Deep learning basics

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Machine learning is a subfield of artificial intelligence.

Intuitively We want to *learn from* and *make predictions on* data.

Technically We want to build a model that approximate well (*e.g.* minimize a loss function) an unknown function.

It is important to note that the function we want to approximate may or may not have a closed form.

Application examples

Supervised learning

- Regression

  Polynomial $(x, y, z) \rightarrow f(x, y, z)$

  House price (surface, nb rooms, city) $\rightarrow$ price

- Classification

  Image classification pixel values $\rightarrow$ cat or dog

  Text classification list of words $\rightarrow$ spam or valid email

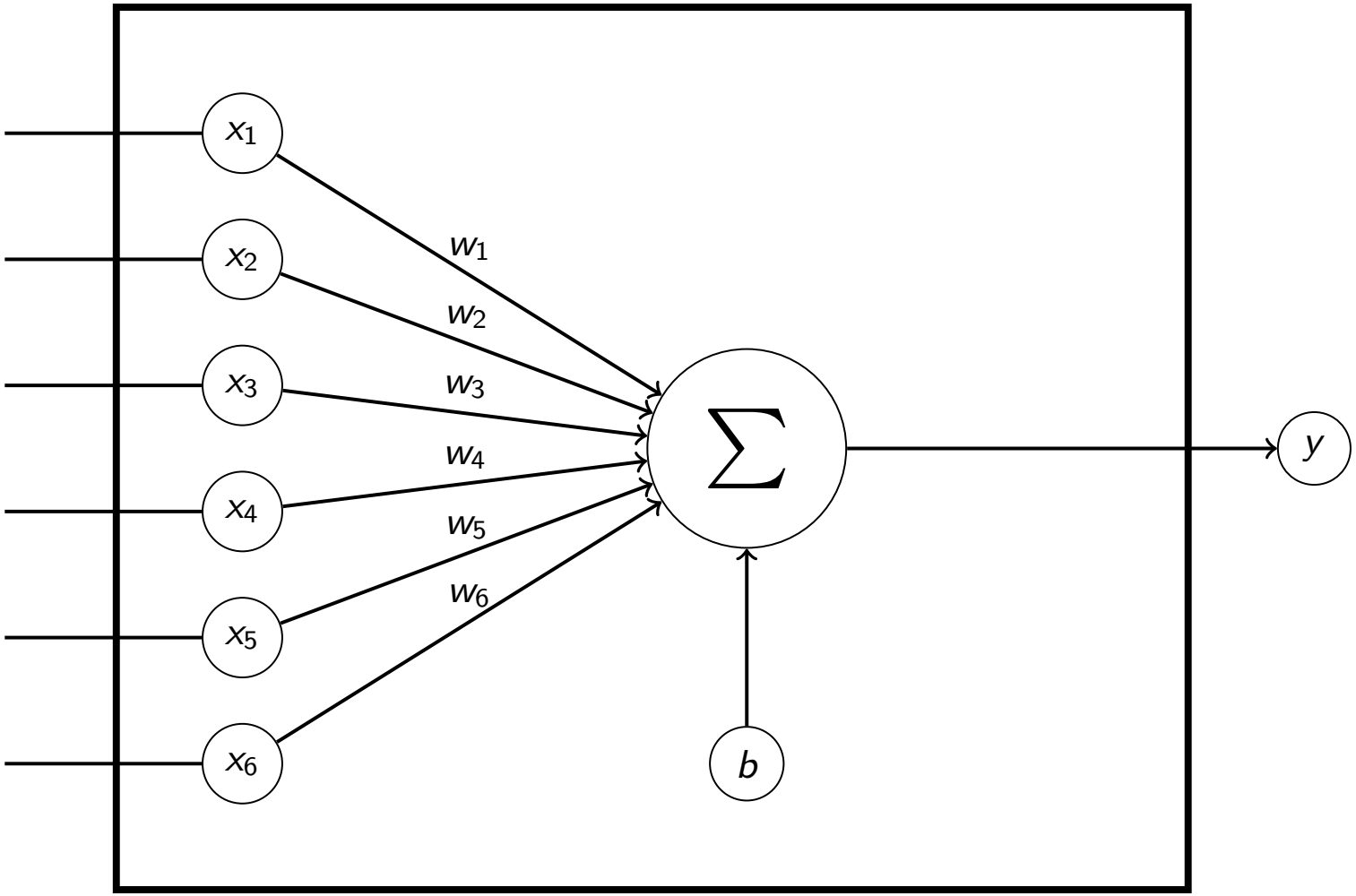
Deep learning

Deep learning is a subfield of machine learning in which we use artificial neural networks to make predictions.

An artificial neural networks is a computation model loosely based on the human brain. It aims to mimic electric signals travelling through neurons in order to make computations.

