

# An introduction to Deep Learning

## Part II - ConvNet

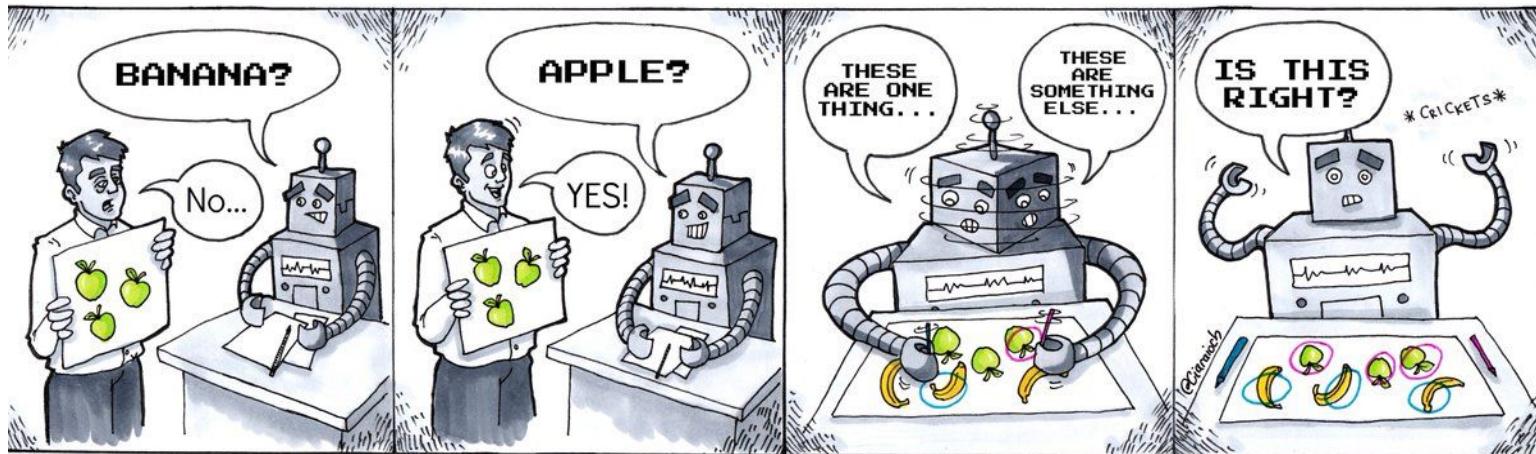
**JB Fiche**, CBS-Montpellier & Plateforme MARS-MRI

**Volker Baecker**, CRBM & MRI

**Cédric Hassen-Khodja**, CRBM & MRI

# Quick reminder of the key concepts

- **Supervised learning** = the data are coming with already labelled data (**ground truth**)

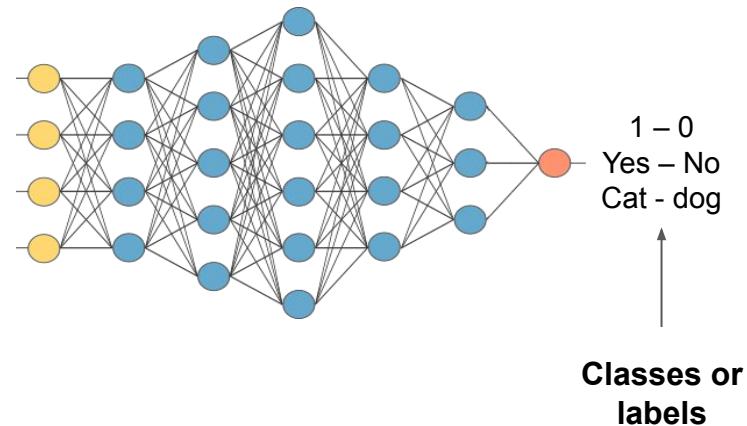
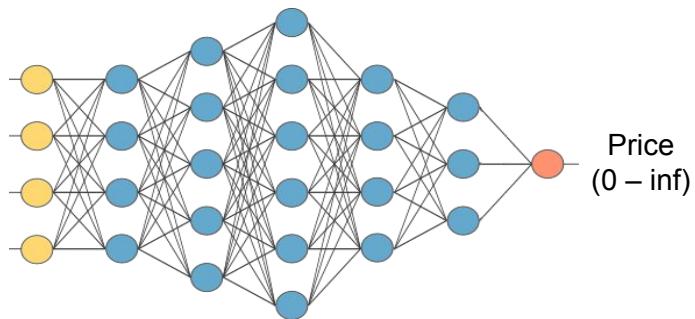


**Supervised Learning**

**Unsupervised Learning**

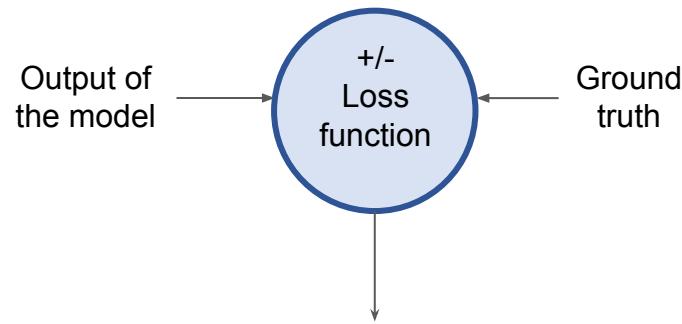
# Quick reminder of the key concepts

- Supervised learning
- **Classification and regression**



# Quick reminder of the key concepts

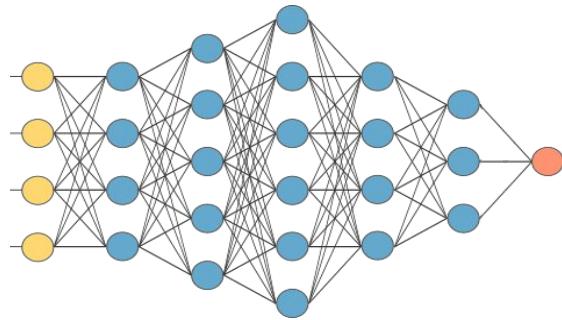
- Supervised learning
- Classification and regression
- **Loss function**



The loss measure the amount of 'disagreement' between the obtained and ideal outputs

# Quick reminder of the key concepts

- Supervised learning
- Classification and regression
- Loss function
- Parameters vs. hyperparameters

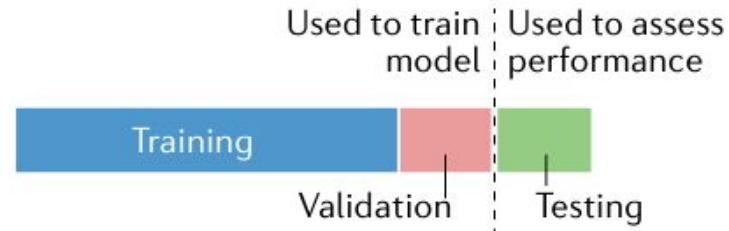


**parameters** : weight and bias of a trained model

**hyperparameters** : all the parameters that could influence the learning process (number of hidden layers, loss function, optimizer, number of epochs, batch size, etc.)

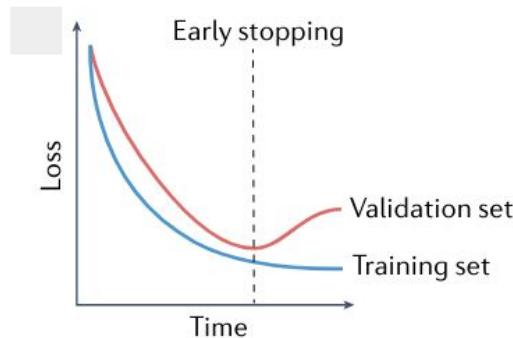
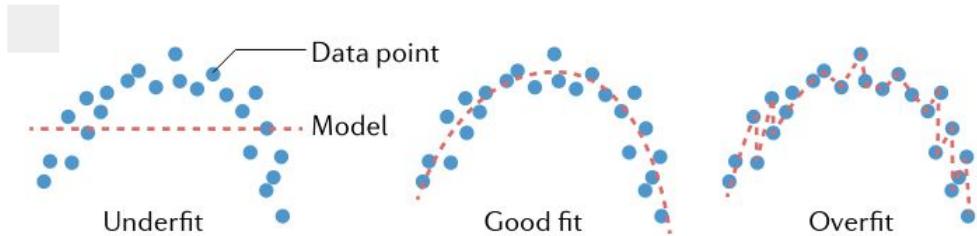
# Quick reminder of the key concepts

- Supervised learning
- Classification and regression
- Loss function
- Parameters vs. hyperparameters
- Training, testing and validation



# Quick reminder of the key concepts

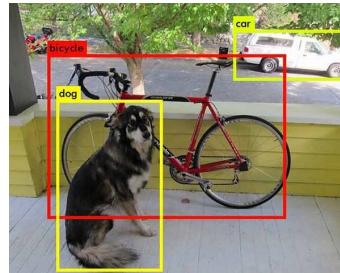
- Supervised learning
- Classification and regression
- Loss function
- Parameters vs. hyperparameters
- Training, testing and validation
- Under / overfitting



# Computer Vision - possible tasks



classification  
“cat”



classification +  
localization  
class + bounding box



Semantic segmentation  
each pixel : class

Person  
Bicycle  
Background

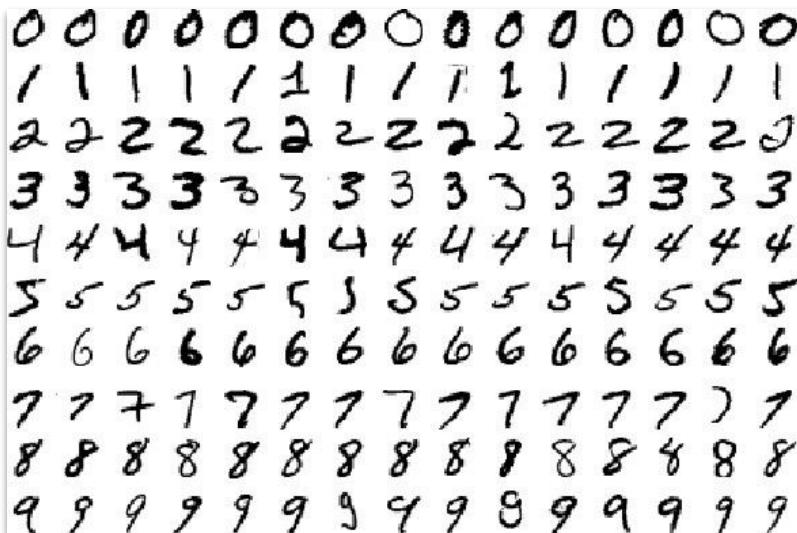


Instance segmentation for each pixel:  
class “person” + instance #1  
class “person” + instance #2 ...

# Outline

- I. Image classification :
  - A. **Introduction to convolutional network : digit classification**
  - B. Application to red-blood cells classification
  - C. Introduction to transfer-learning
- II. Segmentation :
  - A. Application of a fully convolutional network (Unet)
  - B. Instance segmentation with existing tools
- III. Conclusion :

# Working with the MNIST database



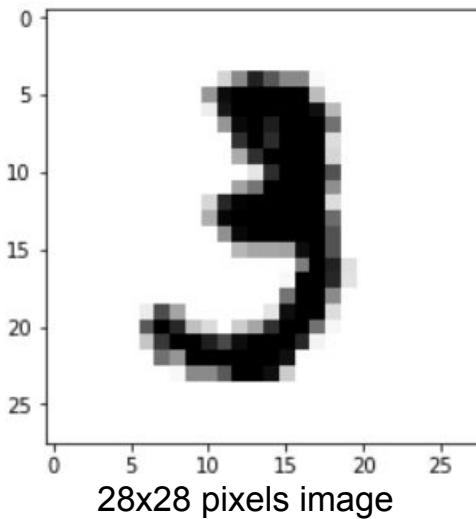
Large database of **handwritten digits** that is commonly used for machine learning.

It contains :

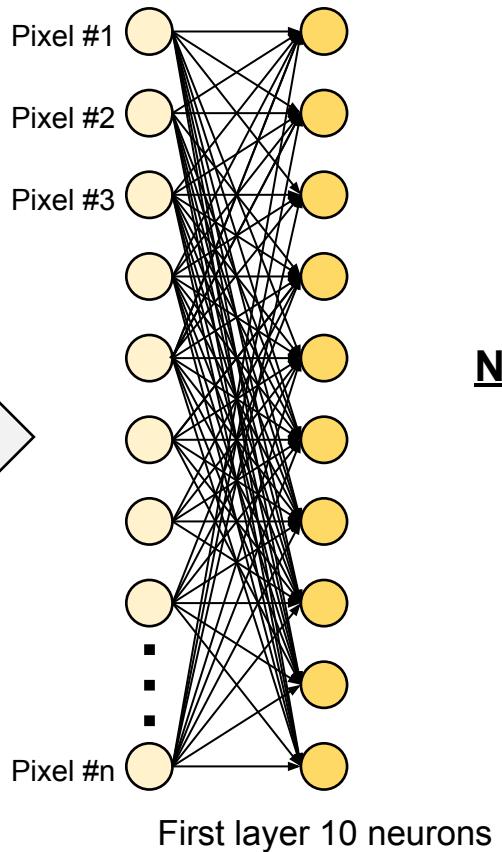
- 60.000 images for training
- 10.000 images for testing/validation

**Ex4\_MNIST\_dense\_vs\_convolutional\_nn.ipynb**

# Image classification with a dense network



784 inputs



**Number of parameters:**

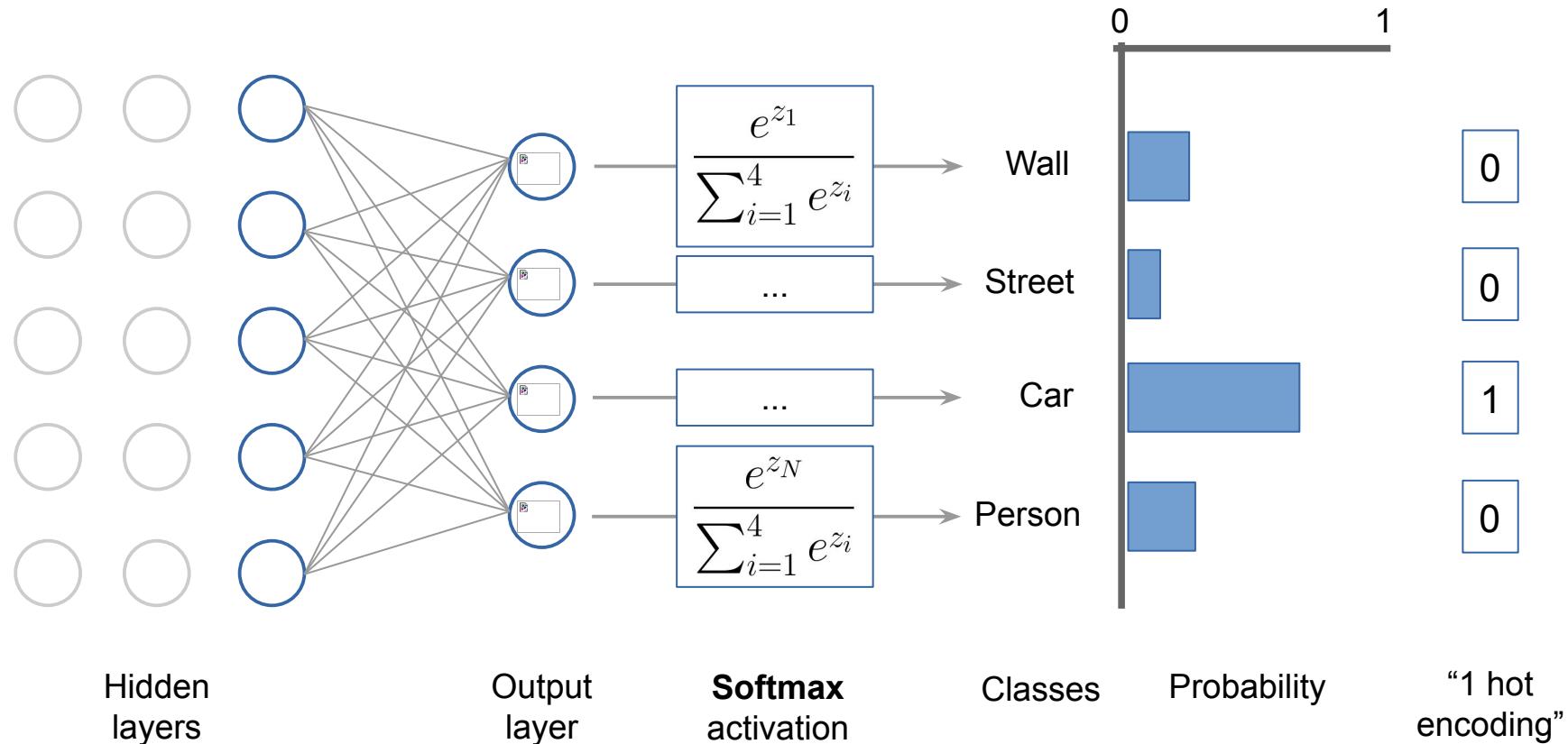
$$784 * 10 + 10 = 7850$$

# How to choose the activation and loss functions ?

Problem type	Last-layer activation	Loss function	Number of neurons in the last layer
Binary classification	'sigmoid'	'binary-crossentropy'	1
Multiclass, single-label classification	'softmax'	'categorical_crossentropy'	As many as the number of classes
Regression to values between 0 and 1	'sigmoid' or 'none'	'mse'	1

