Webinar series

CompBioMed

A Centre of Excellence in Computational Biomedicine

Webinar #12

Getting started with Deep Learning: A gentle introduction and working example

7 July 2020

The webinar will start at 1pm CEST

Presenter:
Juan Durillo Barrionuevo (Leibniz Supercomputing Centre, LRZ)

Moderator:
Katya Ahmad (University College London, UCL)

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 675451

The webinar series is run in collaboration with:

VPH Institute

Building the Virtual Physiological Human

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Welcome!

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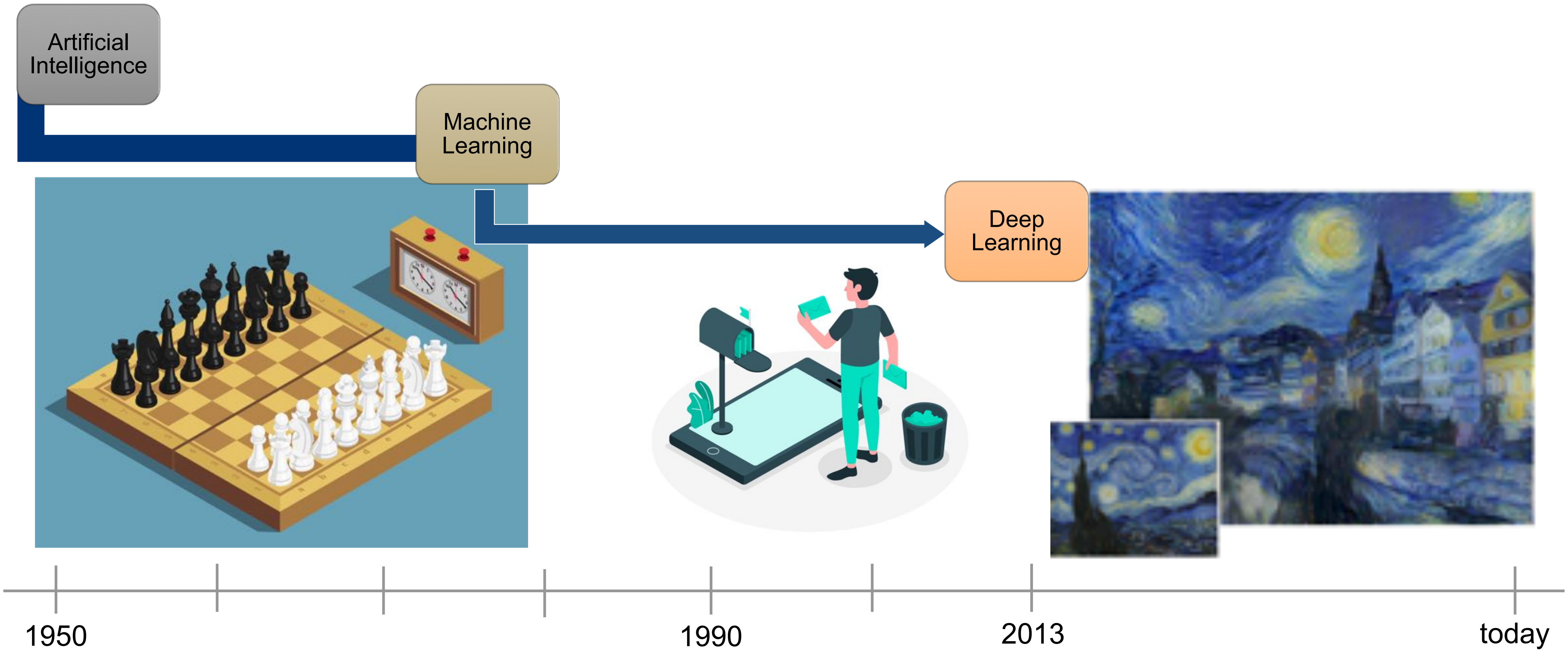
Getting started with Deep Learning: A gentle introduction and working example

07.07.2020 | PD Dr. Juan J. Durillo

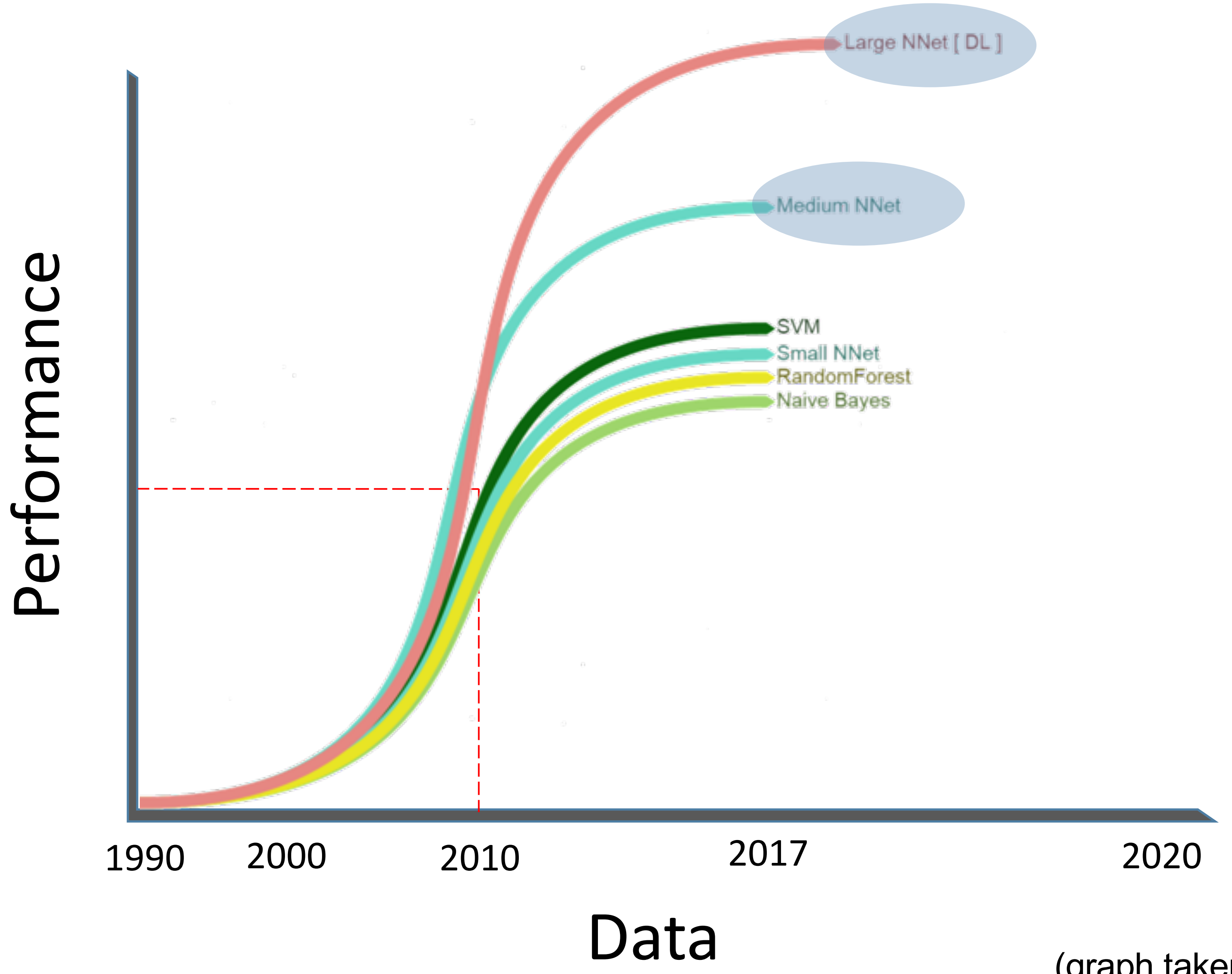
Agenda

- Introduction
- Introduction to (Deep) Neural Networks for Machine Learning
- Computer Vision as working example
- Introduction to Convolutional Neural Networks
- Deep Neural Network Architecture
- Data Augmentation
- Hands on session: Implementing a Convolutional Neural Network from scratch

