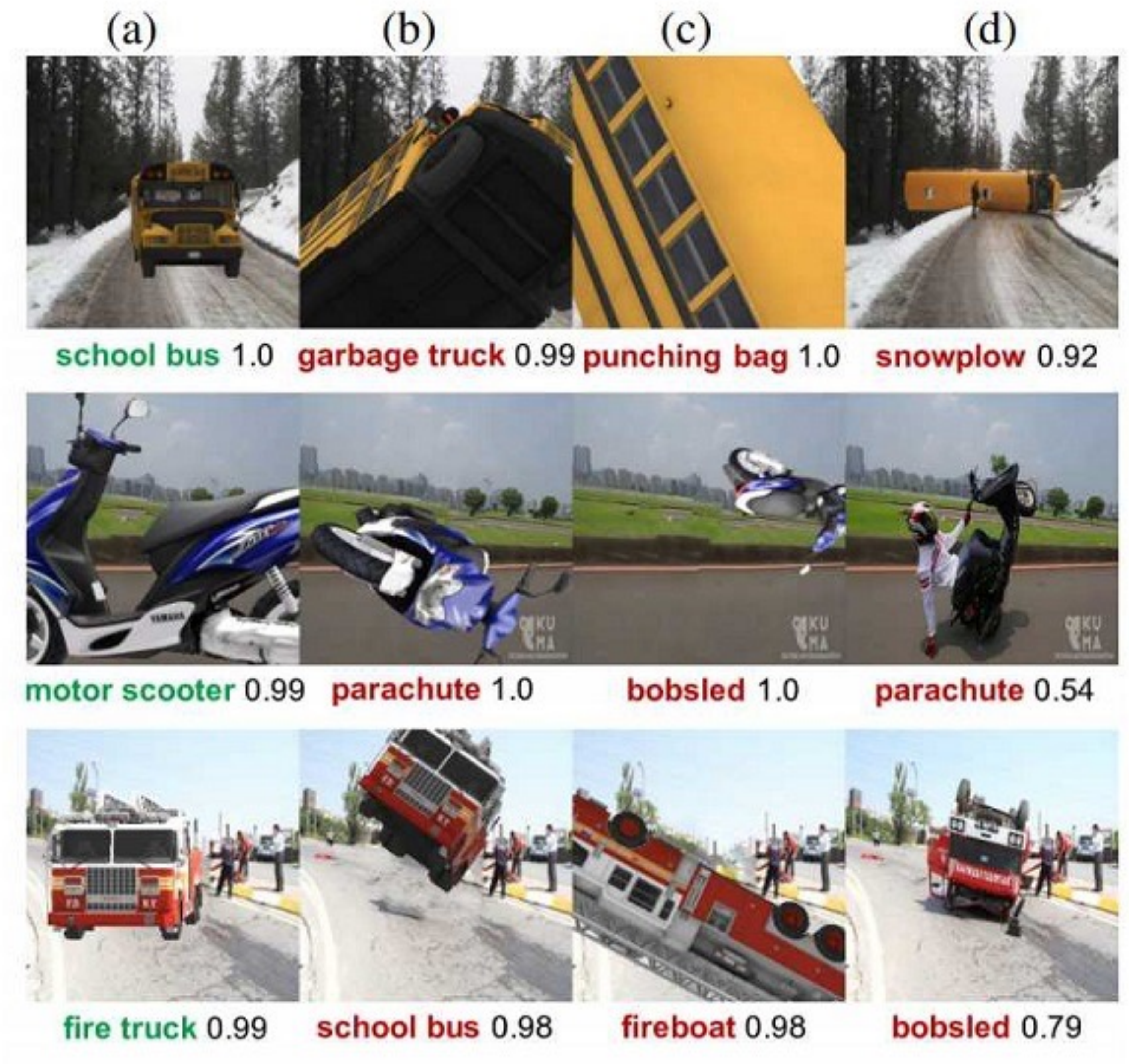






A survey on Image Data Augmentation for Deep Learning. Shorten, Journal of Big Data, 2019

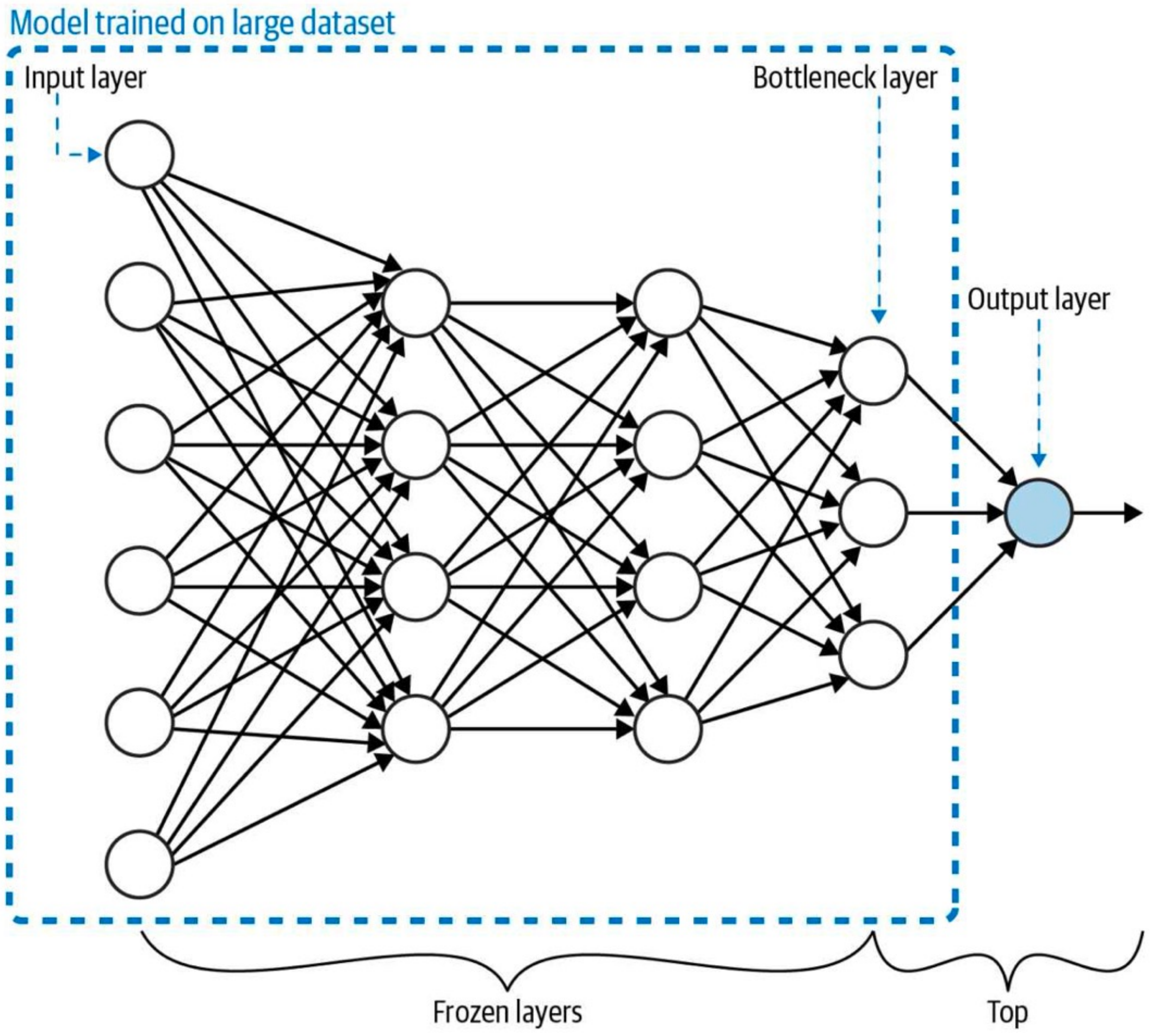
Robustness to input variation

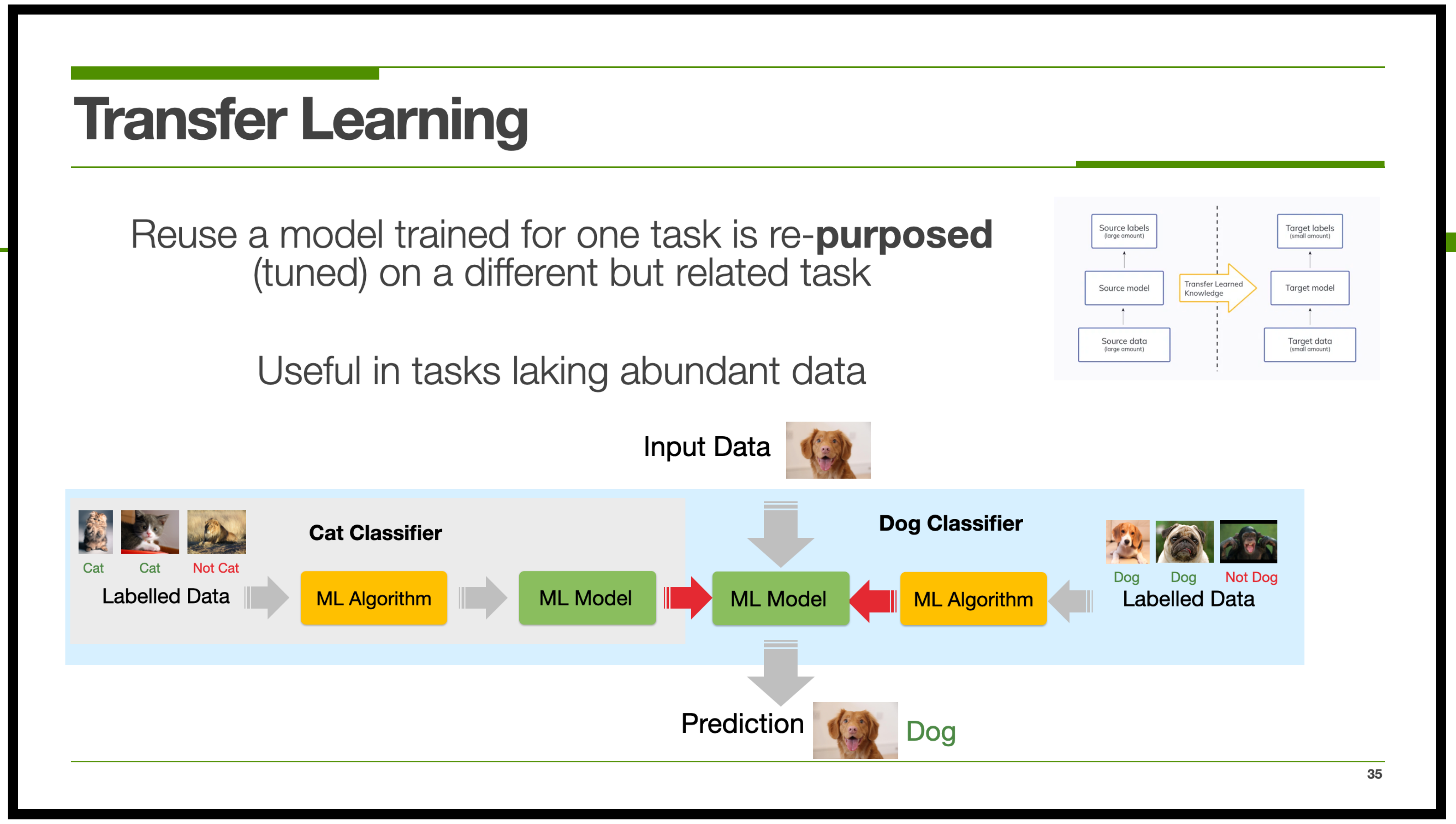


Strike (with) a Pose: Neural Networks Are Easily Fooled by Strange Poses of Familiar Objects. Alcorn et al. 2019