Artificial neural network

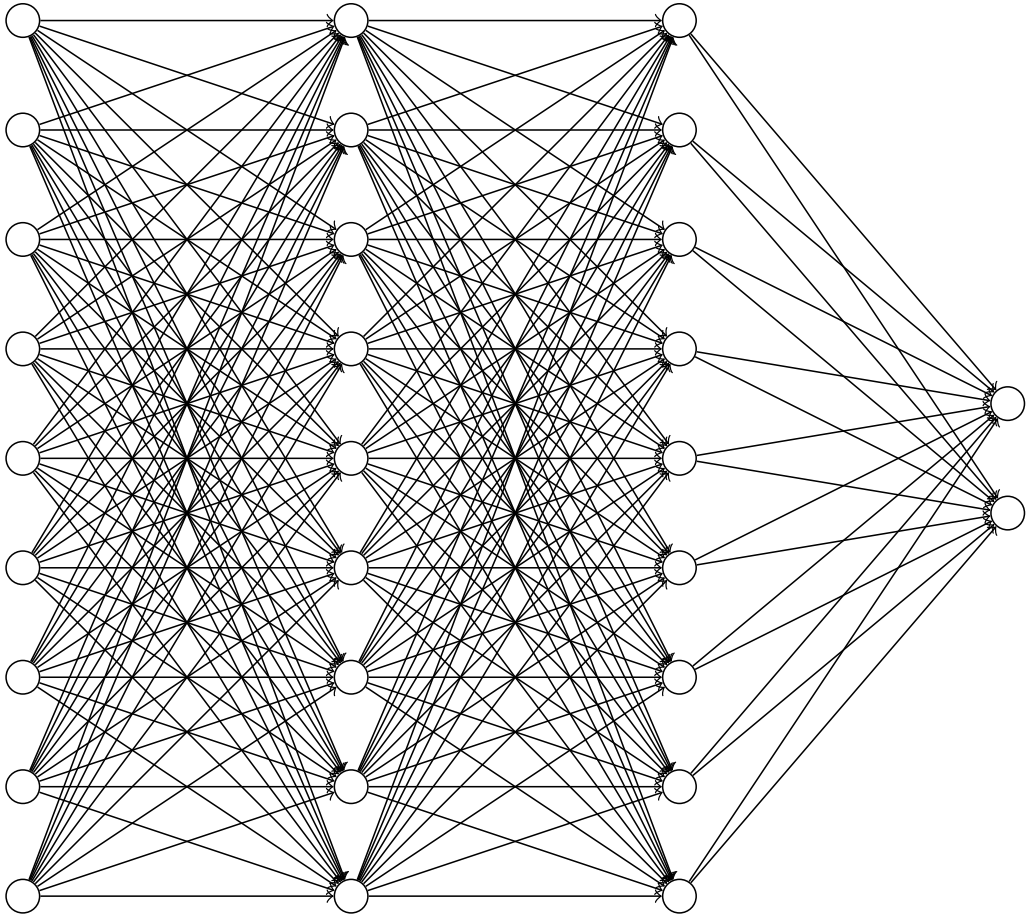
Neuron



$$y = w_1 x_1 + w_2 x_2 + w_3 x_3 + w_4 x_4 + w_5 x_5 + w_6 x_6 + b$$

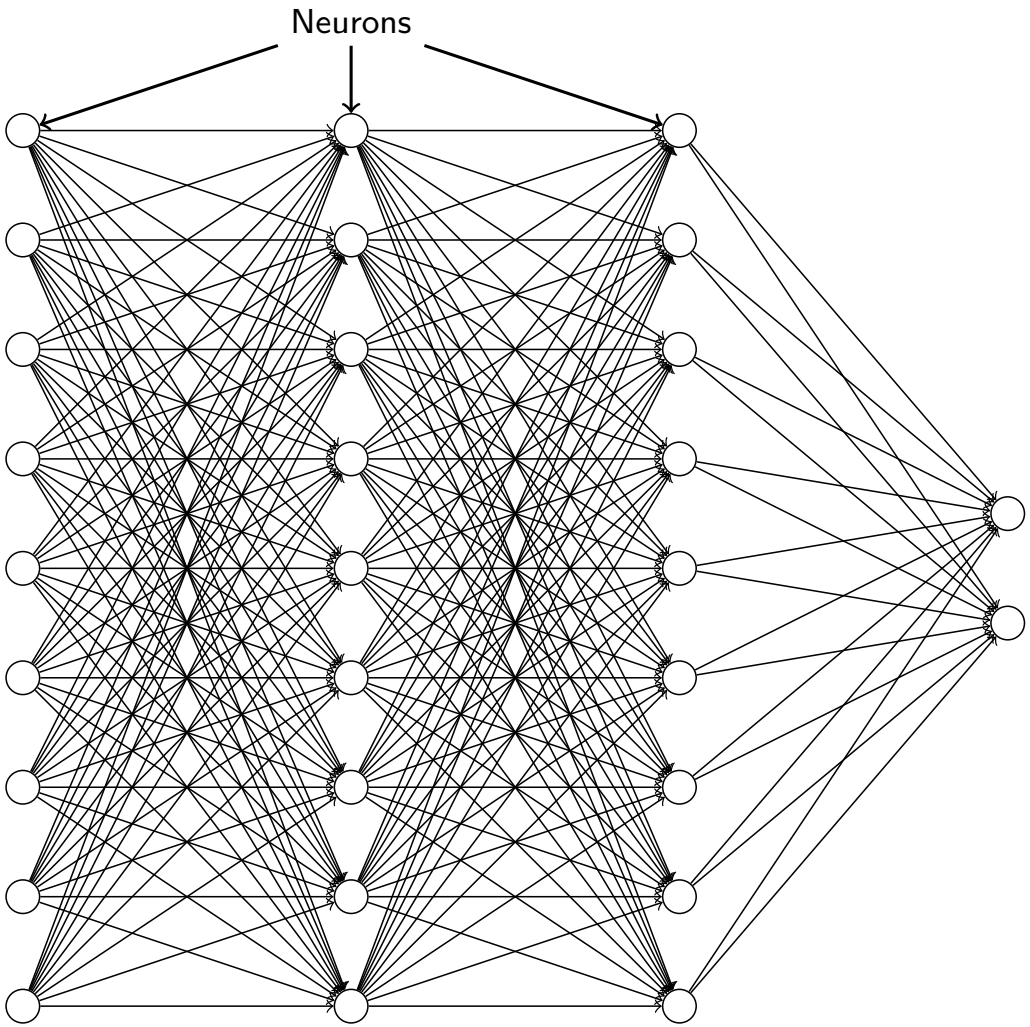
Artificial neural network

Network



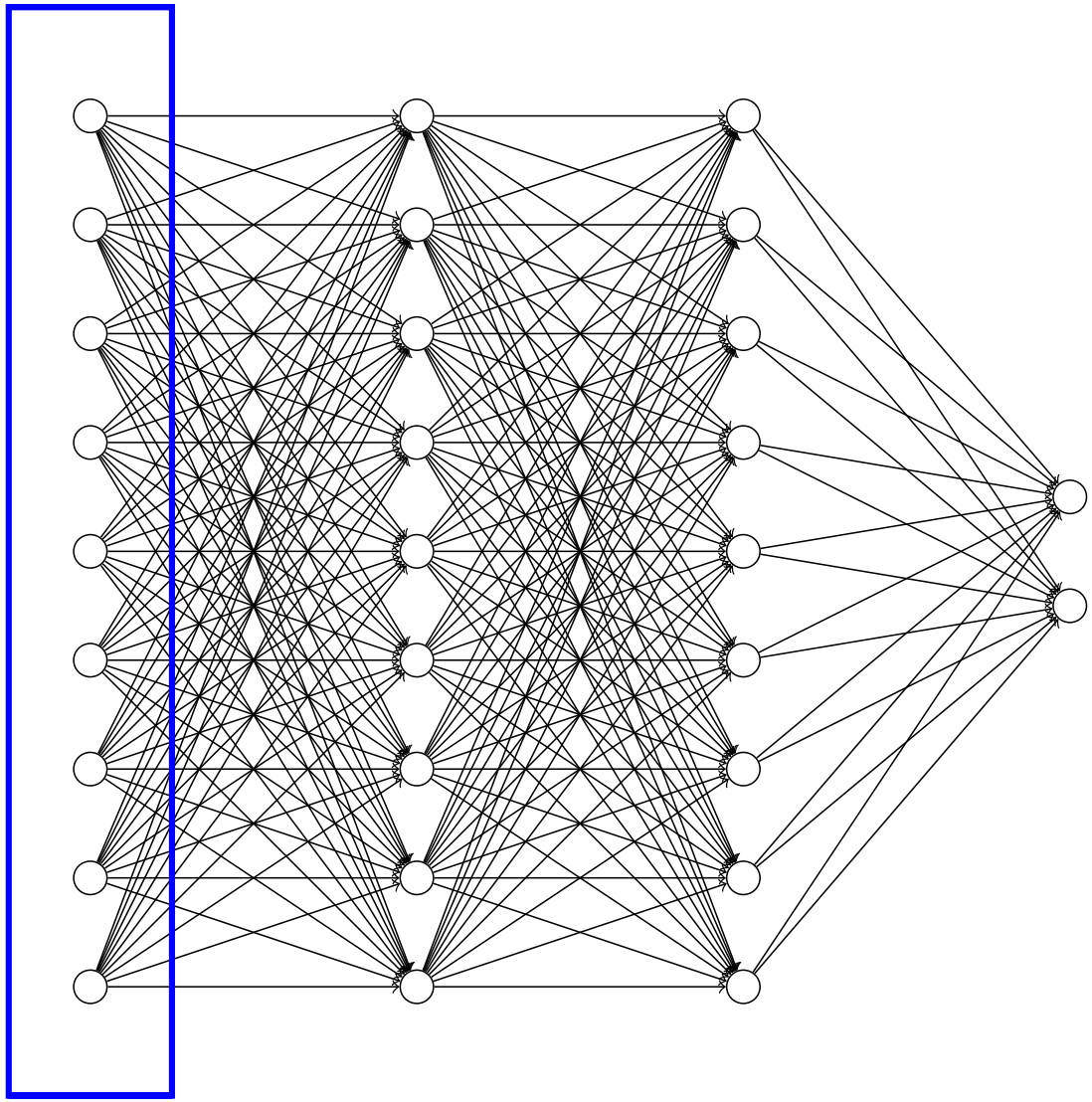
Artificial neural network

Network



Artificial neural network

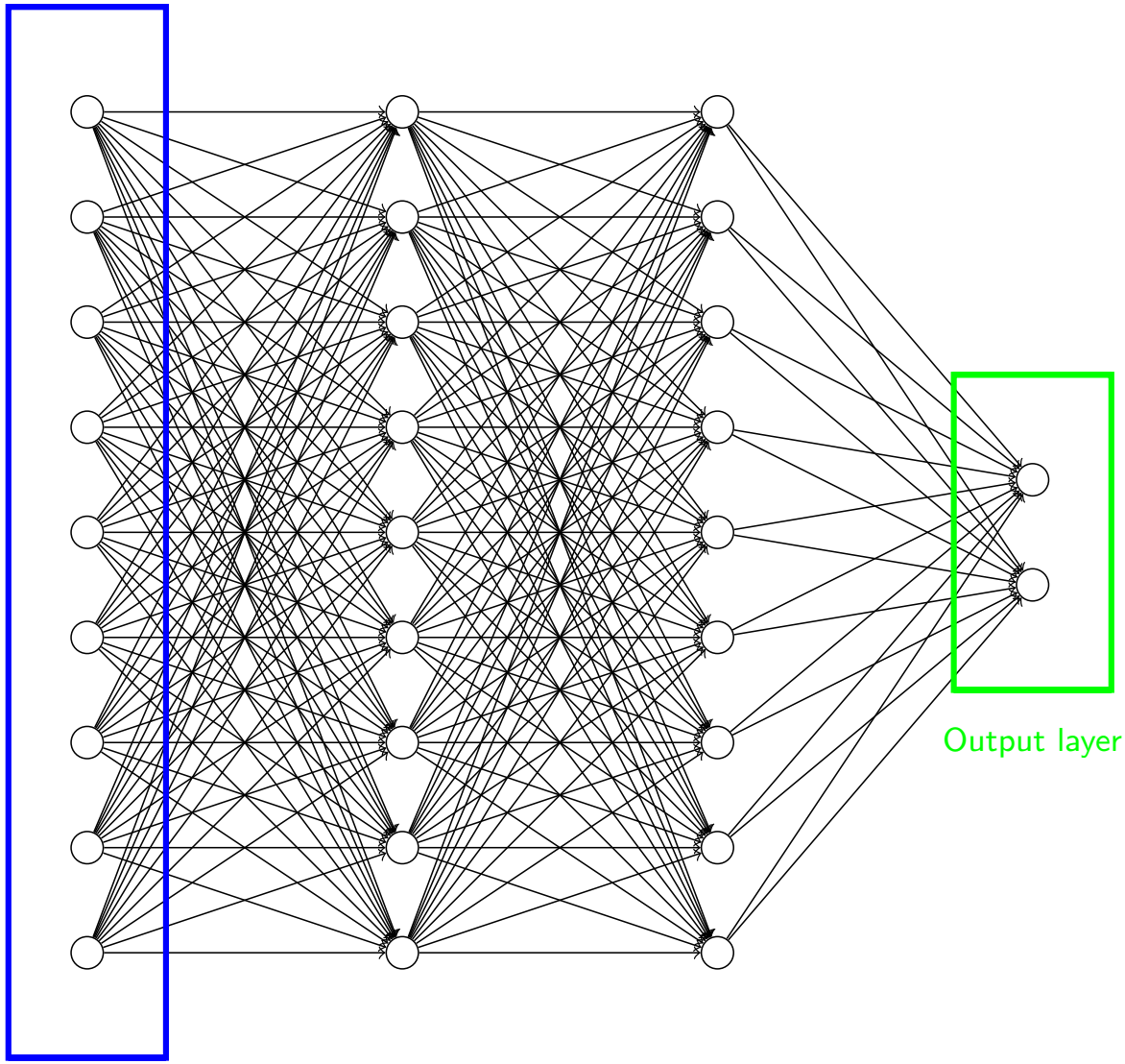
Network



Input layer

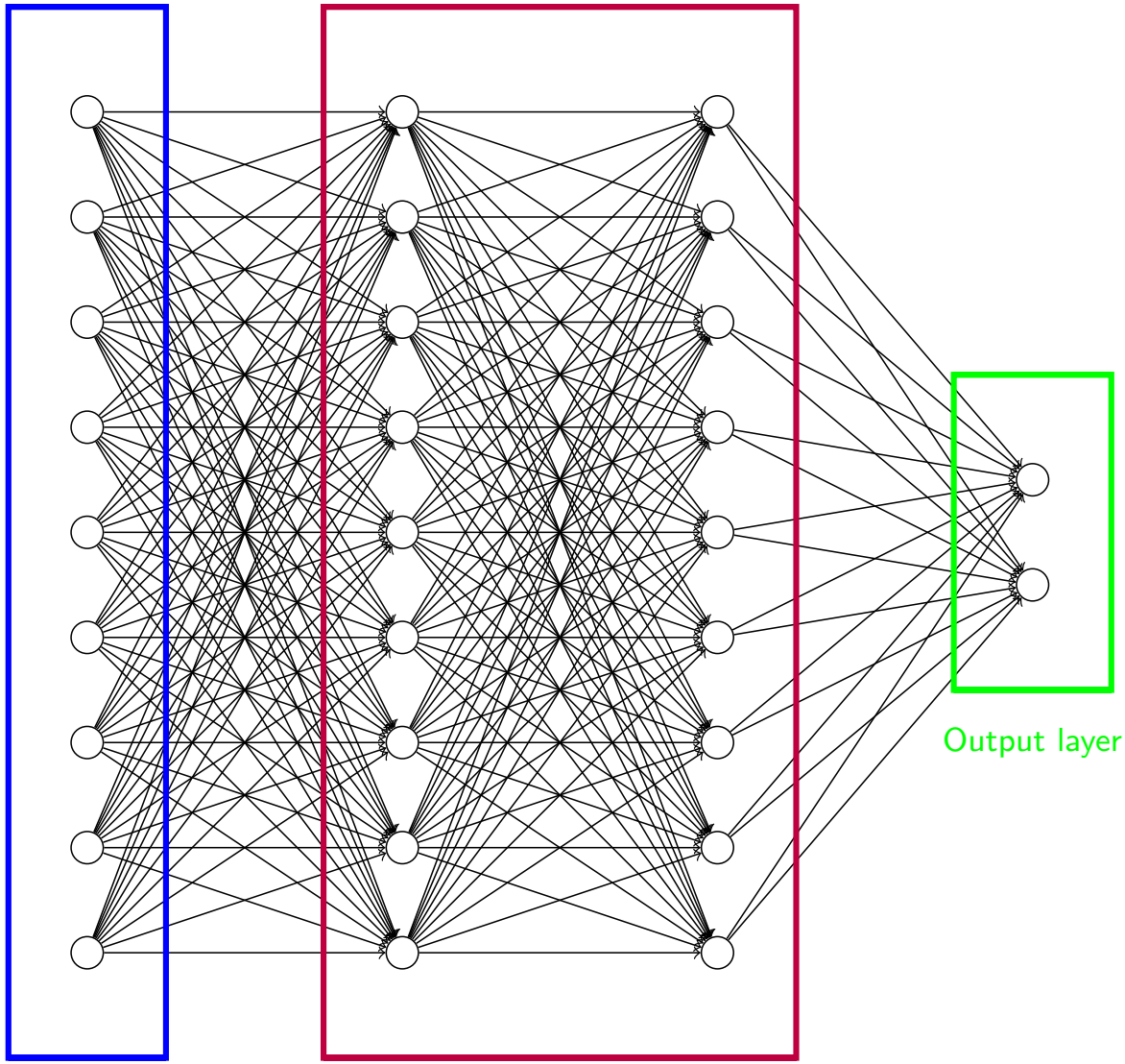
Artificial neural network

Network



Artificial neural network

Network



"Problem" with this definition

We now have a quite complicated framework to compute linear functions.

Neuron	linear function
Neural network	linear combination of neuron outputs

To approximate non linear functions, we would like to have a non linear model.

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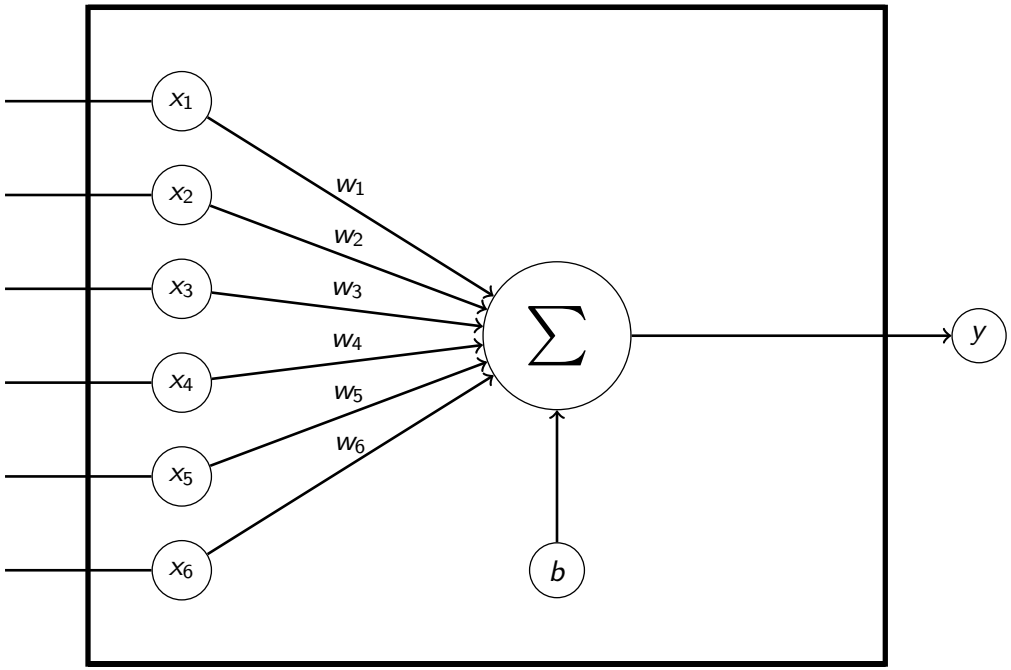
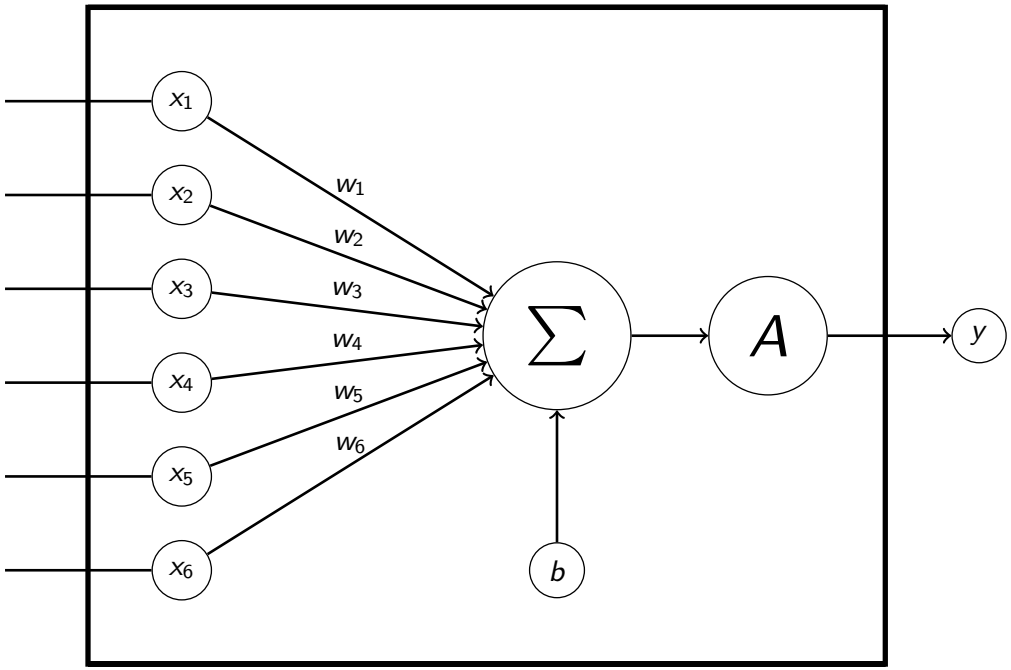
Solution: add nonlinearity to neurons.

Neuron with activation

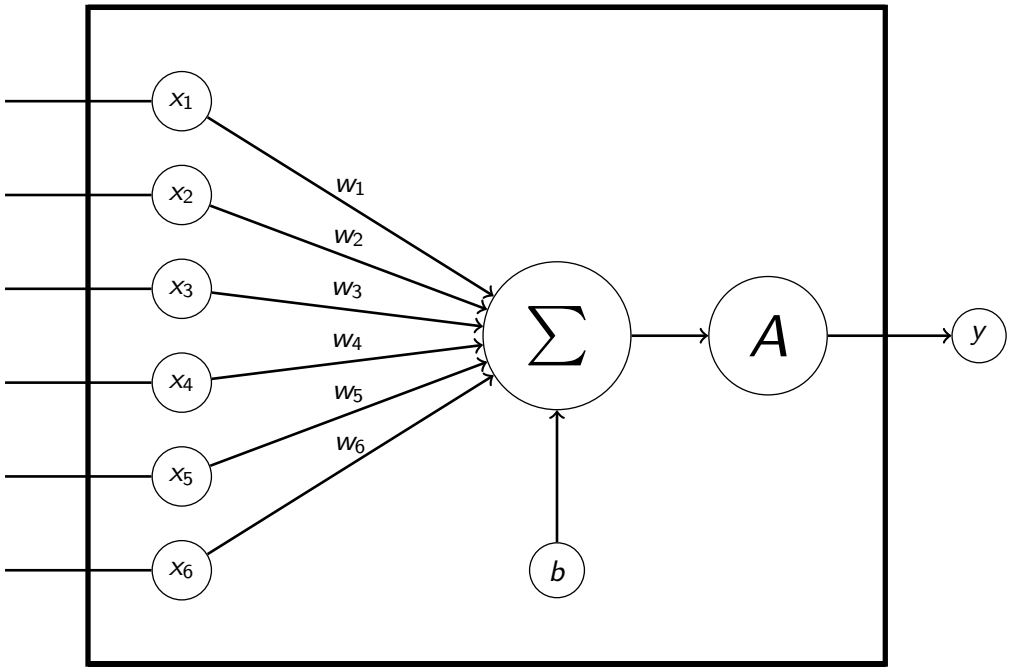


Neuron with activation



$$A(x) = \begin{cases} 0 & \text{if } x < 0 \\ 1 & \text{otherwise} \end{cases}$$

Neuron with activation



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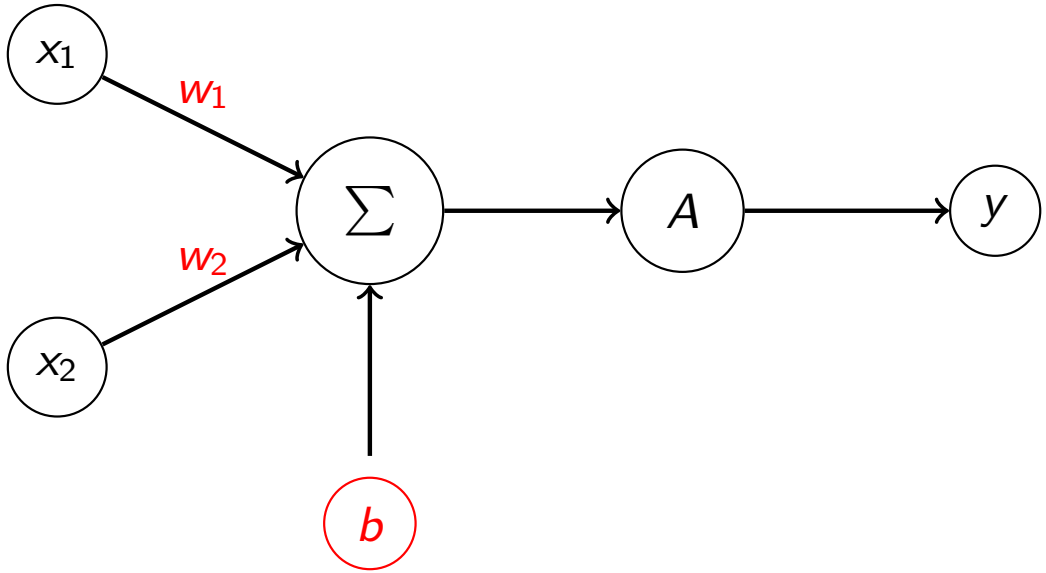
$$y = A(w_1x_1 + w_2x_2 + w_3x_3 + w_4x_4 + w_5x_5 + w_6x_6 + b)$$

Computation example

Binary AND gate

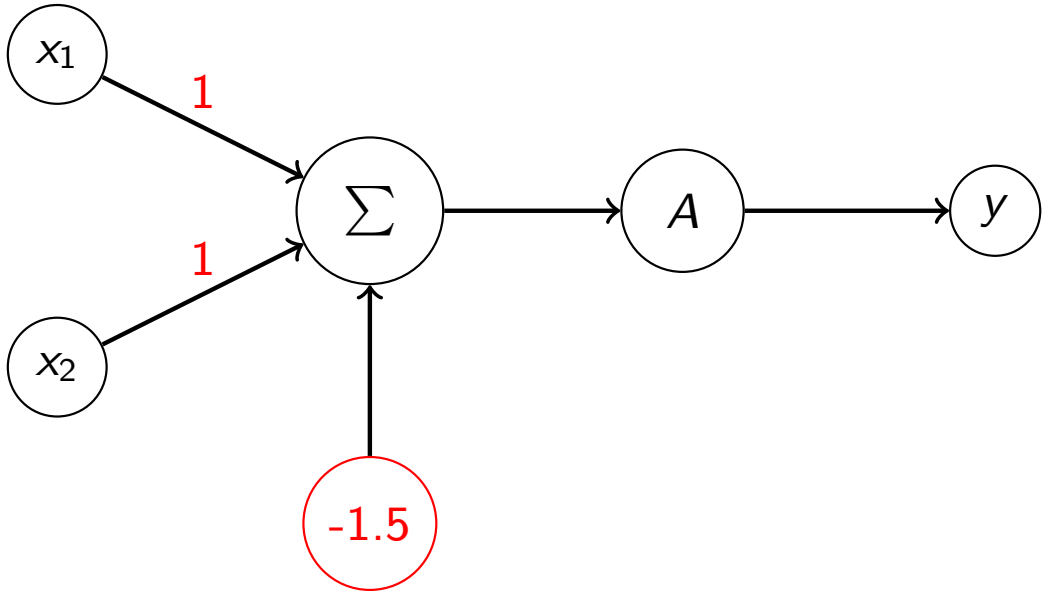


We want to set w_1, w_2 and b such that:

$$A(w_1 x_1 + w_2 x_2 + b) = x_1 \text{ AND } x_2$$

Computation example

Binary AND gate



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Computation example

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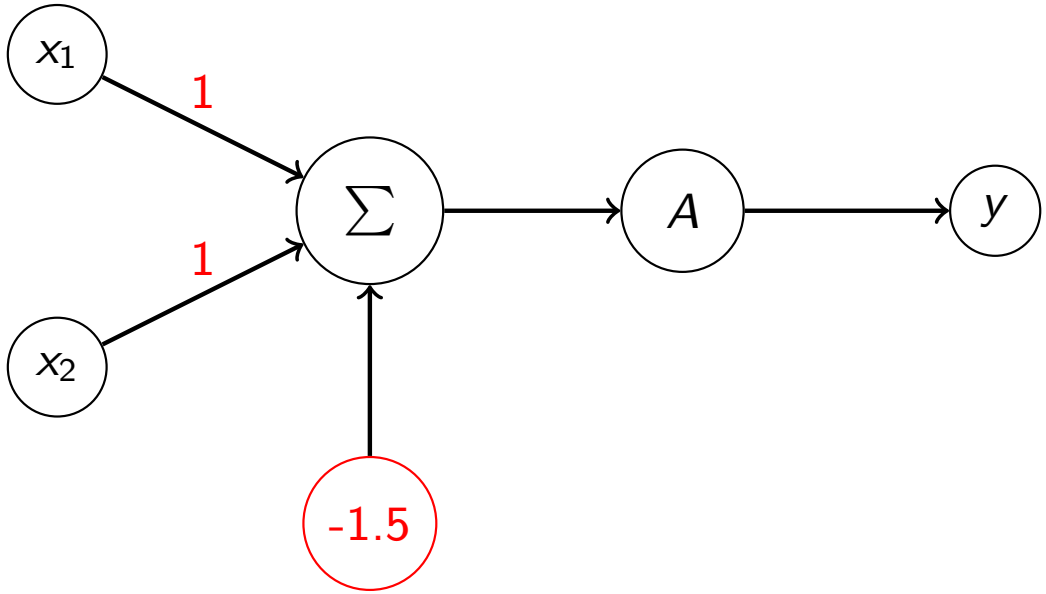