Artificial + Intelligence

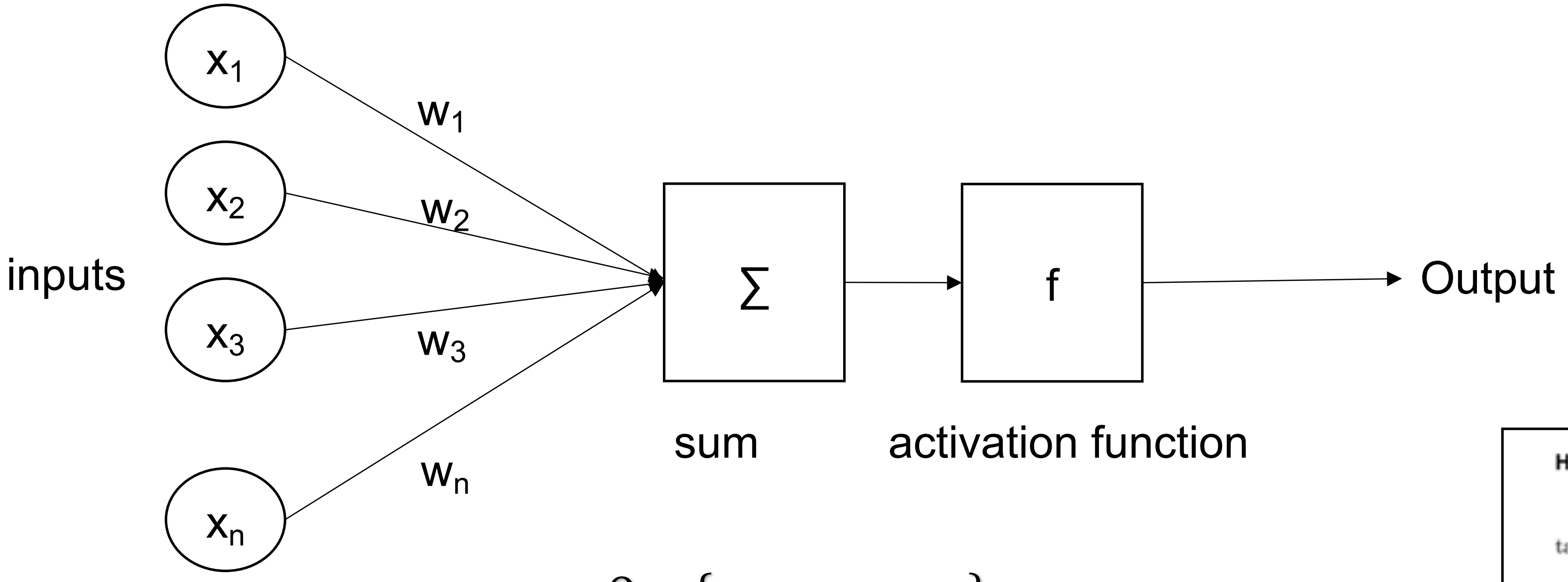


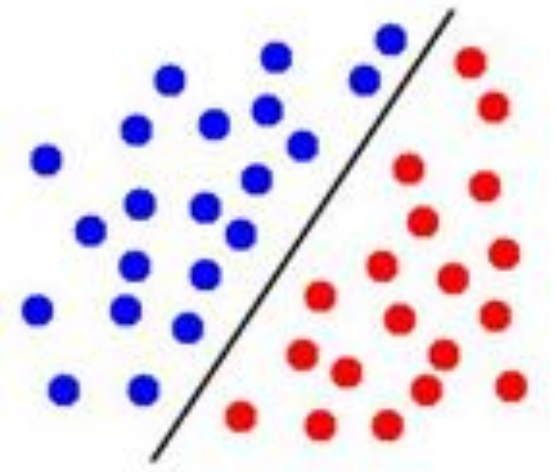
Observable Trend



(graph taken from Nvidia learning institute)

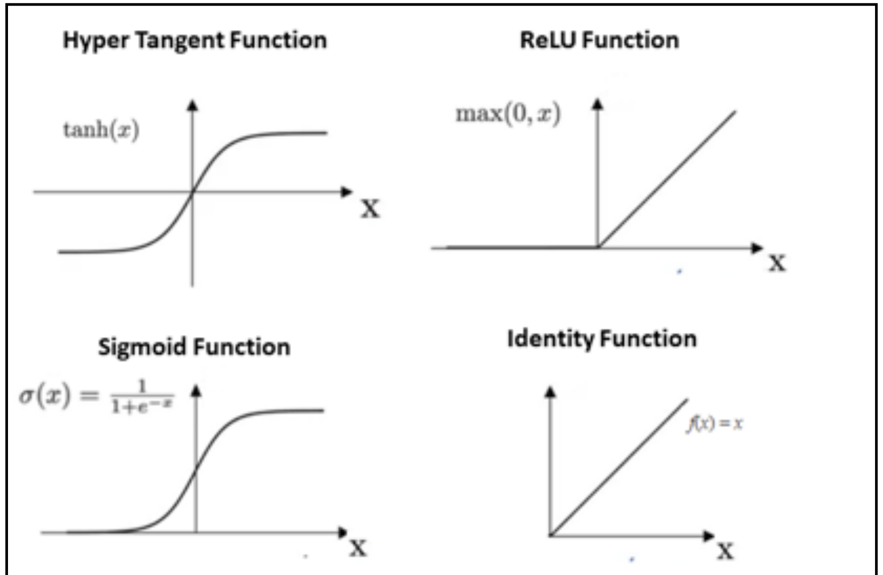
Perceptron – Artificial Neuron





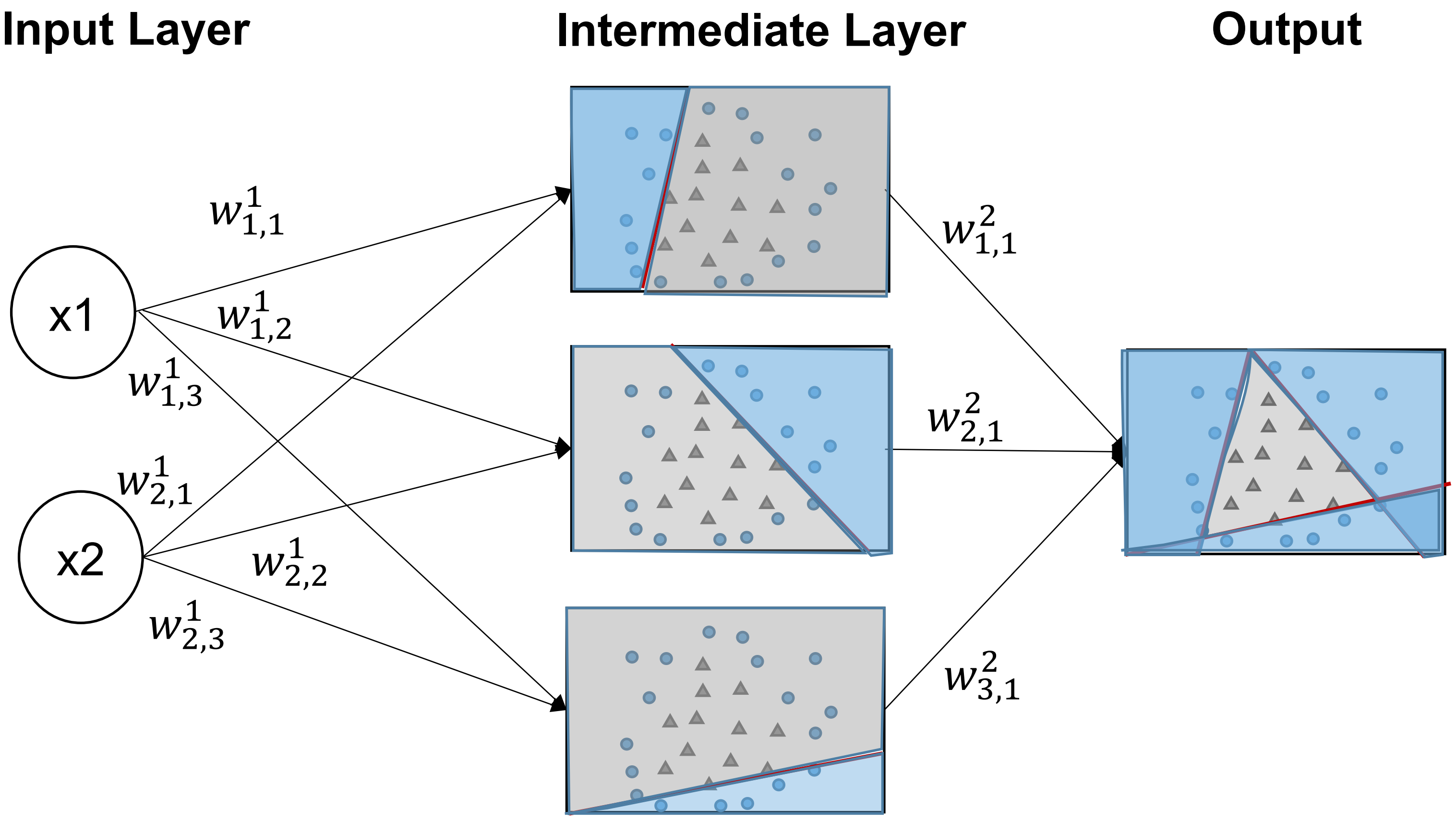
$$\Theta = \{w_1 , w_2 \dots , w_n \}$$

Single artificial neurons work well for linearly separable datasets (indeed output is the activation effect on a linear combination of the input)



most popular activation functions

Neural Network



$$\Theta = \{w^1_{1,1}, w^1_{1,2}, w^1_{1,3}, w^1_{2,1}, w^1_{2,2}, w^1_{2,3}, w^2_{1,1}, w^2_{2,1}, w^2_{2,3}\}$$

- Works well even when the data is not linearly separable

(Supervised) Learning

- Data domain Z: $\mathrm{X} \times \Upsilon$

  X → domain of the input data

  Υ → set of labels (knowledge)

Example (CIFAR10 dataset)

X: 32 x 32 color images

Υ : labels

{truck, car, horse, bird, boat}

- Data Distribution is a probability distribution over a data domain
- Training set $z_1, \ldots, z_n$ from Z assumed to be drawn from the Data Distribution D
- Validation set $v_1, \ldots, v_m$ from Z also assumed to be drawn from D
- A machine learning model is a function that given a set of parameters Θ and z from Z produces a prediction
- The prediction quality is measured by a differentiable non-negative scalar-valued loss function, that we denote $\ell(\Theta; z)$

(Supervised) Learning

- Given Θ we can define the expected loss as: $L(\Theta) = \mathbb{E}_{z \sim D}[\ell(\Theta; z)]$

- Given D, ℓ, and a model with parameter set Θ, we can define learning as:
  "The task of finding parameters Θ that achieve low values of the expected loss, while we are given access to only n training examples"

- The mentioned task before is commonly referred to as *training*

- Empirical average loss given a subset of the training data set $S(z_1, \ldots, z_n)$ as:

$$\hat{L}(\Theta) = \frac{1}{n}\sum_{t=1}^{n}[\ell(\Theta; z_t)]$$

- Usually a proxy function, easier to understand by humans, is used for describing how well the training is performed (e.g., accuracy)