https://arxiv.org/pdf/1811.11553.pdf

Transfer Learning



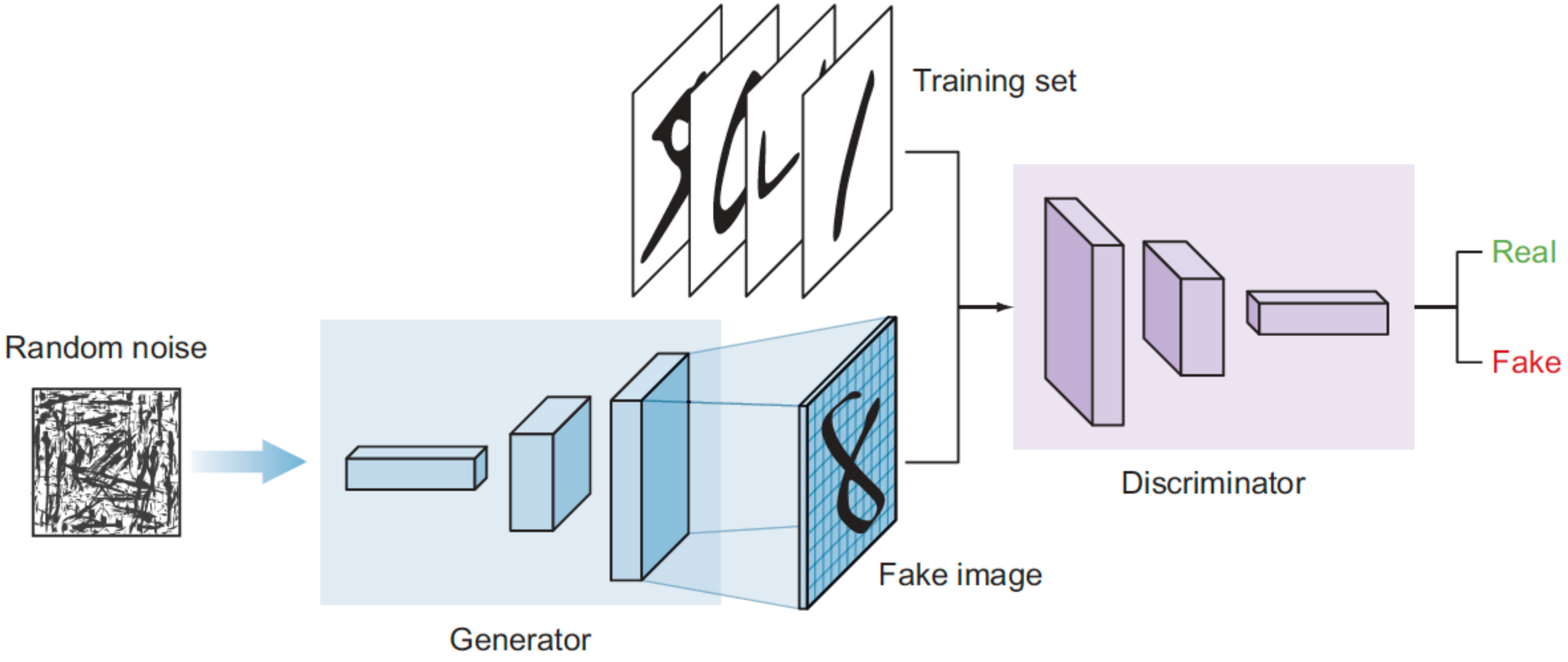


- **Problem**: training custom ML models requires extremely large datasets
- **Transfer learning**: take a model that has been trained on the **same type of data for a similar task** and apply it to a specialised task using our own custom data.
  - **Same data**: same data modality. same types of images (e.g. professional pictures vs. Social media pictures)
  - **Similar tasks**: if you need a new object classification model, use a model pre-trained for object classification