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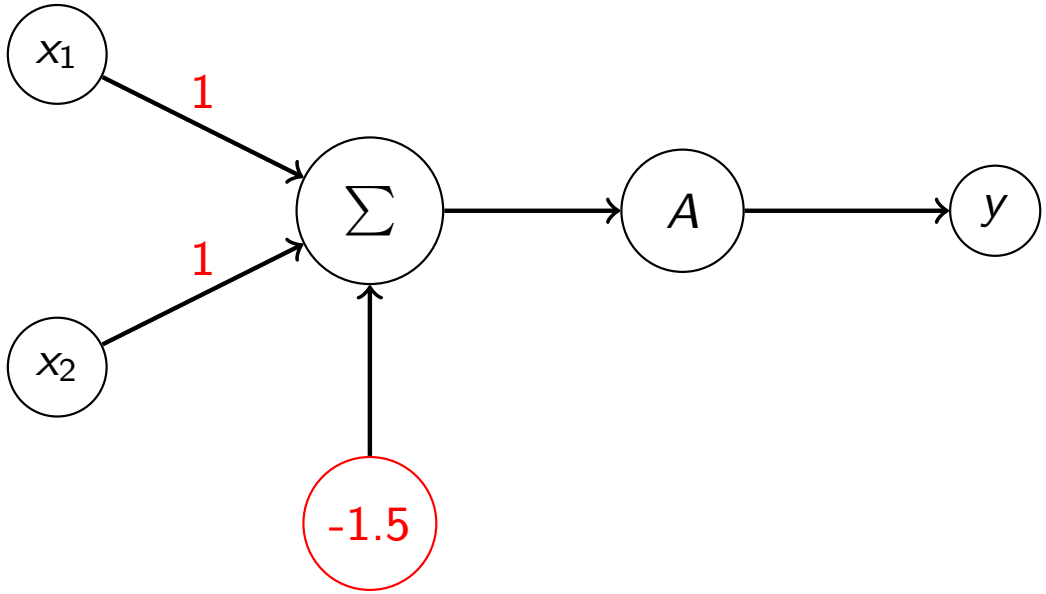
$$x_0 = 0, x_1 = 1. \quad y = A(0 + 1 - 1.5) = A(-0.5) = 0$$

Computation example

Binary AND gate



We want to set w_1, w_2 and b such that:

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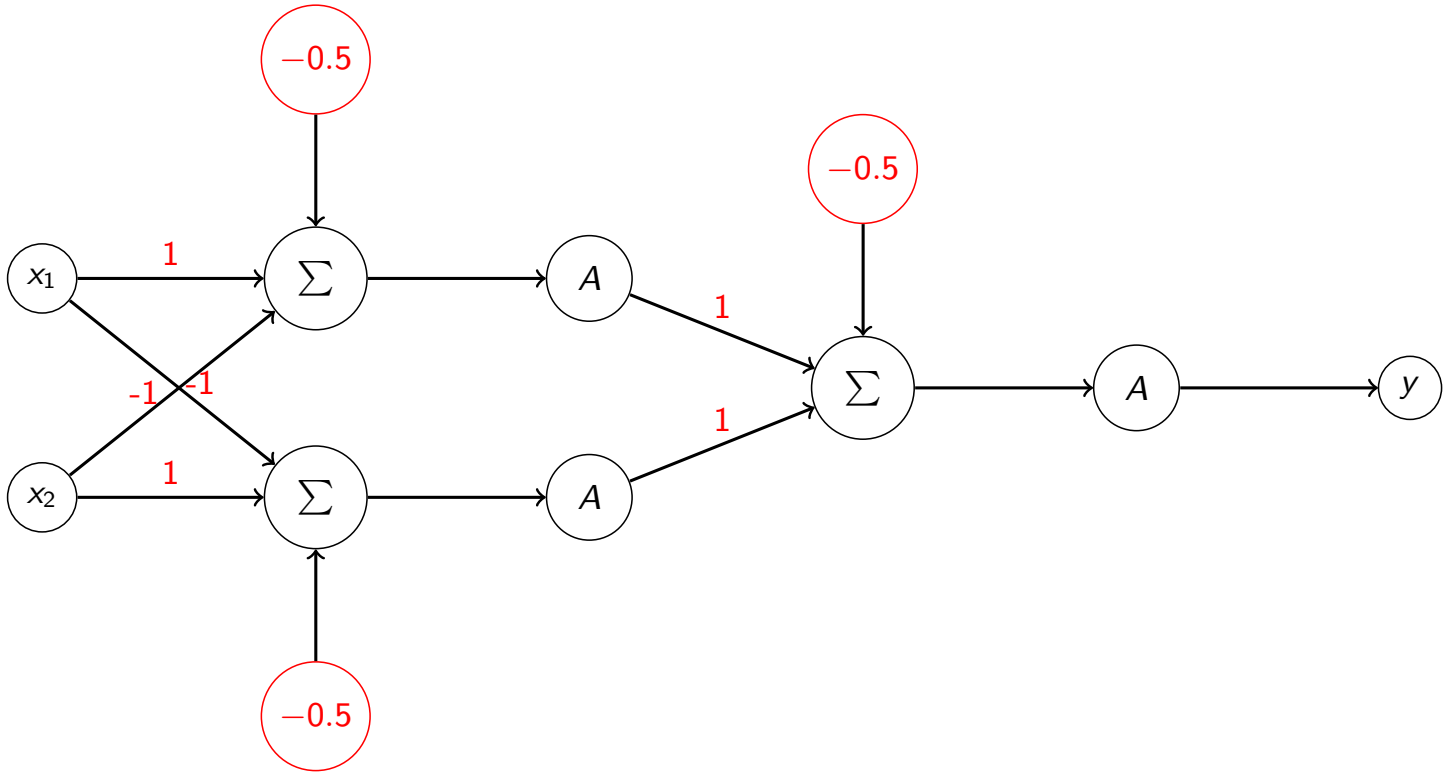
$$x_0 = 0, x_1 = 1. \quad y = A(0 + 1 - 1.5) = A(-0.5) = 0$$

$$x_0 = 1, x_1 = 1. \quad y = A(1 + 1 - 1.5) = A(0.5) = 1$$

Computation example

Binary XOR gate



Model complexity

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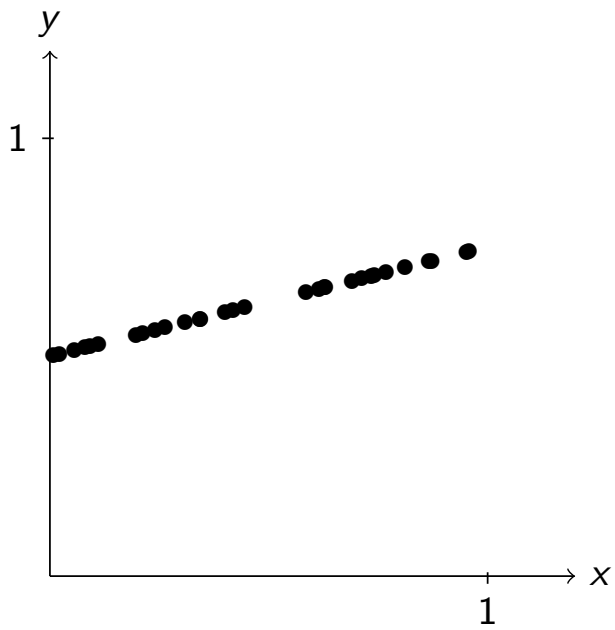
- XOR network: 9 parameters
- dogs vs cats pictures (VGG16 network): 138,357,544 parameters

We should probably look for a way to tune these parameters automatically otherwise it is going to get *really* boring *really* quickly.

Parameter tuning

Line approximation

We have a few sample points and we want to find a line that approximate these points.



Our model is just a line

$$y_{pred} = ax + b$$

We want to find a and b to best match our samples.

First we have a define a loss that measures how good our predictions are.

$$l(x, y, a, b) = (y - y_{pred})^2 = (y - (ax + b))^2$$

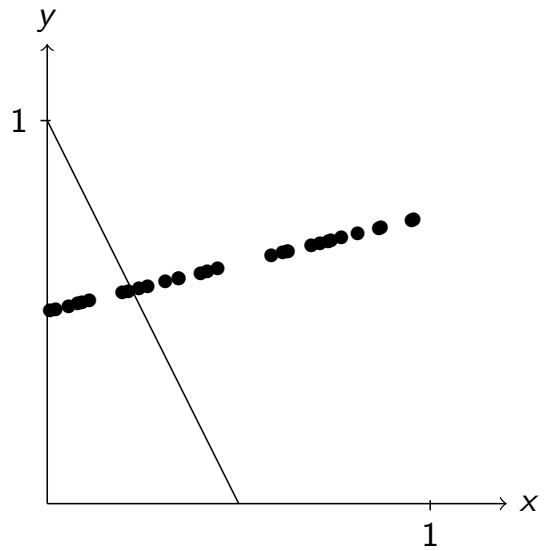
and now, we compute how the loss is affected by small changes of a and b:

$$\frac{dl}{da} = 2x(ax + b - y) \qquad \frac{dl}{db} = 2(ax + b - y)$$

Parameter tuning

Gradient descent

We start with random values: $a = -2$ and $b = 1$



Then, we compute the average of the gradient along all (x, y) couples

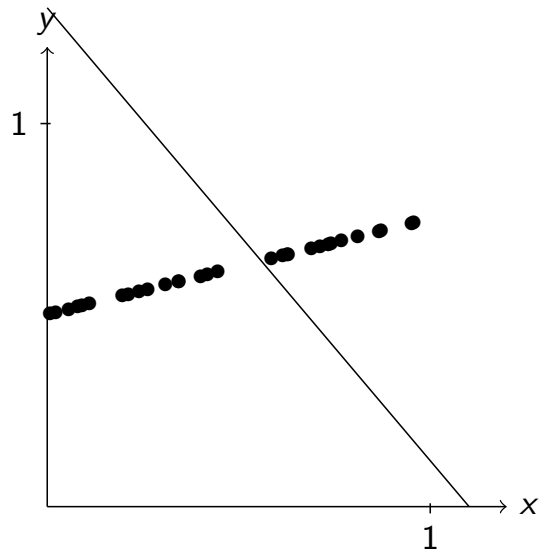
$$a = -2.00 \quad b = 1.00 \quad \overline{\frac{dl}{da}} = -1.07 \quad \overline{\frac{dl}{db}} = -1.37 \quad \overline{l(x, y, a, b)} = 0.860367$$

And update a and b by substracting a small proportion of their gradient.

Parameter tuning

Gradient descent

We start with random values: $a = -2$ and $b = 1$



Then, we compute the average of the gradient along all (x, y) couples

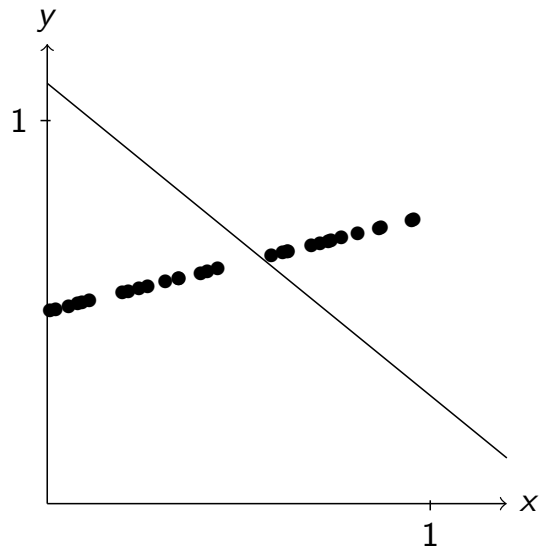
$$a = -1.18 \quad b = 1.30 \quad \overline{\frac{dl}{da}} = -0.17 \quad \overline{\frac{dl}{db}} = 0.09 \quad \overline{l(x, y, a, b)} = 0.159420$$

And update a and b by substracting a small proportion of their gradient.

Parameter tuning

Gradient descent

We start with random values: $a = -2$ and $b = 1$



Then, we compute the average of the gradient along all (x, y) couples

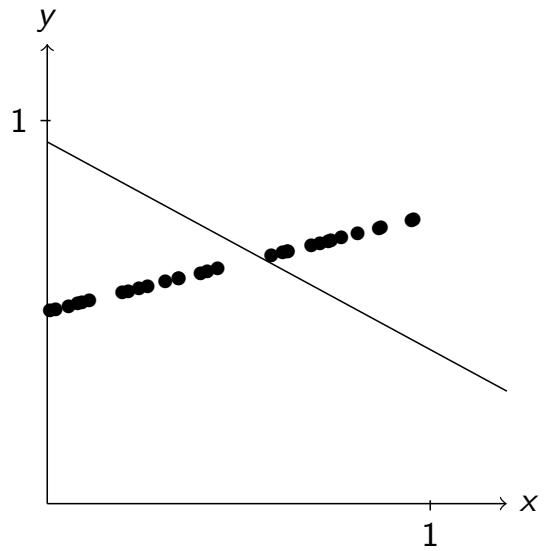
$$a = -0.82 \quad b = 1.10 \quad \overline{\frac{dl}{da}} = -0.13 \quad \overline{\frac{dl}{db}} = 0.07 \quad \overline{l(x, y, a, b)} = 0.088204$$

And update a and b by substracting a small proportion of their gradient.

Parameter tuning

Gradient descent

We start with random values: $a = -2$ and $b = 1$



Then, we compute the average of the gradient along all (x, y) couples

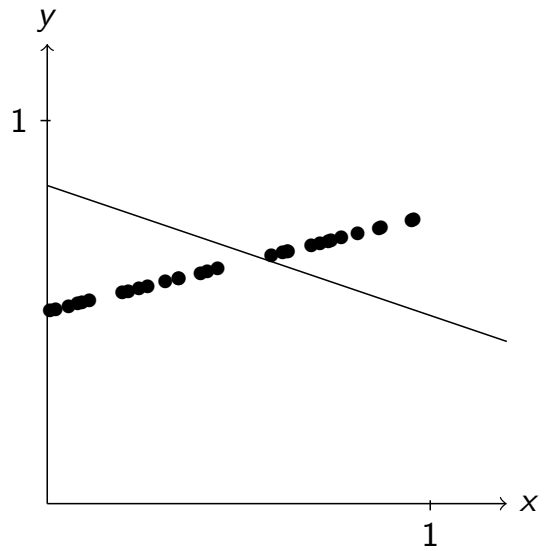
$$a = -0.54 \quad b = 0.94 \quad \overline{\frac{dl}{da}} = -0.09 \quad \overline{\frac{dl}{db}} = 0.05 \quad \overline{l(x, y, a, b)} = 0.048802$$

And update a and b by substracting a small proportion of their gradient.

Parameter tuning

Gradient descent

We start with random values: $a = -2$ and $b = 1$



Then, we compute the average of the gradient along all (x, y) couples

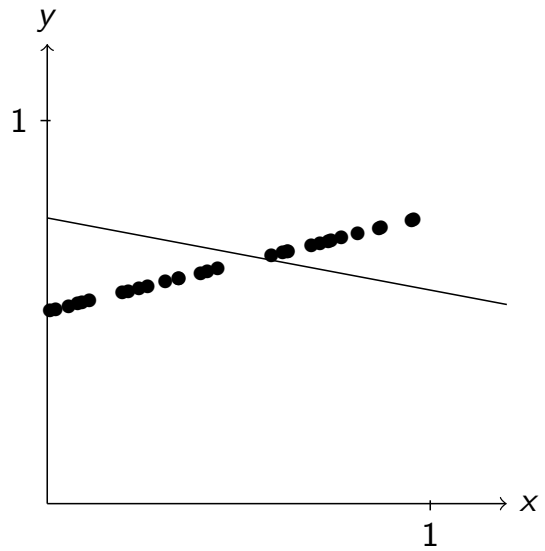
$$a = -0.34 \quad b = 0.83 \quad \overline{\frac{dl}{da}} = -0.07 \quad \overline{\frac{dl}{db}} = 0.04 \quad \overline{l(x, y, a, b)} = 0.027001$$

And update a and b by substracting a small proportion of their gradient.

Parameter tuning

Gradient descent

We start with random values: $a = -2$ and $b = 1$



Then, we compute the average of the gradient along all (x, y) couples

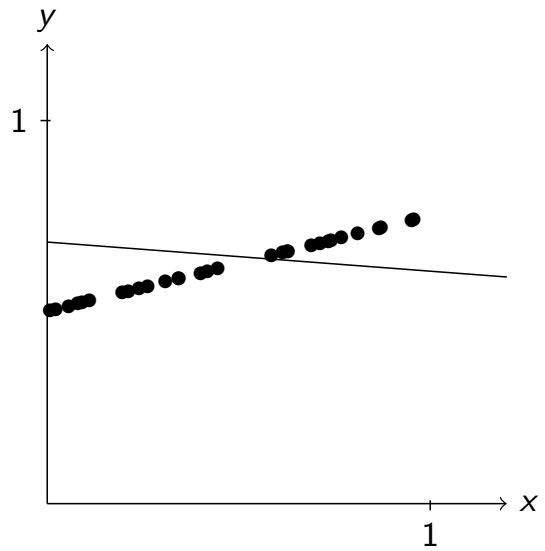
$$a = -0.19 \quad b = 0.75 \quad \overline{\frac{dl}{da}} = -0.05 \quad \overline{\frac{dl}{db}} = 0.03 \quad \overline{l(x, y, a, b)} = 0.014939$$

And update a and b by substracting a small proportion of their gradient.

Parameter tuning

Gradient descent

We start with random values: $a = -2$ and $b = 1$



Then, we compute the average of the gradient along all (x, y) couples

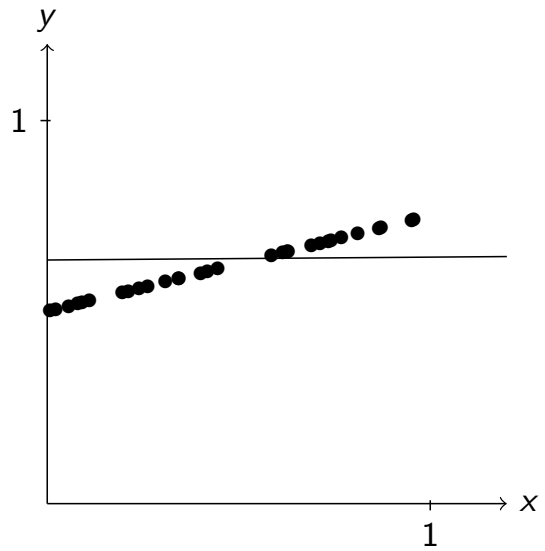
$$a = -0.08 \quad b = 0.68 \quad \overline{\frac{dl}{da}} = -0.04 \quad \overline{\frac{dl}{db}} = 0.02 \quad \overline{l(x, y, a, b)} = 0.008266$$

And update a and b by substracting a small proportion of their gradient.

Parameter tuning

Gradient descent

We start with random values: $a = -2$ and $b = 1$



Then, we compute the average of the gradient along all (x, y) couples

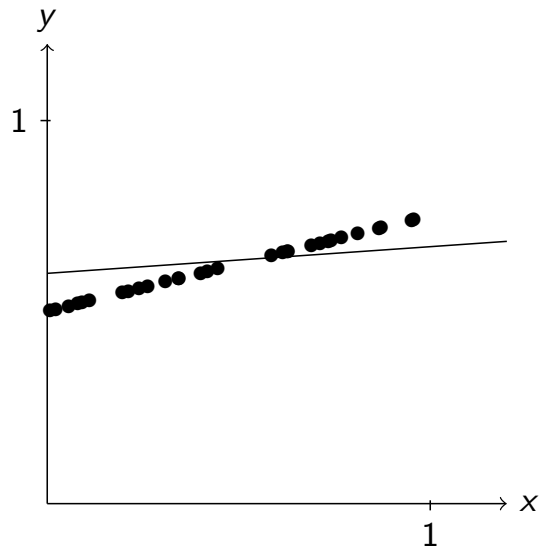
$$a = 0.01 \quad b = 0.64 \quad \overline{\frac{dl}{da}} = -0.03 \quad \overline{\frac{dl}{db}} = 0.02 \quad \overline{l(x, y, a, b)} = 0.004573$$

And update a and b by substracting a small proportion of their gradient.