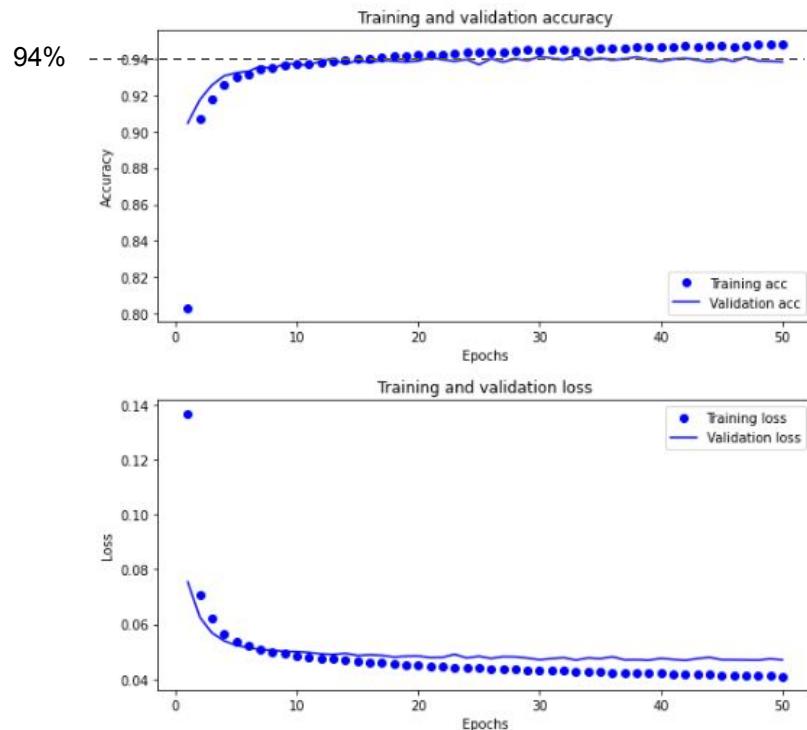
**As a rule-of-thumbs, use 'relu' everywhere else as activation function.**

# Softmax activation

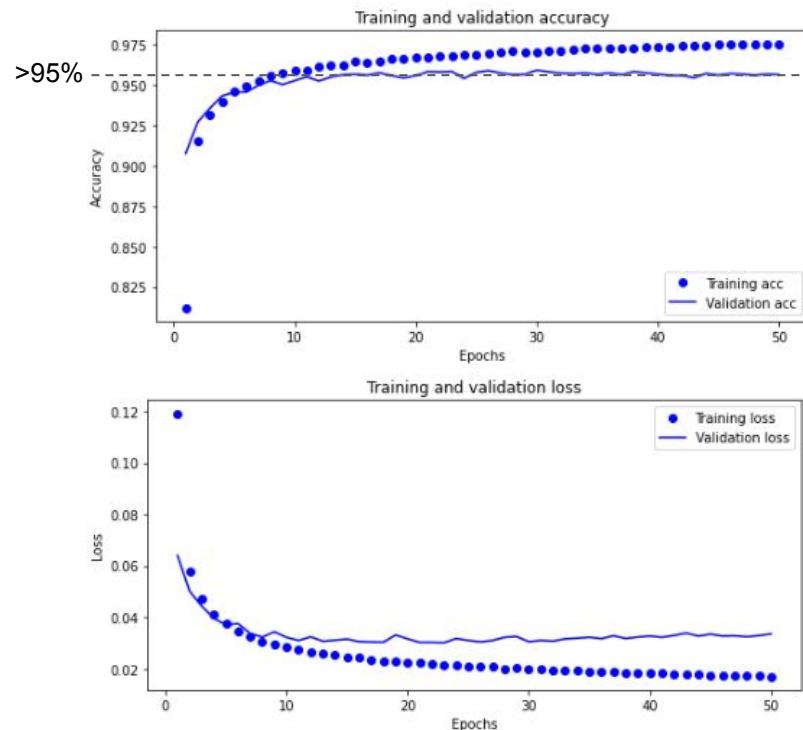


# MNIST classification with a dense network

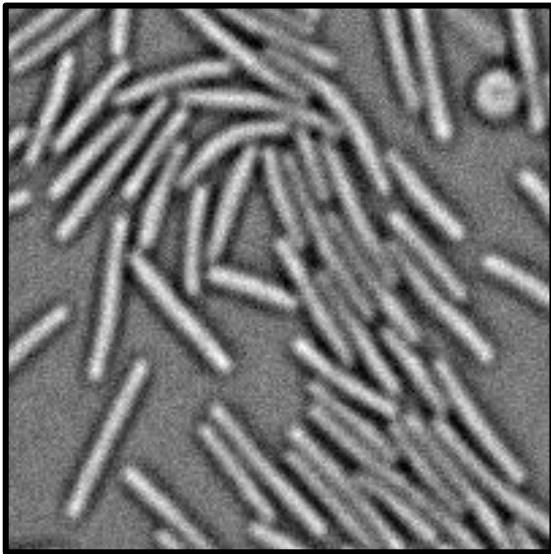
2 layers of 10 neurons : **7960 parameters**



3 layers of 15 neurons : **12175 parameters**

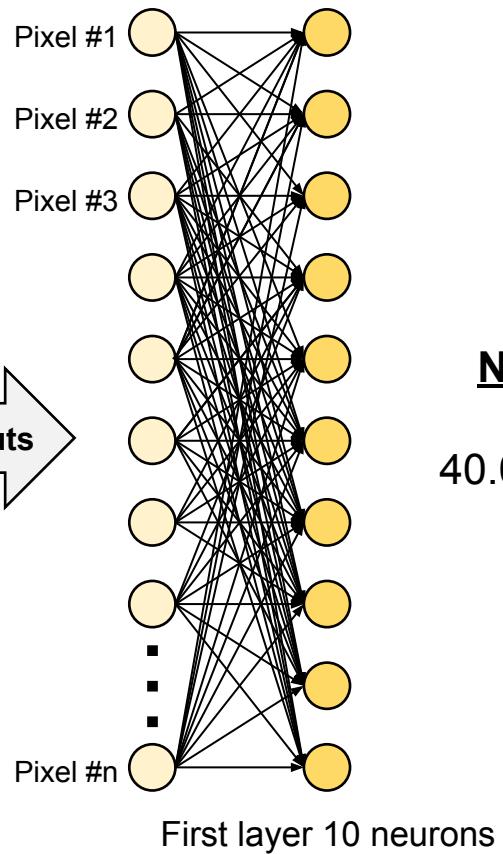


# Dense network for large images?



200x200 pixels image

40.000 inputs



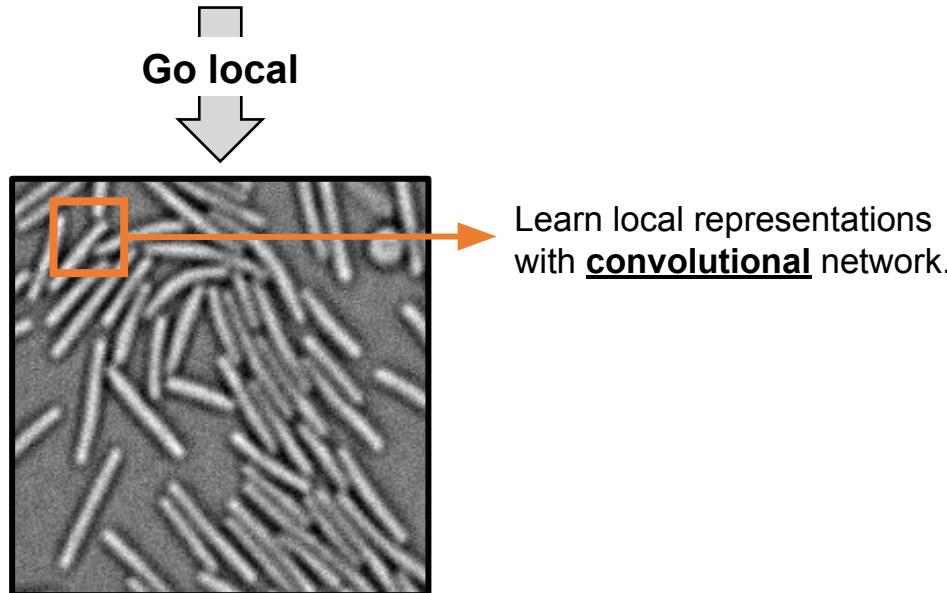
**Number of parameters:**

$$40.000 * 10 + 10 = 400.010 (!!!)$$

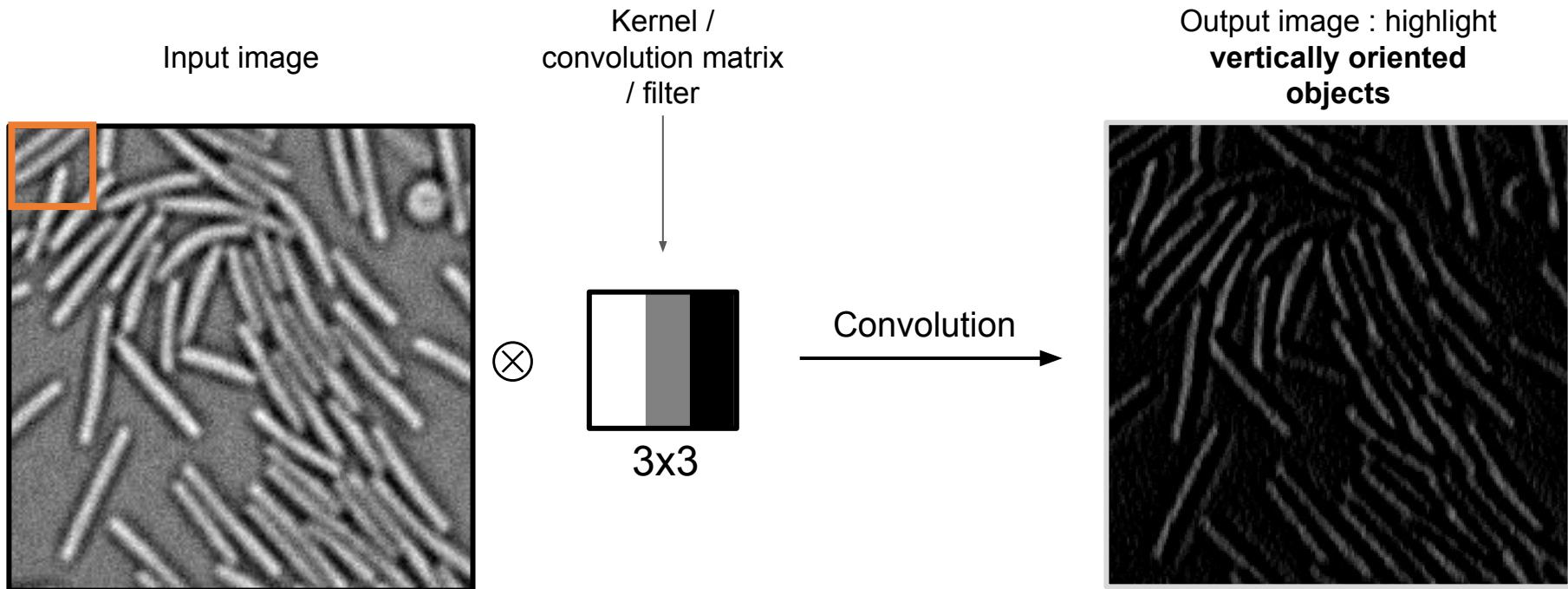
# Image analysis with convolutional network

Densely connected networks are not suited for image analysis:

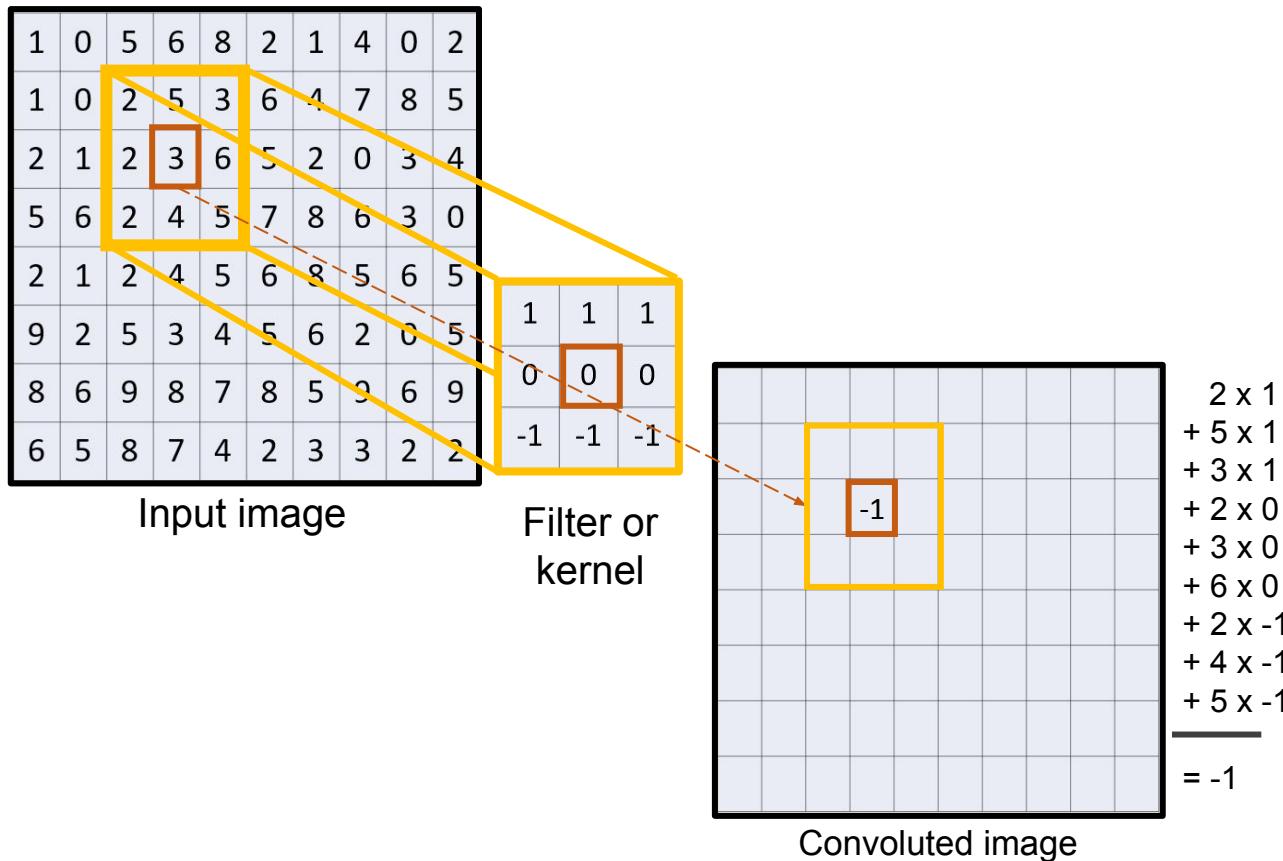
- Too many parameters, even for small images
- Loses the local information around each pixel
- The network architecture depends on the image size