Advanced Computer Vision Techniques

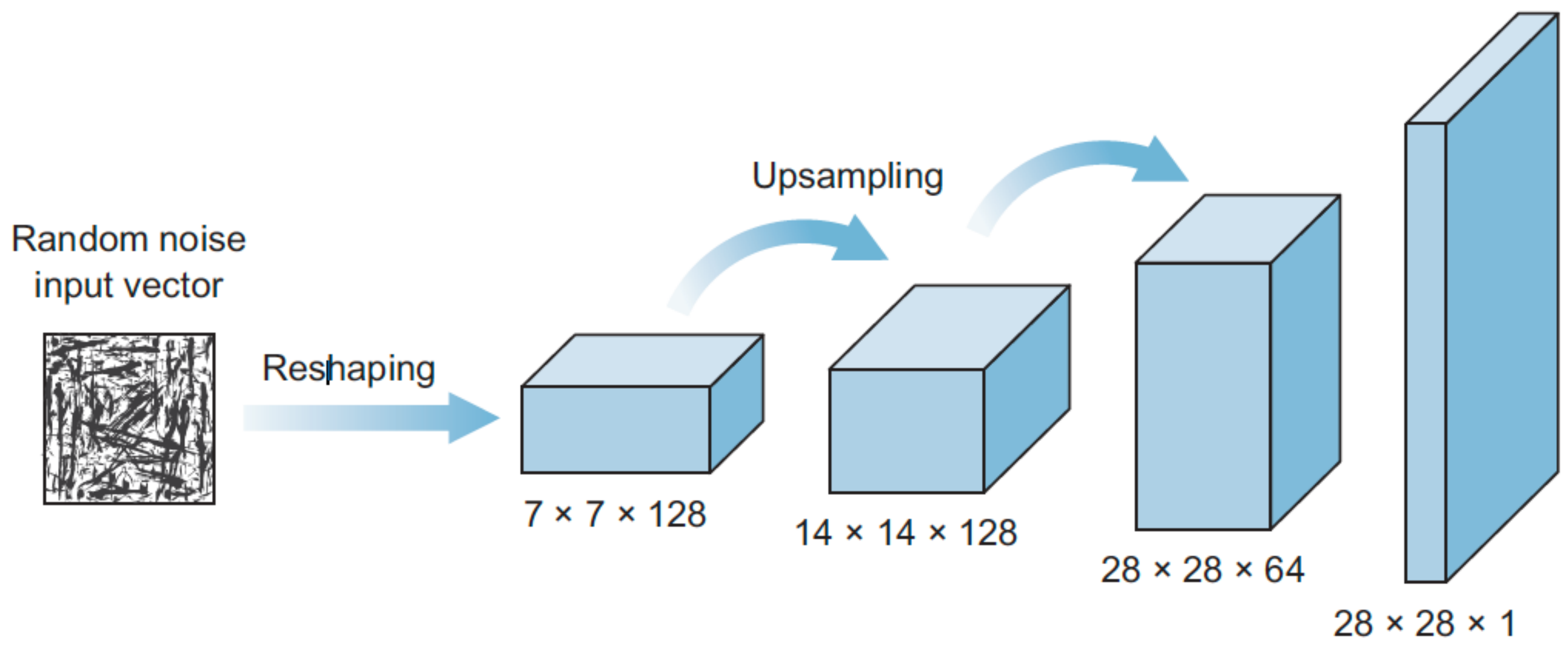
Generative Adversarial Networks

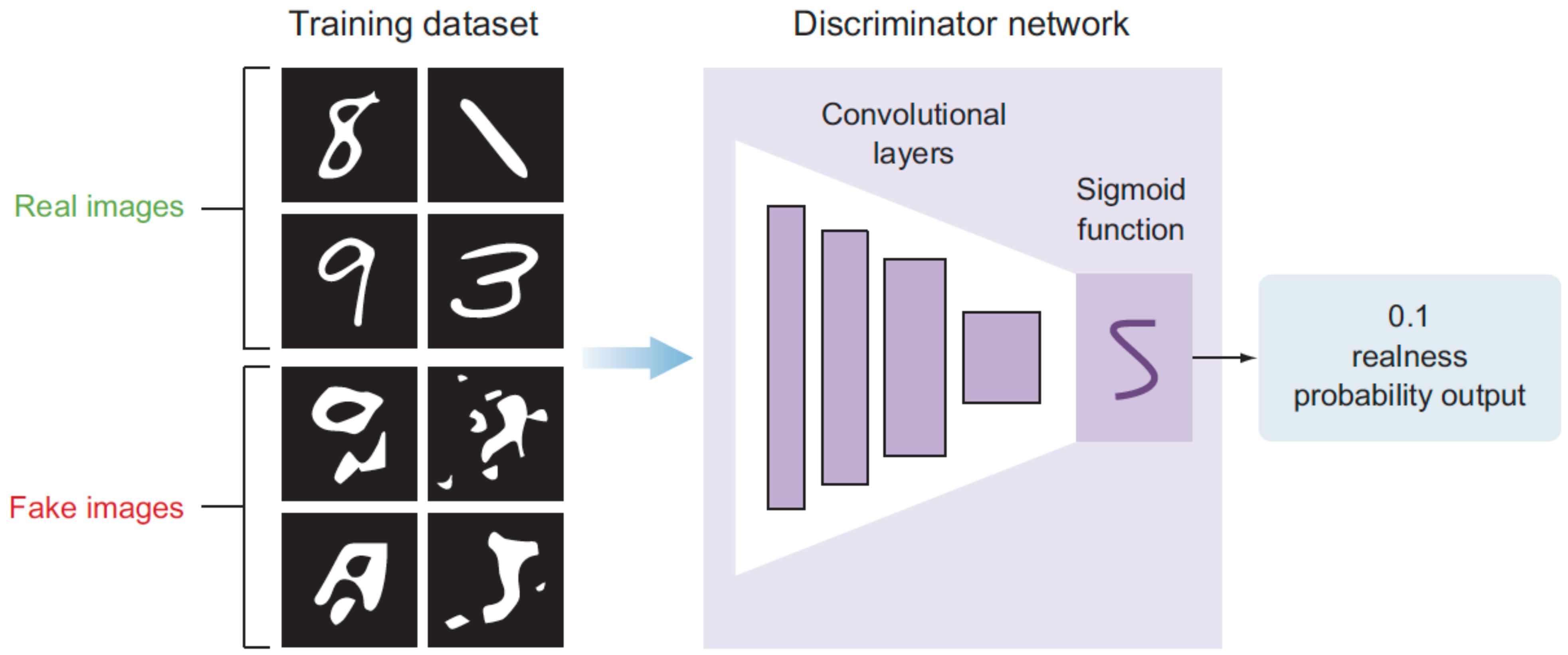
- Learn patterns from the training dataset and create new images that have a similar distribution of the training set
- Two deep neural networks that compete with each other
  - The generator tries to convert random noise into observations that look as if they have been sampled from the original dataset
  - The discriminator tries to predict whether an observation comes from the original dataset or is one of the generator's forgeries

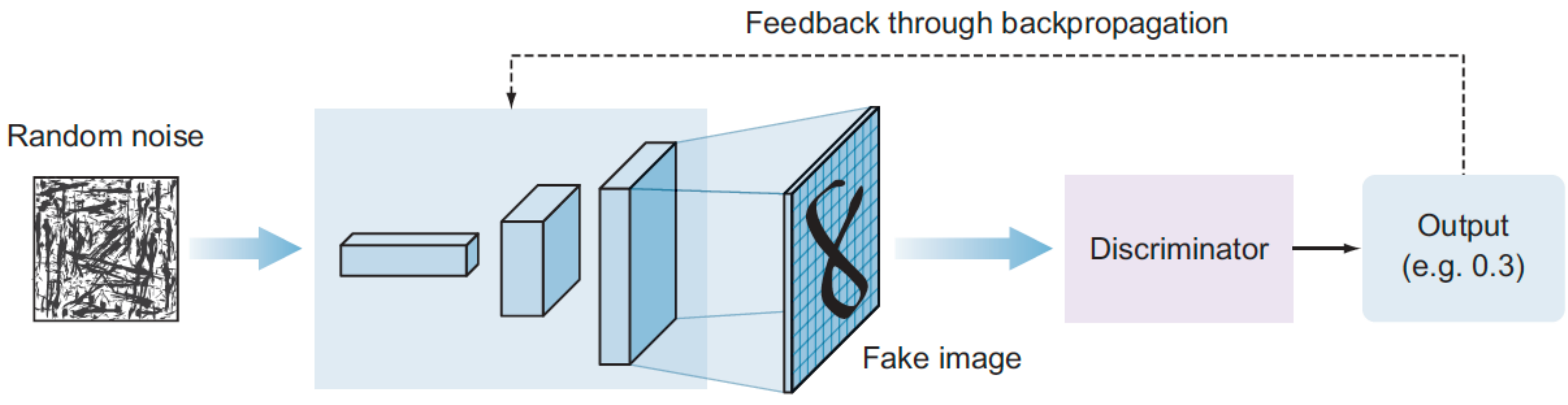


Generative Adversarial Networks

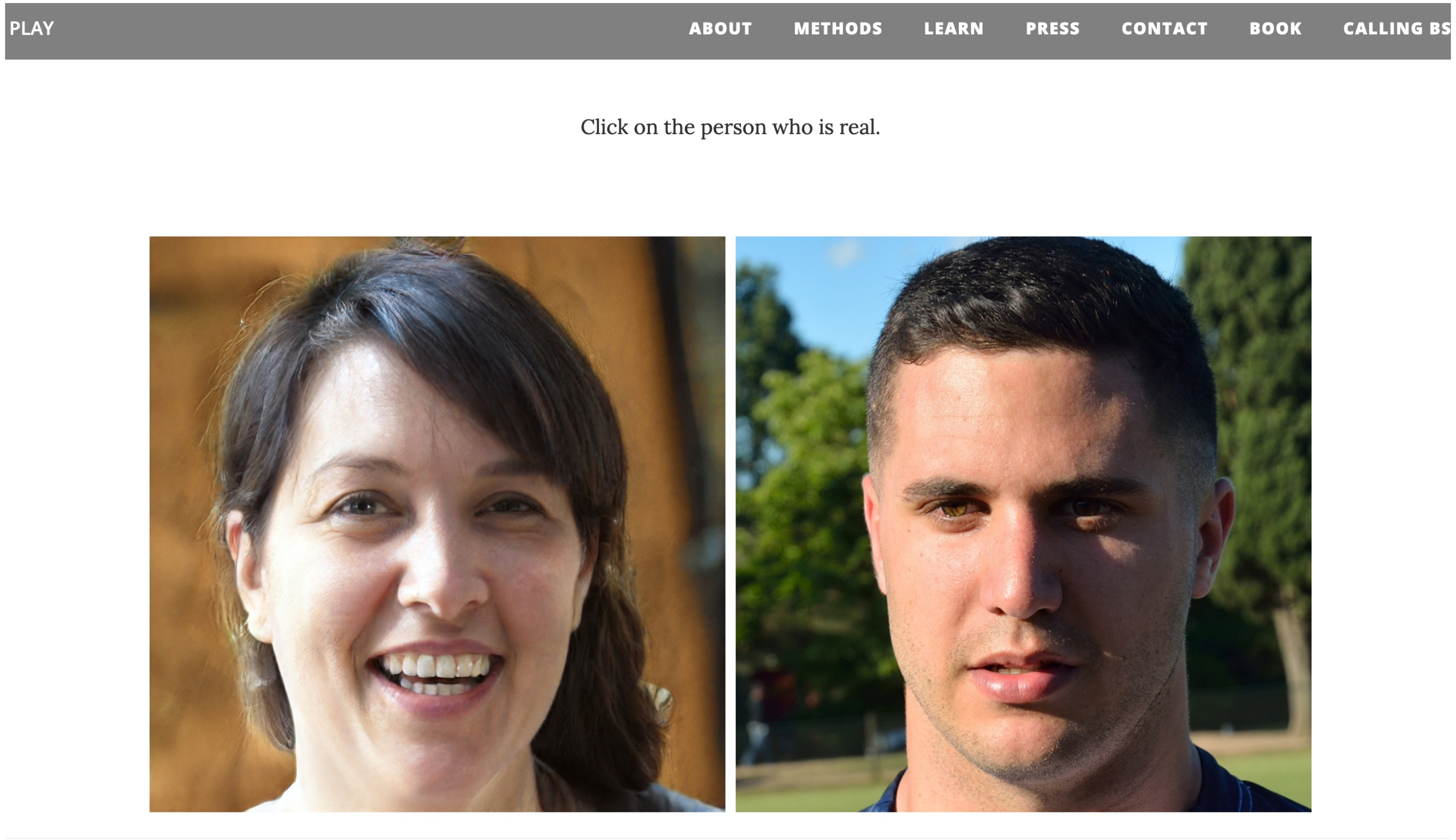
- The generator’s architecture looks like an inverted CNN that starts with a narrow input and is upsampled a few times until it reaches the desired size
- The discriminator’s model is a typical classification neural network that aims to classify images generated by the generator as real or fake