Parameter tuning

Gradient descent

We start with random values: $a = -2$ and $b = 1$



Then, we compute the average of the gradient along all (x, y) couples

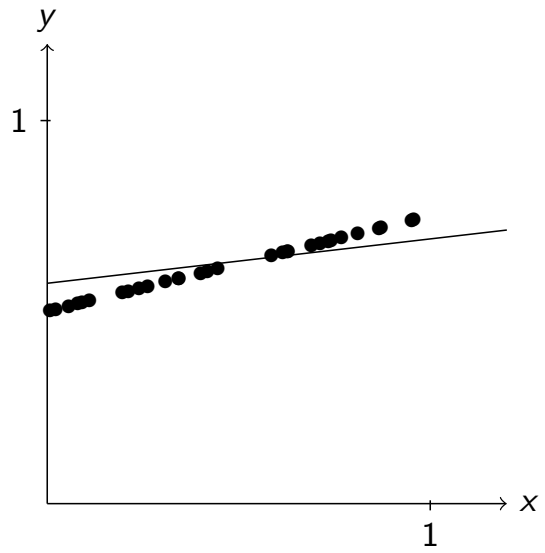
$$a = 0.07 \quad b = 0.60 \quad \overline{\frac{dl}{da}} = -0.02 \quad \overline{\frac{dl}{db}} = 0.01 \quad \overline{l(x, y, a, b)} = 0.002530$$

And update a and b by substracting a small proportion of their gradient.

Parameter tuning

Gradient descent

We start with random values: $a = -2$ and $b = 1$



Then, we compute the average of the gradient along all (x, y) couples

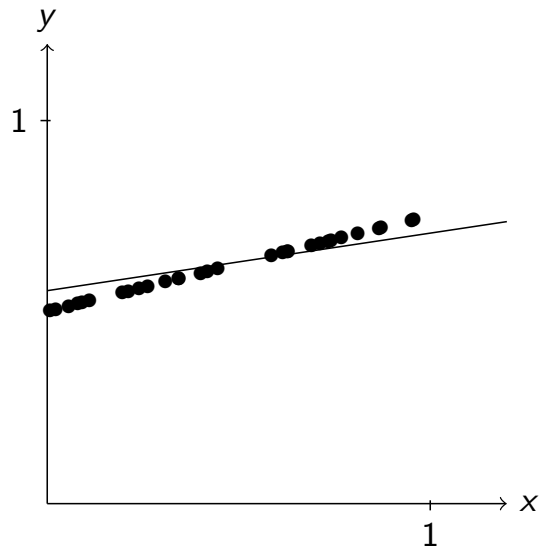
$$a = 0.12 \quad b = 0.58 \quad \overline{\frac{dl}{da}} = -0.02 \quad \overline{\frac{dl}{db}} = 0.01 \quad \overline{l(x, y, a, b)} = 0.001400$$

And update a and b by substracting a small proportion of their gradient.

Parameter tuning

Gradient descent

We start with random values: $a = -2$ and $b = 1$



Then, we compute the average of the gradient along all (x, y) couples

$$a = 0.15 \quad b = 0.56 \quad \overline{\frac{dl}{da}} = -0.01 \quad \overline{\frac{dl}{db}} = 0.01 \quad \overline{l(x, y, a, b)} = 0.000775$$

And update a and b by substracting a small proportion of their gradient.

Parameter tuning

Gradient descent

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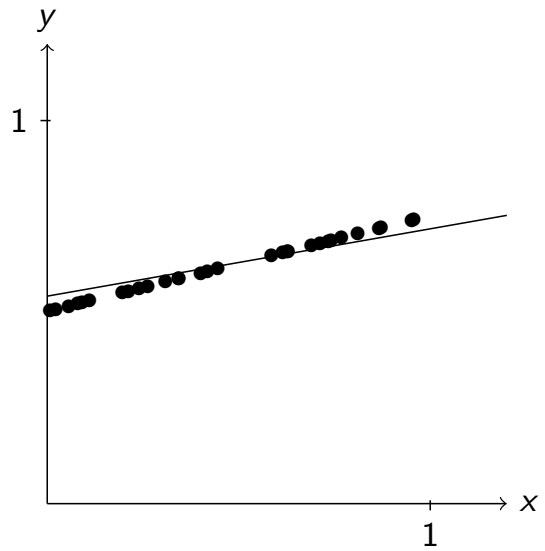

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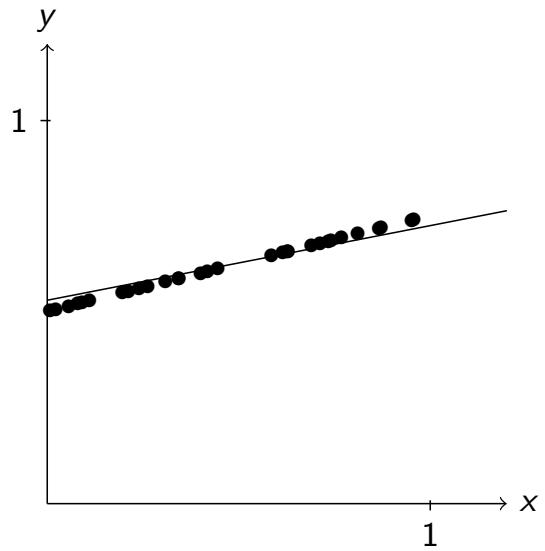
$$a = 0.18 \quad b = 0.54 \quad \overline{\frac{dl}{da}} = -0.01 \quad \overline{\frac{dl}{db}} = 0.00 \quad \overline{l(x, y, a, b)} = 0.000429$$

And update a and b by substracting a small proportion of their gradient.

Parameter tuning

Gradient descent

We start with random values: $a = -2$ and $b = 1$



Then, we compute the average of the gradient along all (x, y) couples

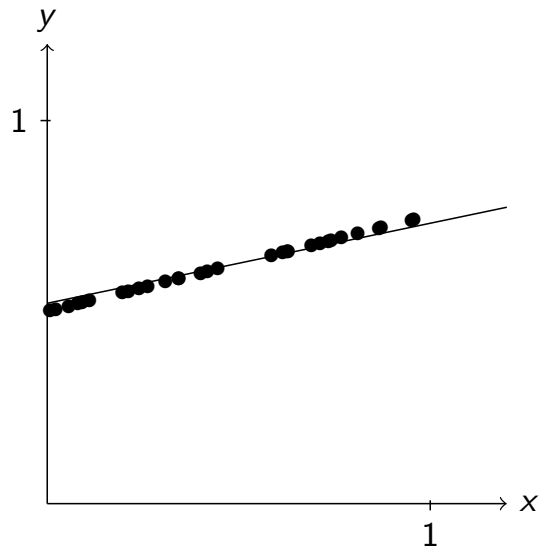
$$a = 0.19 \quad b = 0.53 \quad \overline{\frac{dl}{da}} = -0.01 \quad \overline{\frac{dl}{db}} = 0.00 \quad \overline{l(x, y, a, b)} = 0.000237$$

And update a and b by substracting a small proportion of their gradient.

Parameter tuning

Gradient descent

We start with random values: $a = -2$ and $b = 1$



Then, we compute the average of the gradient along all (x, y) couples

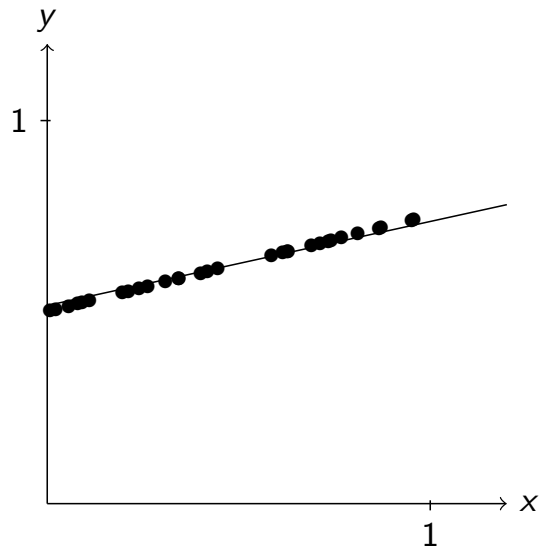
$$a = 0.21 \quad b = 0.52 \quad \overline{\frac{dl}{da}} = 0.00 \quad \overline{\frac{dl}{db}} = 0.00 \quad \overline{l(x, y, a, b)} = 0.000131$$

And update a and b by substracting a small proportion of their gradient.

Parameter tuning

Gradient descent

We start with random values: $a = -2$ and $b = 1$



Then, we compute the average of the gradient along all (x, y) couples

$$a = 0.22 \quad b = 0.52 \quad \overline{\frac{dl}{da}} = 0.00 \quad \overline{\frac{dl}{db}} = 0.00 \quad \overline{l(x, y, a, b)} = 0.000073$$

And update a and b by substracting a small proportion of their gradient.

Parameter tuning

Gradient descent

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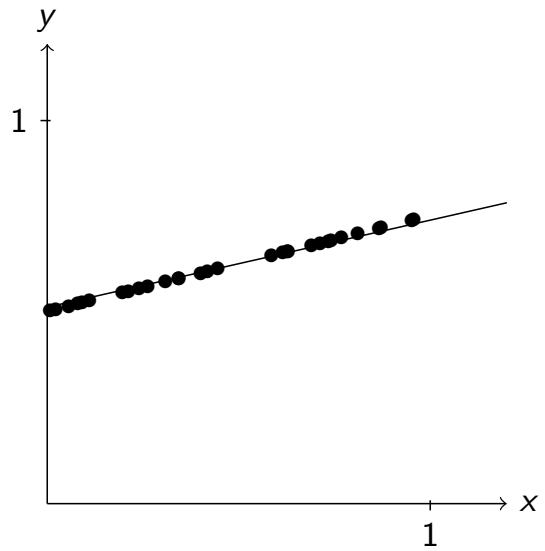


Then, we compute the average of the gradient along all (x, y) couples

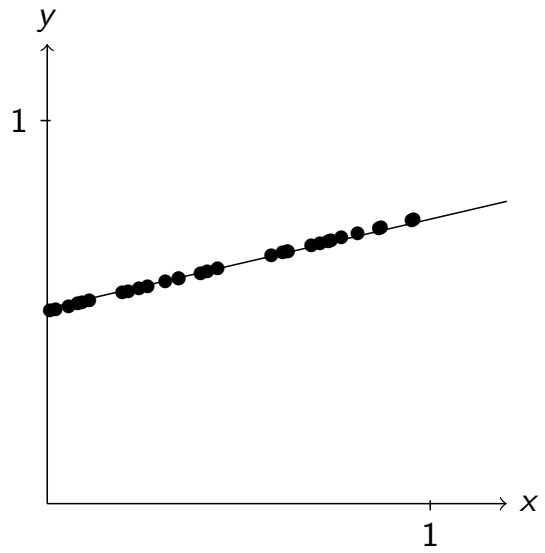
$$a = 0.23 \quad b = 0.51 \quad \overline{\frac{dl}{da}} = 0.00 \quad \overline{\frac{dl}{db}} = 0.00 \quad \overline{l(x, y, a, b)} = 0.000040$$

And update a and b by substracting a small proportion of their gradient.

Parameter tuning

Gradient descent

We start with random values: $a = -2$ and $b = 1$



Then, we compute the average of the gradient along all (x, y) couples

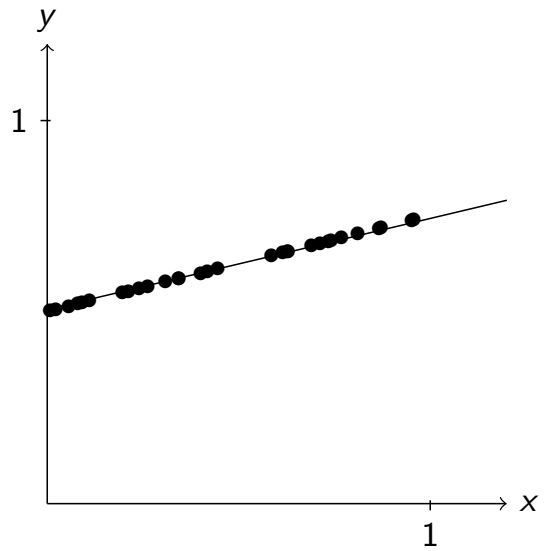
$$a = 0.23 \quad b = 0.51 \quad \overline{\frac{dl}{da}} = 0.00 \quad \overline{\frac{dl}{db}} = 0.00 \quad \overline{l(x, y, a, b)} = 0.000022$$

And update a and b by substracting a small proportion of their gradient.

Parameter tuning

Gradient descent

We start with random values: $a = -2$ and $b = 1$



Then, we compute the average of the gradient along all (x, y) couples

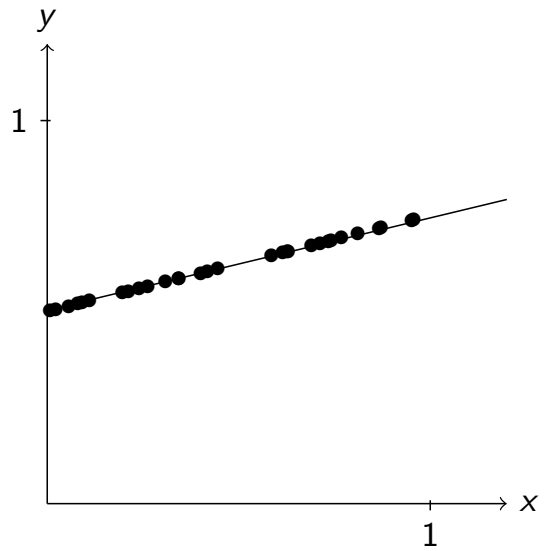
$$a = 0.24 \quad b = 0.51 \quad \overline{\frac{dl}{da}} = 0.00 \quad \overline{\frac{dl}{db}} = 0.00 \quad \overline{l(x, y, a, b)} = 0.000012$$

And update a and b by substracting a small proportion of their gradient.

Parameter tuning

Gradient descent

We start with random values: $a = -2$ and $b = 1$



Then, we compute the average of the gradient along all (x, y) couples

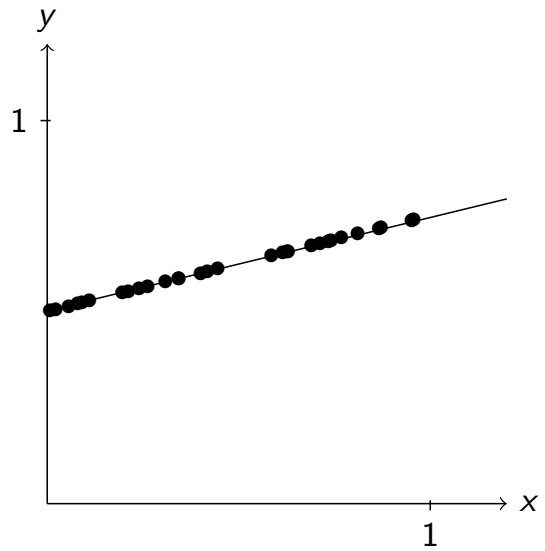
$$a = 0.24 \quad b = 0.51 \quad \overline{\frac{dl}{da}} = 0.00 \quad \overline{\frac{dl}{db}} = 0.00 \quad \overline{l(x, y, a, b)} = 0.000007$$

And update a and b by substracting a small proportion of their gradient.

Parameter tuning

Gradient descent

We start with random values: $a = -2$ and $b = 1$



Then, we compute the average of the gradient along all (x, y) couples

$$a = 0.24 \quad b = 0.50 \quad \overline{\frac{dl}{da}} = 0.00 \quad \overline{\frac{dl}{db}} = 0.00 \quad \overline{l(x, y, a, b)} = 0.000004$$

And update a and b by substracting a small proportion of their gradient.

Parameter tuning

Problem with ANN

Using gradient descent, we know how to minimize (or at least reach a local minima) a differentiable function.

Parameter tuning

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Problem: The function computed by our neural network is not differentiable because of the activation function.

$$A(x) = \begin{cases} 0 & \text{if } x < 0 \\ 1 & \text{otherwise} \end{cases}$$

Parameter tuning

Problem with ANN

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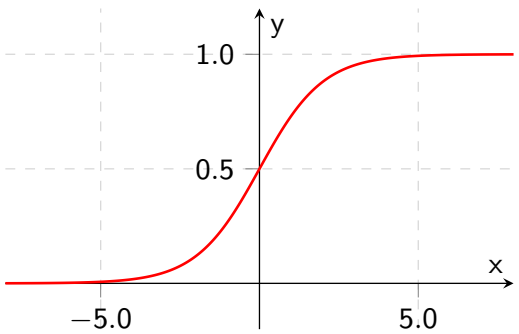
Problem: The function computed by our neural network is not differentiable because of the activation function.

$$A(x) = \begin{cases} 0 & \text{if } x < 0 \\ 1 & \text{otherwise} \end{cases}$$

Solution: We replace it by a differentiable function that does the same job.

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



Convolution

Motivation

For now, our networks computes a nonlinear function of the inputs. If we work with images, it has to learn the *spacial structure* of the data by itself, which takes a long time.

A nice way to help it is to build convolution layers into the network.