(Supervised) Learning

- The dominant algorithms for training neural networks are based on mini-batch stochastic gradient descent (SGD)

- Given an initial point Θ_0 SGD attempt to decrease $\hat{L}$ via the sequence of iterates

$$\Theta_t \leftarrow \Theta_{t-1} - n_t g(\Theta_{t-1}; B_t)$$

$$g(\Theta; B) = \frac{1}{|B|} \sum_{z \epsilon B} \nabla \ell(\Theta; z)$$

Definitions	
	B_t: random subset of training examples
	n_t: positive scalar (learning rate)
	epoch: update the weights after going over all training set

Computer Vision

- Why? Focus on a kind of Deep Neural Network called Convolutional Neural Network (CNN)
- CNNs ability to extract multi-scale localized spatial features and compose them to construct highly expressive representations led to breakthroughs in almost all machine learning areas

COMPUTER VISION TASKS

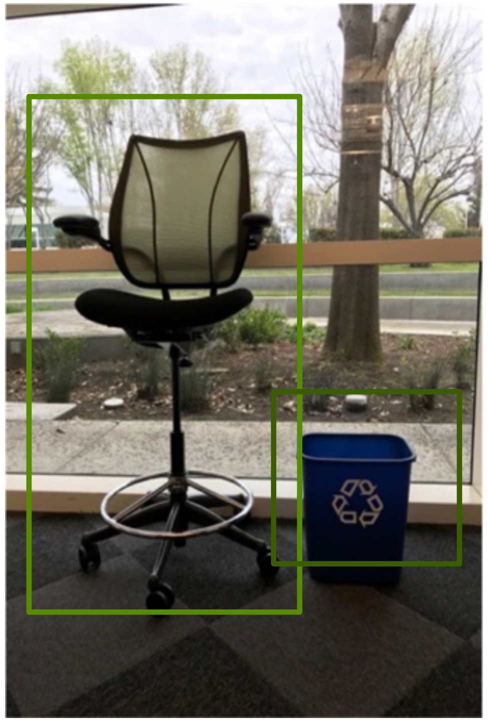
Image Classification

predicting the type or class of an object in an image

Image Classification + Localization

predicting the type or class on an object in an image and draw a bounding box around it

Object Detection



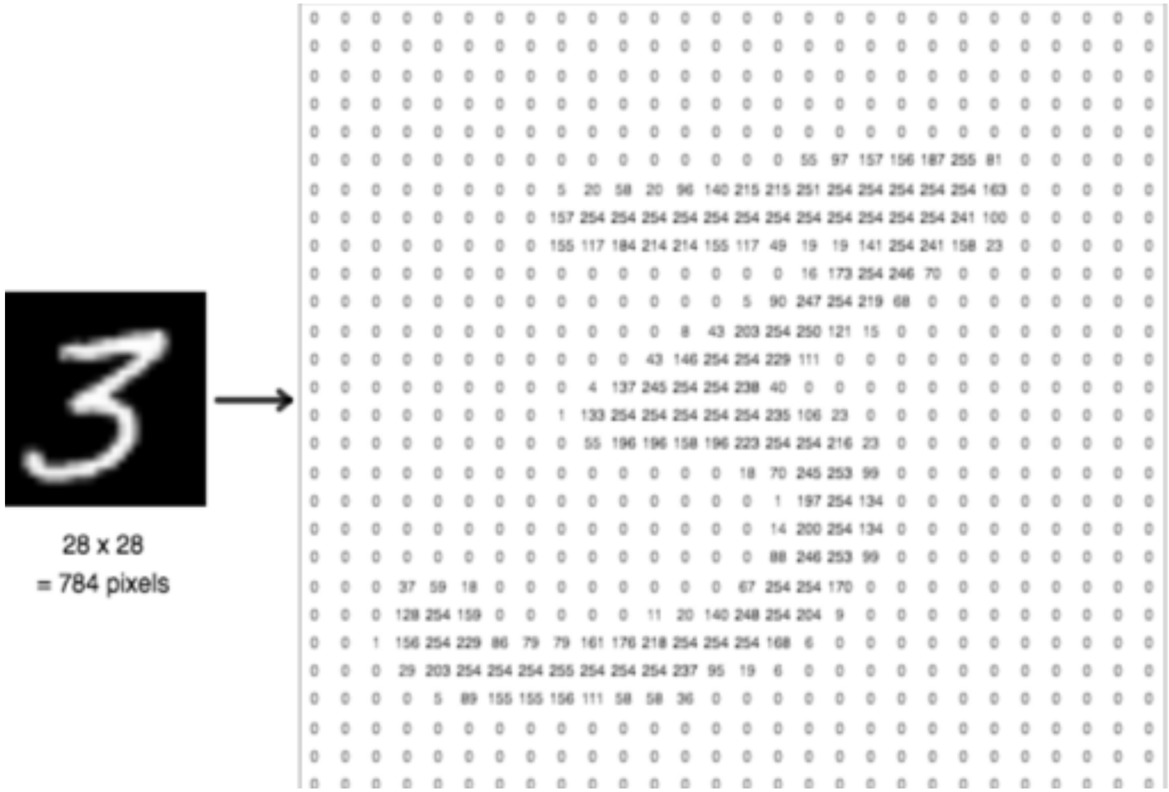
predicting the location of objects in an image via bounding boxes and the classes of the located objects

Image Segmentation

predicting the class to which each pixel in the image belongs to

(inspired by a slide used in cs231n lecture from Stanford University)

On Input Representation



image

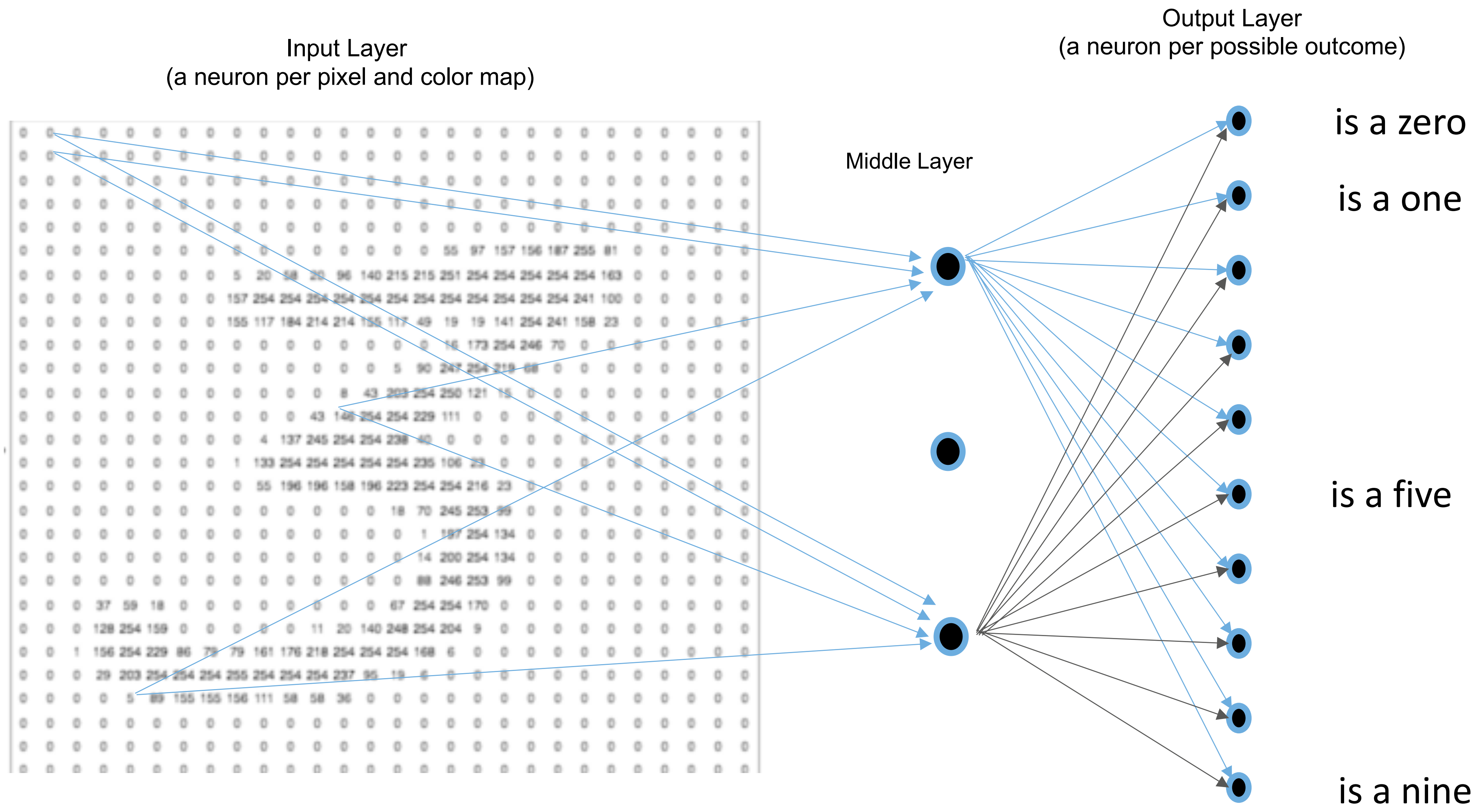
```
dict=['EOS','a','my','sleeps','on','dog','cat','the','bed','floor']
```

sentence = ['a', 'dog', 'sleeps', 'on', 'the', 'floor', 'EOS']