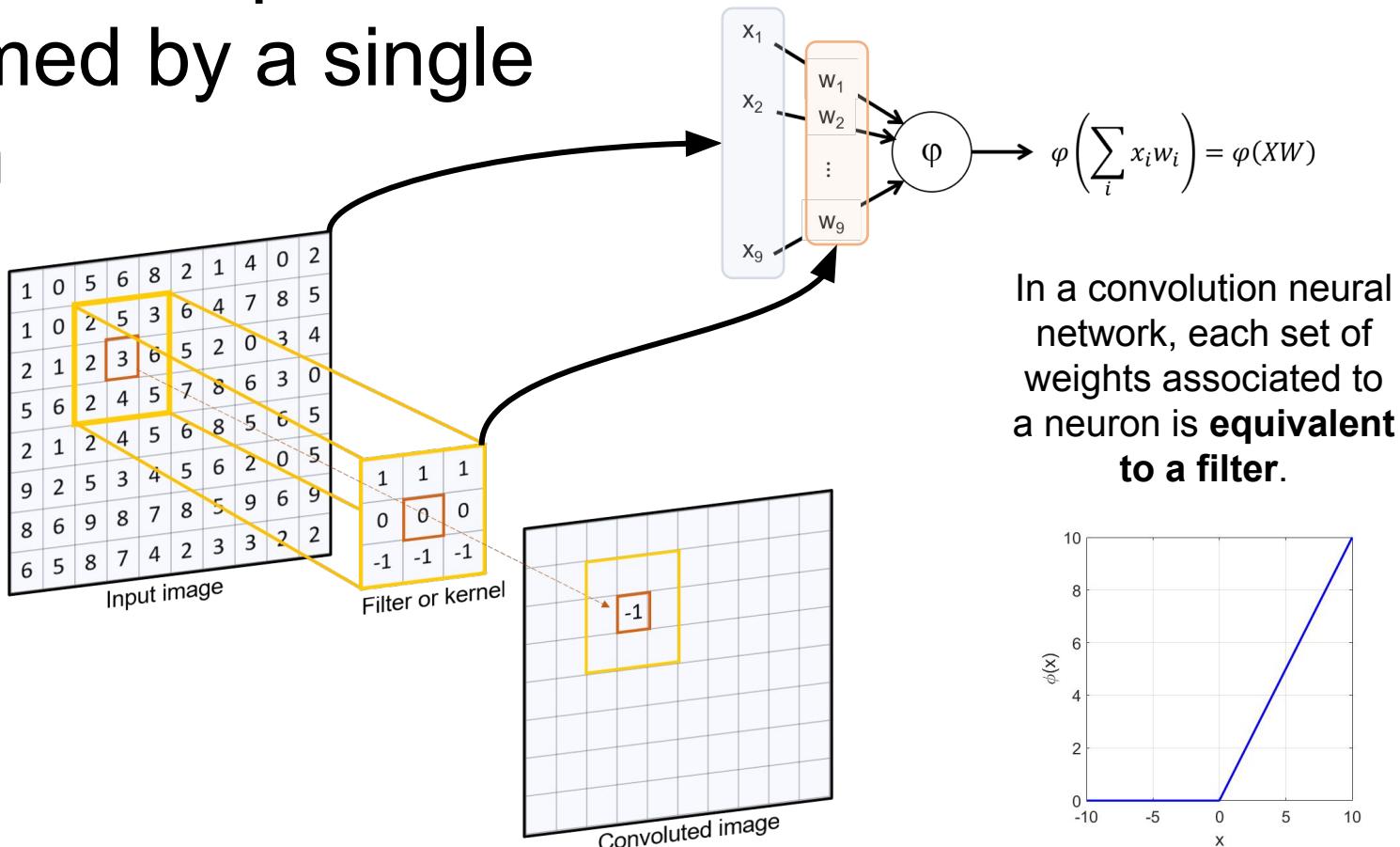
# What is convolution?



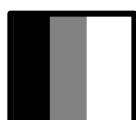
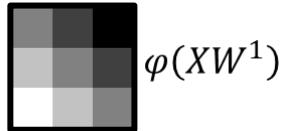
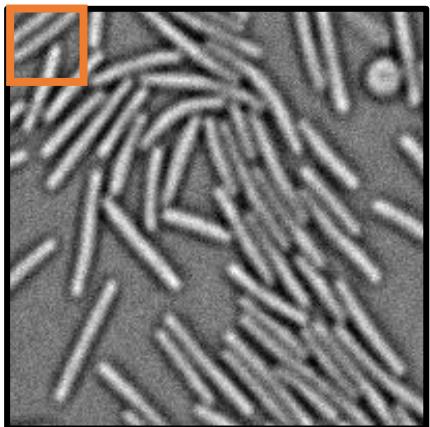
# Convolution operation in one scheme



# Convolution operation performed by a single neuron



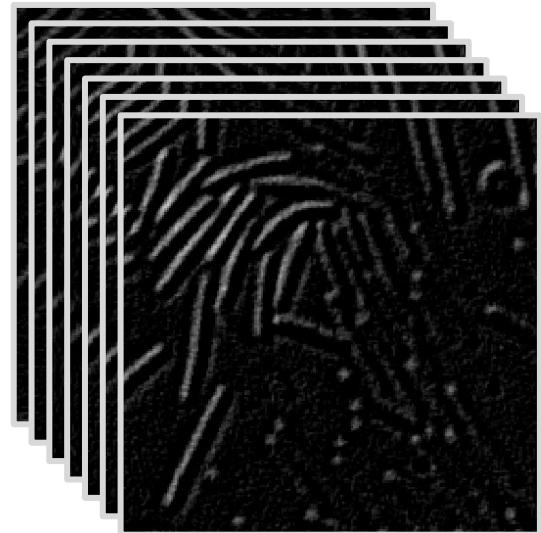
# Features map



$$\varphi(XW^n)$$

Convolution  
& ReLu

Each filters will help **highlights specific & useful features** of the image (edge orientation, poles, texture, etc.)



**Features maps**

# ConvNet syntax

Convolution part

```
modelCNN = Sequential([  
  
    # Convolution Layer 1  
    → Conv2D(16, (3, 3), activation='relu', input_shape=(28, 28, 1)), # 16 different 3x3 kernels -- so 32 feature maps  
    → MaxPooling2D(pool_size=(2, 2)), # Pool the max values over a 2x2 kernel  
  
    # Convolution Layer 2  
    → Conv2D(16, (3, 3), activation='relu'), # 16 different 3x3 kernels  
    → MaxPooling2D(pool_size=(2, 2)),  
  
    # Convolution Layer 3  
    → Conv2D(16, (3, 3), activation='relu'), # 16 different 3x3 kernels  
  
    Flatten(), # Flatten final 3x3x16 output matrix into a 144-length vector  
  
    # Fully Connected Layer 4  
    → Dense(10), # 10 FCN nodes  
    Activation('relu'),  
    → Dense(10), # Necessary for the last layer since we have 10 classes  
    Activation('softmax'),  
])
```

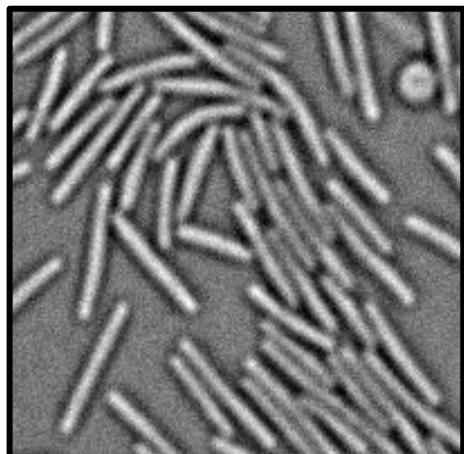
Dense part

→ Convolution layer

→ MaxPooling layer

→ Dense layer

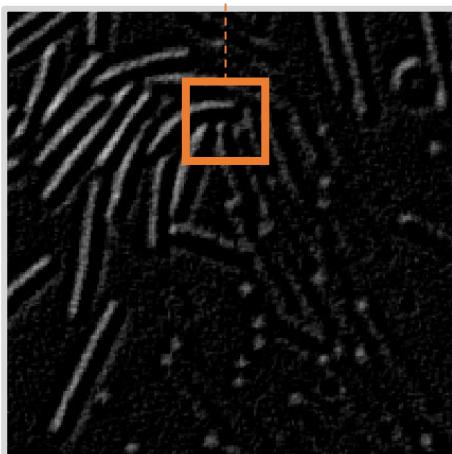
# Goal of the max-pooling layer



200 x 200 pixels



$\otimes$



200 x 200 pixels

1	4	5	2
0	1	6	2
7	0	0	4
1	5	2	2

Max pooling  
2x2

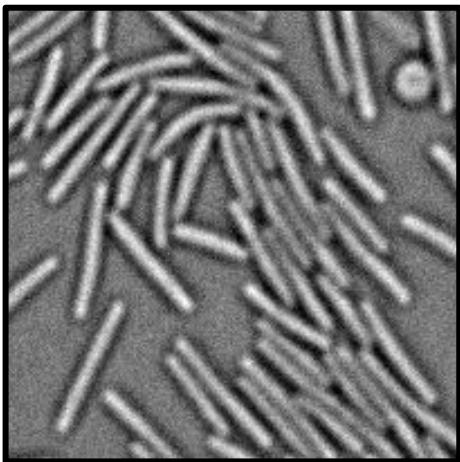
4	6
7	4



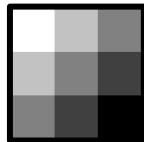
100 x 100 pixels

# Goal of the max-pooling layer

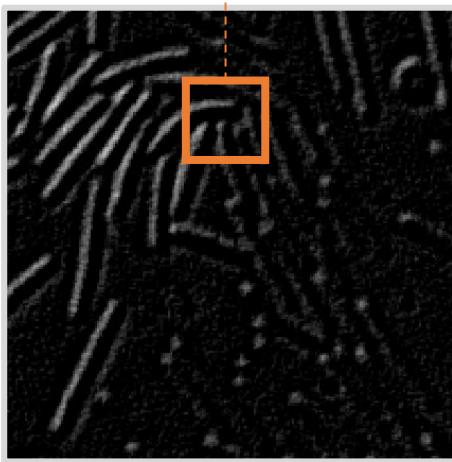
1. **Reduce the spatial resolution** of the feature maps while keeping only the most relevant information
2. **Lowering memory and computing requirements**
3. Create translation invariance



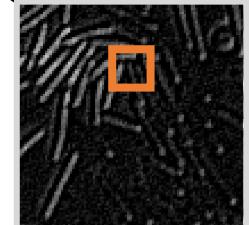
$\otimes$



=



200 x 200 pixels



100 x 100  
pixels

# MNIST classification with a ConvNet

```
modelCNN = Sequential([
    # Convolution Layer 1
    Conv2D(16, (3, 3), activation='relu', input_shape=(28, 28, 1)),
    MaxPooling2D(pool_size=(2, 2)),

    # Convolution Layer 2
    Conv2D(16, (3, 3), activation='relu'),
    MaxPooling2D(pool_size=(2, 2)),

    # Convolution Layer 3
    Conv2D(16, (3, 3), activation='relu'),
    Flatten(),

    # Fully Connected Layer 4
    Dense(15),
    Activation('relu'),
    Dense(10),
    Activation('softmax'),
])
```

Model: "sequential\_2"

Layer (type)	Output Shape	Param #
conv2d_6 (Conv2D)	(None, 26, 26, 16)	160
max_pooling2d_4 (MaxPooling2D)	(None, 13, 13, 16)	0
conv2d_7 (Conv2D)	(None, 11, 11, 16)	2320
max_pooling2d_5 (MaxPooling2D)	(None, 5, 5, 16)	0
conv2d_8 (Conv2D)	(None, 3, 3, 16)	2320
flatten_2 (Flatten)	(None, 144)	0
dense_4 (Dense)	(None, 15)	2175
activation_4 (Activation)	(None, 15)	0
dense_5 (Dense)	(None, 10)	160
activation_5 (Activation)	(None, 10)	0