Which face is real? - https://www.whichfaceisreal.com/



- Try this https://thispersondoesnotexist.com/

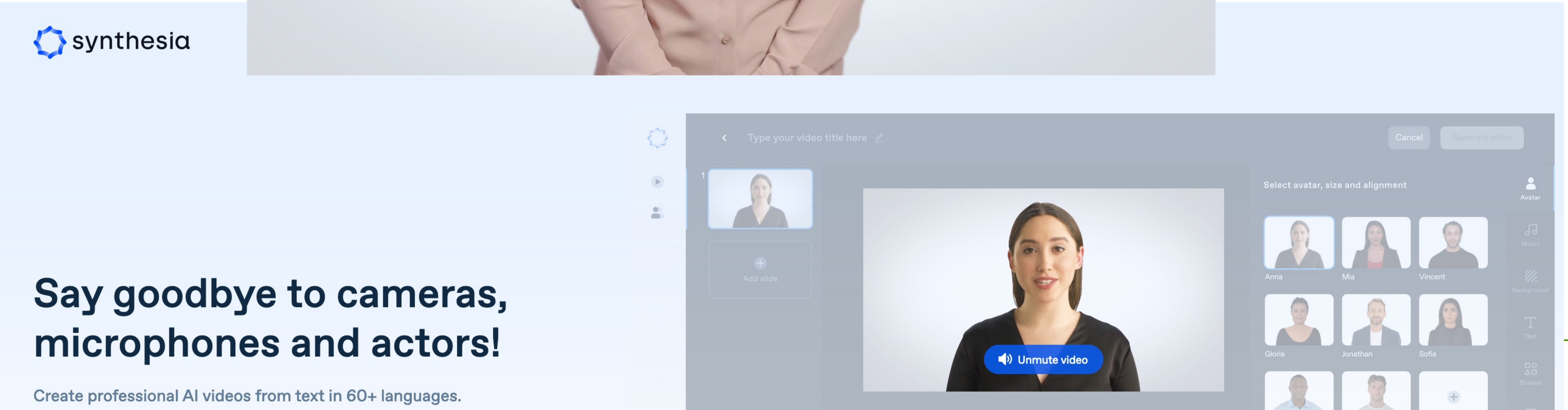
Image super-resolution GAN

- A good technical summary

https://blog.paperspace.com/image-super-resolution/

https://newatlas.com/super-resolution-weizmann-institute/23486/

Synthetic Video Generation



Text-to-image Generation

TEXT PROMPT an illustration of a baby daikon radish in a tutu walking a dog

AI-GENERATED IMAGES

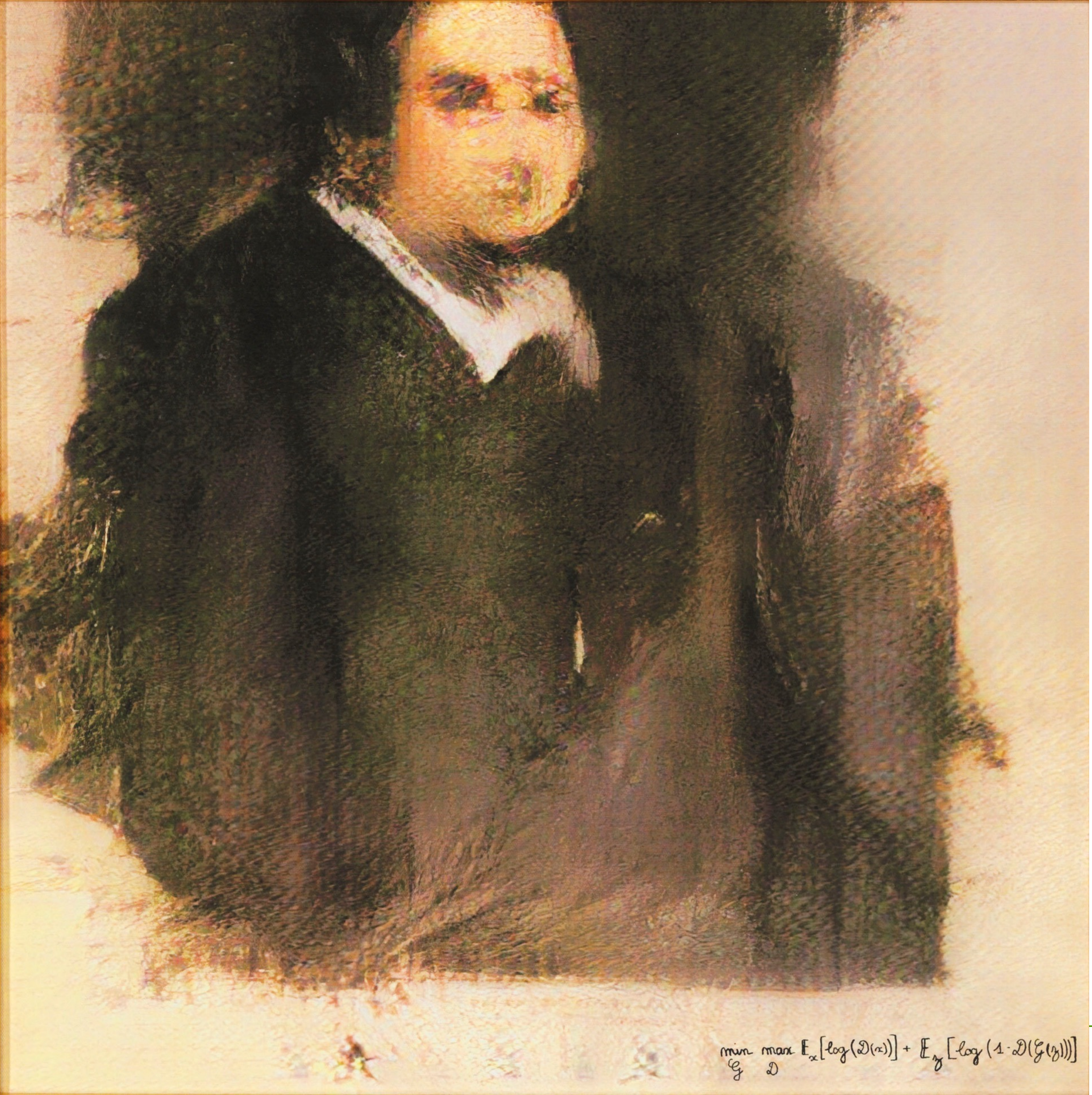
Edit prompt or view more images↓

TEXT PROMPT an armchair in the shape of an avocado. . . .

AI-GENERATED IMAGES

Edit prompt or view more images↓

- https://openai.com/blog/dall-e/



- ML-generated painting sold for $432,500
- The network trained on a dataset of 15,000 portraits painted between the fourteenth and twentieth centuries
- Network “learned” the style, and generated a new painting

https://en.wikipedia.org/wiki/Edmond_de_Belamy

Neural Style Transfer

Content Image | Style Image | Stylized Result

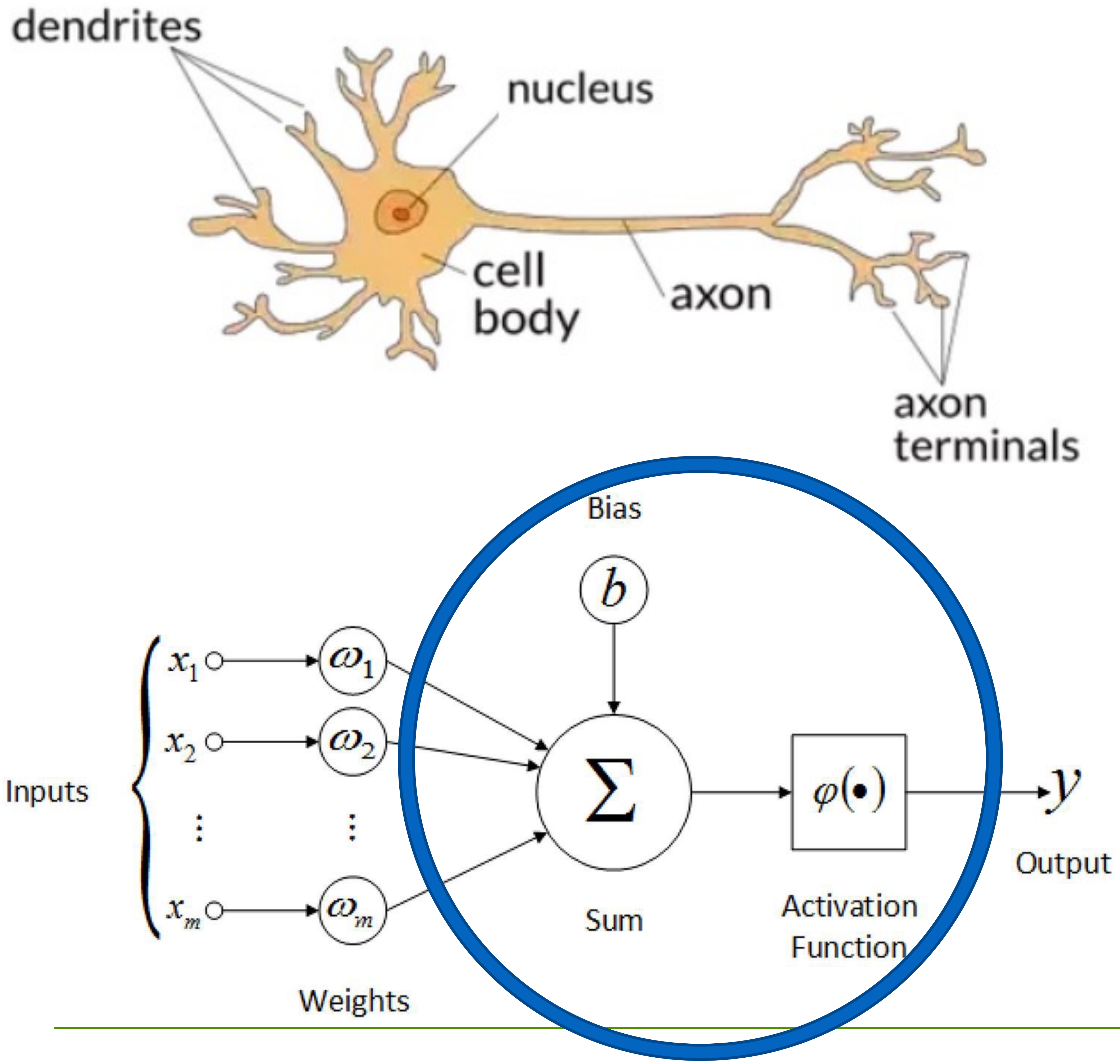
https://fluxml.ai/experiments/styleTransfer/