Convolution

Kernel

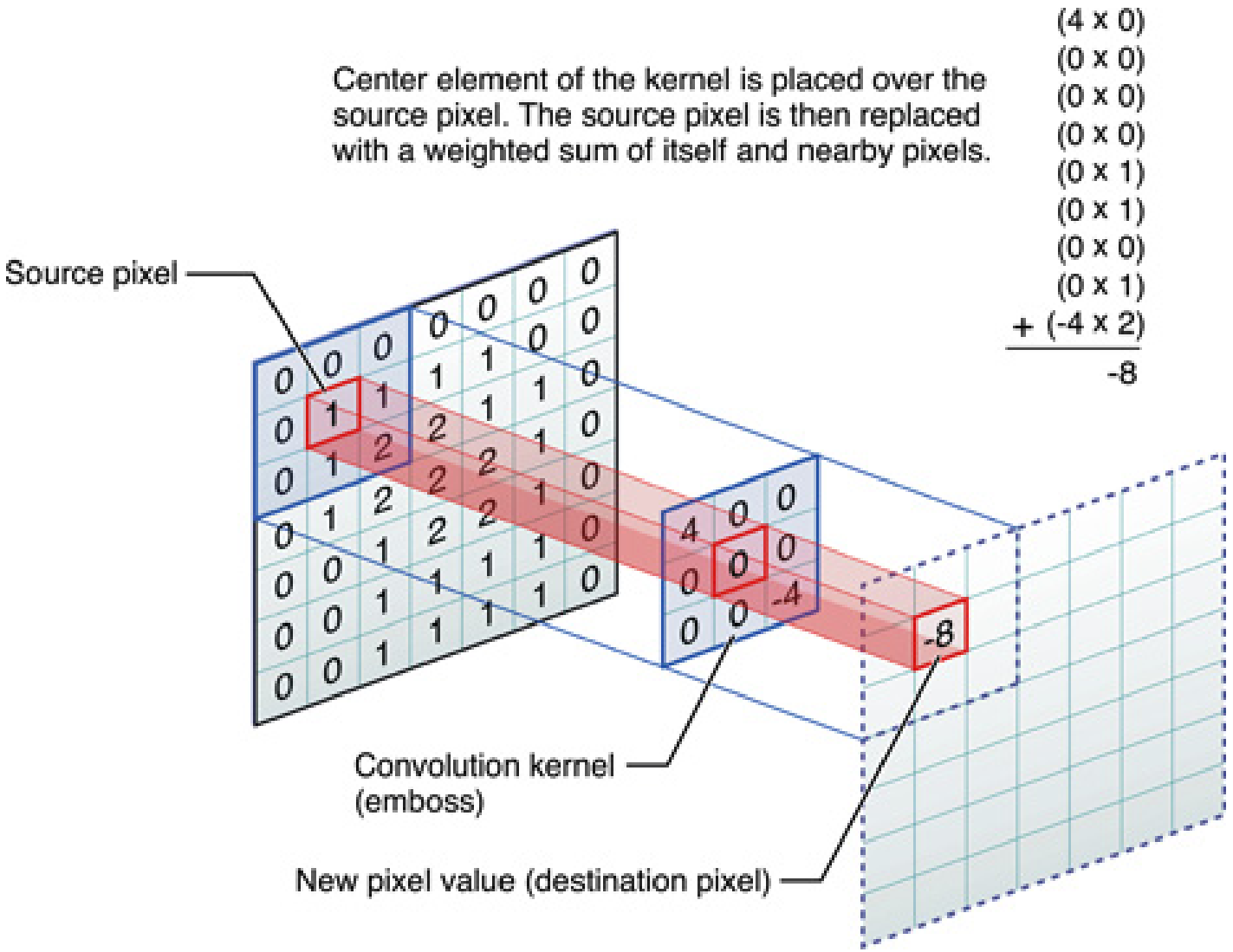
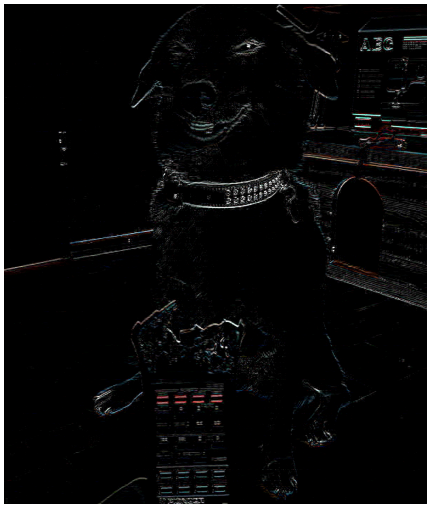


Image from `http://stats.stackexchange.com/`

Convolution

Example: Sobel operators

$$\begin{pmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{pmatrix}$$



$$\begin{pmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{pmatrix}$$

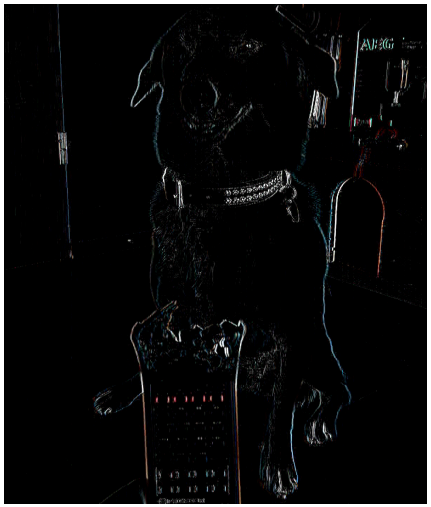


Image from `http://www.reddit.com/`

Convolutional neural network

VGG network (2014)

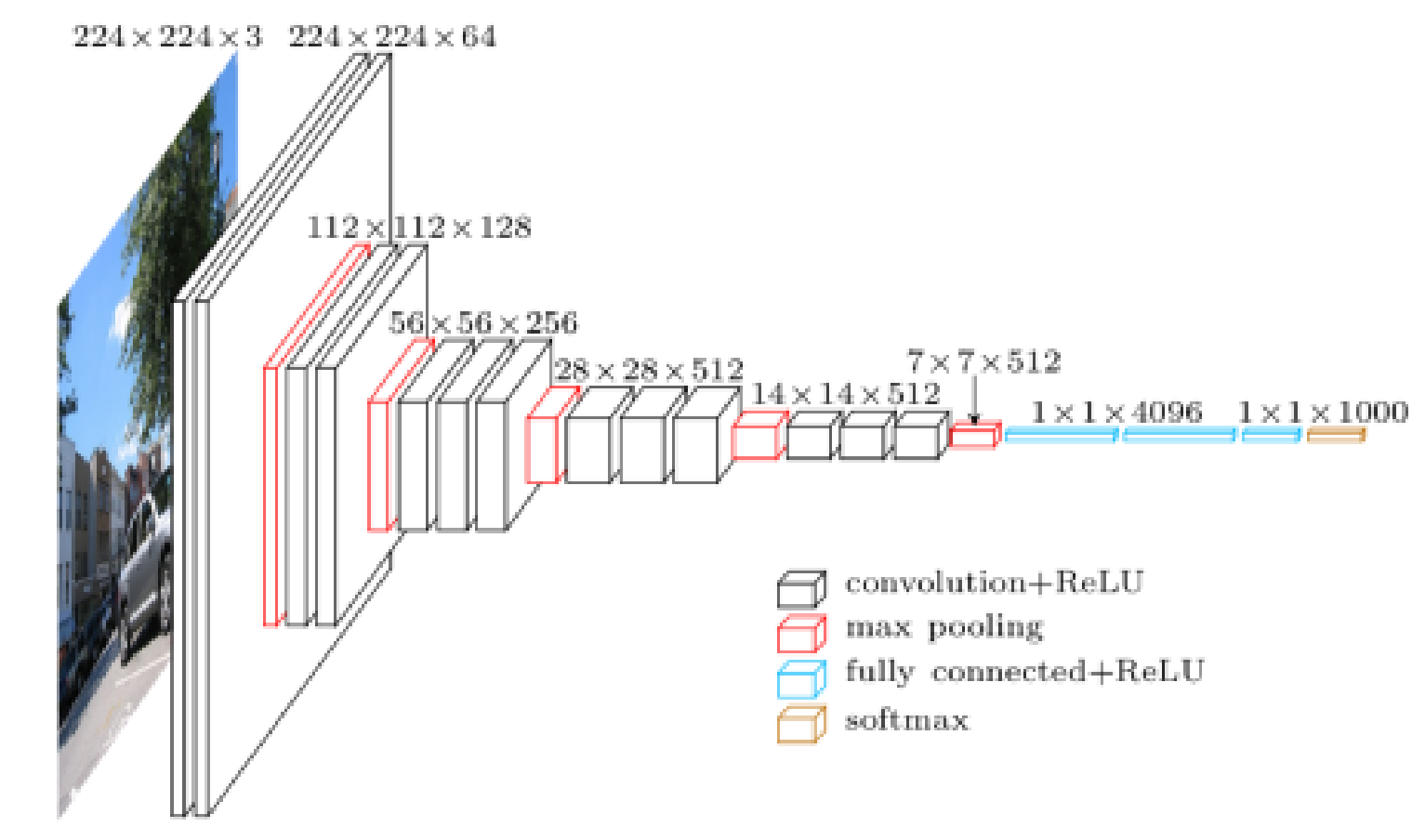
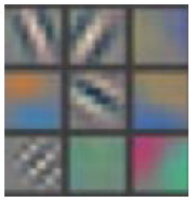


Image from `https://www.cs.toronto.edu/~frossard/post/vgg16/`

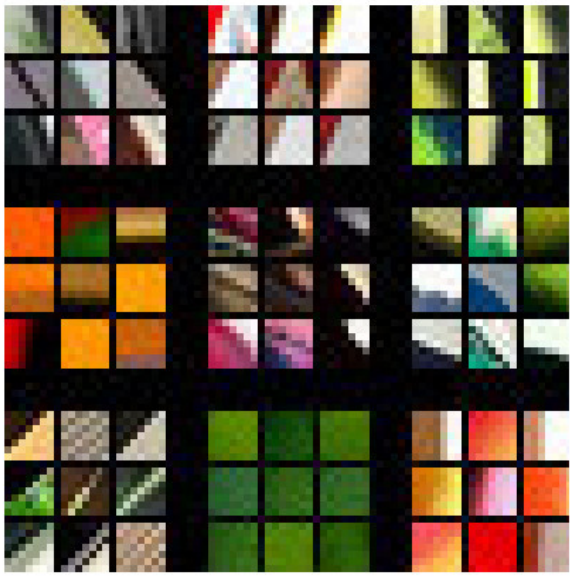
Convolution

What do filter recognize?

Image from `http://www.matthewzeiler.com/pubs/arxive2013/eccv2014.pdf`



Layer 1



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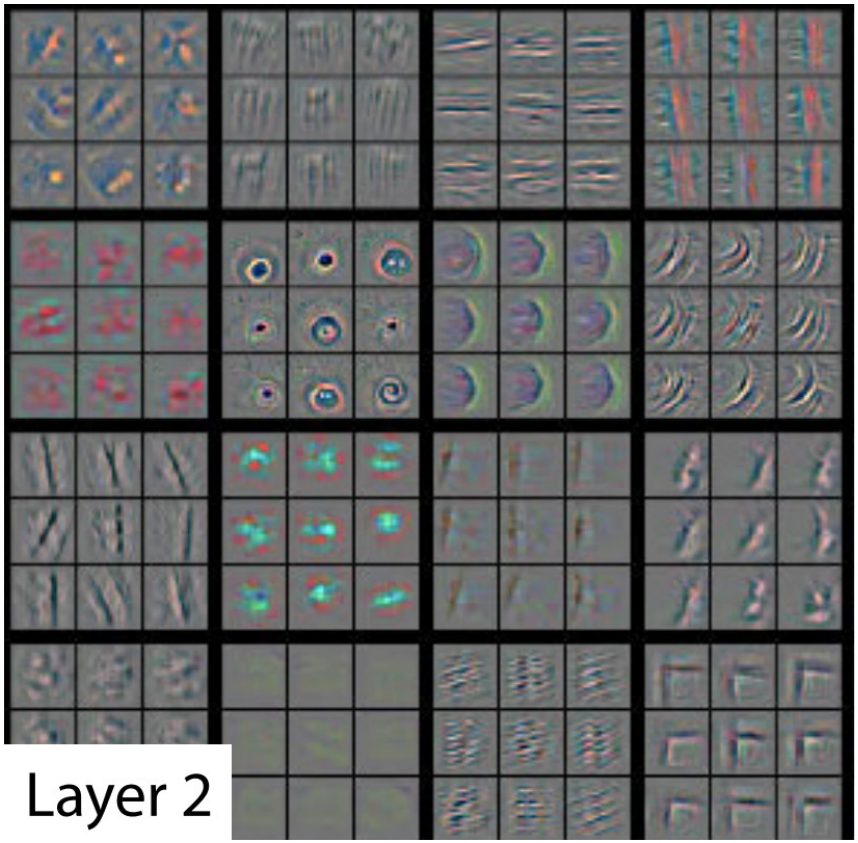

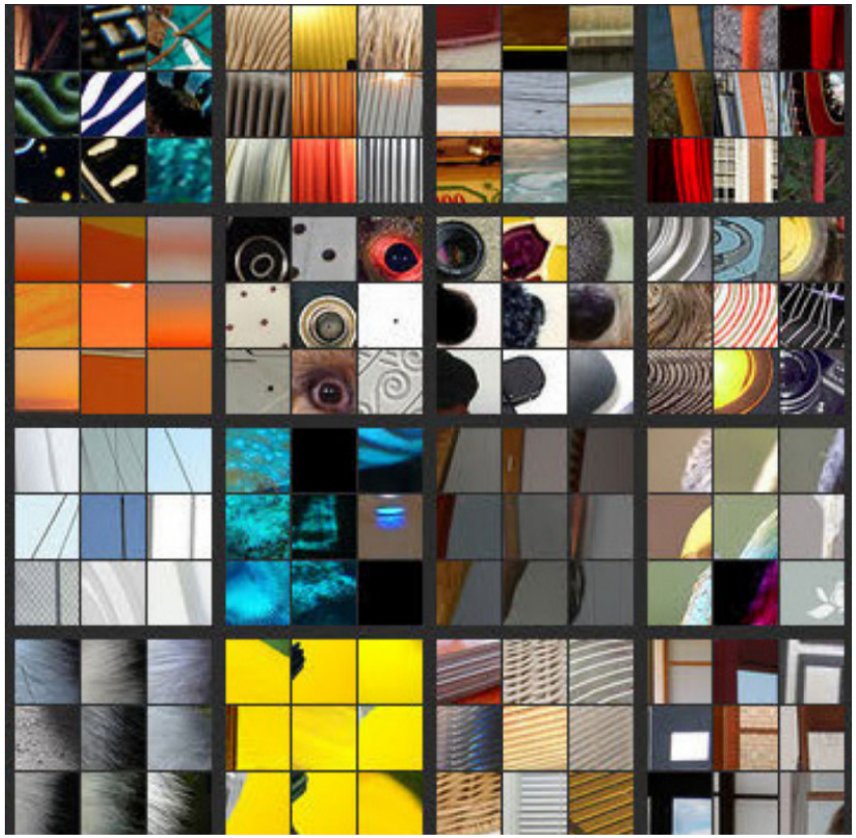

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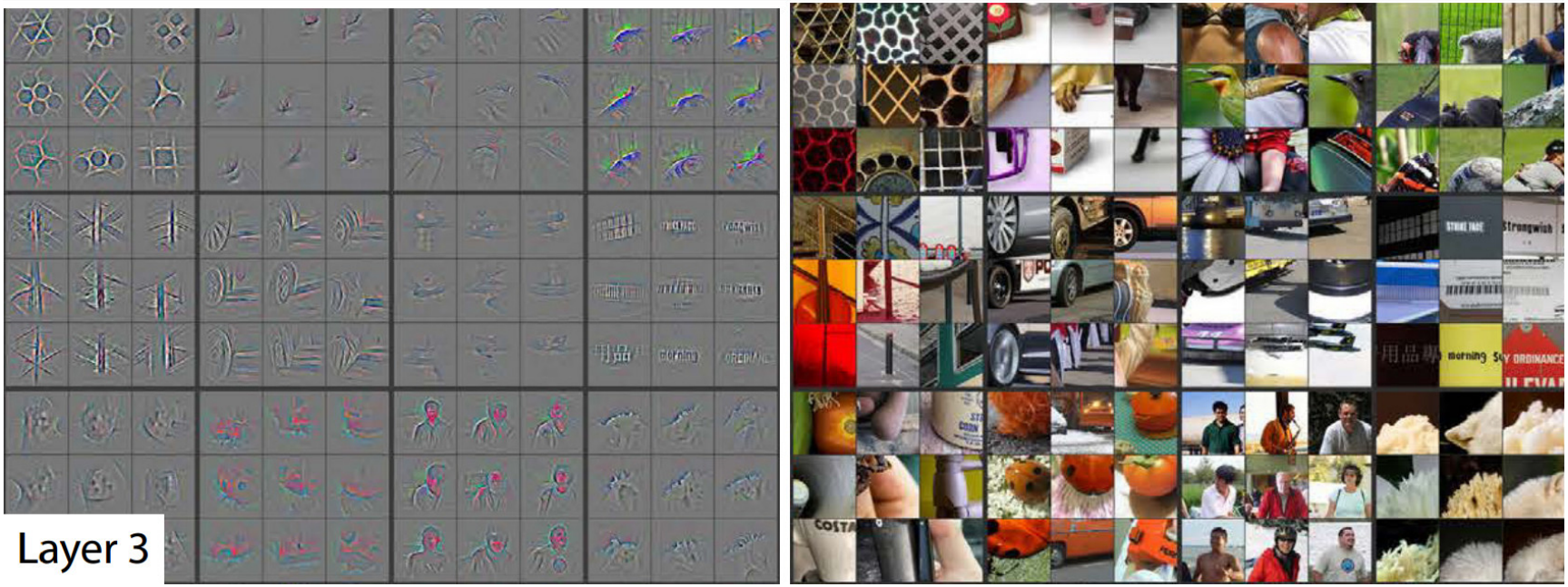