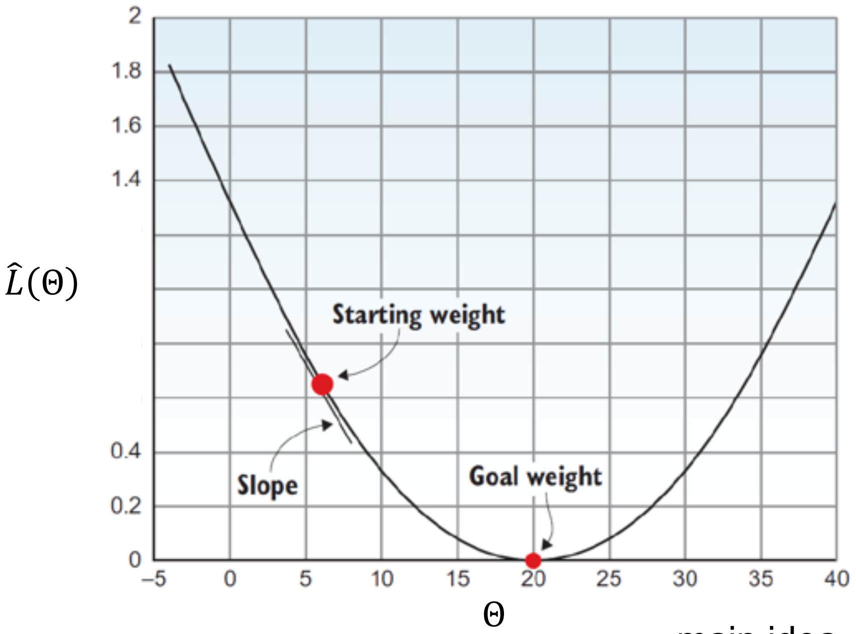
```
[[ 0.  1.  0.  0.  0.  0.  0.  0.  0.  0.]
 [ 0.  0.  0.  0.  0.  1.  0.  0.  0.  0.]
 [ 0.  0.  0.  1.  0.  0.  0.  0.  0.  0.]
 [ 0.  0.  0.  0.  1.  0.  0.  0.  0.  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  1.  0.  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  1.]
 [ 1.  0.  0.  0.  0.  0.  0.  0.  0.  0.]]
```

language

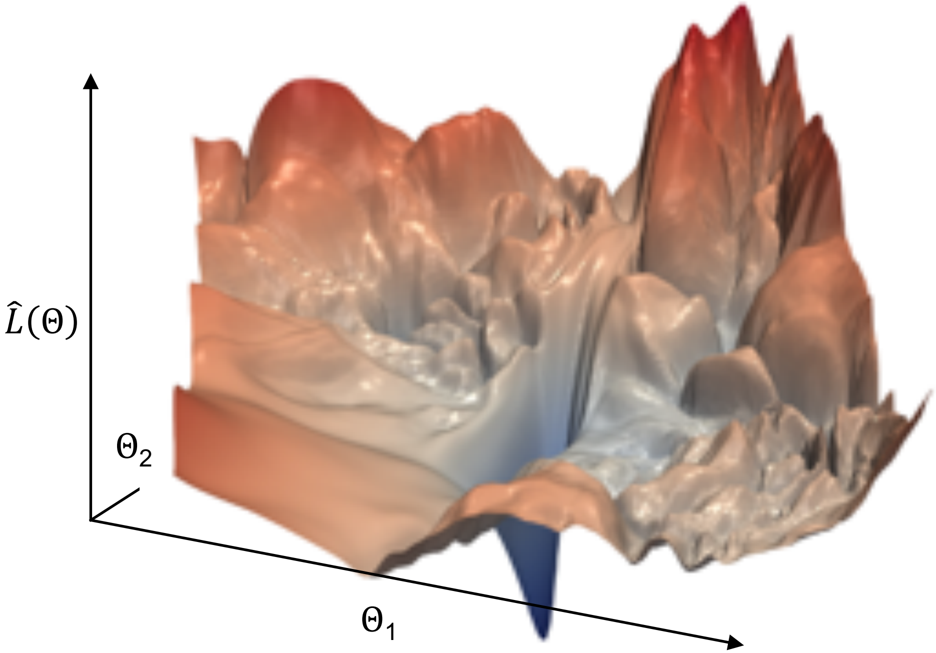
Neural Networks for Image Classification



Training Neural Networks



main idea



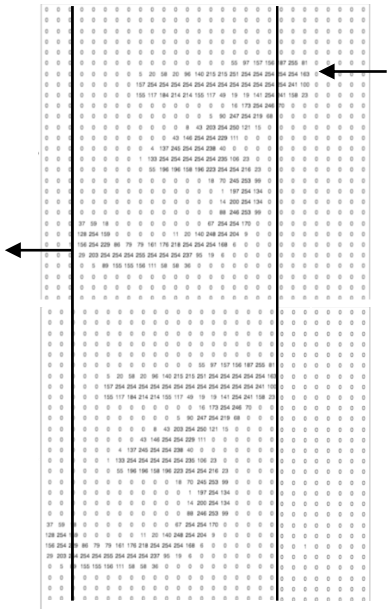
how the surface looks like in reality

<u>Stochastic Gradient Descent</u>

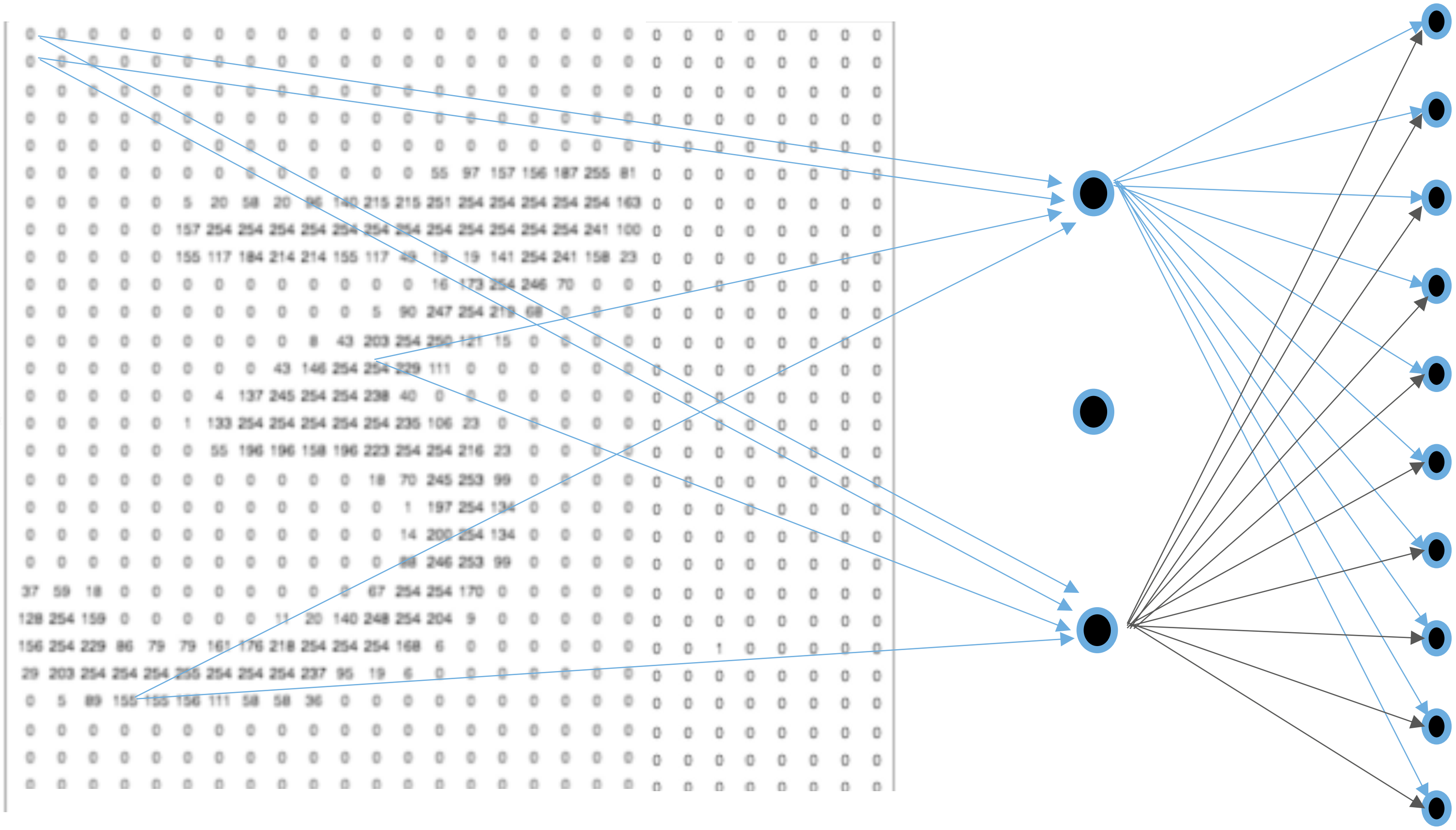
$$\Theta_t \leftarrow \Theta_{t-1} - \eta_t g(\Theta_{t-1}; B_t)$$

$$g(\Theta; B) = \frac{1}{|B|} \sum_{z \epsilon B} \nabla \ell(\Theta; z)$$

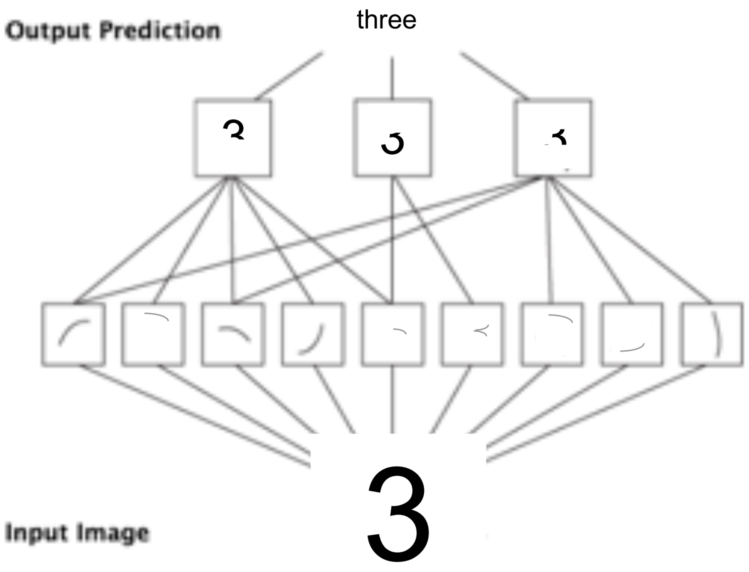
Neural Networks for Image Classification