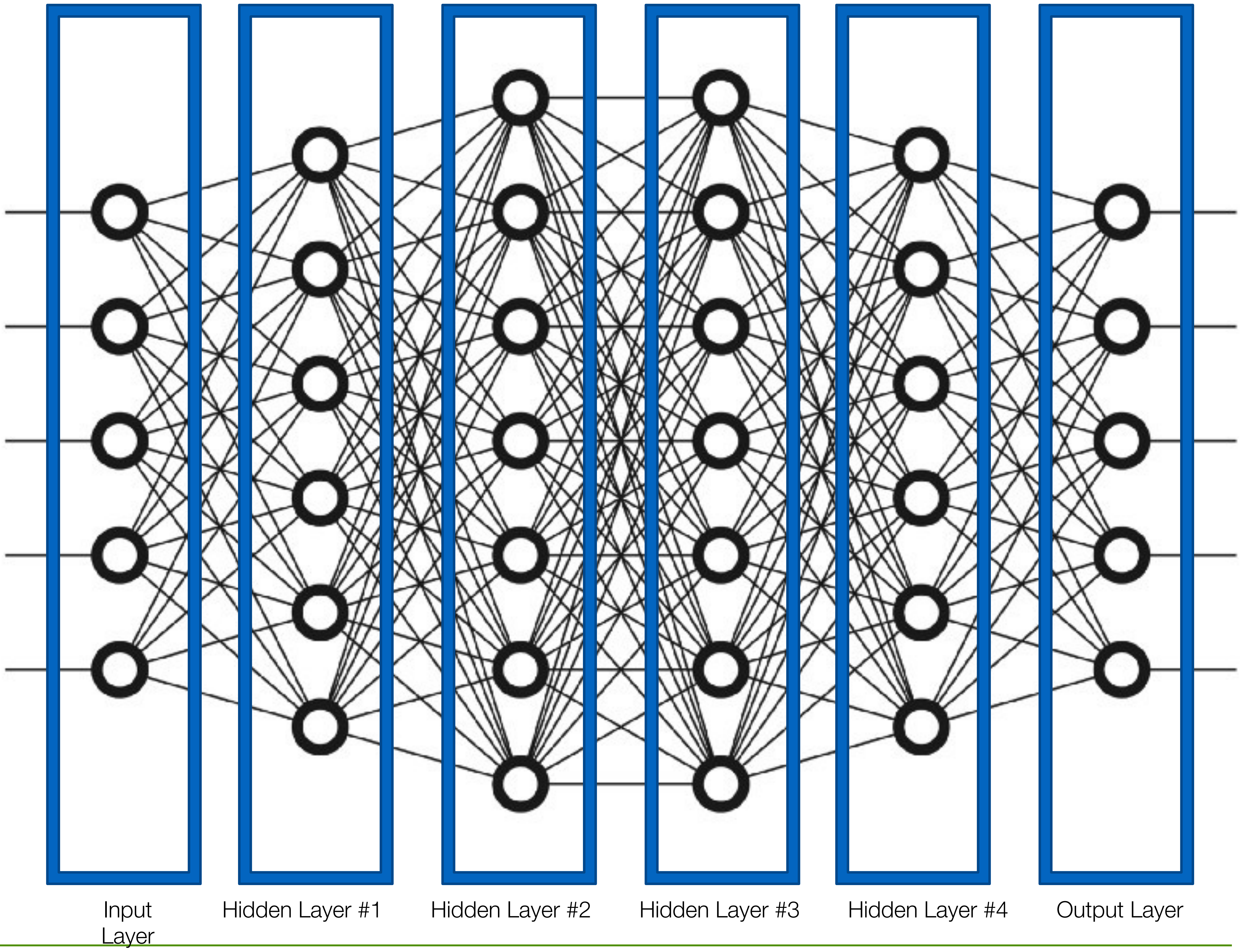
https://replicate.com/rinongal/stylegan-nada

Deepfakes

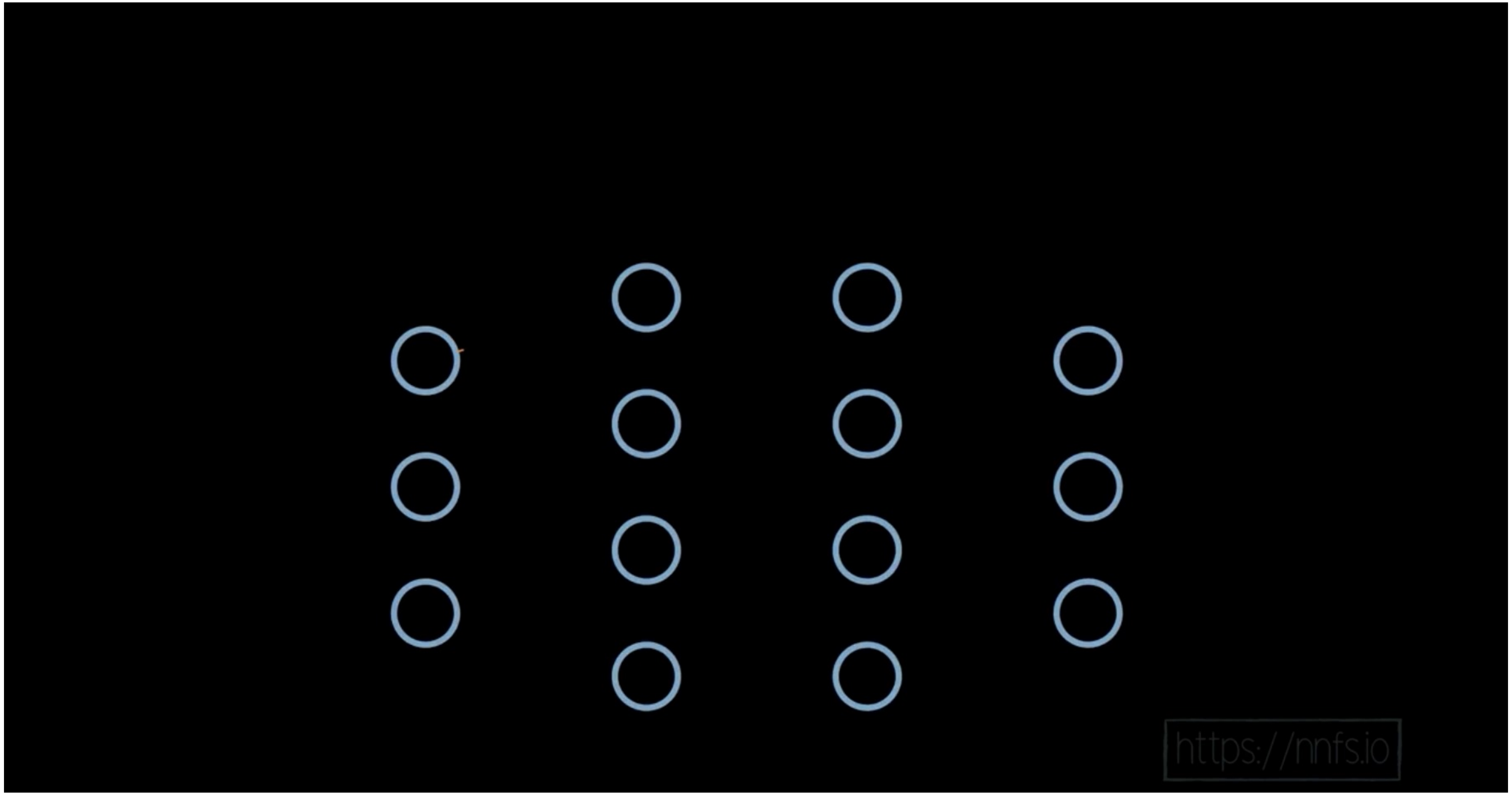
Advanced: Backpropagation in DNNs

From a Neuron to a Deep Neural Network (DNN)





How exactly does a Neuron in a DNN work?

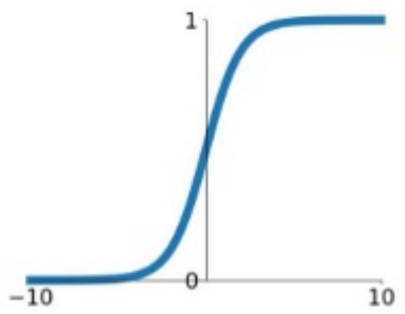


Source: "*What is backpropagation* really *doing?*"—YouTube walk-through (see last slide)