Total params: 7,135  
Trainable params: 7,135  
Non-trainable params: 0

# MNIST classification with a ConvNet

```
modelCNN = Sequential([
    # Convolution Layer 1
    Conv2D(16, (3, 3), activation='relu', input_shape=(28, 28, 1)),
    MaxPooling2D(pool_size=(2, 2)),

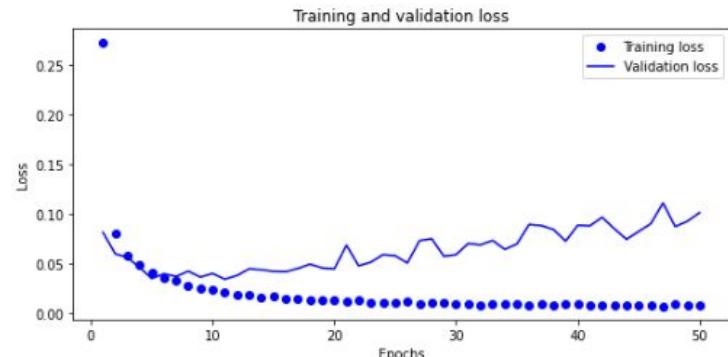
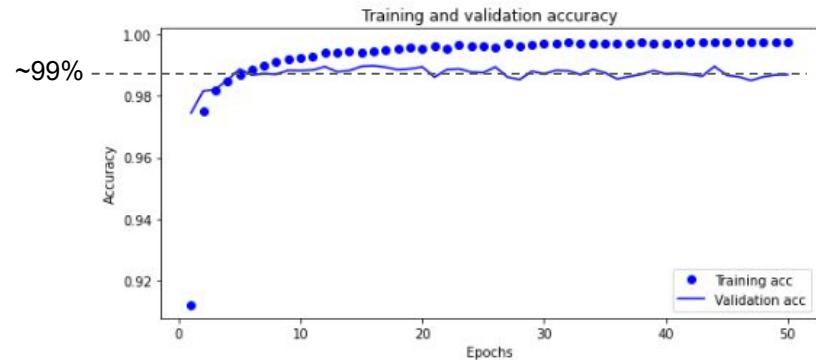
    # Convolution Layer 2
    Conv2D(16, (3, 3), activation='relu'),
    MaxPooling2D(pool_size=(2, 2)),

    # Convolution Layer 3
    Conv2D(16, (3, 3), activation='relu'),

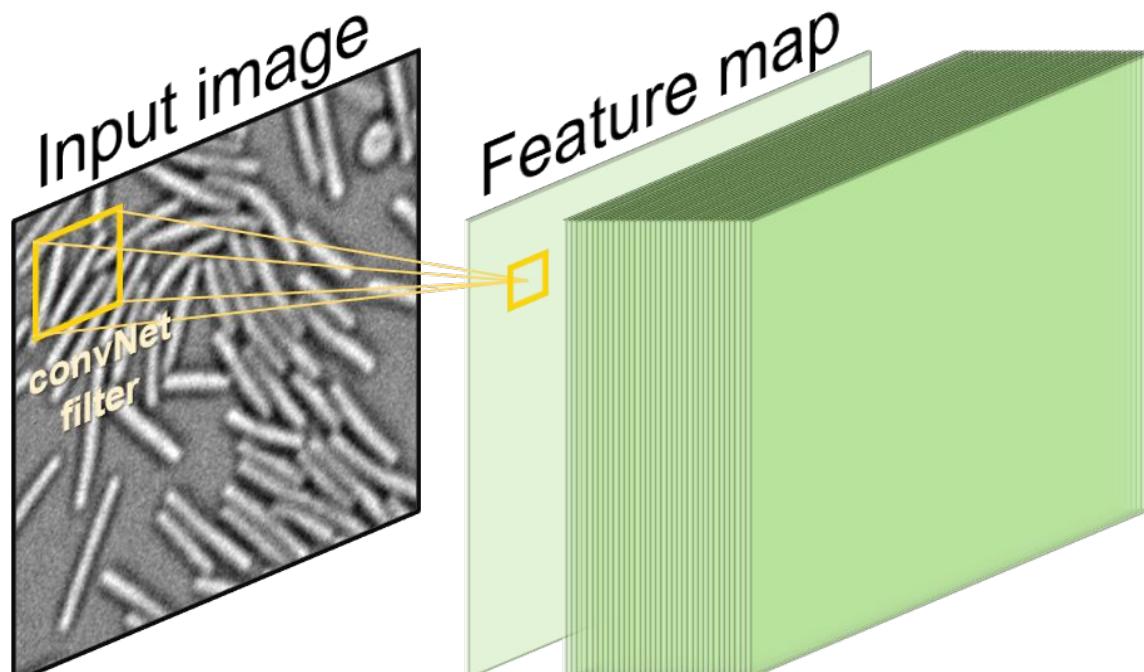
    Flatten(),

    # Fully Connected Layer 4
    Dense(15),
    Activation('relu'),
    Dense(10),
    Activation('softmax'),
])
```

3 convolution layers of 16 kernel and 2 dense layers of 10 neurons : **7135 parameters**

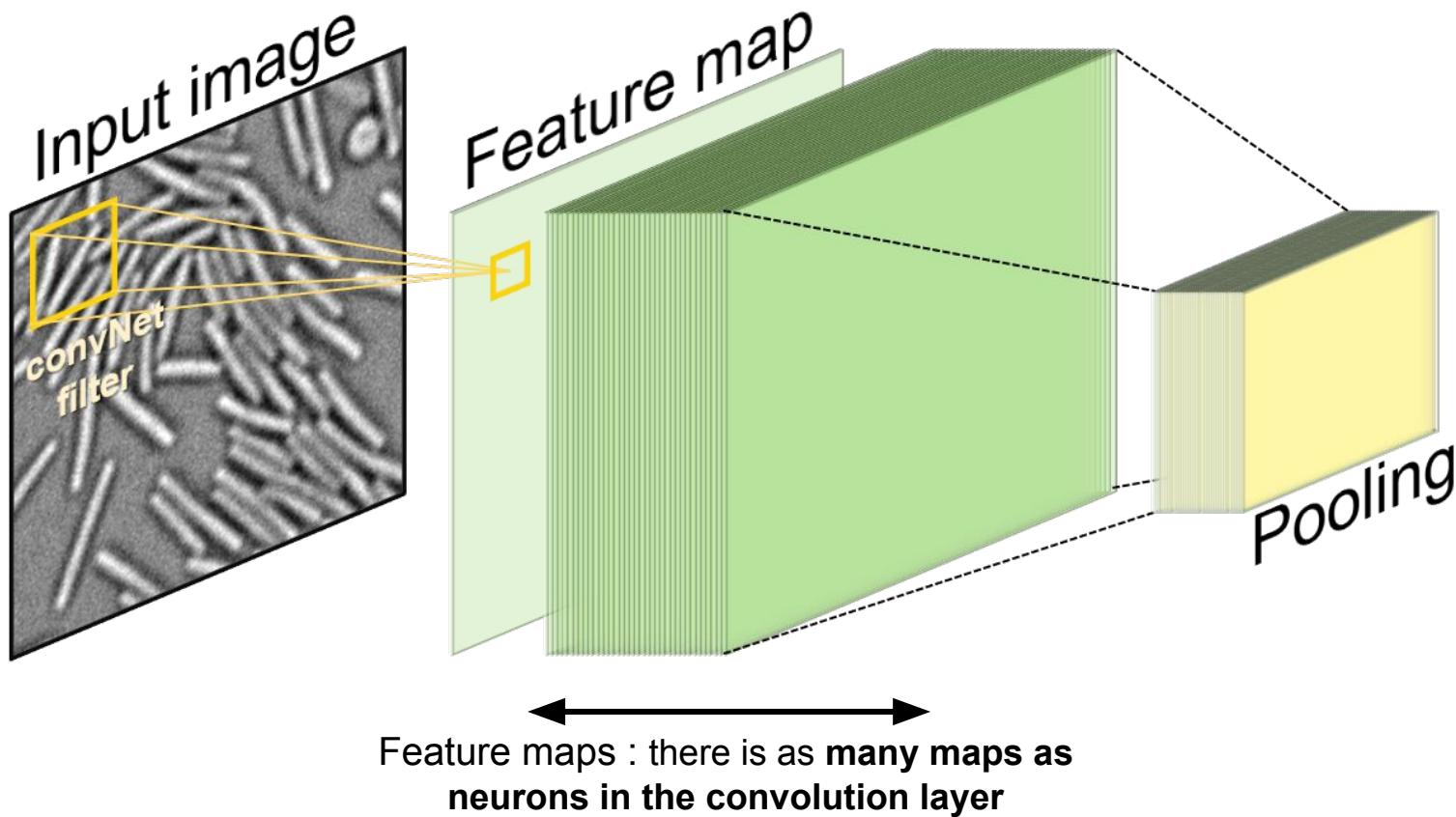


# ConvNet summary

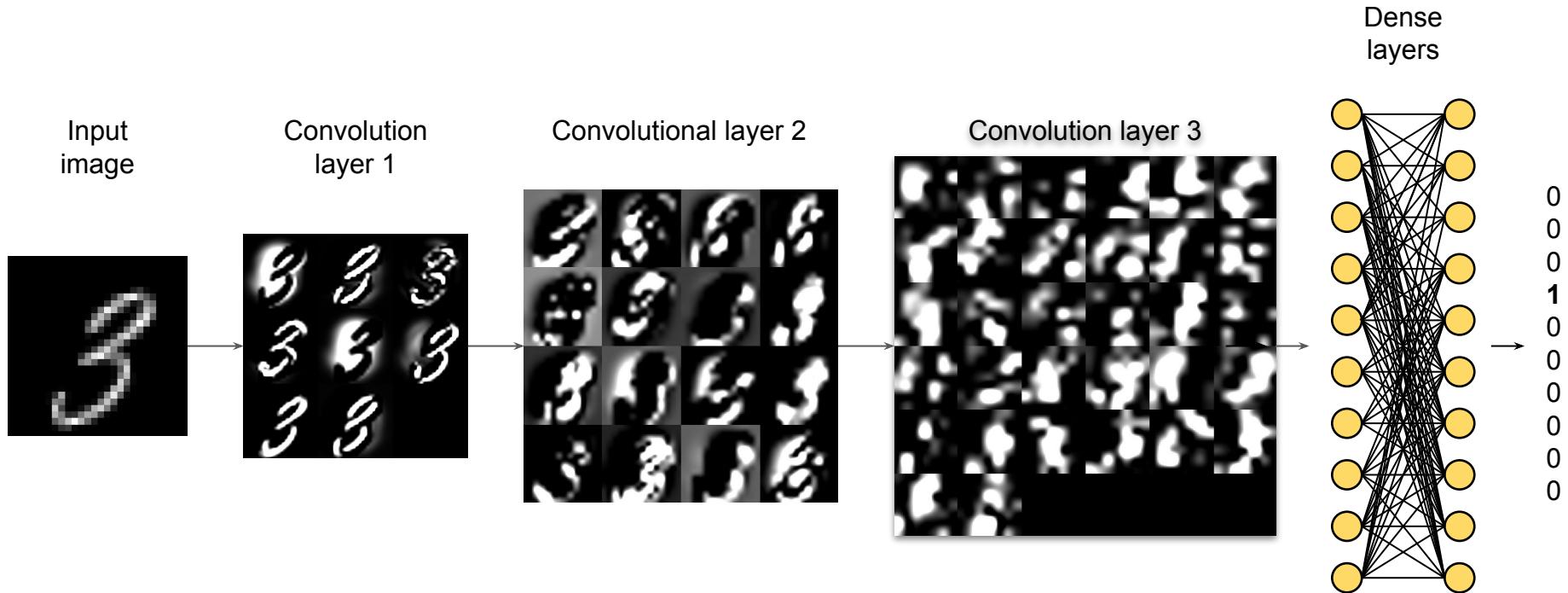


Feature maps : there is as **many maps** as  
neurons in the convolution layer

# ConvNet summary



# ConvNet summary



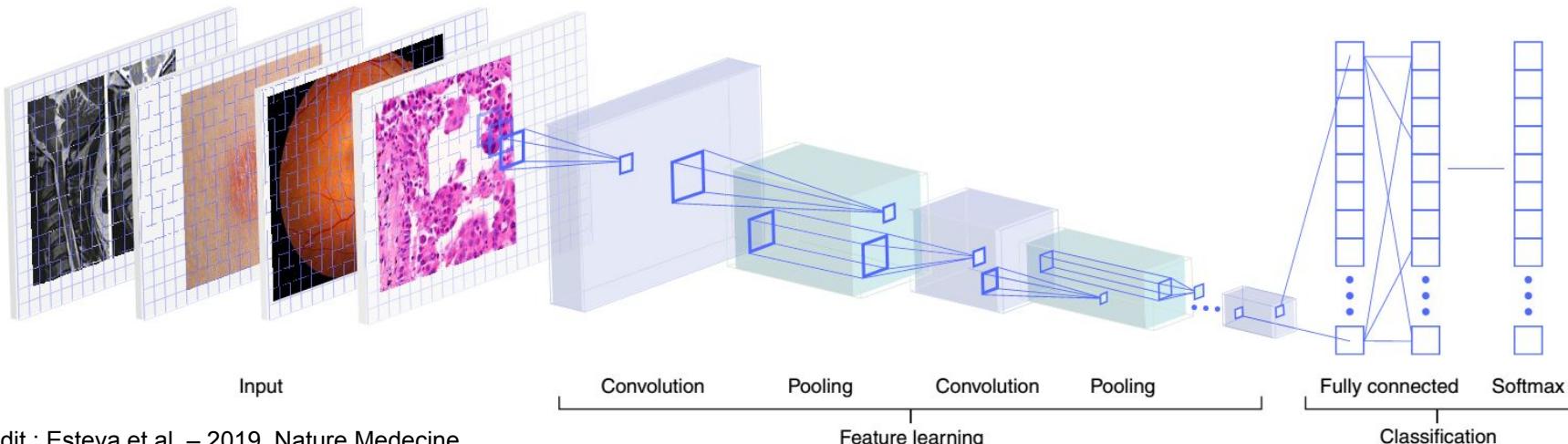
# ConvNet architecture for image classification

The first part of the network is **using convolution layers to learn the features**

- **Convolution layers → features extraction**
- **Pooling → downsampling**

The second part is classifying those features using **densely connected layers** in order to predict the right output.

- Lots of parameters → **heavy on the memory**
- Image input size is fixed → **not flexible**



# Outline

- I. Image classification :
  - A. Introduction to convolutional network : digit classification
  - B. Application to red-blood cells classification**
  - C. Introduction to transfer-learning
- II. Segmentation :
  - A. Application of a fully convolutional network (Unet)
  - B. Instance segmentation with existing tools
- III. Conclusion :

# Example 5: Red blood cell image classification

Example: Ex5\_RBC\_image\_classification.ipynb

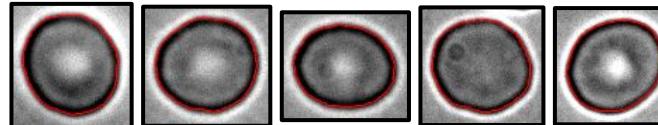
1. Build your own convolutional network for image classification
2. Understand how to detect overfitting and which strategies to avoid it
3. Introduction to transfer learning



Viviana  
Claveria

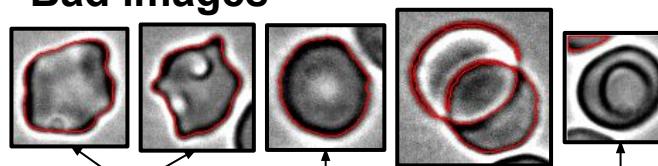
Manouk  
Abkarian

## Good images



In-focus image of RBC  
with a properly defined  
contour (red)

## Bad images



Poor quality images that  
need to be discarded  
from the analysis

Sick cells

Out-of-  
focus

Overlapping

Failed  
contour

# Start with a good baseline model

A good practice is to **start working with a network architecture that is known to be efficient for your problem**. For example, the VGG16 architecture is easy to implement and well documented for image classification.

```
model = Sequential([  
  
    # Convolution Layer 1-2  
    Conv2D(32, (3, 3), activation='relu', input_shape=(85,85,3)), #32 different 3x3 kernels  
    Conv2D(32, (3, 3), activation='relu'),  
    MaxPooling2D(pool_size=(2, 2)), # pool the max values over a 2x2 kernel  
  
    # Convolution Layer 3-4  
    Conv2D(64, (3, 3), activation='relu'), #64 different 3x3 kernels  
    Conv2D(64, (3, 3), activation='relu'),  
    MaxPooling2D(pool_size=(2, 2)),  
  
    # Convolution Layer 5-6  
    Conv2D(128, (3, 3), activation='relu'), #128 different 3x3 kernels  
    Conv2D(128, (3, 3), activation='relu'),  
    MaxPooling2D(pool_size=(2, 2)),  
  
    Flatten(), # flatten the output of the last layer (7,7,128) into a single vector of length 6272  
  
    # Fully Connected Layers  
    Dense(256, activation = 'relu', kernel_initializer='random_normal', bias_initializer='zeros'), # 256 FCN nodes  
    Dense(128, activation = 'relu', kernel_initializer='random_normal', bias_initializer='zeros'), # 128 FCN nodes  
    Dense(1, activation = 'sigmoid', kernel_initializer='random_normal', bias_initializer='zeros'),  
])  
  
model.compile(optimizer = 'adam',  
              loss='binary_crossentropy',  
              metrics=['accuracy'])  
  
model.summary()
```

Convolution block #1 {

Convolution block #2 {

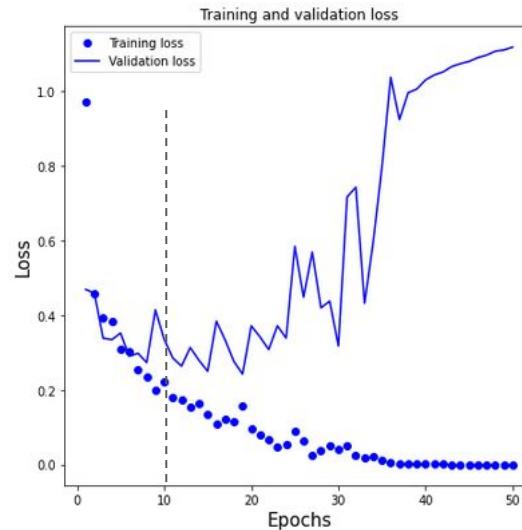
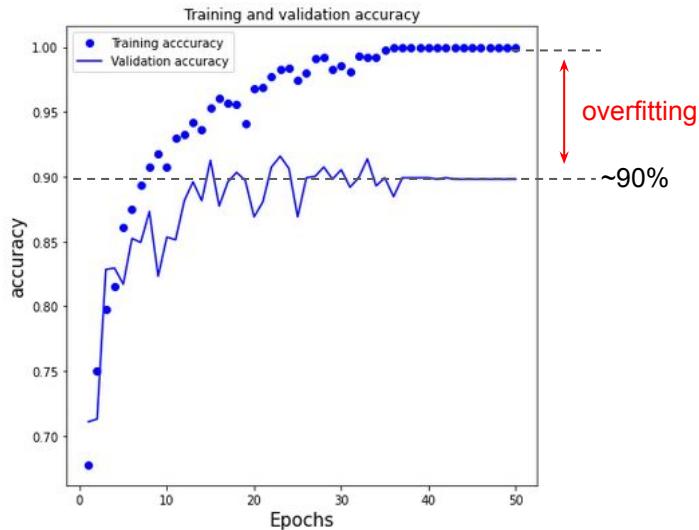
Convolution block #3 {

Fully connected network {

VGG1 : Number of trainable parameters : 1,925,921



# Start with a good baseline model



We observe that the training and validation loss & accuracy are diverging after epoch #10. **The network is no longer learning useful features.**

- Overfitting
- Validation loss & accuracy are noisy
- The global accuracy of the network is ~92.9% when tested on the testing set.