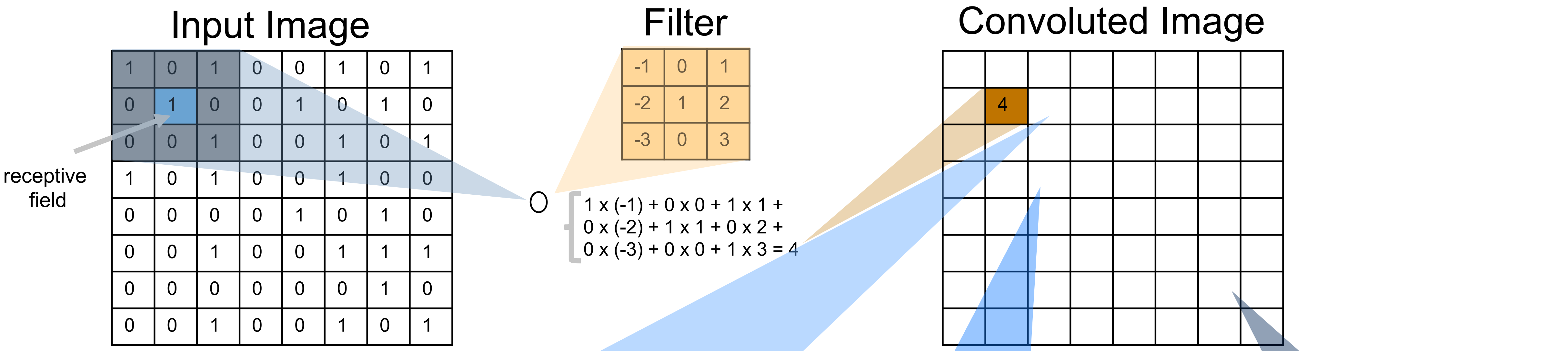
shift to the left



No More Feature Engineering: Learning Features From Data



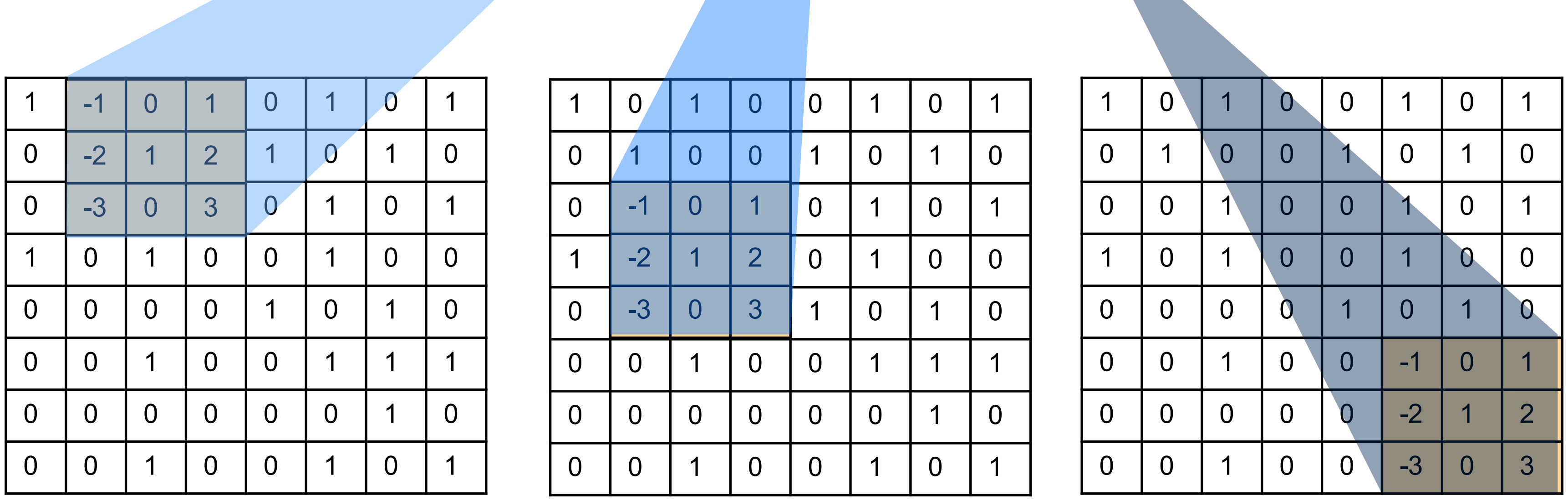
Learning features from data: Convolutions



Filter is convoluted with all the pixels of the image

How many units the filter moves horizontally or vertically is called **stride** and can be different in both dimensions

The stride defines the size of the convoluted image



Learning features from data: Understanding filters

Input Image:

Can we get only vertical lines out of this picture?

1	0	-1

filter 1

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

filter 2

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

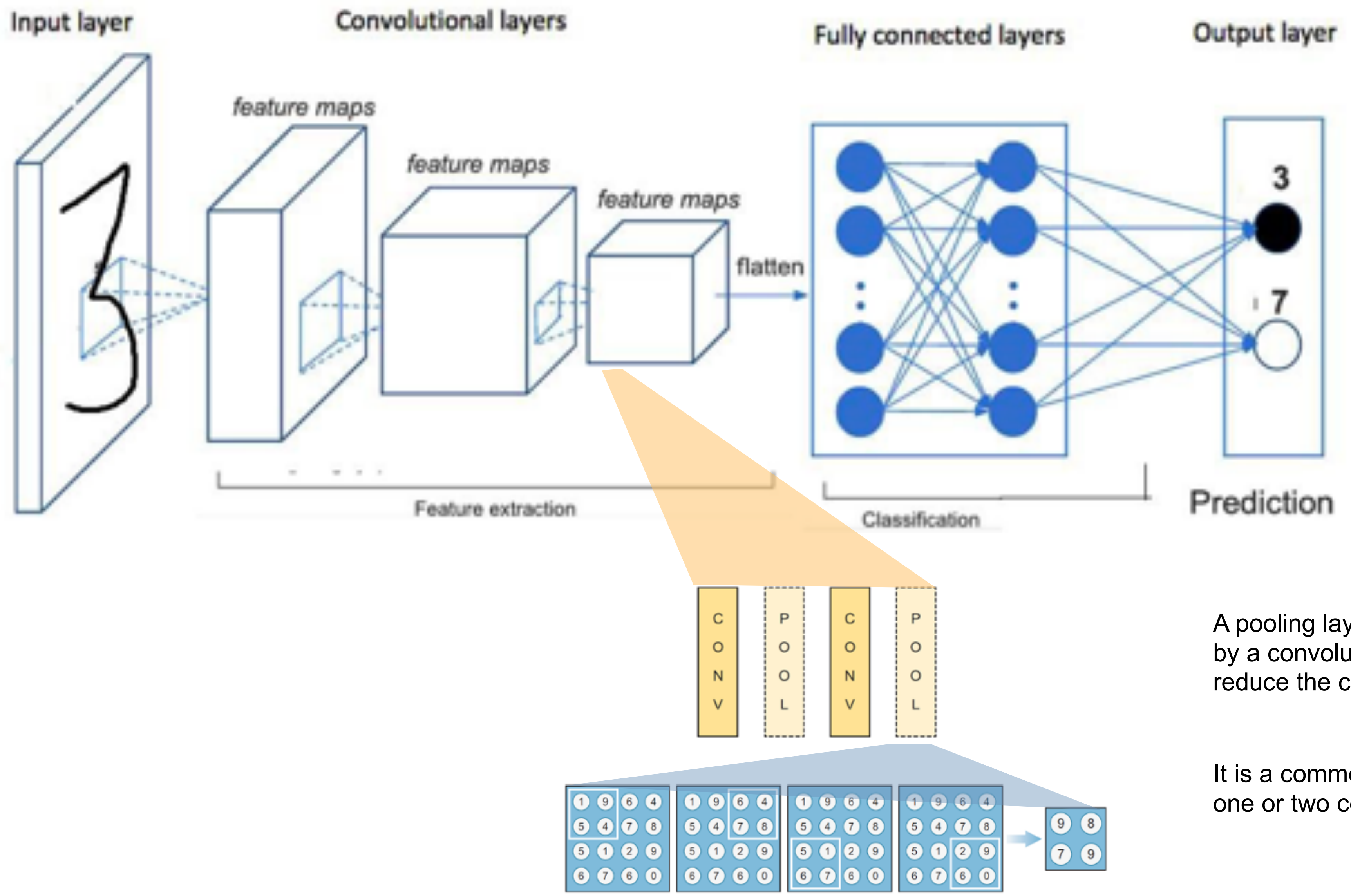
filter 3

try the code yourself (in octave)!

```
 I=imread(<path-to-image>);
GRAY=rgb2gray(I)
FILTER=[ 1 0 -1; 1 0 -1; 1 0 -1]; % filter 2
CONVOLUTED=conv2(GREY,FILTER);
Imwrite(CONVOLUTED, <path-to-result>);
```

*The London skyline image is designed by Freepik

Convolutional Neural Networks (CNN)



A pooling layer down sample the feature maps produced by a convolution into smaller number of parameters to reduce the computational complexity.