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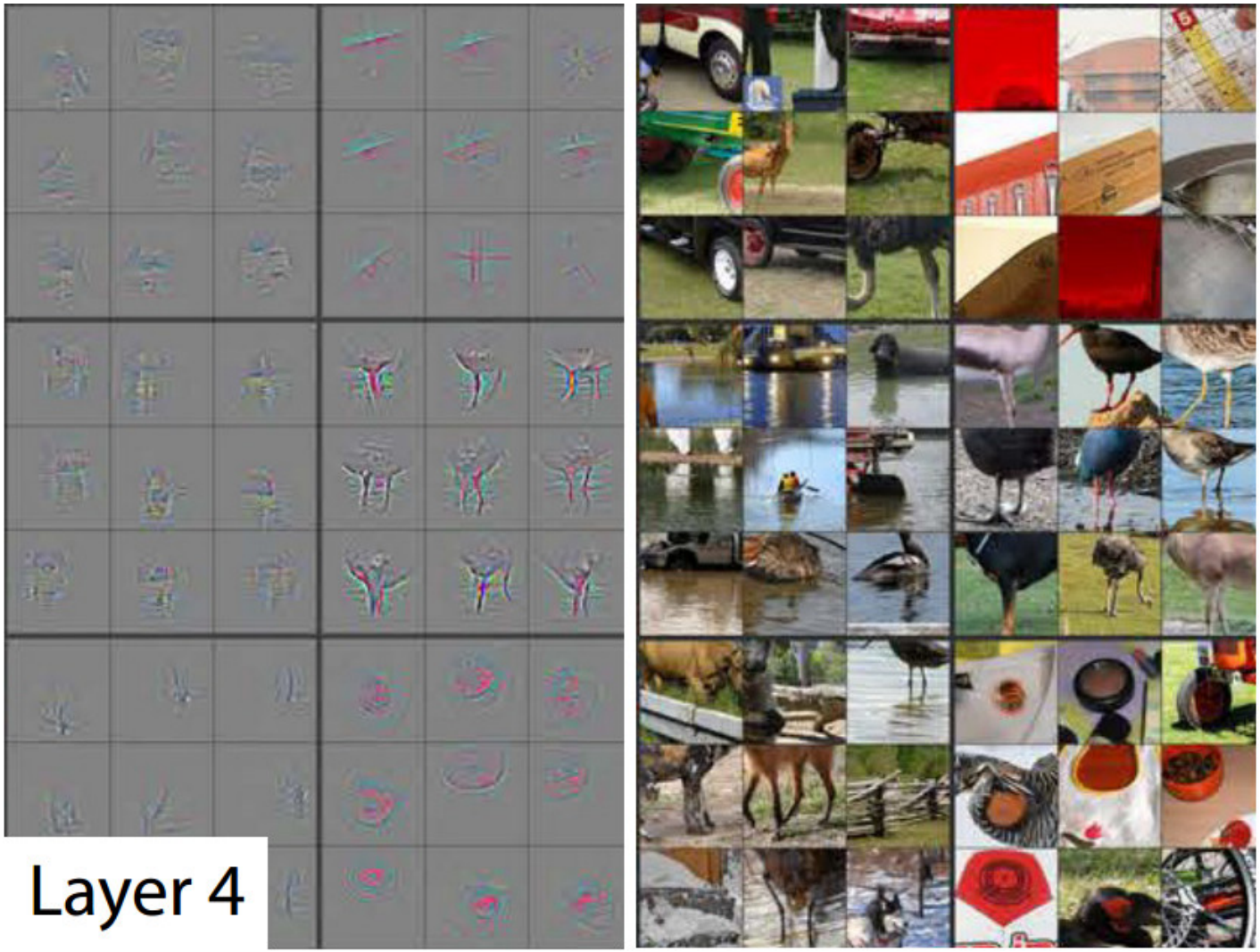

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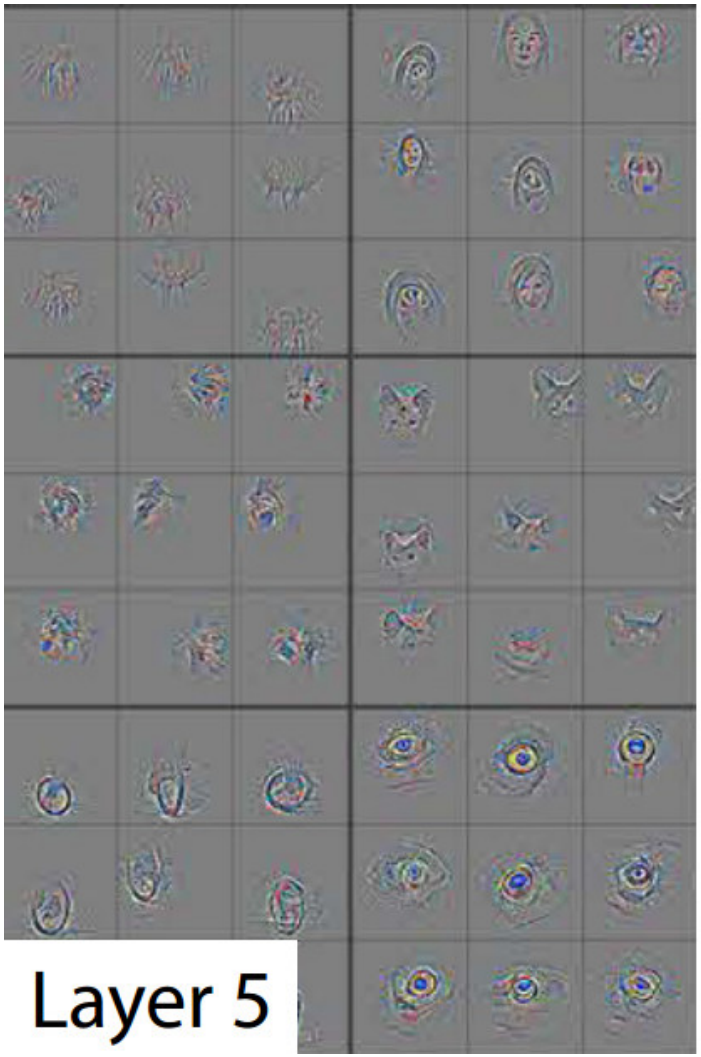
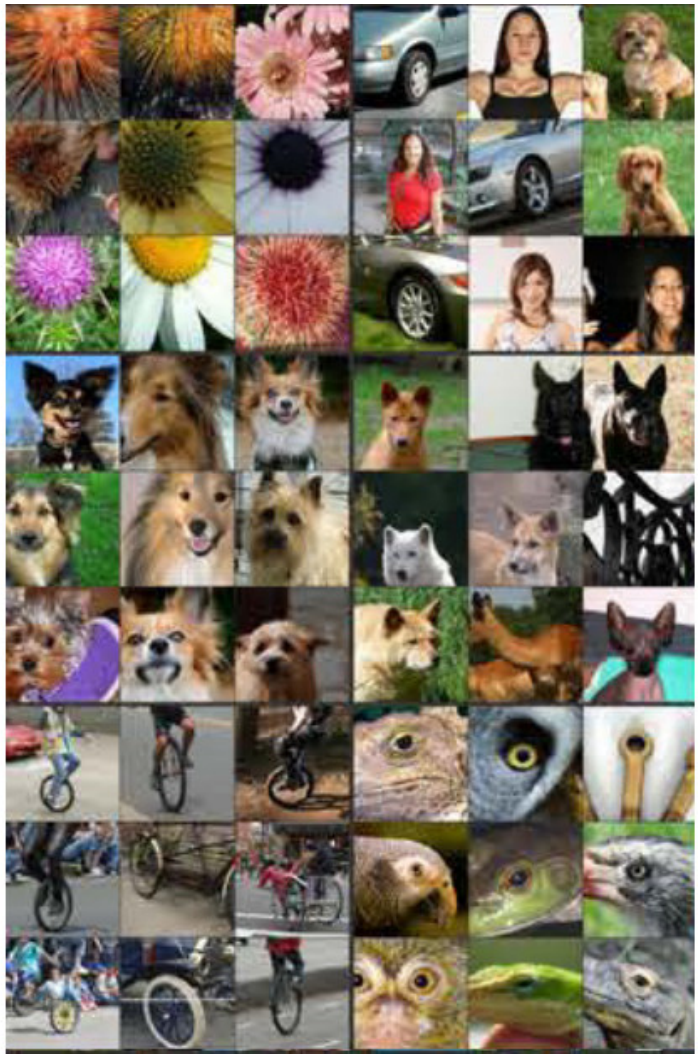




Convolutional neural network

VGG network (2014)

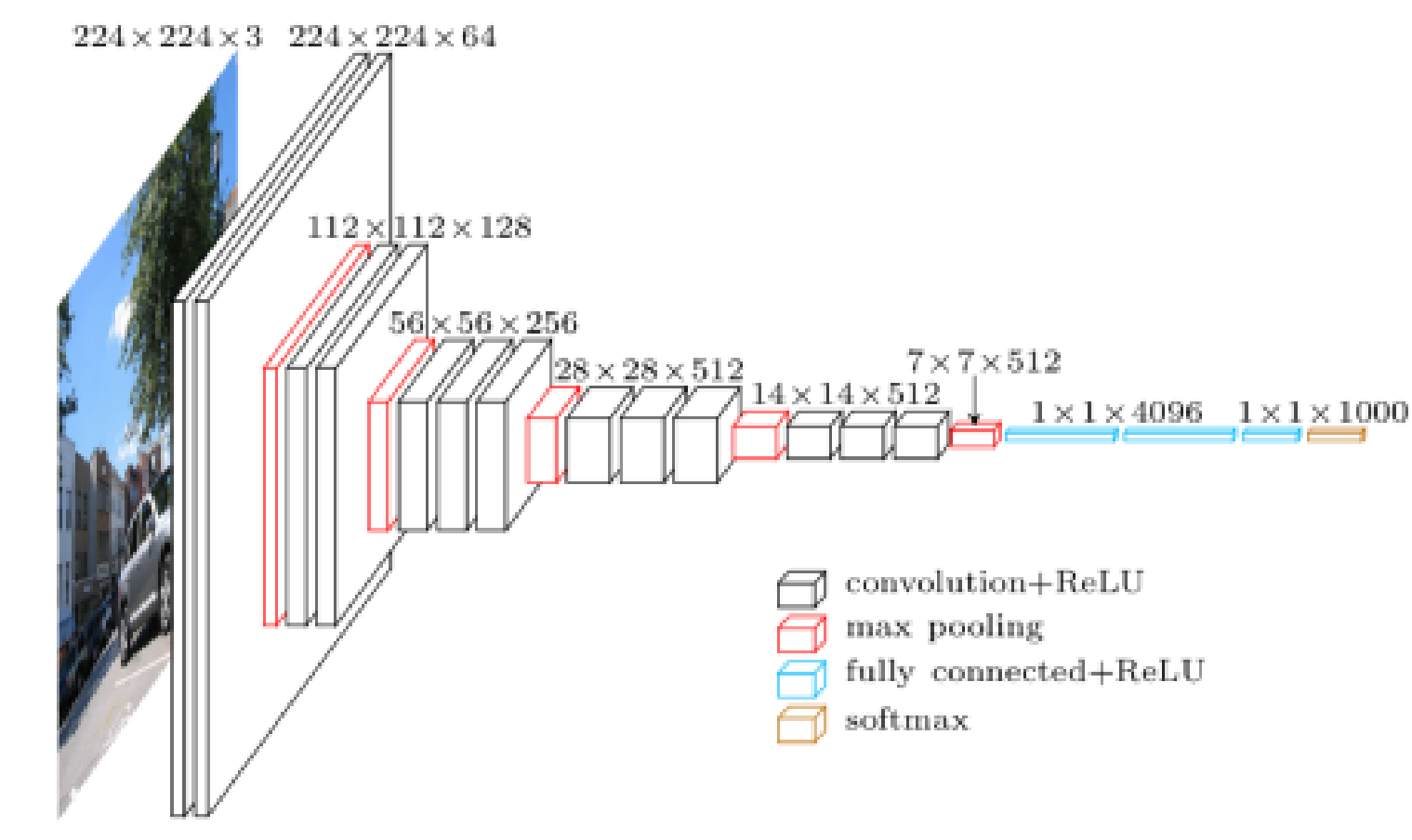
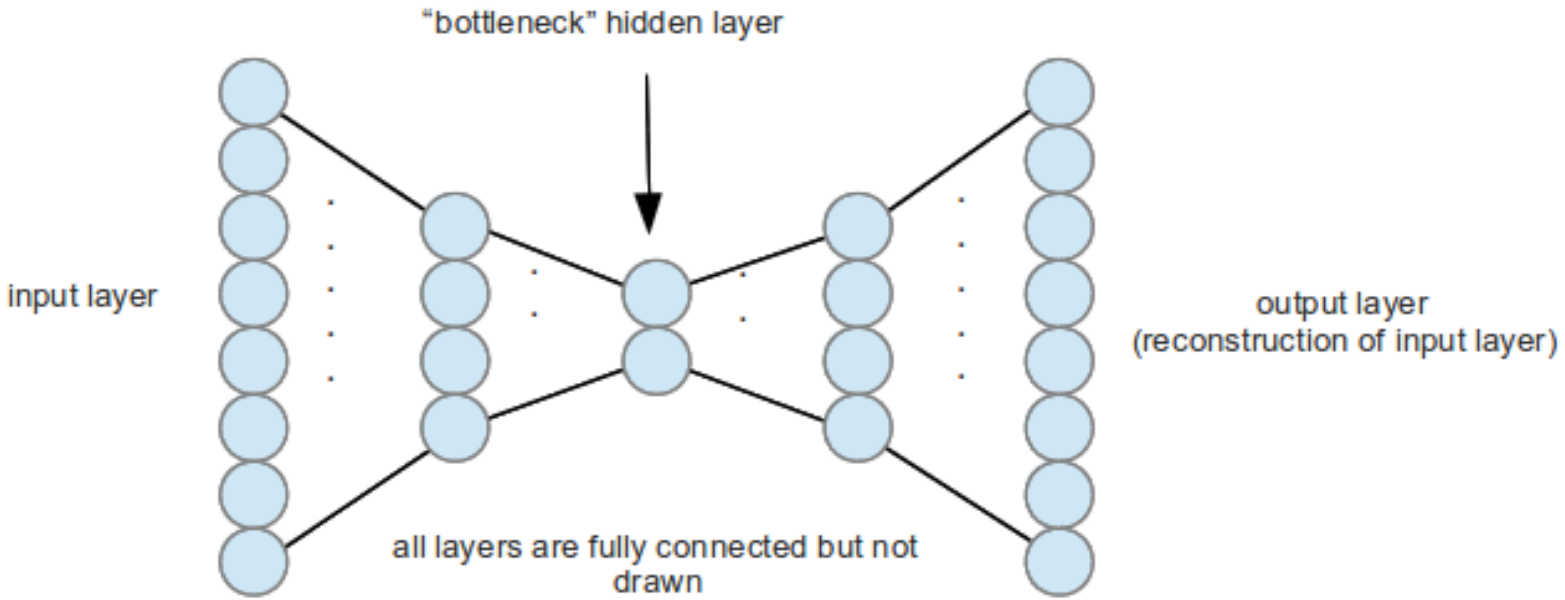


Image from `https://www.cs.toronto.edu/~frossard/post/vgg16/`

Architecture examples

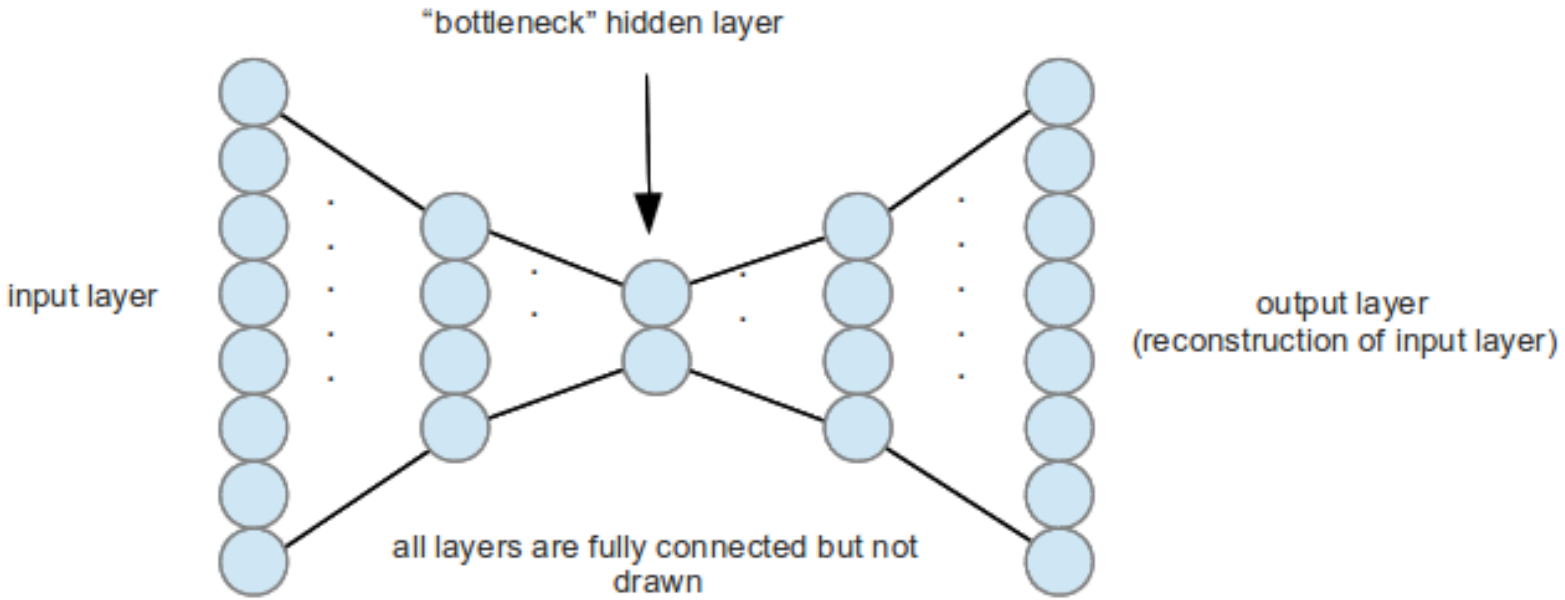
Autoencoder: data encoding



Hinton, Salakhutdinov (2006)

Architecture examples

Autoencoder: data encoding

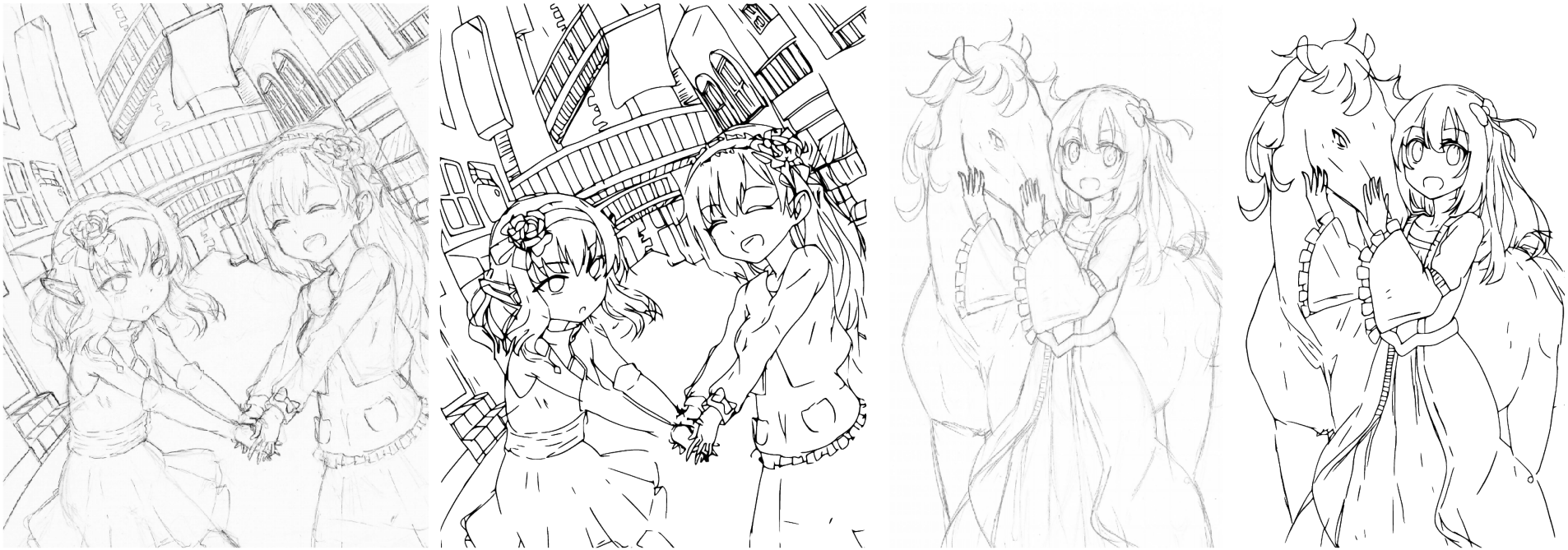


Hinton, Salakhutdinov (2006)

If we cut this autoencoder at the bottleneck, we get two parts: an encoder and a decoder. The encoder is an encoder highly specific to the content the network has been trained with.