# Reduce the network size

Since overfitting means that the network is learning features specific to the training set, one strategy is to reduce the size of the network and check whether the property of the network are improving.

```
model = Sequential([  
    # Convolution Layer 1  
    Conv2D(32, (3, 3), activation='relu', input_shape=(85,85,3)), #32 different 3x3 kernels  
    MaxPooling2D(pool_size=(2, 2)), # pool the max values over a 2x2 kernel  
  
    # Convolution Layer 2  
    Conv2D(64, (3, 3), activation='relu'), #64 different 3x3 kernels,  
    MaxPooling2D(pool_size=(2, 2)),  
  
    # Convolution Layer 3  
    Conv2D(128, (3, 3), activation='relu'), #128 different 3x3 kernels  
    MaxPooling2D(pool_size=(2, 2)),  
  
    Flatten(), # flatten the output of the last convolution layer  
  
    # Fully Connected Layers  
    Dense(128, activation = 'relu', kernel_initializer='random_normal', bias_initializer='zeros'), # 128 FCN nodes  
    Dense(64, activation = 'relu', kernel_initializer='random_normal', bias_initializer='zeros'), # 64 FCN nodes  
    Dense(1, activation = 'sigmoid', kernel_initializer='random_normal', bias_initializer='zeros'),  
])  
  
model.compile(optimizer = 'adam',  
              loss='binary_crossentropy',  
              metrics=['accuracy'])  
  
model.summary()
```

Convolution block #1 {

Convolution block #2 {

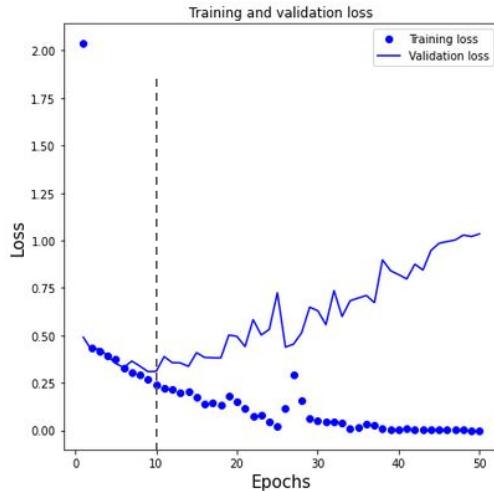
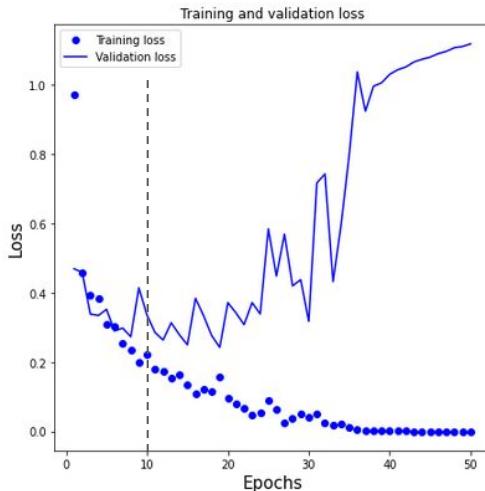
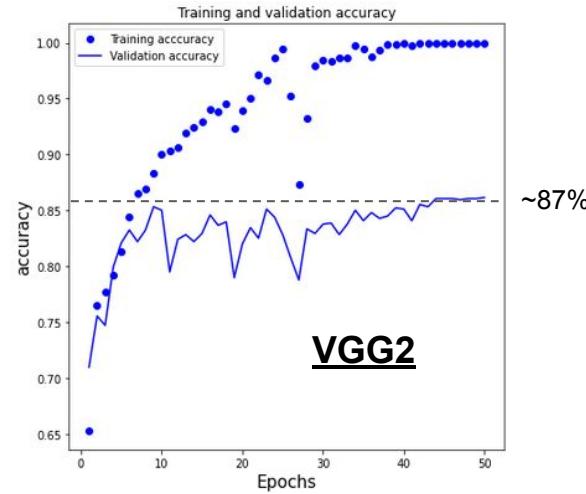
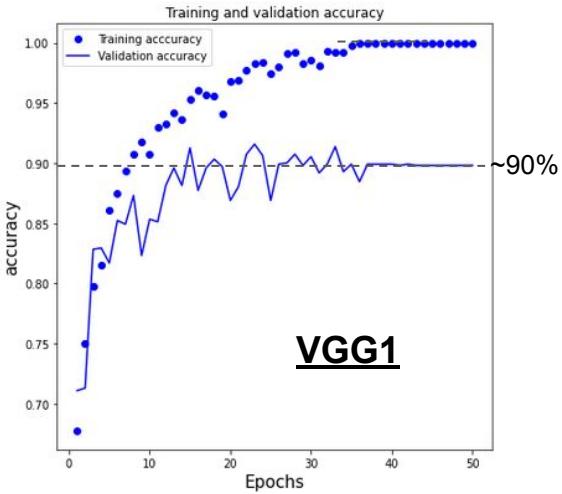
Convolution block #3 {

Fully connected network {

VGG2 : Number of trainable parameters : 1,150,273

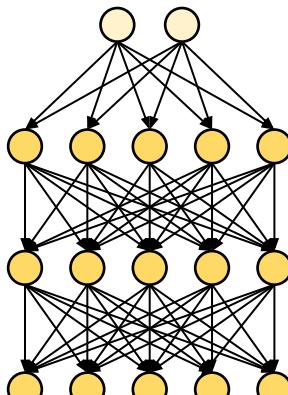


# Comparison VGG 1 & 2

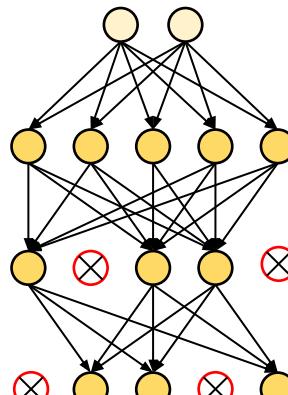


# How to reduce overfitting?

- Reduce the size of the network
- Dropout, randomly “turning-off” neurons of the network



No dropout

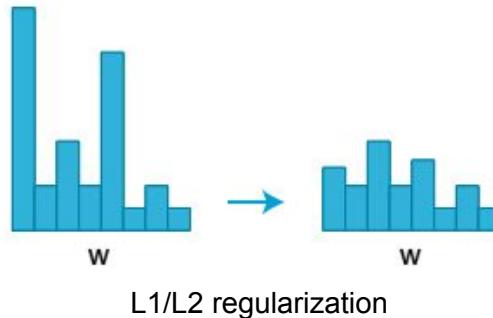


Dropout with 40% probability

Dropout is used to avoid co-adaptation of neurons → enforce the fact that neurons should **learn and work independently**.

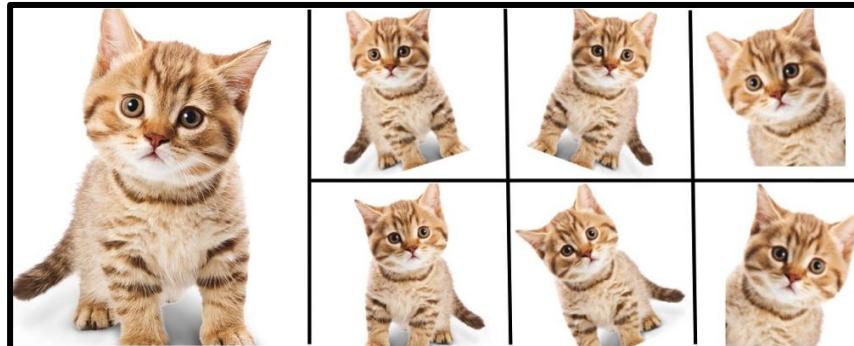
# How to reduce overfitting?

- **Reduce the size of the network**
- **Dropout**, randomly “turning-off” neurons of the network
- **Weight regularization L<sub>1</sub> & L<sub>2</sub>**, a strategy to force the weights to take only small values during the training



# How to reduce overfitting?

- **Reduce the size of the network**
- **Dropout**, randomly “turning-off” neurons of the network
- **Weight regularization  $L_1$  &  $L_2$** , a strategy to force the weights to take only small values during the training
- Increase the size of the training set:
  - Add new images to the training set
  - Use **data augmentation**



# VGG baseline and Dropout regularization :

Image augmentation layer

Dropout 20%

Dropout 20%

Dropout 20%

Dropout 50%

Dropout 50%

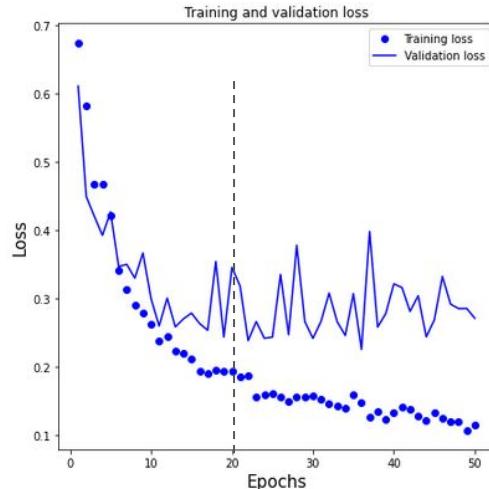
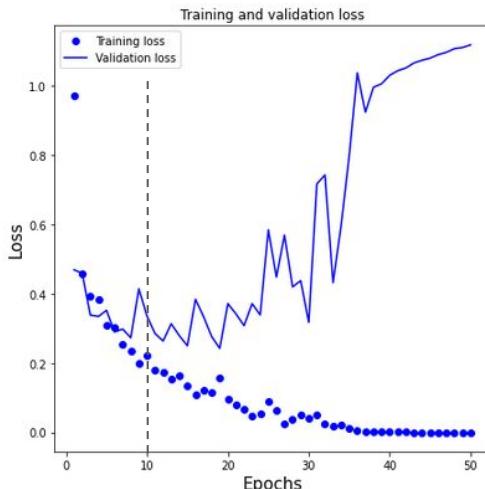
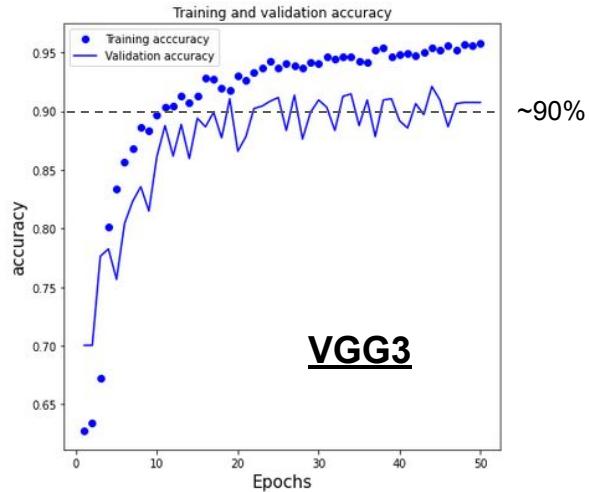
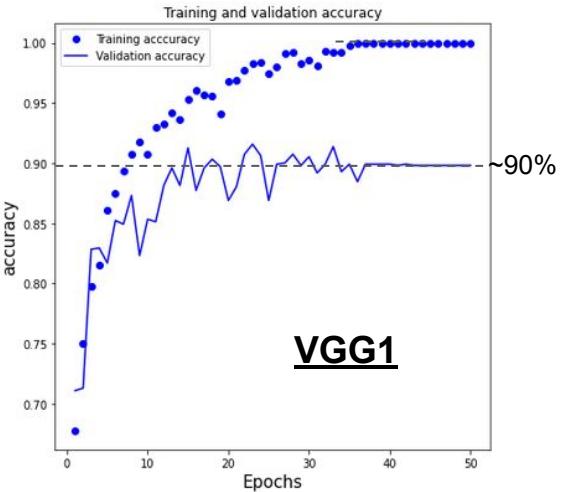
```
model = Sequential([
    Input(shape=(85, 85, 3)),
    Rescaling(scale=1./255),
    RandomFlip(mode="horizontal_and_vertical"),
    # Convolution Layer 1-2
    Conv2D(32, (3, 3), activation='relu'), #32 different 3x3 kernels
    Conv2D(32, (3, 3), activation='relu'),
    MaxPooling2D(pool_size=(2, 2)), # pool the max values over a 2x2 kernel
    Dropout(0.2),
    # Convolution Layer 3-4
    Conv2D(64, (3, 3), activation='relu'), #64 different 3x3 kernels,
    Conv2D(64, (3, 3), activation='relu'),
    MaxPooling2D(pool_size=(2, 2)),
    Dropout(0.2),
    # Convolution Layer 5-6
    Conv2D(128, (3, 3), activation='relu'), #128 different 3x3 kernels,
    Conv2D(128, (3, 3), activation='relu'),
    MaxPooling2D(pool_size=(2, 2)),
    Dropout(0.2),
    Flatten(), # flatten the output of the last convolution layer
    # Fully Connected Layers
    Dense(256, activation = 'relu'), # 256 FCN nodes
    Dropout(0.5),
    Dense(128, activation = 'relu'), # 128 FCN nodes
    Dropout(0.5),
    Dense(1, activation = 'sigmoid')
])
```

VGG3 : Number of trainable parameters : 1,925,921



# Comparison VGG 1 & 3

- Dropout & image augmentation help reduced the overfitting
- Global accuracy calculated with the testing set :
  - VGG1 : 92.9%
  - VGG2 : 89.9%
  - **VGG3 : 94.4%**



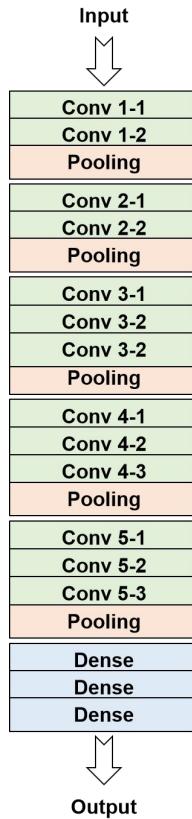
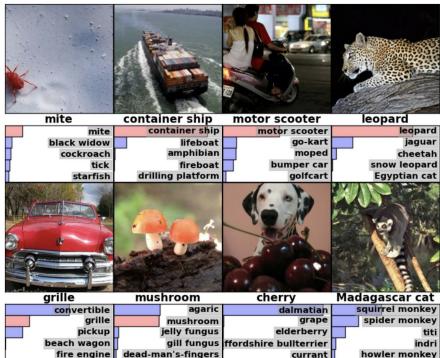
# What did we learn?