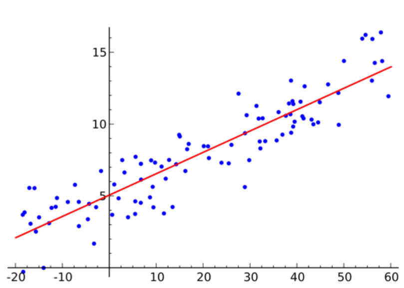
It is a common practice to add pooling layers after each one or two convolutions layers in the CNN architecture.

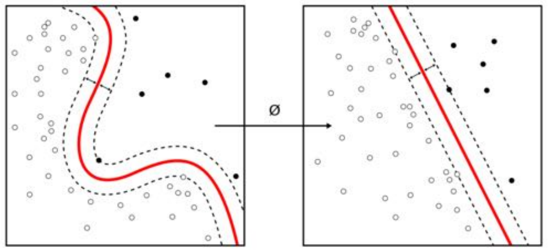
Differences in the Workflow and Challenges

Classic Machine Learning [1990 : now]

Input → Hand Designed **Features** → Model / Mapping → Output

Examples [Regression and SVMs]

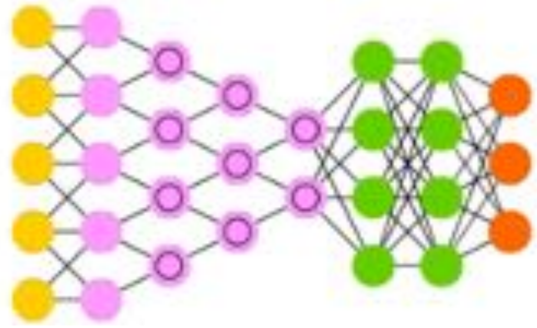




Deep/End-to-End Learning [2012 : now]

Input → Simple Features → Complex Features → Model/ Mapping → Output

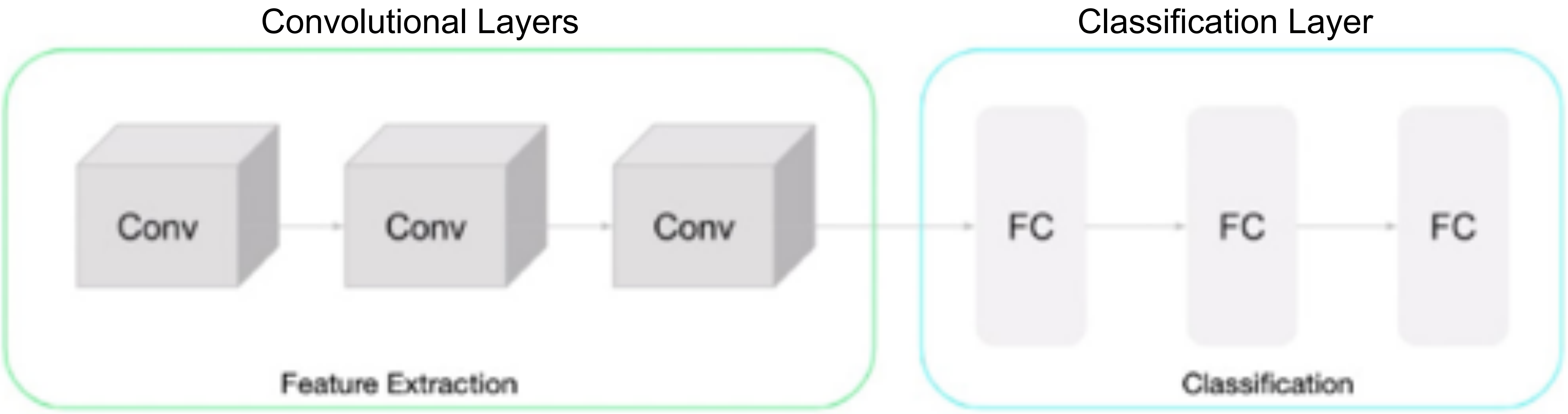
Example [Conv Net]



Deep Neural Networks have shown ability to outperform humans in many tasks, but with a high price tag:

- Computational cost of training networks, compound by identifying an optimal **architecture**
- Significant volumes of data, which **might not** always be **available**

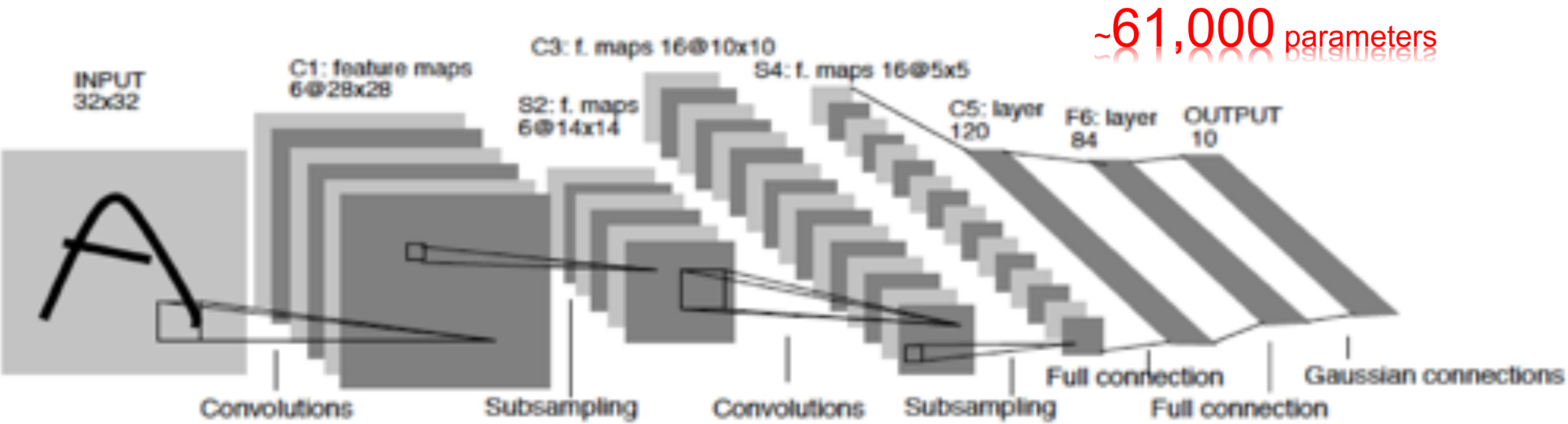
CNN Architecture: A Common Pattern and its Influence



The execution time required during a forward pass through a neural network is bounded from below by the number of floating point operations (FLOPs).

This FLOP count depends on the deep neural network architecture and the amount of data.

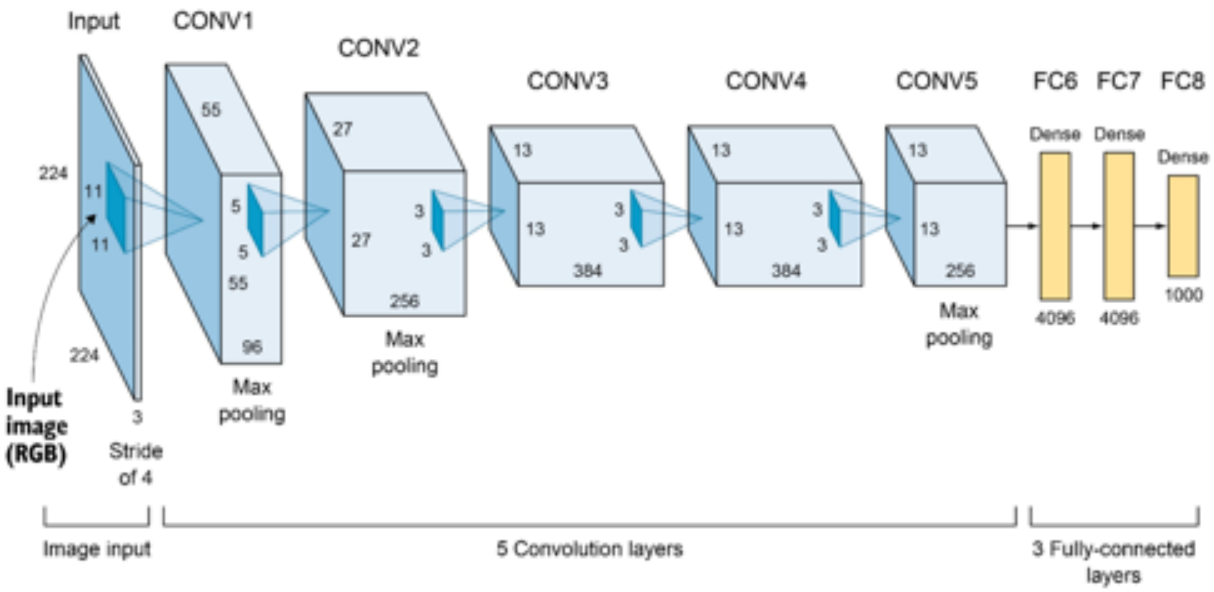
LeNet Architecture



Architecture summary :