Architecture examples

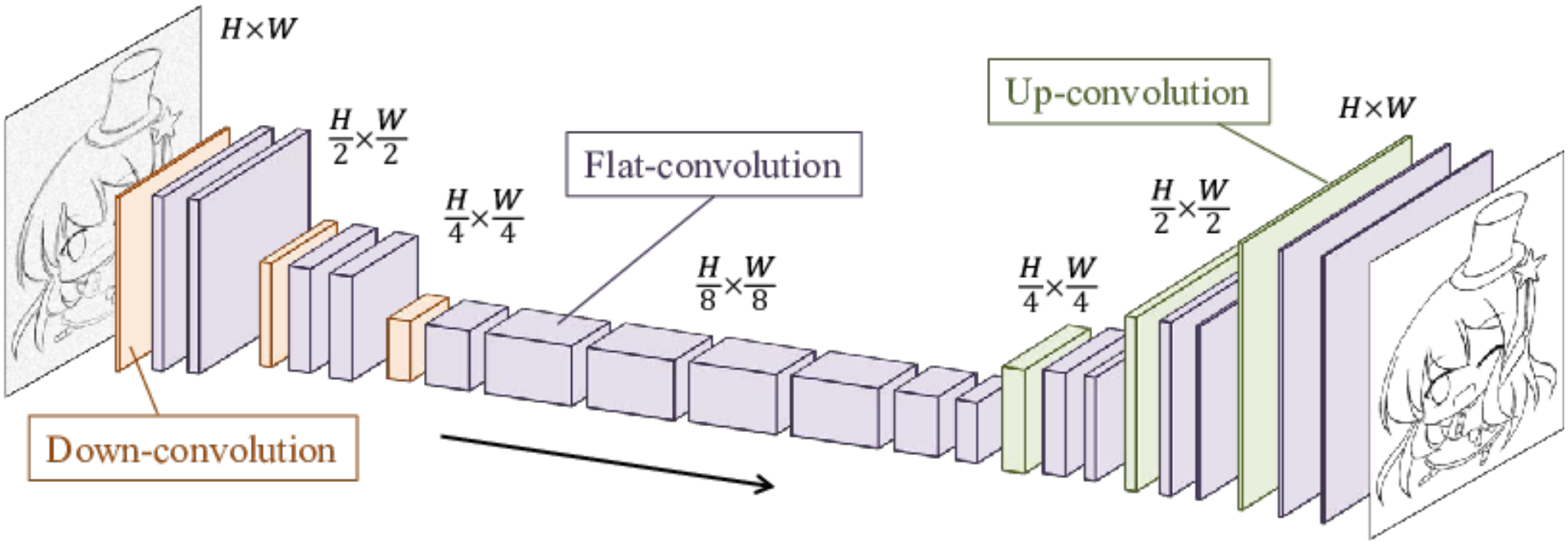
CNN + Autoencoder network: drawing simplification



Simo-Serra, Iizuka, Sasaki, Ishikawa (2016)

Architecture examples

CNN + Autoencoder network: drawing simplification



Simo-Serra, Iizuka, Sasaki, Ishikawa (2016)

Architecture examples

Neural style

Consider an image I and its image by the convolution layers of the VGG network $Conv(I)$.

Architecture examples

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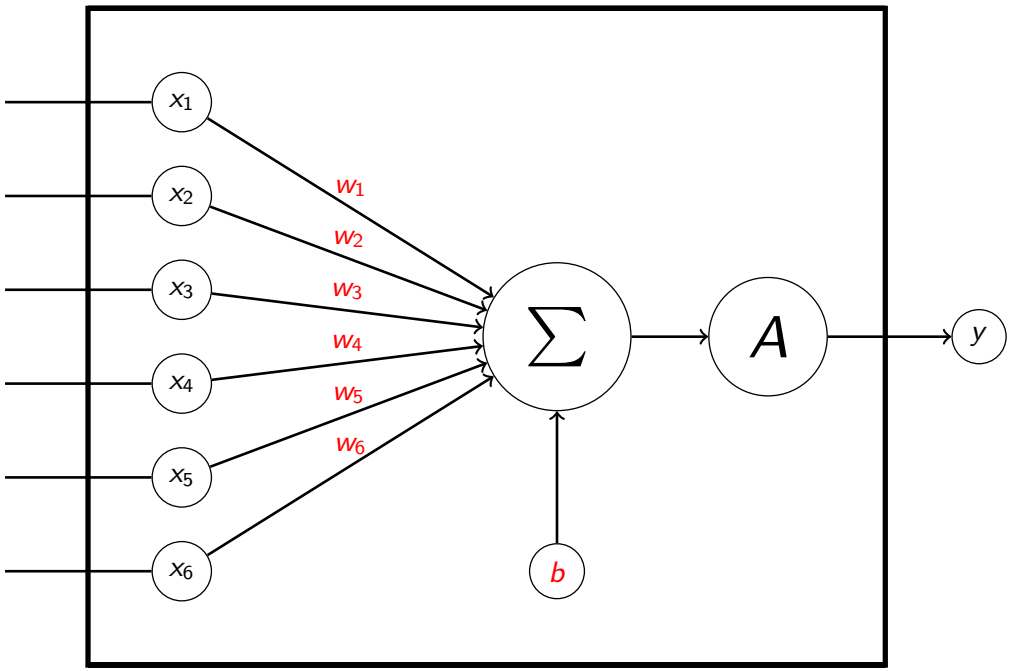
We can reconstruct a picture I' with the same content as I by applying gradient descent on the pixels in order to obtain $Conv(I)$ as output, starting with white noise.



Architecture examples

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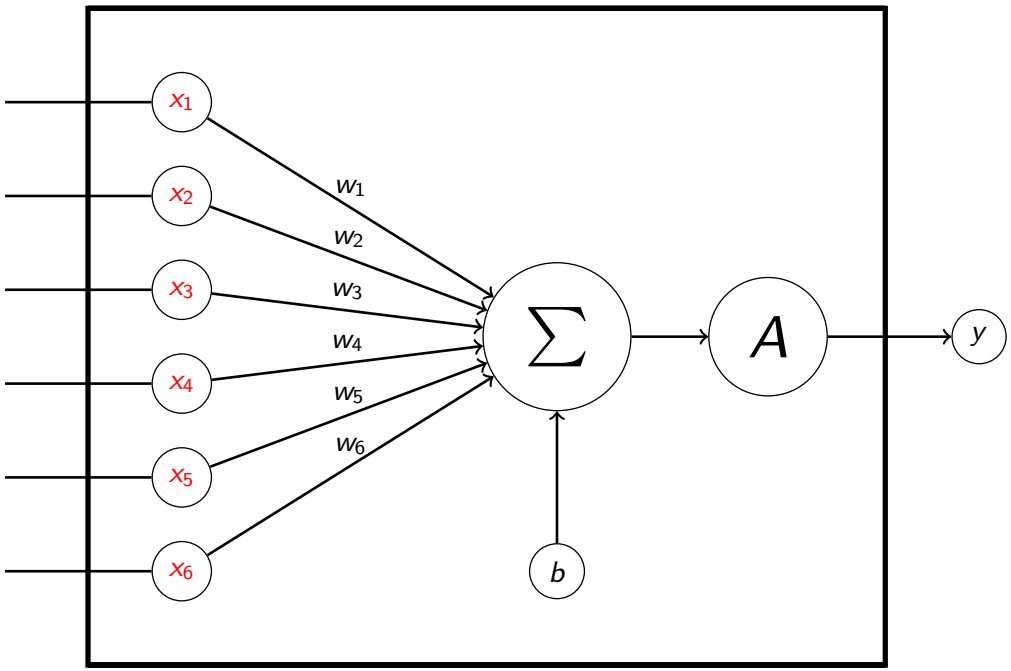


Gatys, Ecker and Bethge built a formula to extract the *style* of an image using the convolutional layers of the VGG network (2015).

They build the following Gram matrix:

$$G_{ij}^{l} = \sum_{k} F_{ik}^{l} F_{jk}^{l}$$

where F_{ij}^{l} is the j-th output of the i-th filter of the l-th convolutional layer.

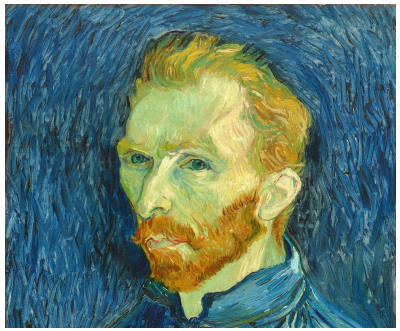
Architecture examples

Neural style

Let's take a random image from the internet.

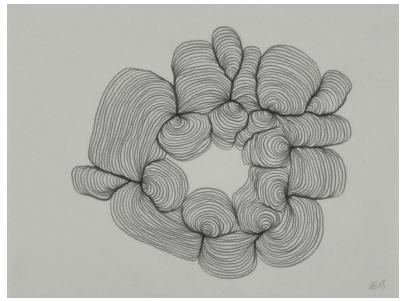
Architecture examples

Neural style

α content() + β style() = 

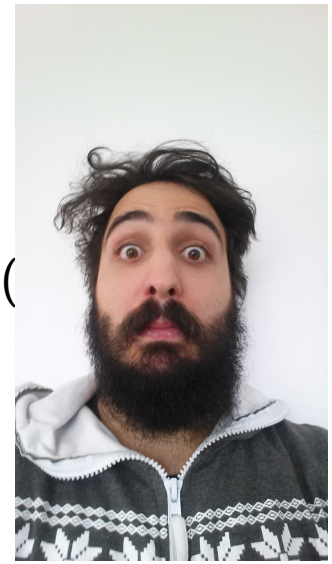
Architecture examples

Neural style

α content() + β style() = 

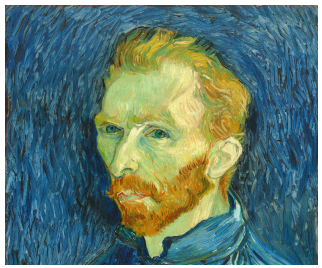
Architecture examples

Neural style

α content() + β style() = 

Architecture examples

Neural style

α content() + β style() = 

Architecture examples

Recurrent neural network

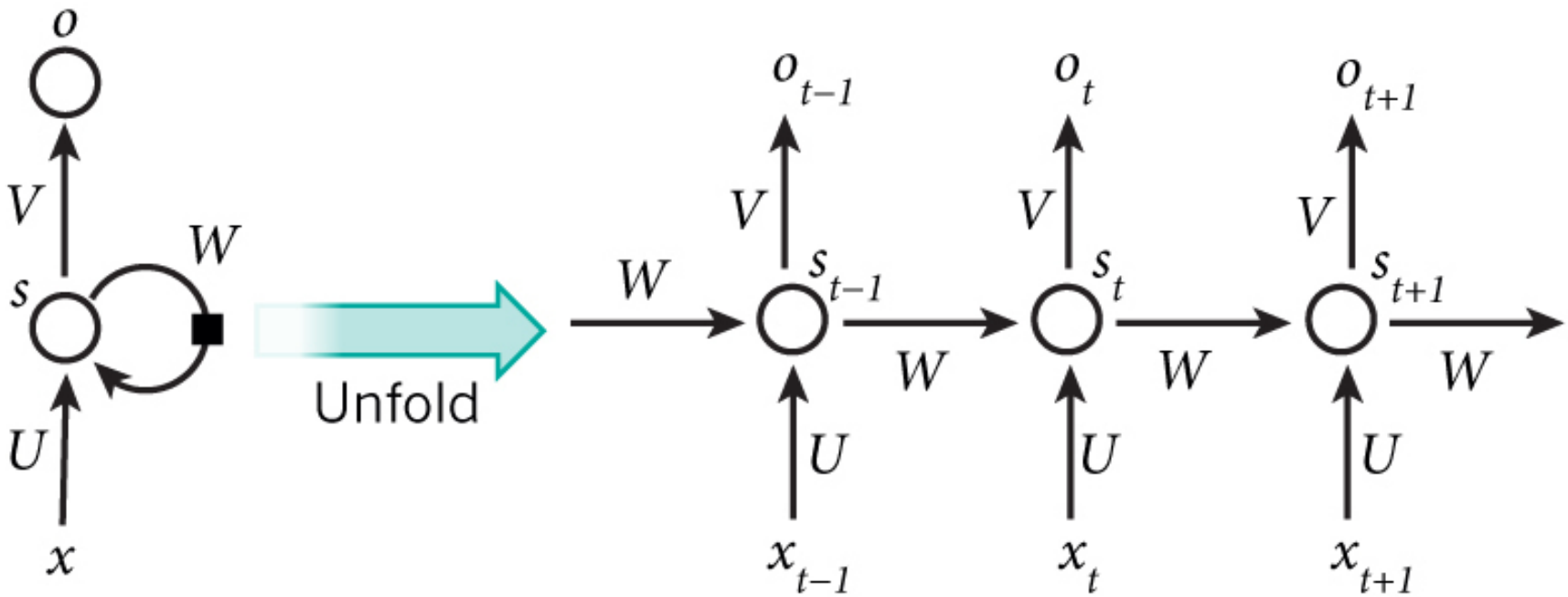


Image from `http://www.wildml.com`

Architecture examples

Sequence to class network: text classifier

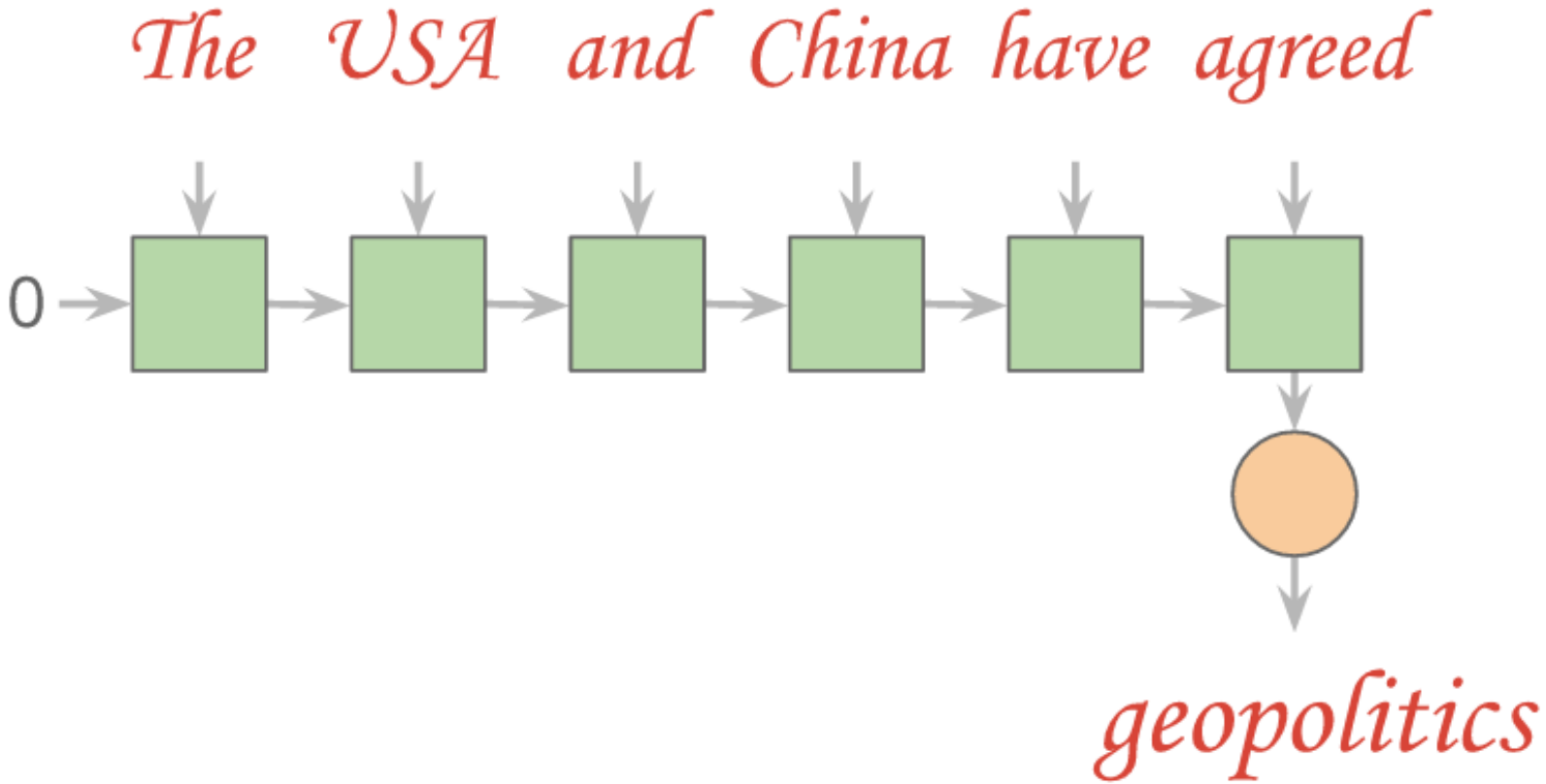


Image from Martin Gorner

Architecture examples

Sequence to sequence network: Neural Machine Translation

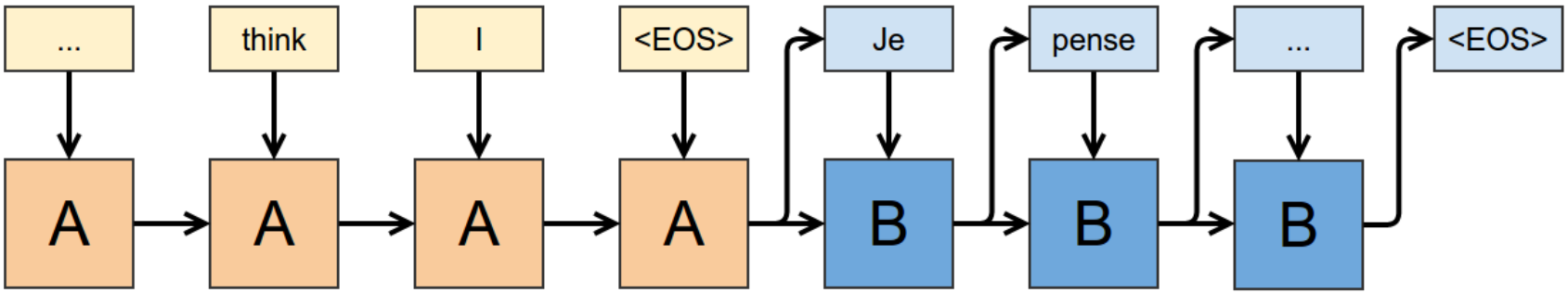


Image from `https://colah.github.io`

Google, September 2016: "The Google Translate mobile and web apps are now using GNMT (Google NMT) for 100% of machine translations from Chinese to English—about 18 million translations per day."