- How to create and use a **convolutional neural network for image classification** :
    - convolution layer
    - max-pool layer
  - Recognize **overfitting** and methods to reduce it while **optimizing the performances of the network** :
    - dropout
    - regularization
    - **image augmentation**
    - batch normalization
    - transfert learning
    - ...
- 
- There is no “unique solution”. It strongly depends on your dataset. Need to use a “try & error” strategy.

# Outline

- I. Image classification :
  - A. Introduction to convolutional network : digit classification
  - B. Application to red-blood cells classification
  - C. Introduction to transfer-learning**
- II. Segmentation :
  - A. Application of a fully convolutional network (Unet)
  - B. Instance segmentation with existing tools
- III. Conclusion :

# Using a pre-trained convNet for our problem



Many networks **trained on million of images** can be downloaded from internet :

<https://keras.io/applications/>  
Greenwald et al. - 2022



138,357,544

# Using a pre-trained convNet for our problem



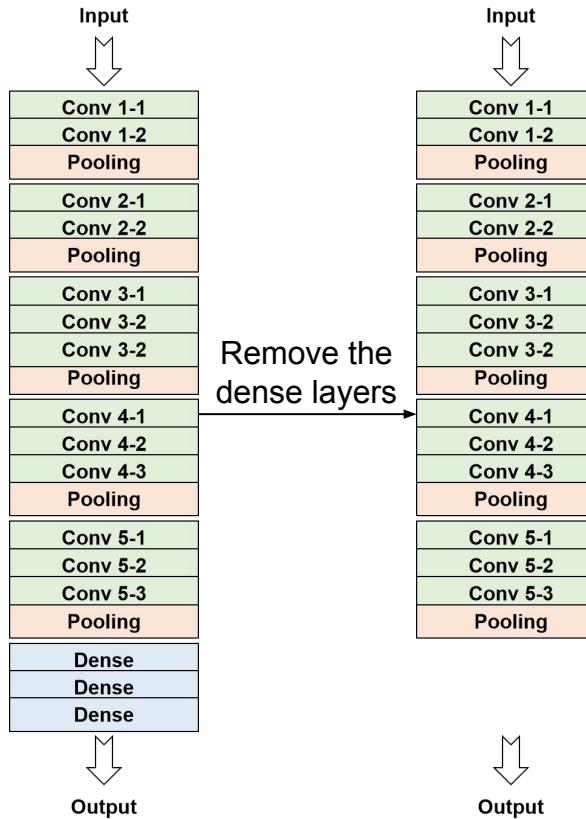
Many networks **trained on million of images** can be downloaded from internet :

<https://keras.io/applications/>

Greenwald et al. - 2022



138,357,544



# Using a pre-trained convNet for our problem

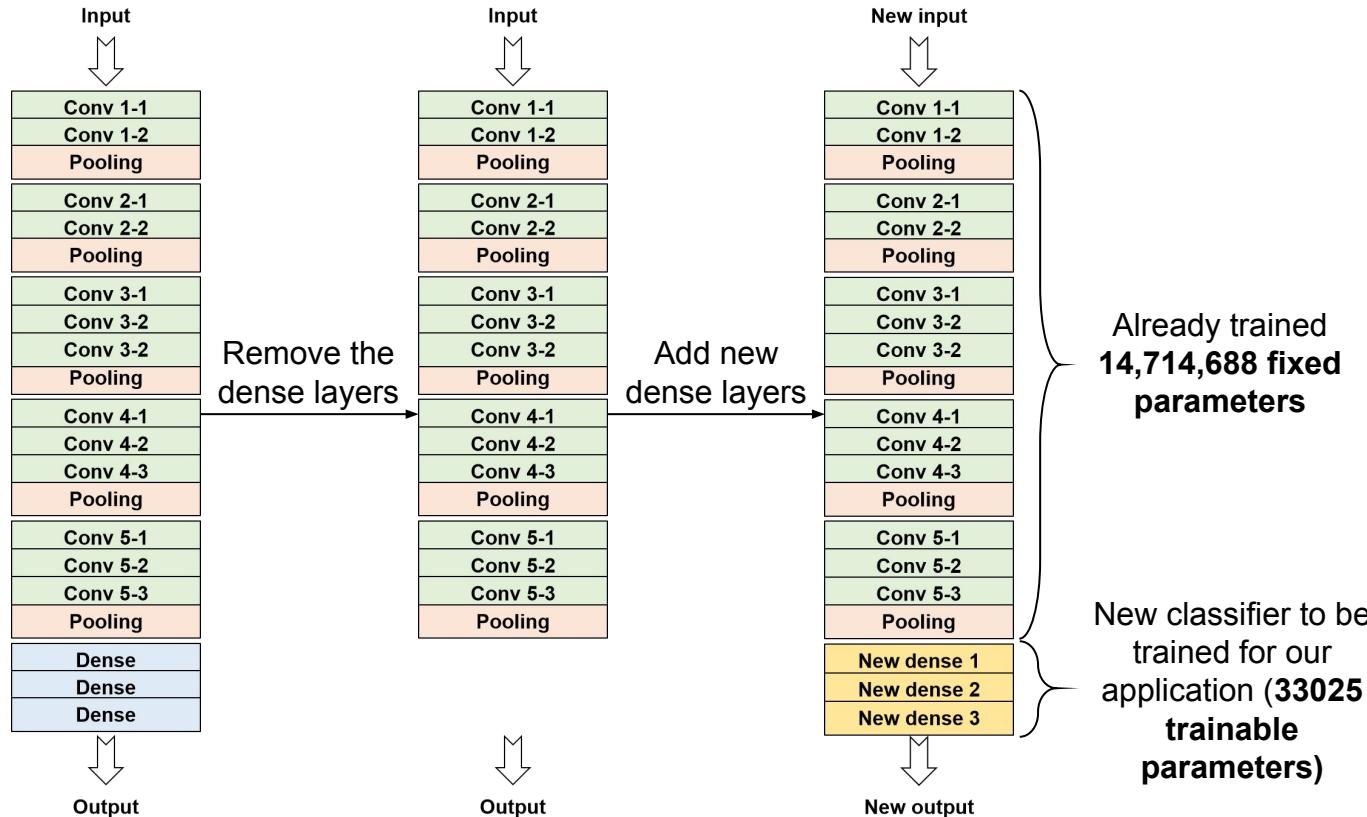


Many networks **trained on million of images** can be downloaded from internet :

<https://keras.io/applications/>  
Greenwald et al. - 2022



138,357,544



# Transfer learning syntax

Load the pre-trained VGG16 network

Define the new network, adding the classifier

```
# from keras.applications import the vgg16 network pretrained on the imagenet
# database. The include_top option is set to zero, meaning that the classifier
# part (composed of a dense network) is removed.
#
conv_base = keras.applications.vgg16.VGG16(
    include_top=False,
    weights='imagenet',
    input_shape=(IMG_WIDTH, IMG_HEIGHT, IMG_CHANNEL)
)

# build the new network using the trained VGG16 network and adding a new classifier
#
model_VGG = Sequential([
    # Initialization, normalization and image augmentation
    Input(shape=(IMG_WIDTH, IMG_HEIGHT, IMG_CHANNEL)),
    Rescaling(scale=1./255),
    RandomFlip(mode="horizontal_and_vertical"),

    # Add the VGG16 network without the classifier
    conv_base,
    Flatten(),

    # Create the fully connected layers for the final classification
    Dense(256, activation = 'relu'), # 256 FCN nodes
    Dropout(0.5),
    Dense(128, activation = 'relu'), # 128 FCN nodes
    Dropout(0.5),
    Dense(1, activation = 'sigmoid'),
])

```

New input



Conv 1-1

Conv 1-2

Pooling

Conv 2-1

Conv 2-2

Pooling

Conv 3-1

Conv 3-2

Conv 3-2

Pooling

Conv 4-1

Conv 4-2

Conv 4-3

Pooling

Conv 5-1

Conv 5-2

Conv 5-3

Pooling

New dense 1

New dense 2

New dense 3



New output

Already trained  
**14,714,688 fixed parameters**

New classifier to  
be trained for our  
application (**33025  
trainable  
parameters**)

# Fine-tuning

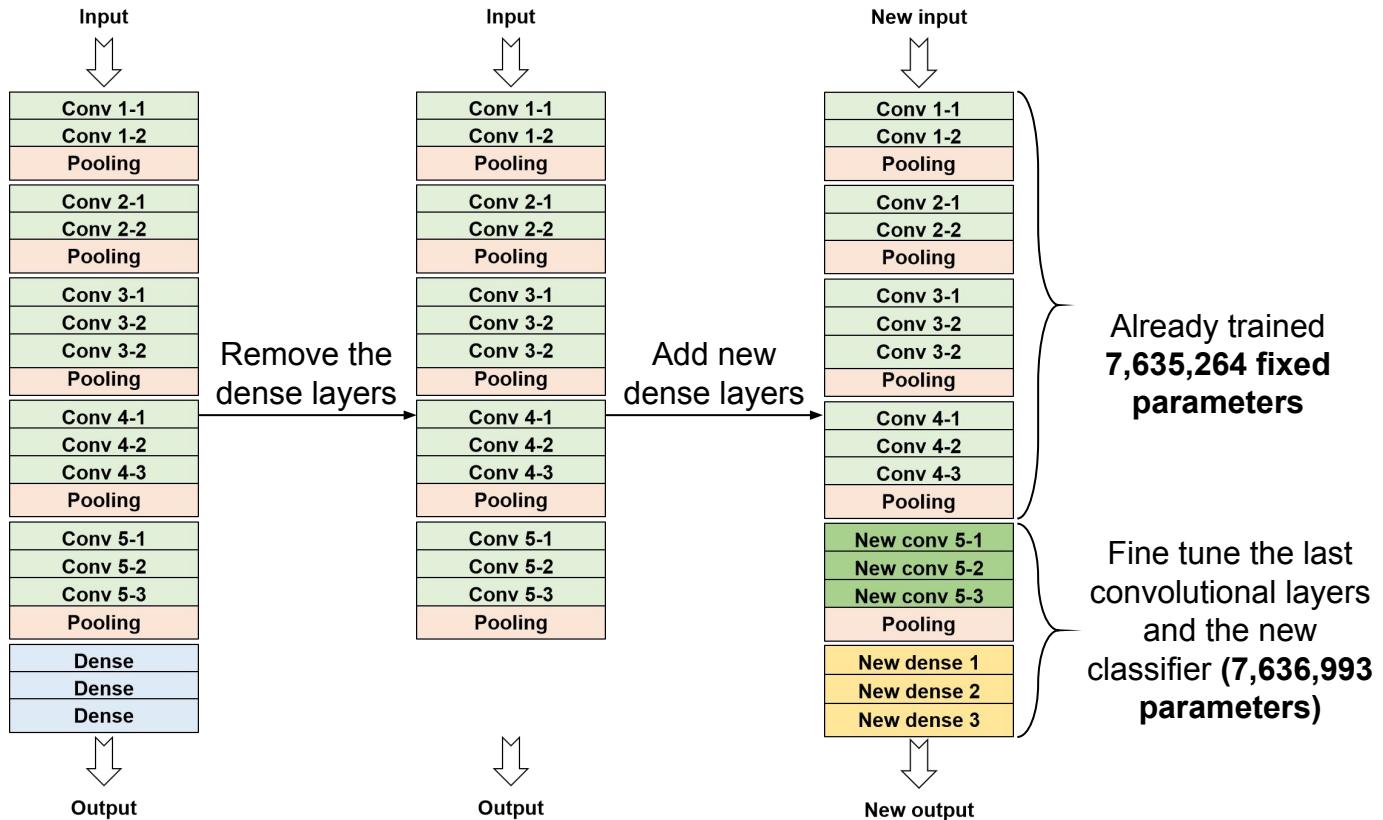


Many networks **trained on million of images** can be downloaded from internet :

<https://keras.io/applications/>  
Greenwald et al. - 2022



138,357,544



# Fine tuning syntax

Load the pre-trained VGG16 network

Define the new network, adding the classifier

Allow to retrain the 4 last layers of VGG16

```
# from keras.applications import the vgg16 network pretrained on the imagenet
# database. The include_top option is set to zero, meaning that the classifier
# part (composed of a dense network) is removed.
#
conv_base = keras.applications.vgg16.VGG16(
    include_top=False,
    weights='imagenet',
    input_shape=(IMG_WIDTH, IMG_HEIGHT, IMG_CHANNEL))

# build the new network using the trained VGG16 network and adding a new classifier
#
model_VGG = Sequential([
    # Initialization, normalization and image augmentation
    Input(shape=(IMG_WIDTH, IMG_HEIGHT, IMG_CHANNEL)),
    Rescaling(scale=1./255),
    RandomFlip(mode="horizontal_and_vertical"),

    # Add the VGG16 network without the classifier
    conv_base,
    Flatten(),

    # Create the fully connected layers for the final classification
    Dense(256, activation = 'relu'), # 256 FCN nodes
    Dropout(0.5),
    Dense(128, activation = 'relu'), # 128 FCN nodes
    Dropout(0.5),
    Dense(1, activation = 'sigmoid'),
])

# The conv_base is composed of 19 layers. The last 4 layers are related to
# block5. Therefore, only the four last layers will be set to "trainable".
#
conv_base.trainable = True
for n in range(15):
    conv_base.layers[n].trainable = False
```