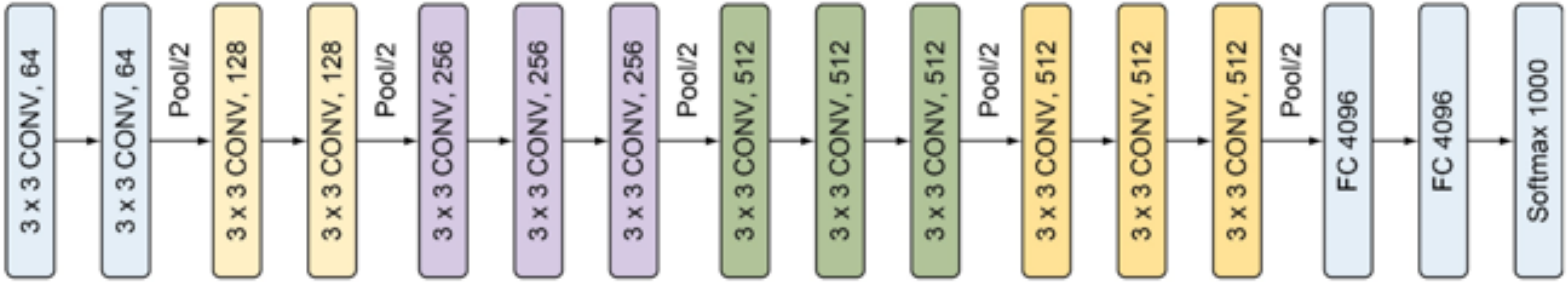
- 3 convolutional layers filters in all the layers equal to 5x5
  (layer 1 depth = 6, layer 2 depth = 16, layer 3 depth = 120)
- As activation function the tanh function is used