Architecture examples

Sequence to sequence network: Neural Conversation Model

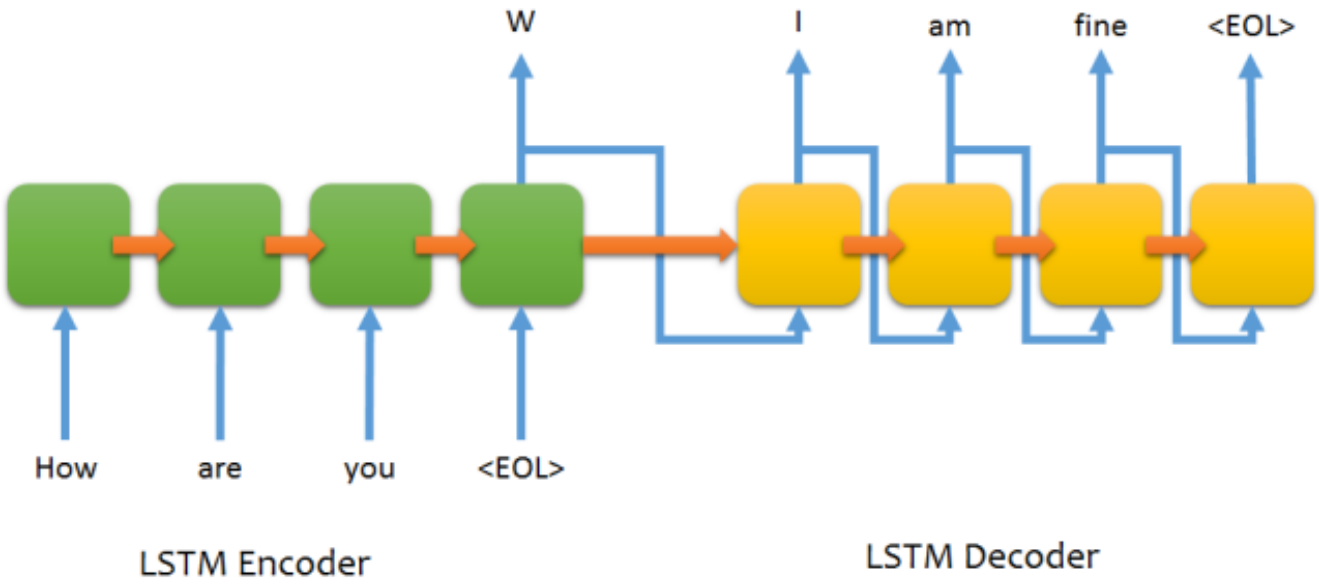


Image from `https://github.com/farizrahman4u/seq2seq`

Really early stage, hard to overcome challenges (context, coherent personality, . . .)

Architecture examples

Image to sequence: automatic captioning

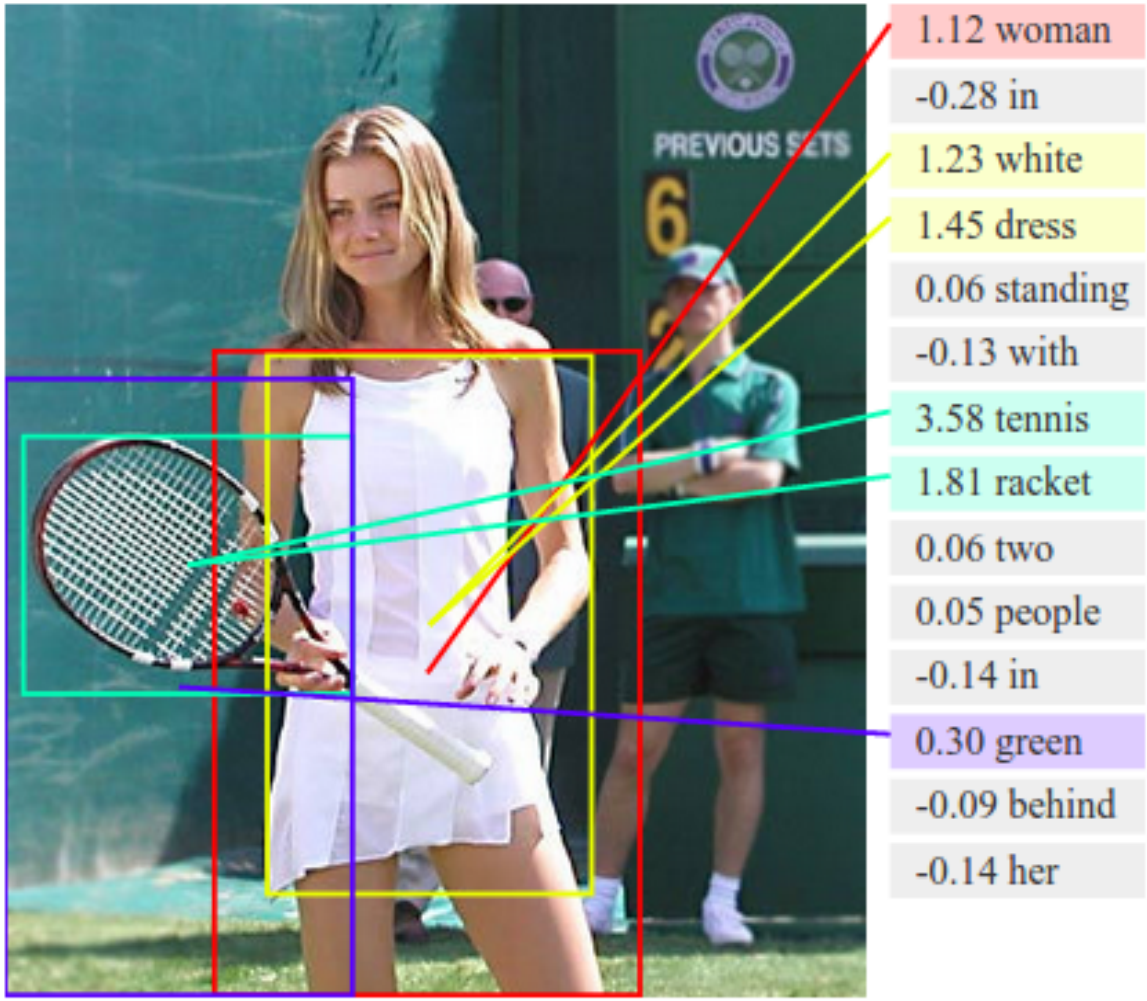


Image from `https://quantumfrontiers.com`

Architecture examples

Image to sequence: automatic captioning

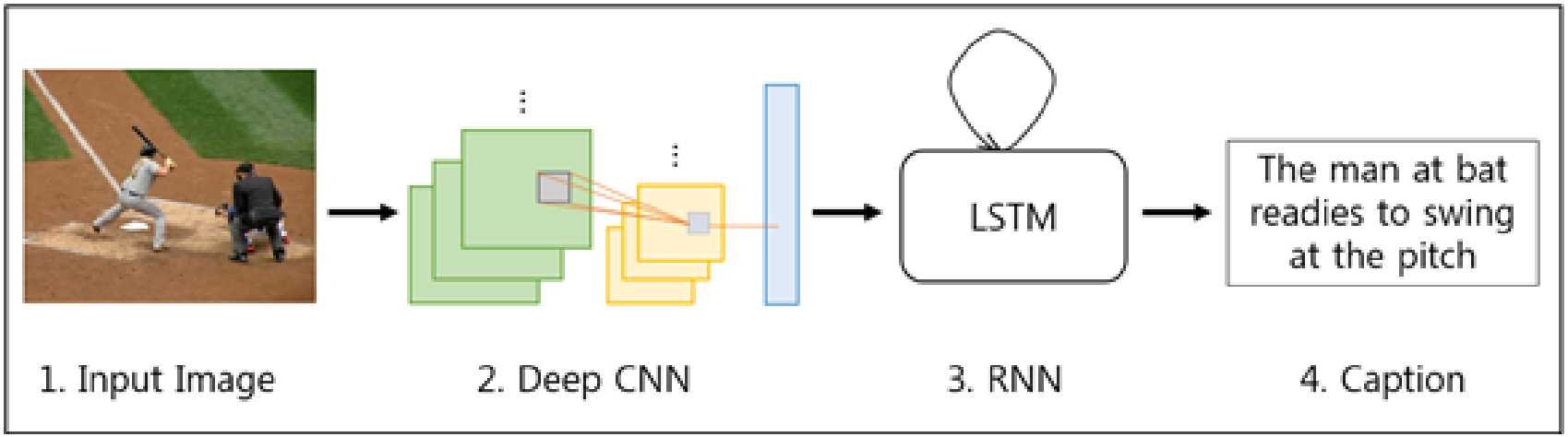


Image from `http://brain.kaist.ac.kr/`

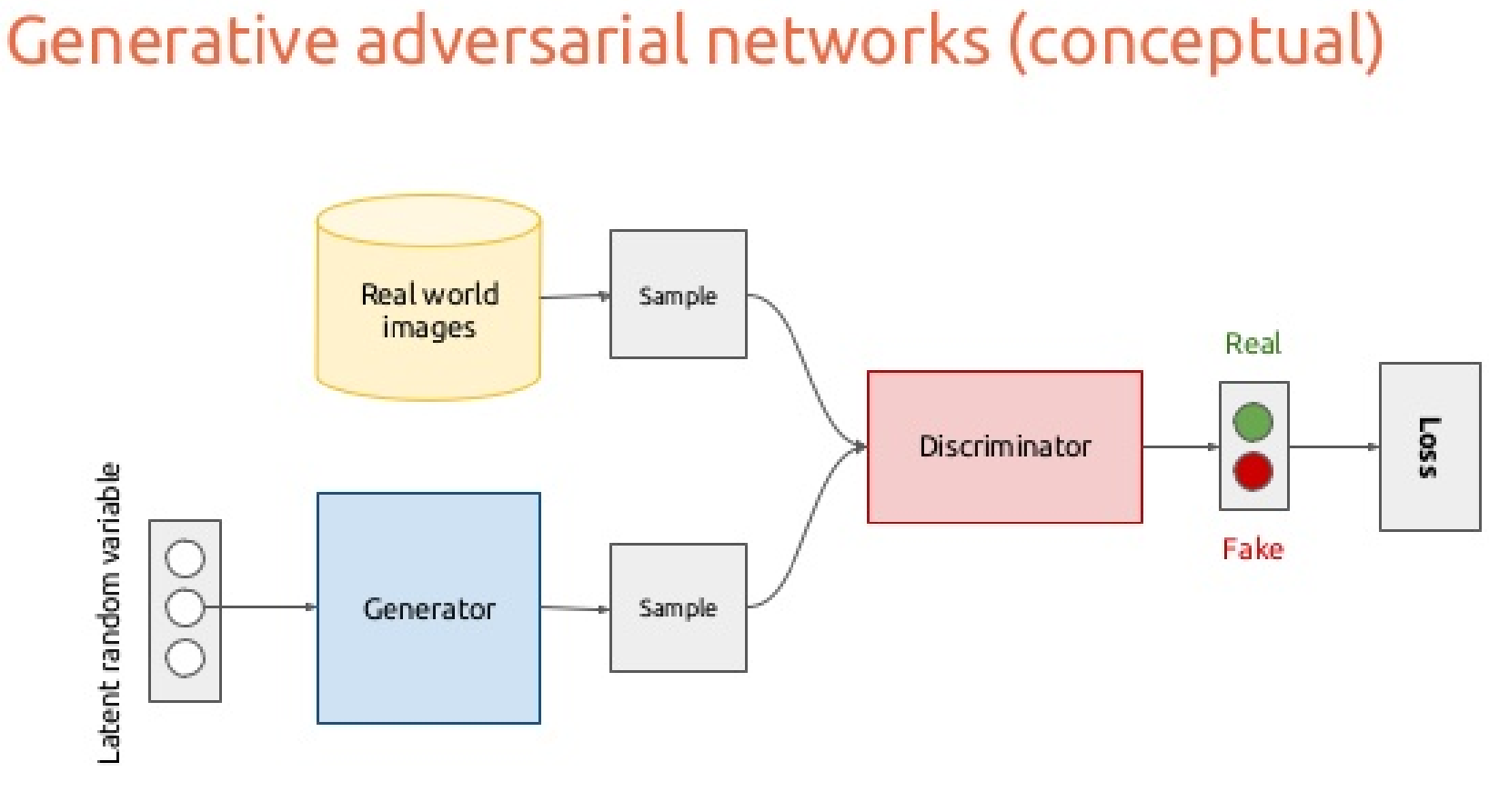


Image from `http://wiki.tum.de/`

Architecture examples

Generative adversarial network: text to image

Han Zhang et al. (2016)

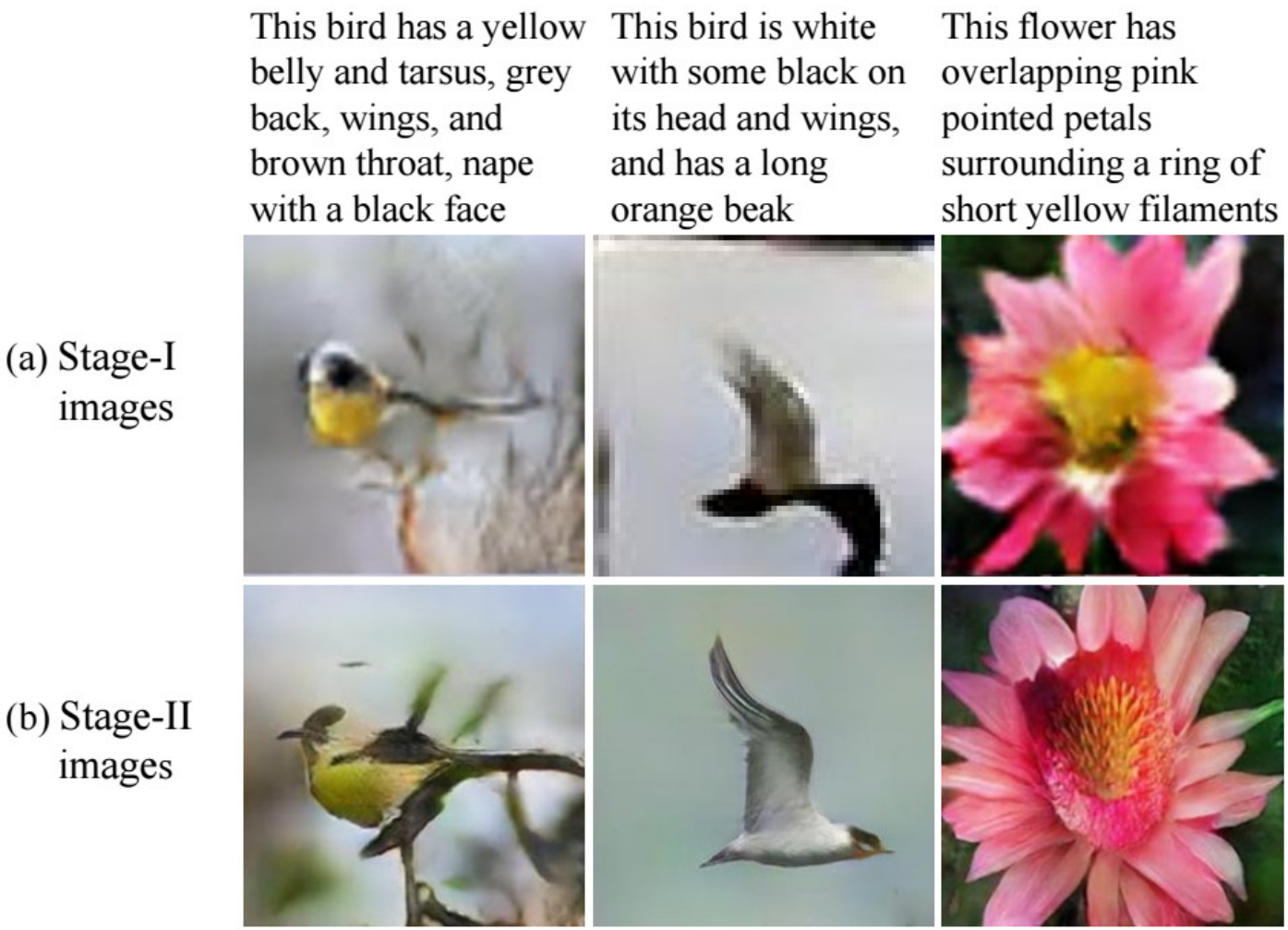


Image from `https://arxiv.org/pdf/1612.03242.pdf`