New input



Conv 1-1

Conv 1-2

Pooling

Conv 2-1

Conv 2-2

Pooling

Conv 3-1

Conv 3-2

Conv 3-2

Pooling

Conv 4-1

Conv 4-2

Conv 4-3

Pooling

New conv 5-1

New conv 5-2

New conv 5-3

Pooling

New dense 1

New dense 2

New dense 3



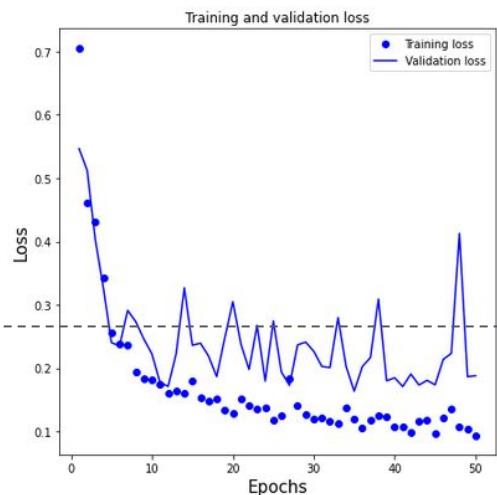
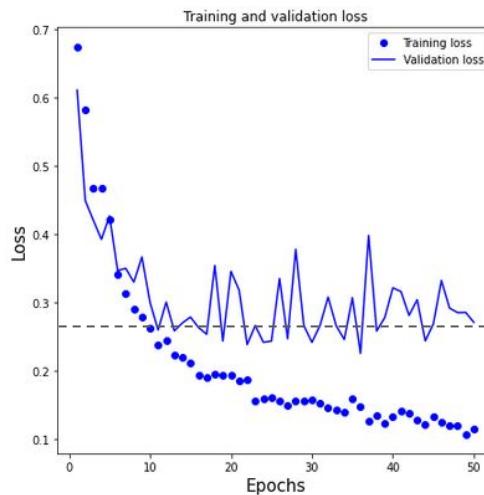
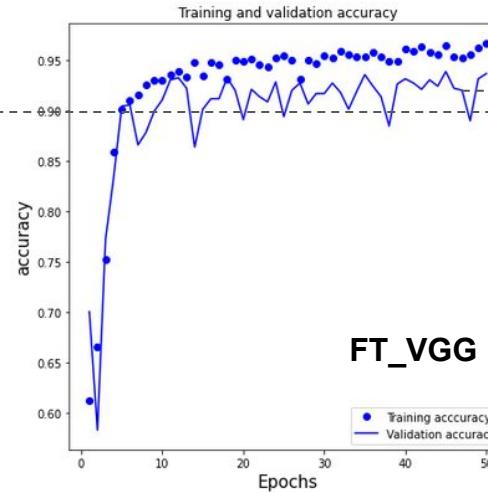
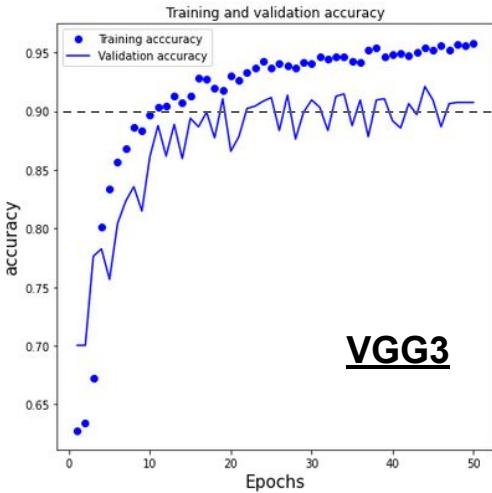
Already trained  
**7,635,264 fixed parameters**

Fine tune the last convolutional layers and the new classifier  
**(7,636,993 parameters)**

New output

# Comparison VGG 1 & Fine tuning

- Dropout & image augmentation help reduced the overfitting
- Global accuracy calculated with the testing set :
  - VGG1 : 92.9%
  - VGG2 : 89.9%
  - **VGG3** : 94.4%
  - **FT\_VGG** : 95.2%



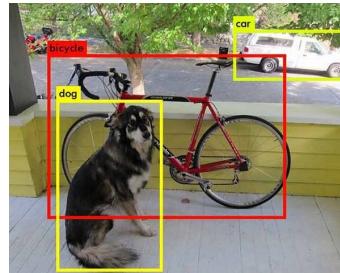
# Outline

- I. Image classification :
  - A. Introduction to convolutional network : digit classification
  - B. Application to red-blood cells classification
  - C. Introduction to transfer-learning
- II. Segmentation :
  - A. Application of a fully convolutional network (Unet)
  - B. Instance segmentation with existing tools
- III. Conclusion :

# Computer Vision - possible tasks



**classification**  
“cat”



**classification +  
localization  
class + bounding box**

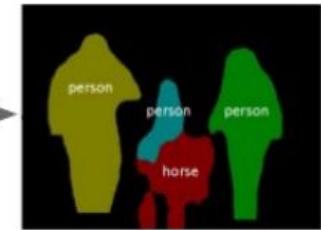


→ predict



Person  
Bicycle  
Background

**Semantic segmentation**  
each pixel : class



**Instance segmentation for each pixel:**  
class “person” + instance #1  
class “person” + instance #2 ...

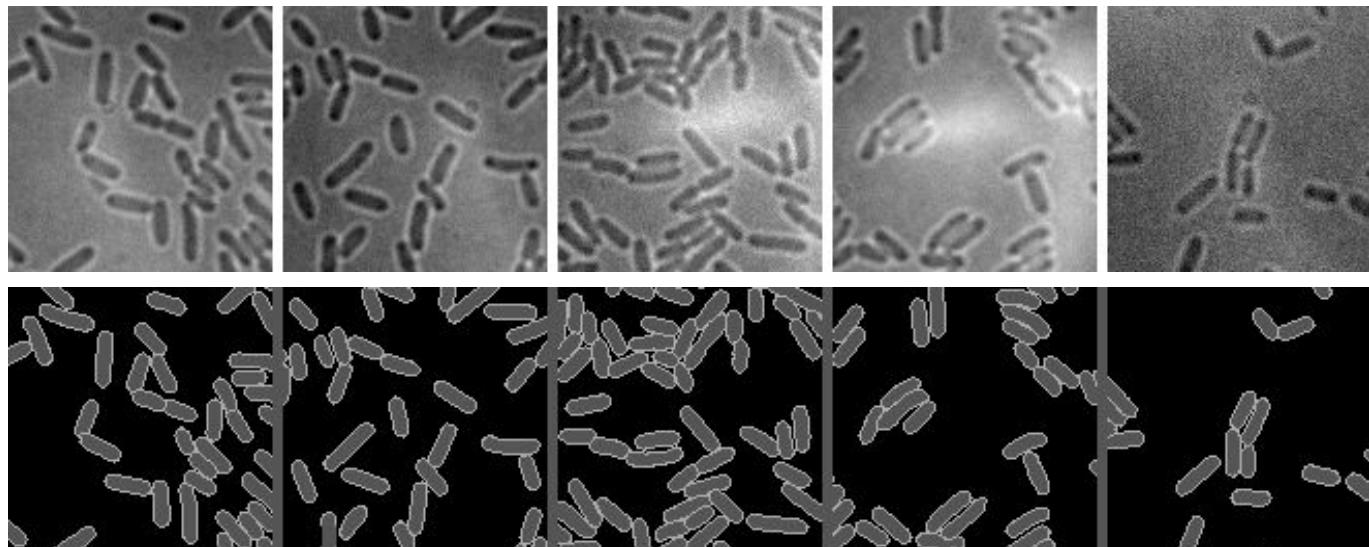
# Example 6: Bacteria segmentation

Example: Ex6\_bacteria\_segmentation\_unet.ipynb

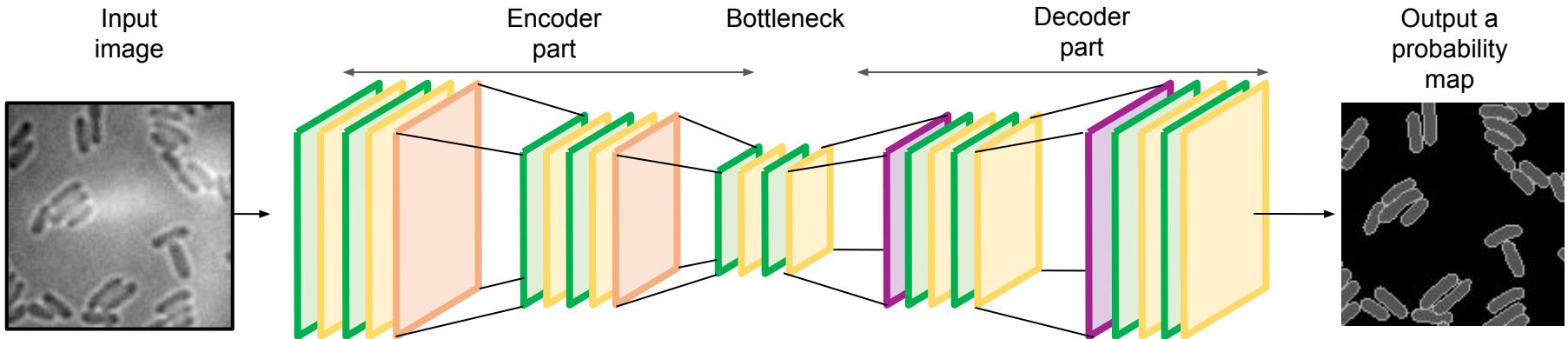
1. Introduction to semantic segmentation
2. Illustration of a Unet application



Caroline Clerté



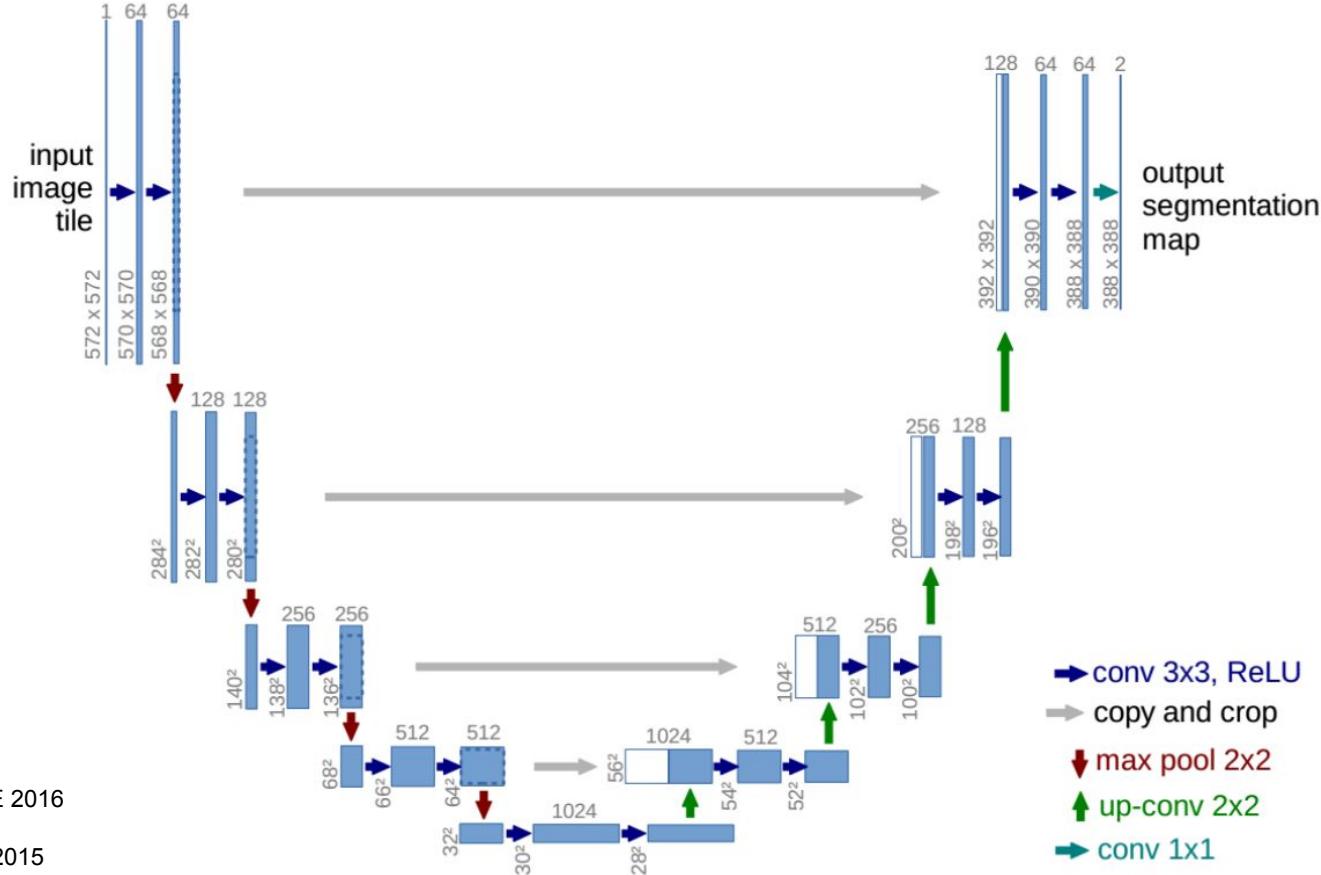
# Fully convolutional network



This type of neural network architecture has many advantages :

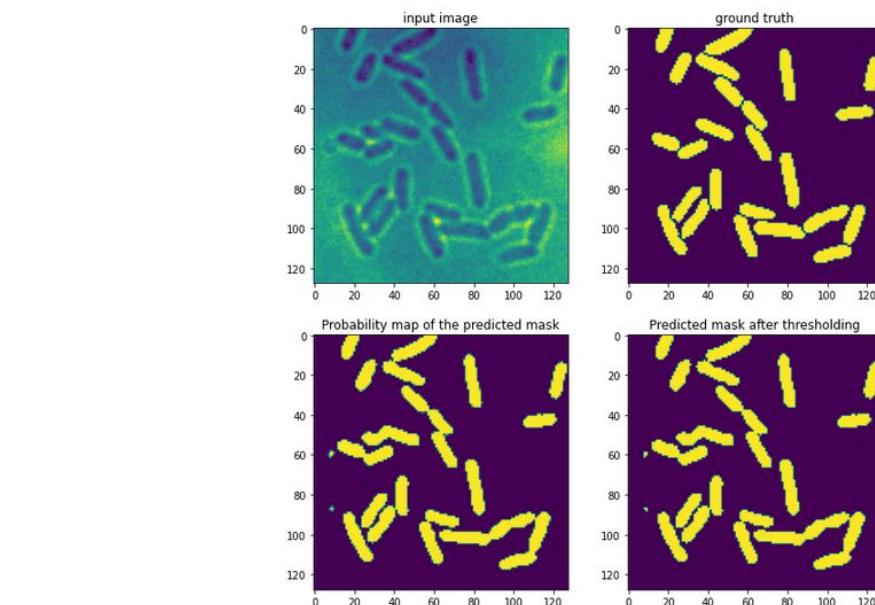
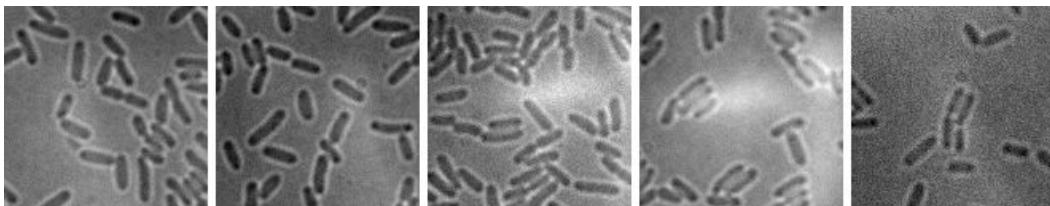
- **simple** to implement
- **fast**
- **low number of parameters** since there is no densely connected layers
- “no” restriction on the size of the input images
- the output image is already segmented

# The Unet : a very popular network



Badrinarayanan et al. IEEE 2016  
Noh et al. ArXiv 2015  
Ronnerberger et al. ArXiv 2015

# Comments on example 6



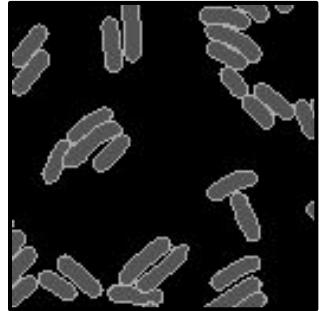
Data set is composed of **98 training (2014 cells)** & **32 testing (512 cells)** images.

For a good generalization, the data have been acquired with different :

- density
- focus
- illumination

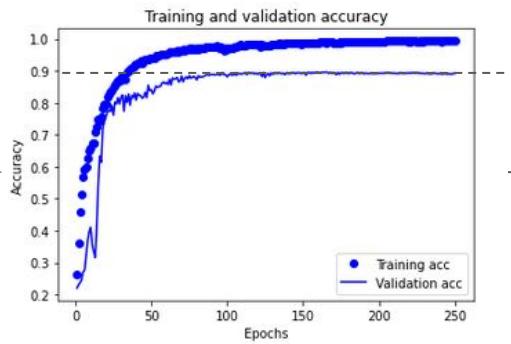
The network is rather small (for example comparing to the network used for image classification) since the number of Unet is composed of “only” 4,119,153 trainable parameters.