Activation Functions for Forward Propagation

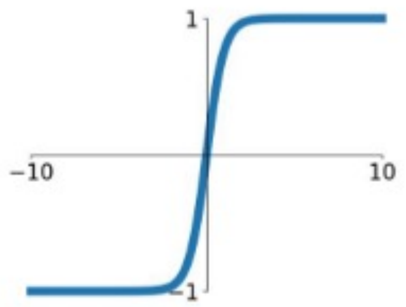
Sigmoid

$\sigma(x) = \frac{1}{1+e^{-x}}$



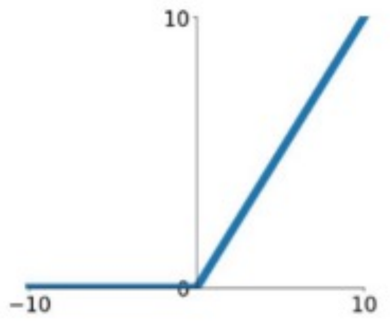
tanh

$\tanh(x)$



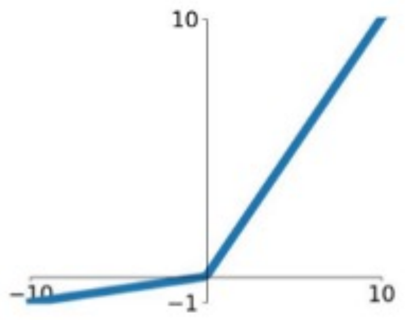
ReLU

$\max(0, x)$



Leaky ReLU

$\max(0.1x, x)$

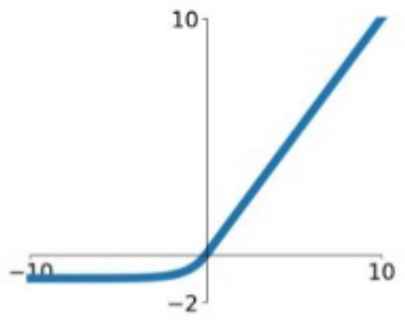


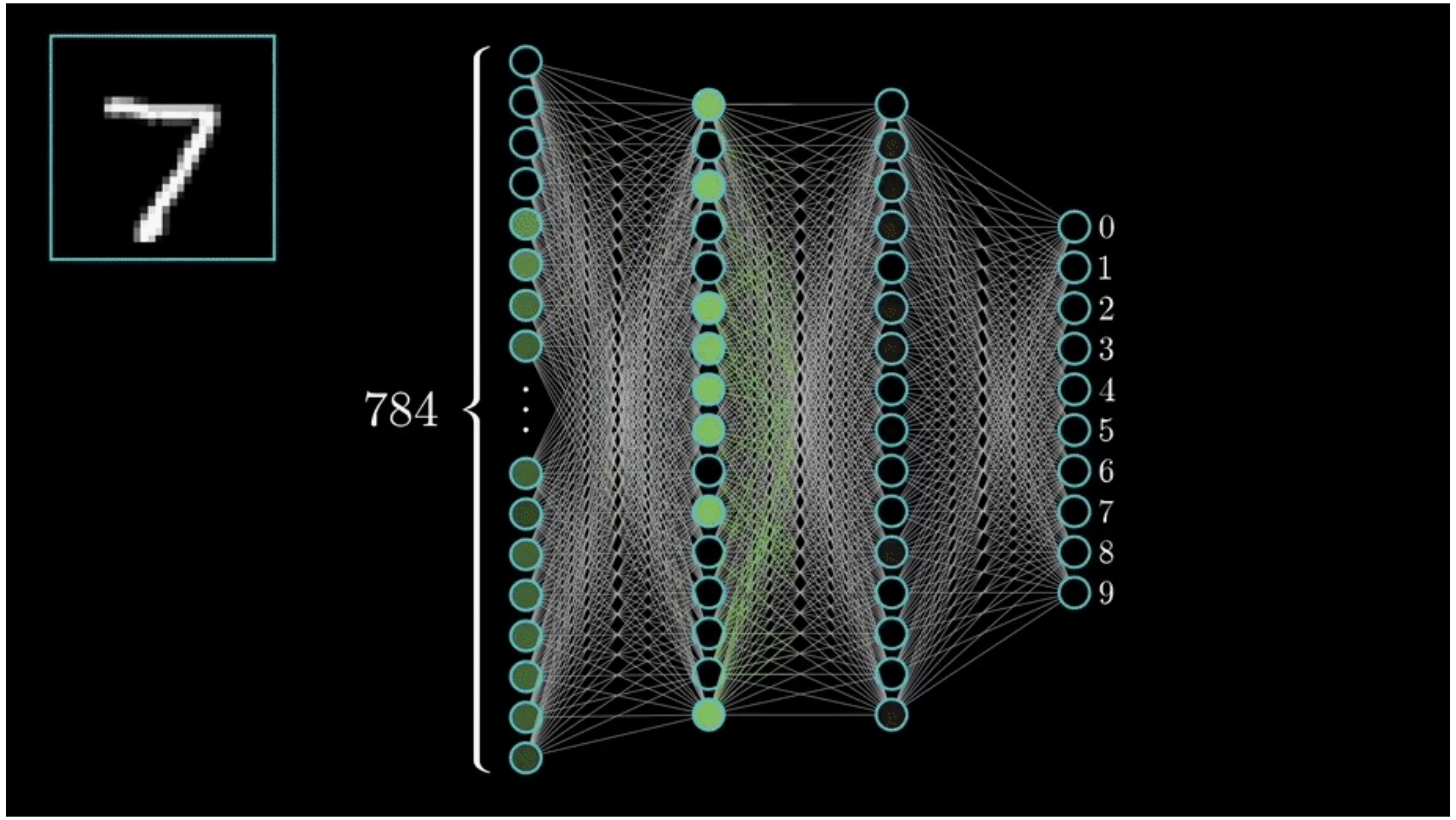
Maxout

$\max(w_1^T x + b_1, w_2^T x + b_2)$

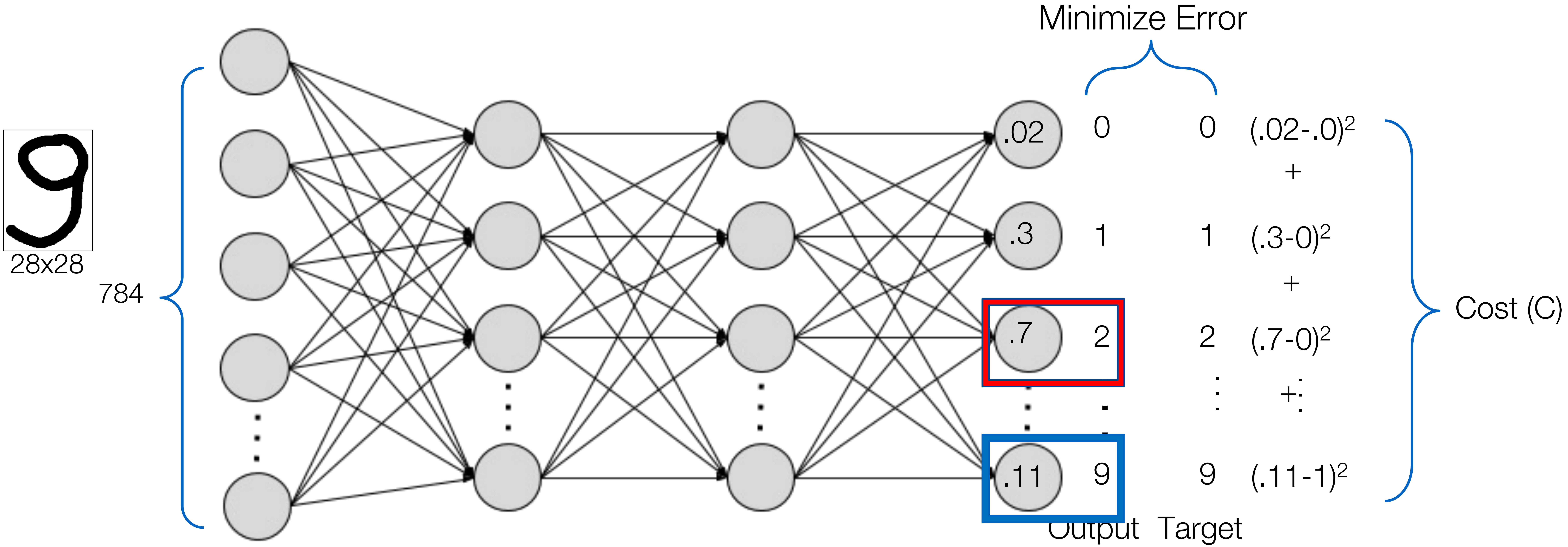
ELU

$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$





But how does a DNN learn?