AlexNet and VGG Architectures



AlexNet

~60,000,000 parameters

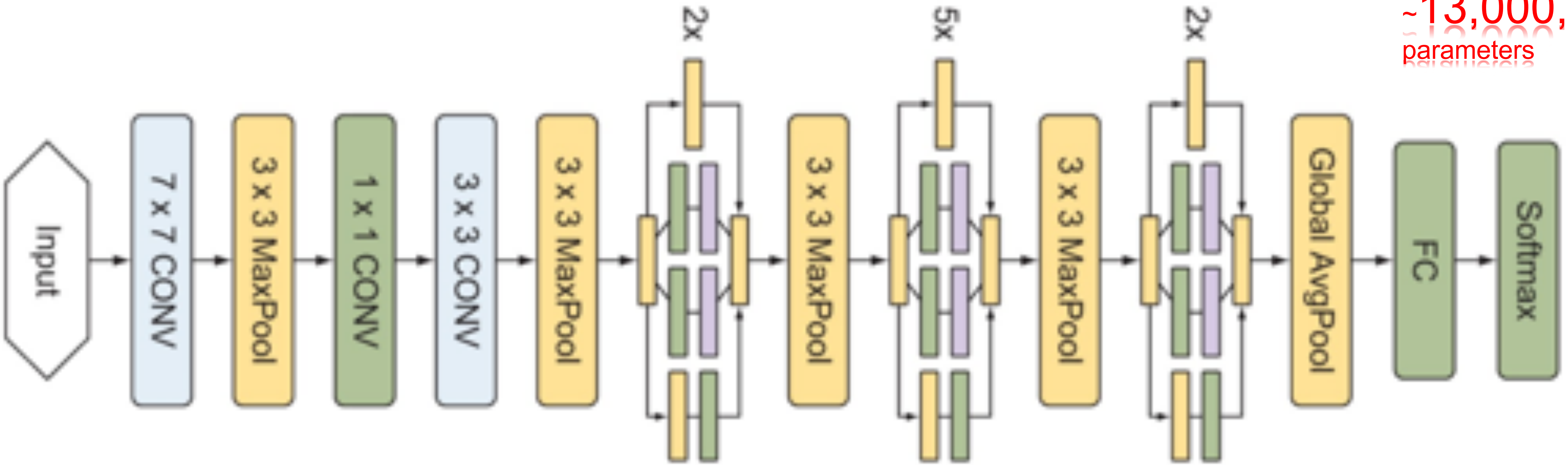


VGG16

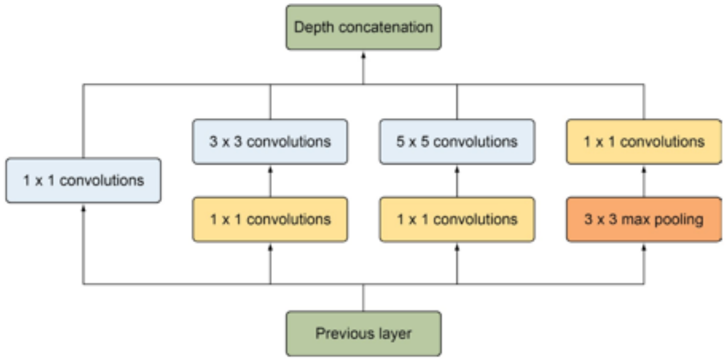
~138,000,000 parameters

GoogleNet

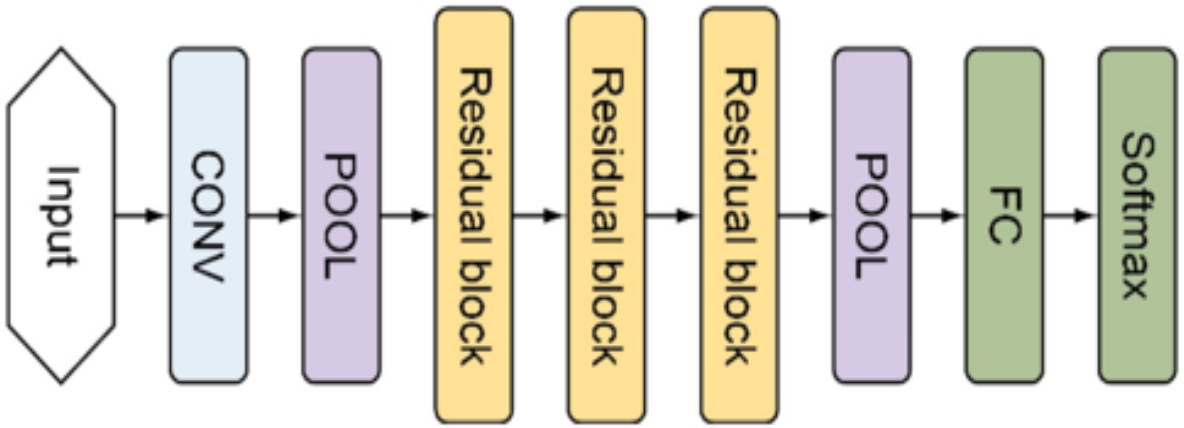
~13,000,000 parameters

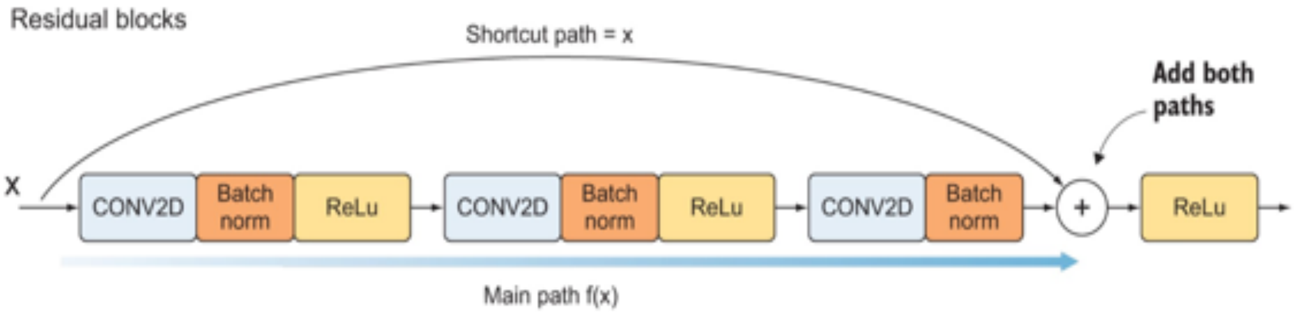


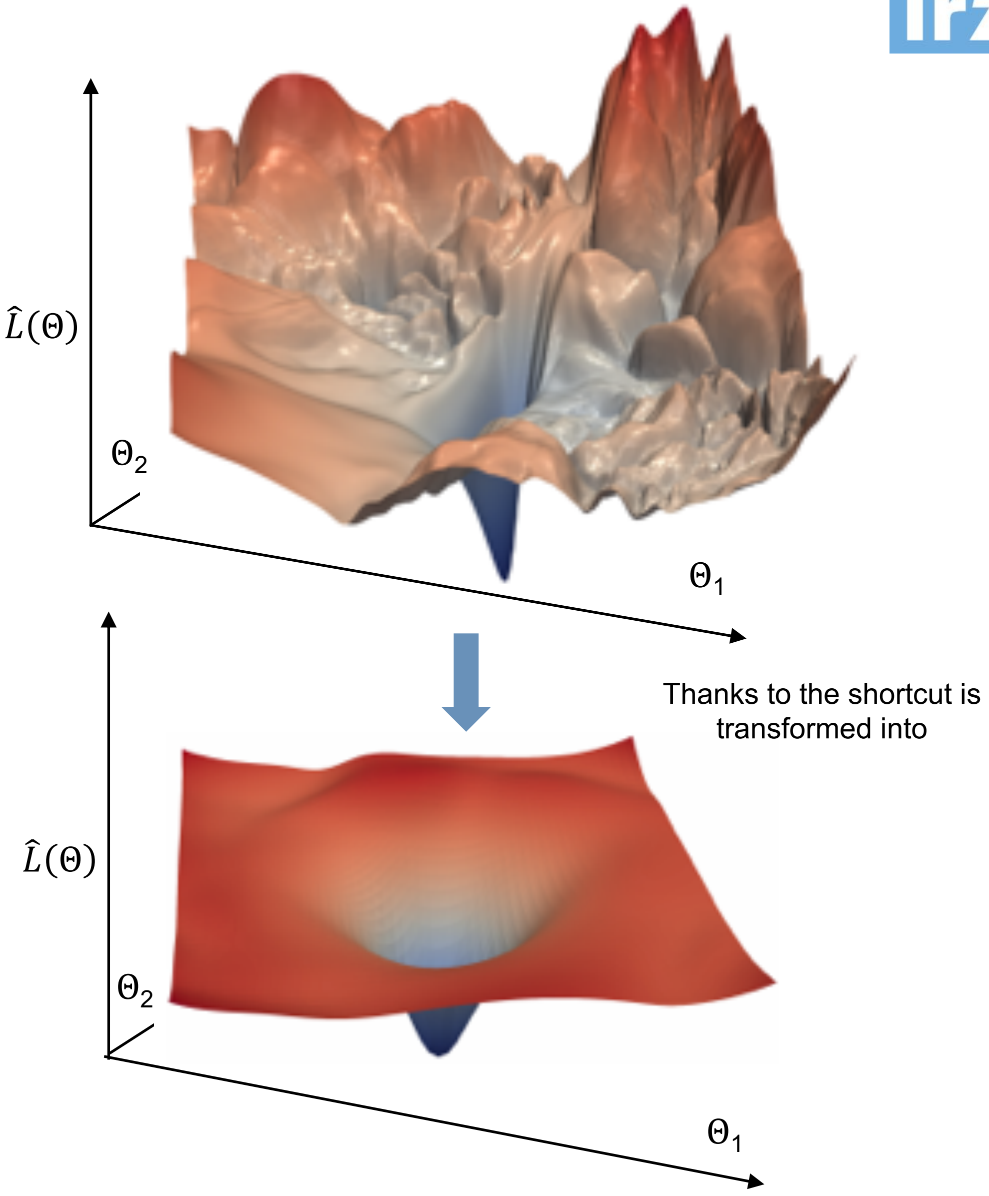
- What is the best kernel size for each layer?
- Concatenating filters instead of stacking them for reducing computational expenses



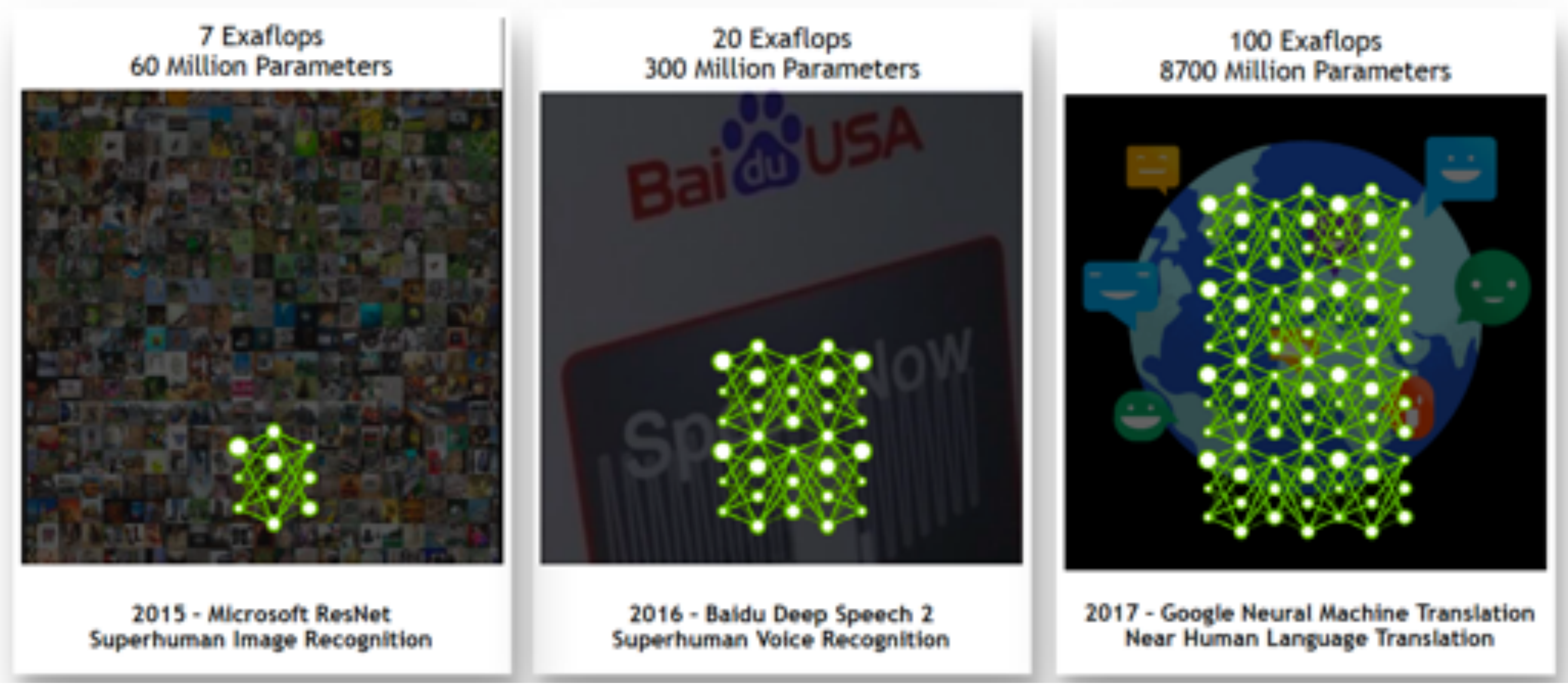
RestNet


Input
CONV
POOL
Residual block
Residual block
Residual block
POOL
FC
Softmax


Residual blocks
Shortcut path = x
Add both paths
x
CONV2D
Batch norm
ReLu
CONV2D
Batch norm
ReLu
CONV2D
Batch norm
+
ReLu
Main path f(x)

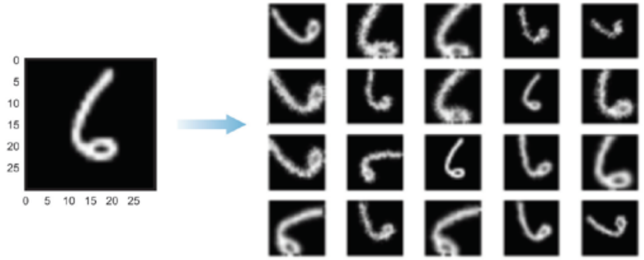

$\hat{L}(\Theta)$
Θ_2
Θ_1
Thanks to the shortcut is transformed into
$\hat{L}(\Theta)$
Θ_2
Θ_1

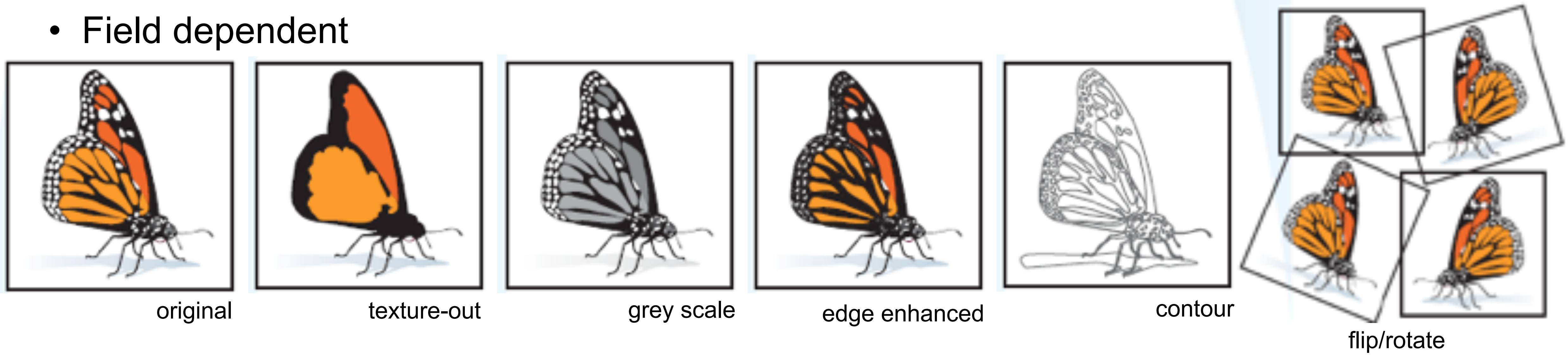
Increasing complexity



How much data?

- A non desired issue with NN is known as overfitting
  - high accuracy in the training set
  - poor generalization (low accuracy in the validation and test sets)
- Overfitting is possibly more noticeable in DNNs due to the large number of parameters
- Getting more data not always viable
- Data augmentation
  - Field dependent





Hands on: A quick code review of the LeNet Implementation using Keras and Tensorflow

Summary

- Brief introduction to Deep Learning with emphasis in Deep Convolutional Neural Networks
- Review of basic concepts: from perceptron to the learning task
- Debrief of most important concepts of neural network architectures
- Introduction to data augmentation
- Code review

Q&A

To pose a question, you can write your question in the “Questions” tab

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 675451

Thank you for participating!

…don't forget to fill in our feedback questionnaire…

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to download the slides
and to keep updated on our upcoming trainings

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