# Comments on example 6



$U_{\text{net}}$

Training



~90%

Test

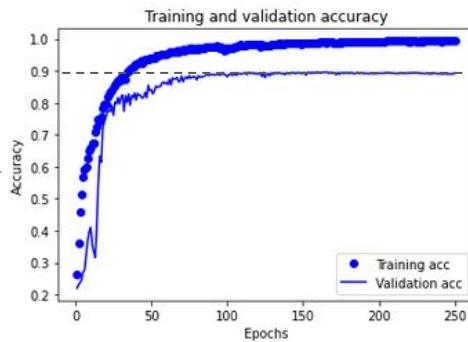


# Comments on example 6



$U_{\text{net}}$

Training



~90%

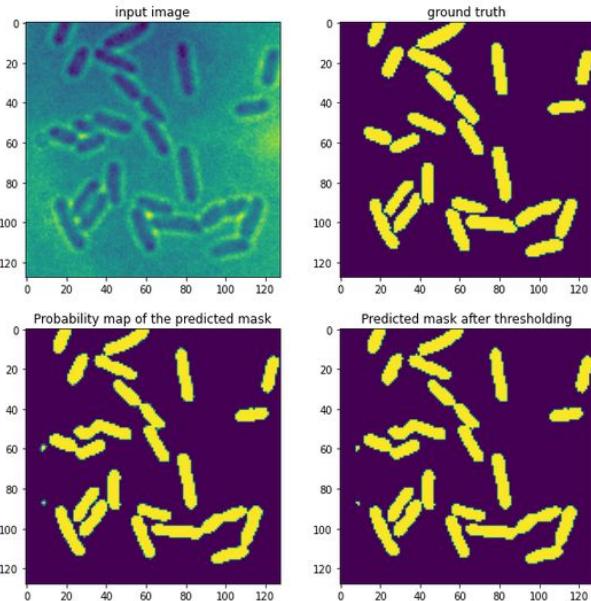
Test



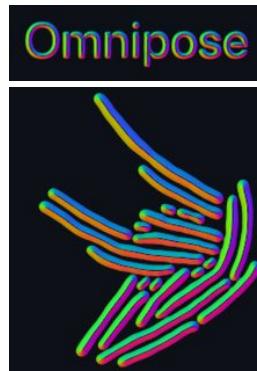
For segmentation problem, the pixel **accuracy is not a good metrics**, particularly when the density of objects to segment is low. Metrics such as **IoU or dice** should be used instead.

$$\frac{2x}{x + y} = 0.45$$

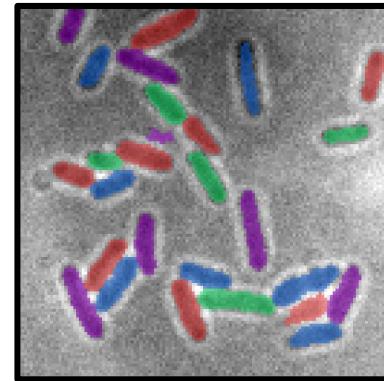
# Take advantage of existing tools!



Segmented map is fairly good but it would require further image analysis & tuning of the network to get the cells well separated.

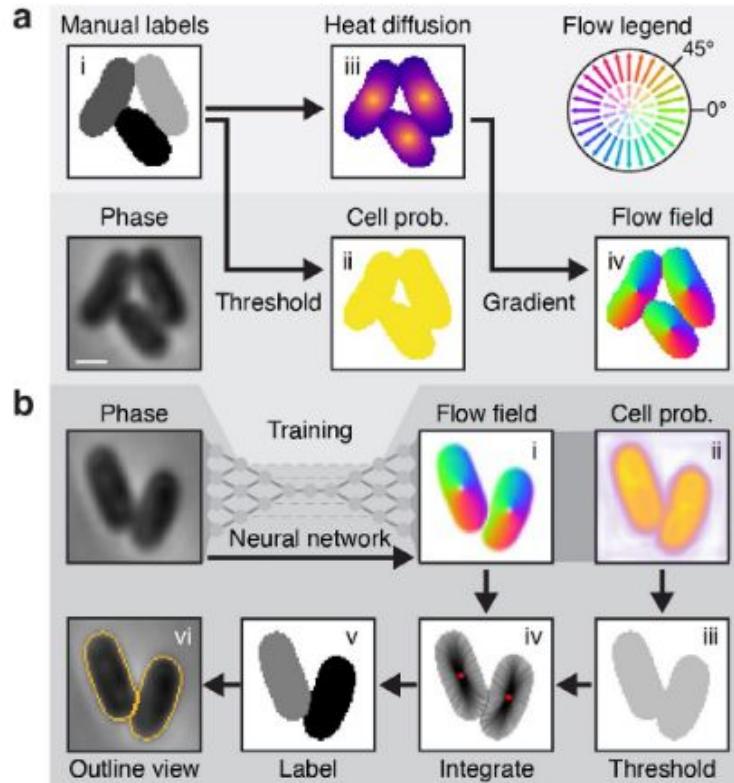


Many pre-trained network are freely available on github and can be **used or re-trained for your applications**.

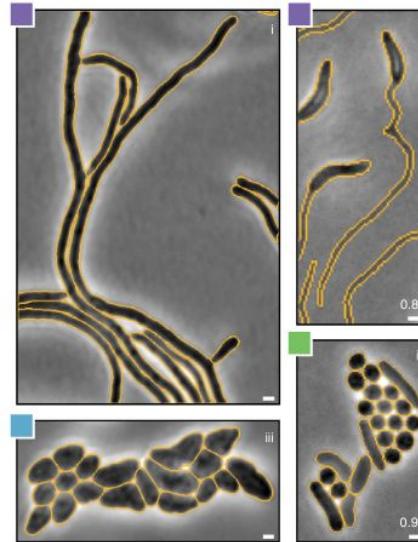


Segmentation results obtained with the model **bact\_phase\_omni** freely accessible on  
<https://github.com/kevinjohncutler/omnipose/>

# Omnipose ... is still Unet, but smarter!



Omnipose is a Unet not only trained to **output a probability map** but also a **flow-field map** that will **detecting the cells**, whatever their shape.



# Many other tools available for segmentation

<https://github.com/stardist/stardist> - Schmidt et al. - 2018 Cell Detection with Star-Convex Polygons

<https://github.com/hci-unihd/plant-seg> - Wolny et al. - 2020 Accurate and versatile 3D segmentation of plant tissues at cellular resolution

<https://github.com/MouseLand/celppose> - Stringer et al. 2021 Celppose: a generalist algorithm for cellular segmentation

<https://github.com/kevinjohncutler/omnipose> - Cutler et al. - 2022 Omnipose: a high-precision morphology independent solution for bacterial cell segmentation

<https://github.com/vanvalenlab/intro-to-deepcell> - Greenwald et al. - 2022 Whole-cell segmentation of tissue images with human-level performance using large-scale data annotation and deep learning

All these networks are **freely accessible, well documented and providing :**

- pre-trained models
- user-friendly GUI for simple tests
- scripts for running / training



<https://github.com/HenriquesLab/ZeroCostDL4Mic>

# Example 7: Nuclei segmentation

Example: Ex7\_nuclei\_segmentation\_stardist.ipynb

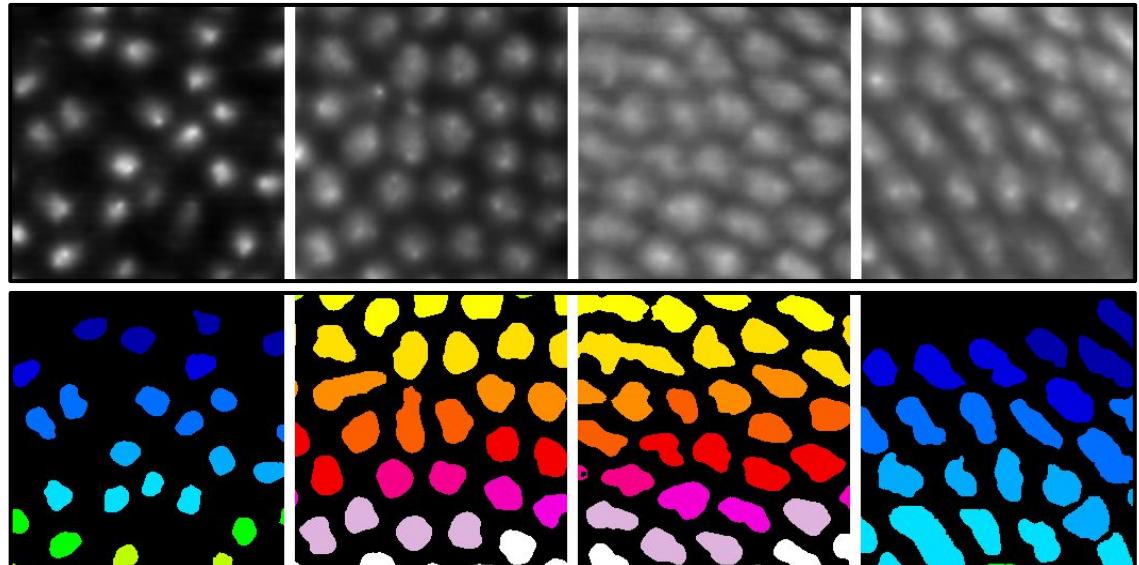
1. Example of instance segmentation
2. Application of starDist for 2D segmentation



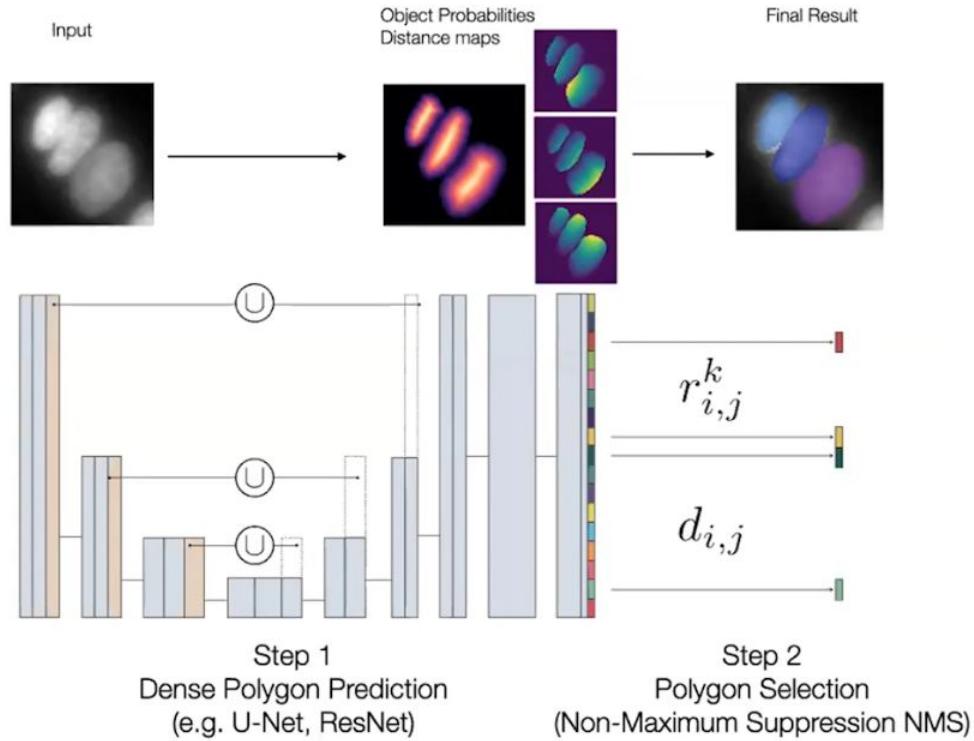
Sergio Espinola



Marcelo Nöllmann



# StarDist



**Important:**  
**Assumes objects are star-convex**



# **Outline**

## **I. Image classification :**

- A. Introduction to convolutional network : digit classification
- B. Application to red-blood cells classification
- C. Introduction to transfer-learning

## **II. Segmentation :**

- A. Application of a fully convolutional network (Unet)
- B. Instance segmentation with existing tools

## **III. Conclusion :**

# Take home messages

## I. Do I need deep learning for my problem ?

“The hardest and the most time-consuming part of any deep learning is acquiring training data. [...] You typically need hundreds or thousands of examples at minimum, and creating the annotations itself is tedious.”

Beth Cimini

# Take home messages

## I. Do I need deep learning for my problem ? Can it work for my problem?

“The hardest and the most time-consuming part of any deep learning is acquiring training data. [...] You typically need hundreds or thousands of examples at minimum, and creating the annotations itself is tedious.”

Beth Cimini

“People kind of expect that these models can just perform miracles, but if the information that you want to pull out isn’t there in the data, then in my view and also in my experience, it’s unlikely to work,”

David Van Valen

# Take home messages

- I. Do I need deep learning for my problem ? Can it work for my problem?
- II. Start with **simple data** and a **solid baseline**

How much data is enough? We observed diminishing returns to training data at ~10<sup>4</sup>–10<sup>5</sup> labels. We believe that the effort required to go beyond this scale is warranted when accuracy is a paramount concern, for example for models applied across projects or in clinical contexts, which is the case for Mesmer. This effort is also worthwhile for generating gold-standard datasets to benchmark model performance. For other use cases, smaller datasets and bespoke models may suffice.

Greenwald et al. - 2022

# Take home messages

- I. Do I need deep learning for my problem ? Can it work for my problem?
- II. Start with **simple data** and a **solid baseline**
- III. Setup your **own evaluation strategy** :
  - build a test set representative of your problem
  - choose the right performance indicators for your problem

# Take home messages

- I. Do I need deep learning for my problem ? Can it work for my problem?
- II. Start with **simple data** and a **solid baseline**
- III. Setup your **own evaluation strategy**
- IV. **Know your data** : Supervised machine learning is **DATA driven**, not **algorithm driven**
  - your training set should be as representative as possible of your data
  - double/triple check for errors

# Take home messages

- I. Do I need deep learning for my problem ? Can it work for my problem?
- II. Start with **simple data** and a **solid baseline**
- III. Setup your **own evaluation strategy**
- IV. **Know your data** : Supervised machine learning is **DATA driven**, not **algorithm driven**
- V. Check for already existing tools that could be adapted to your data

# How to start with Deep Learning (for free)?

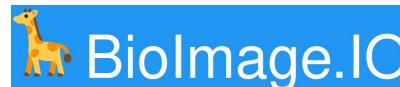
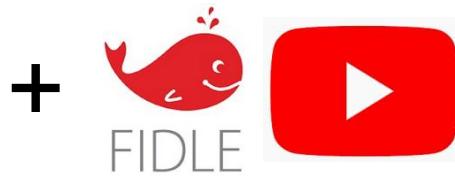


## Python 3 – open source

For DL, the open-source **TensorFlow** and **PyTorch** libraries are used.



**Colab (google)**  
free GPU  
python jupyter



<https://csbdeep.bioimagecomputing.com/>

<https://github.com/HenriquesLab/ZeroCostDL4Mic>

<https://www.youtube.com/c/DigitalSreeni>

<https://www.youtube.com/c/CNRSFormationFDL?app=desktop>

<https://cs230.stanford.edu/lecture/>

<https://bioimage.io/#/>

<https://www.kaggle.com/>

[https://bbbc.broadinstitute.org/image\\_sets](https://bbbc.broadinstitute.org/image_sets)