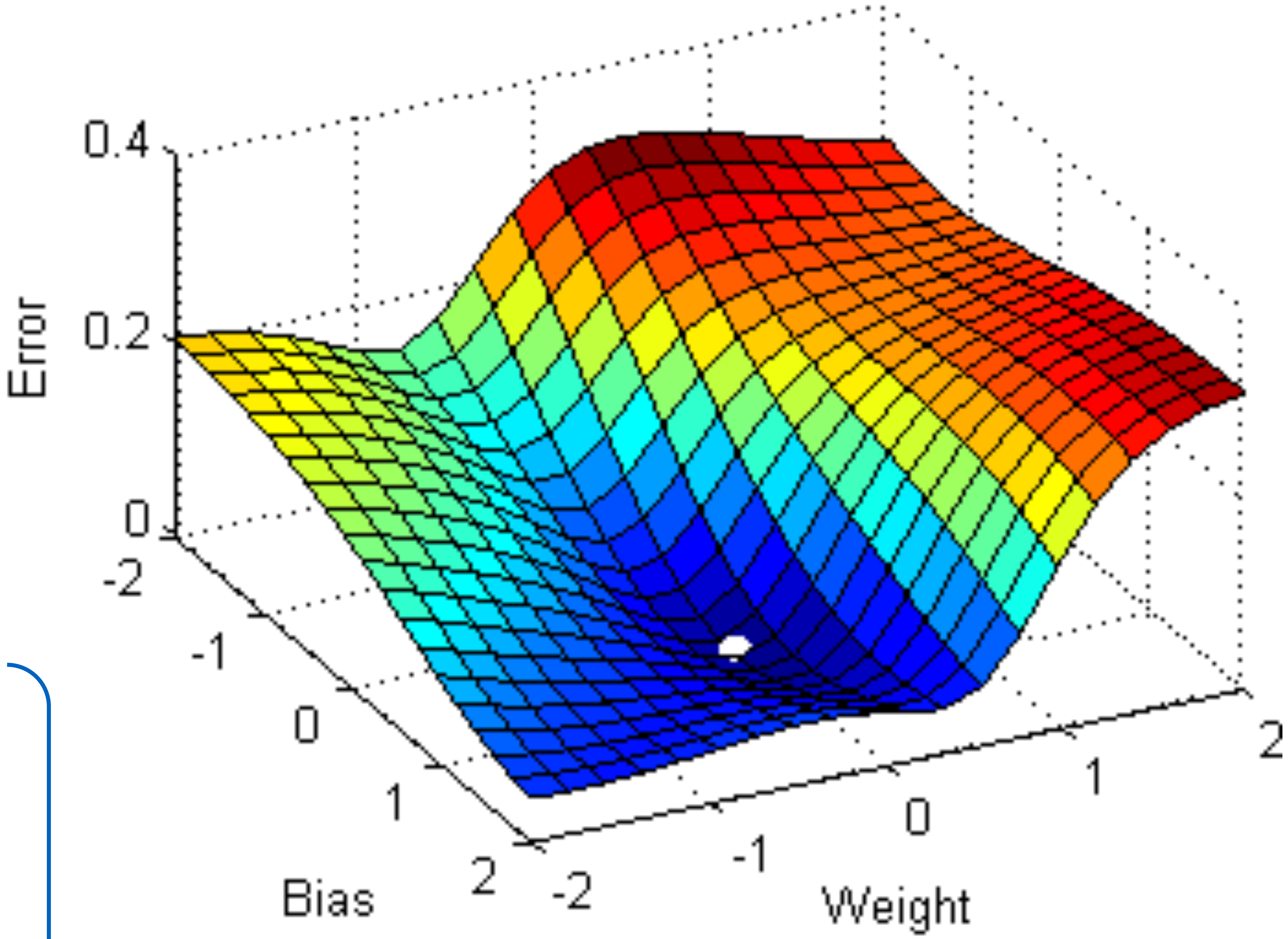


We want to minimize $C(W, B, S^r, E^r)$

Stochastic Gradient Descent

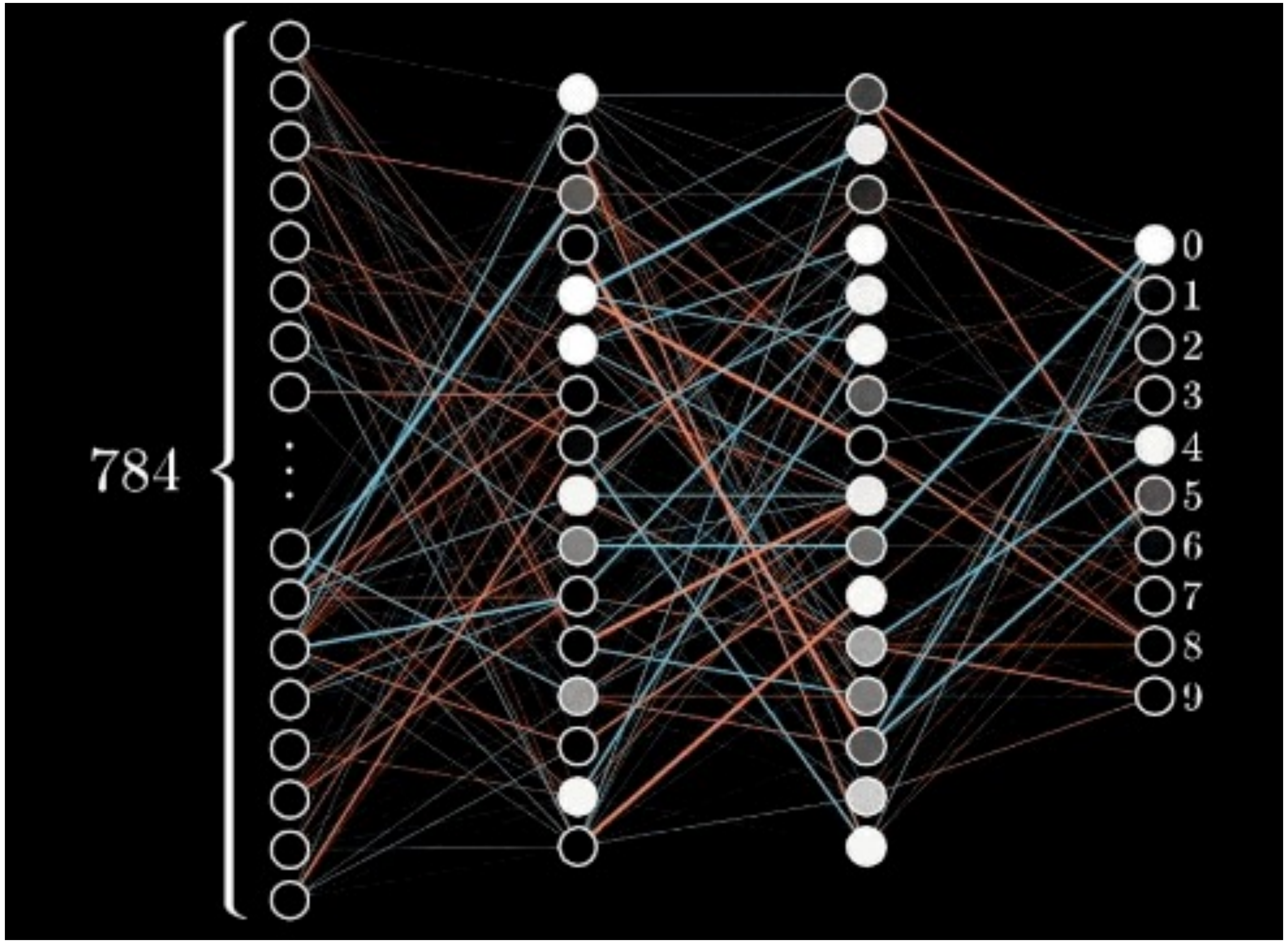
- 1. Compute ∇C (gradient direction of cost function)
- 2. Small step towards the -∇C direction
- 3. Repeat

$$\overrightarrow{W} = \begin{pmatrix} 1.1 \\ 3.8 \\ -2.2 \\ \vdots \\ 1.4 \\ 2.12 \\ -1.4 \end{pmatrix} \qquad -\nabla C(\overrightarrow{W}) = \begin{pmatrix} .1 \\ .2 \\ -.3 \\ \vdots \\ 1.4 \\ -.05 \\ .2 \end{pmatrix}$$

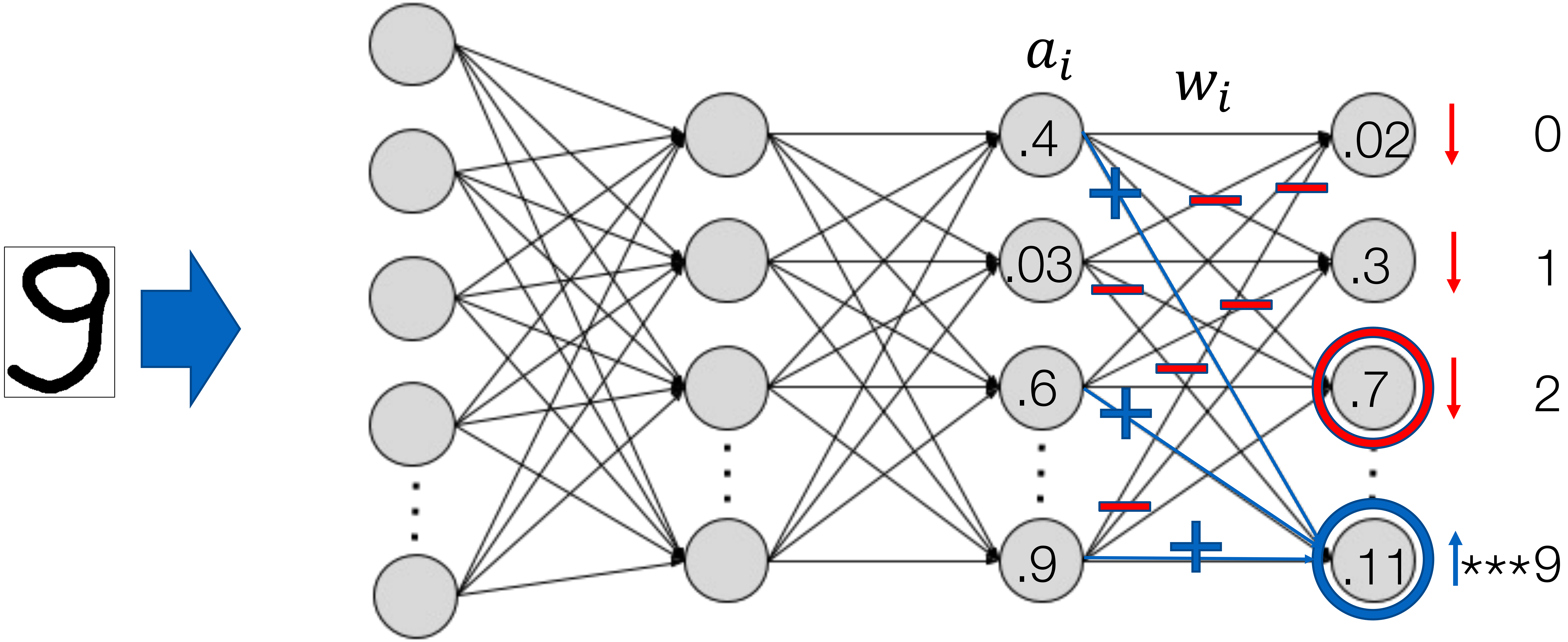


Backpropagation for computing Stochastic Gradient Descent

- Increase bias (b) and weights (w_i) in proportion to previous layer activations (a_i)
- Change activations from the previous layer (a_i) in proportion to weights (w_i)
- Repeat over the entire training dataset



1. Increase bias (*b*) and weights (w_i) in proportion to previous layer activations (a_i)

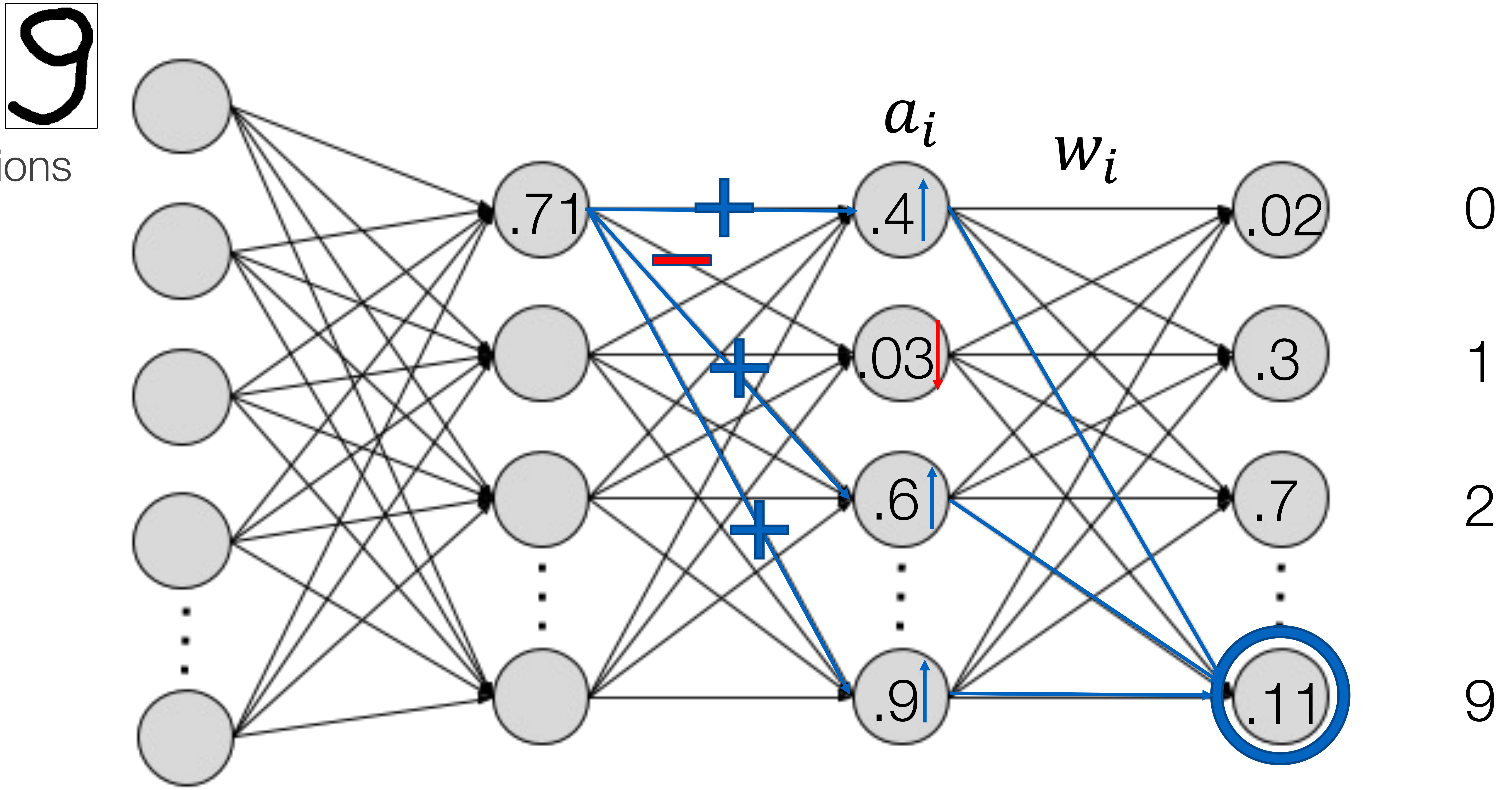


Focus on the activation of the neuron we want to increase:

$$.11 = \sigma(w_0 a_0 + w_1 a_1 + \cdots + \ w_{n-1} a_{n-1} + b)$$

2. Change the activations from the previous layer (a_i) in proportion to weights (w_i)

- We can't directly alter the activations of neurons
- We seek to maximize magnitude
- We gradually produce a list of changes to apply per layer
- We recursively apply the same process backwards



"When 2 connected cell neurons fire simultaneously, the connection between them strengthens" – Donald Hebb (1949)

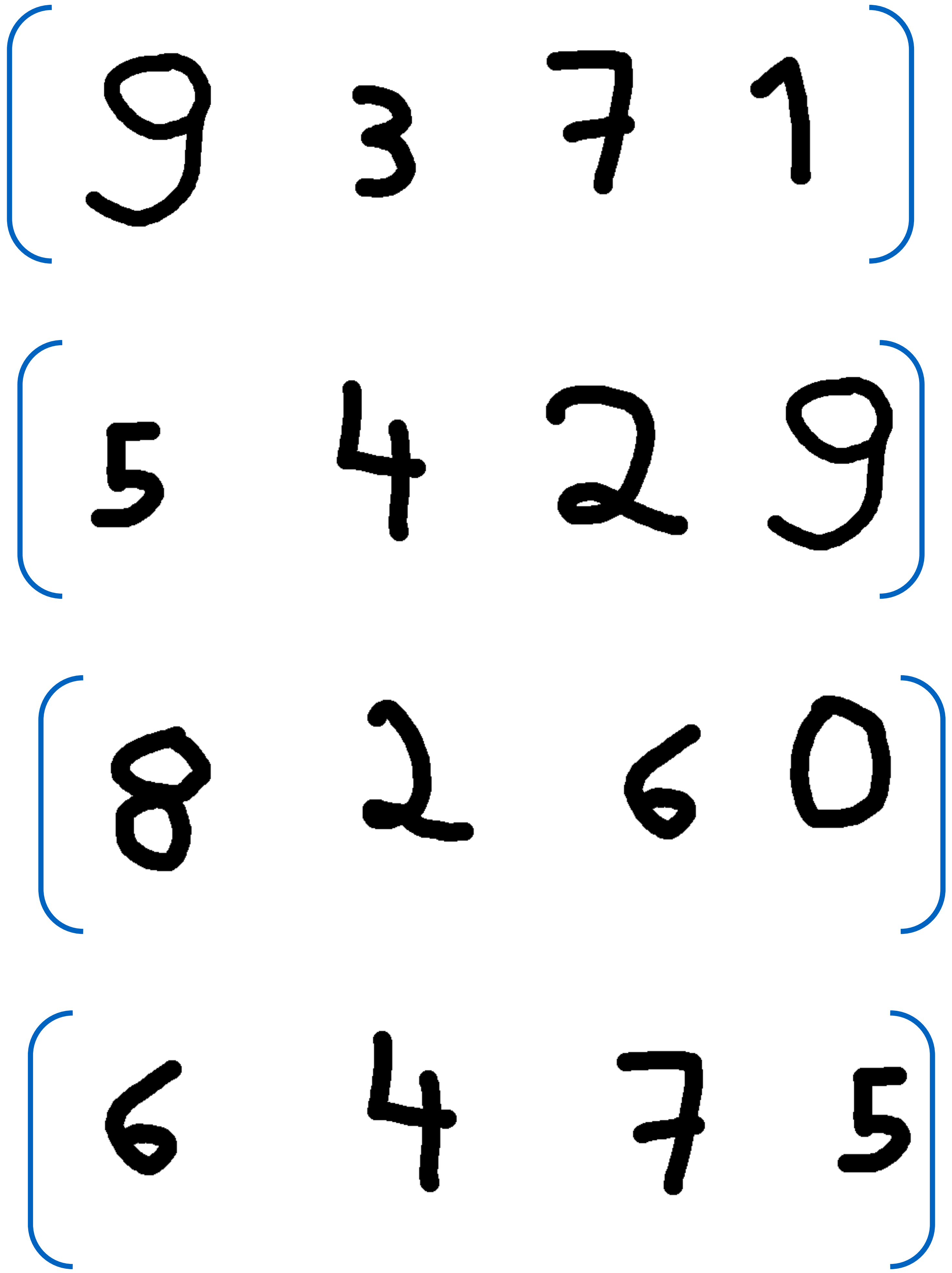
3. Repeat for the entire Training Dataset

	2	1	6	2	7	. . .	Average over all training dataset
w_0	-.02	+.5	-.21	-.1	+.4	. . .	+.01
w_1	+.3	-.31	-.07	+.2	-.12	. . .	+.09
w_2	+.1	+.03	-.09	+.1	+.02	. . .	-.03
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
w_{n-1}	+.05	-.01	+.04	-.03	-.17	. . .	-.19

$$= -\nabla C(w_1, w_2, \ldots w_{n-1})$$

Backpropagation with Batching

- Computationally expensive process if done case by case, instead:
  - Shuffle dataset
  - Divide in batches
  - Compute a gradient descent “step” per batch



Compute step with backprop for batch #1

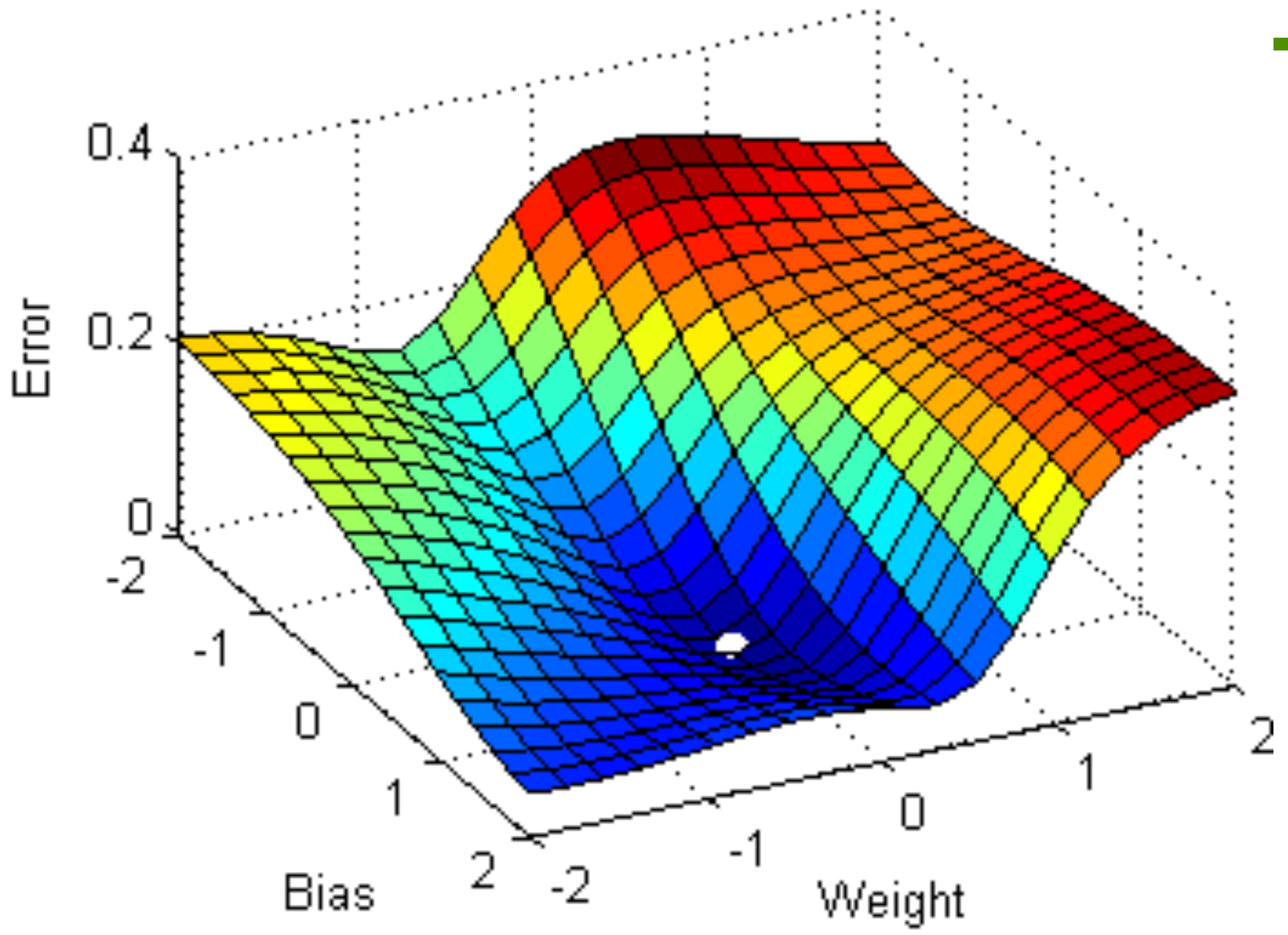
Compute step with backprop for batch #2

Compute step with backprop for batch #3

Compute step with backprop for batch #4

Recap

- Back propagation is the algorithm that determines how a single training example (case) would alter neurons' weights and biases for achieving the most rapid decrease to the cost.
- By dividing our training dataset in batches, the network will converge to a local minimum of the cost function (C) by making gradual adjustments.
- NOTE #1: The training dataset should be sufficiently large for backpropagation to work.
- NOTE #2: Ineffective with "noisy" training data



Admin

Credits

- CMU Computer Vision course - Matthew O'Toole. http://16385.courses.cs.cmu.edu/spring2022/
- CIS 419/519 Applied Machine Learning. Eric Eaton, Dinesh Jayaraman. https://www.seas.upenn.edu/~cis519/spring2020/
- Deep Learning Patterns and Practices - Andrew Ferlitsch, Maanning, 2021
- Machine Learning Design Patterns - Lakshmanan, Robinson, Munn, 2020
- Grokking Machine Learning. Luis G. Serrano. Manning, 2021
- Deep Learning for Vision Systems. Mohamed Elgendy. Manning, 2020

Advanced Machine Learning For Design

Lecture 5: Machine Learning for Image Processing (part 2)

Evangelos Niforatos

18/10/2023

aml4d-ide@tudelft.nl
https://aml4design.github.io/