Machine learning introduction

Part II – Deep Neural Networks

1 The deep networks

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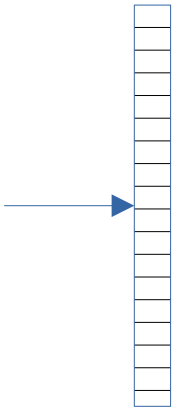
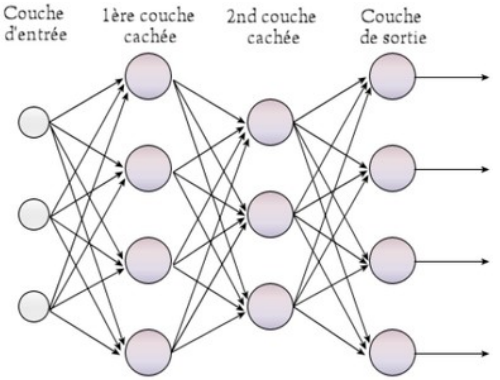
Part II-1 : the deep networks

- **The beginning: image recognition**
  - ‘Classic’ approach:
    - Detection of features (circles, lines, rectangles…)





    - These features are used to fill a vector (number, position…)
    - A neural network is then trained on this vector
      - Not very reliable, error rate >25 % at ILSVRC 2011

Part II-1 : the deep networks

- **Deep learning**

  - Can a neural network generate such a feature vector from image ?
  - Problems:
    - More layers means more neurons and more connections to train

      → If the dataset is too small, the network would fail to generalize !
    - More neurons also means more computational resources

  - For many decades, neural networks were limited both by available resources and by available data sets.

Part II-1 : the deep networks

- **Deep learning**

  - Since middle of 2000s:
    - Computing power significantly increased
      - Parallelization on GPU (e.g. CUDA, 2007)
      - Dedicated architectures (Tensor Processing Unit, 2016)

    - But also collected data
      - GAFA and private life
      - Big data
      - Captcha
      - voluntarism

    - Open-source Dataset COCO (Common Objects in COntext) :
      >200k labeled images, 80+ classes

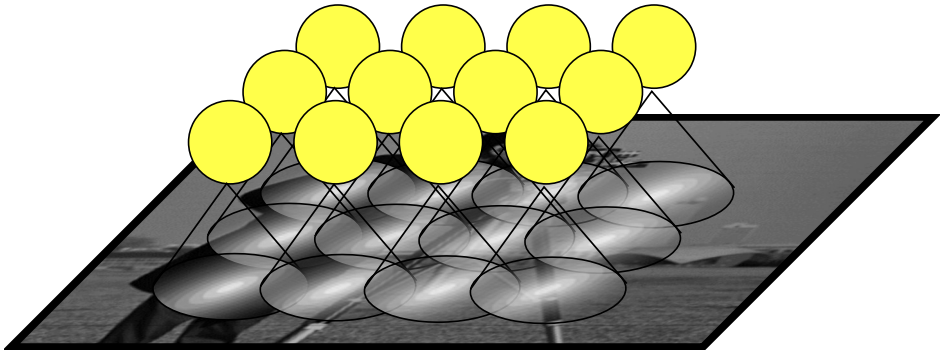
Part II-1 : the deep networks

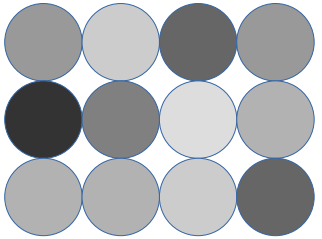
- **Deep learning**

  - But still not sufficient !
    - Example :

      an image of 100x100 pixels requires 10 000 connections per input neuron !

    - Biological inspiration :
      - 1968: analysis on animals show that neurons of first processing layers are connected to small area of the retina
      - Several neurons detects the same feature

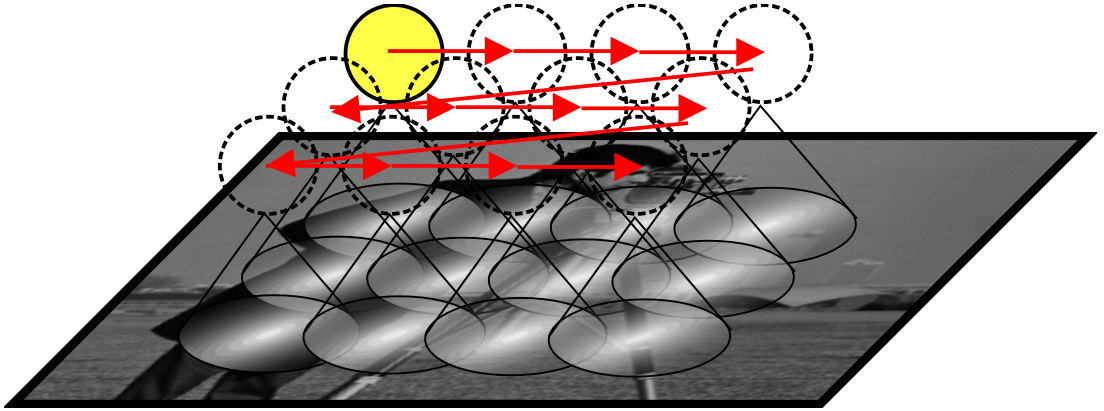


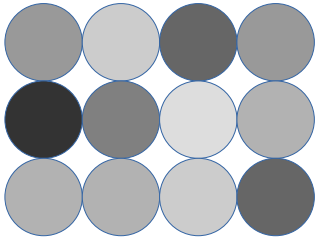


Detection of a feature
on the whole image

Part II-1 : the deep networks

- **Deep learning**
  - Yann Le Cunn (middle of 2000s) :
    - Idea: each neuron define a small feature and is applied on each position of the image



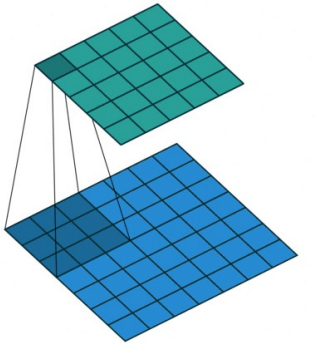


  - Feature detection with few weights
  - Works like a convolution → *convolutional neurons*

Part II-1 : the deep networks

- **Convolutions**
  - A kernel

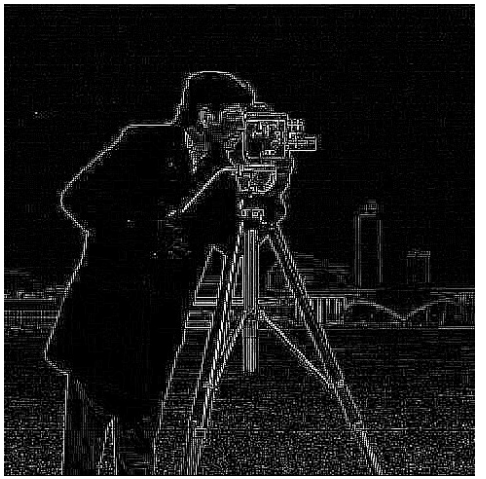
$$\begin{bmatrix} 0 & 0{,}25 & 0{,}5 & 0{,}25 & 0 \\ 0{,}25 & 0{,}5 & 0{,}75 & 0{,}5 & 0{,}25 \\ 0{,}5 & 0{,}75 & 1 & 0{,}75 & 0{,}5 \\ 0{,}25 & 0{,}5 & 0{,}75 & 0{,}5 & 0{,}25 \\ 0 & 0{,}25 & 0{,}5 & 0{,}25 & 0 \end{bmatrix}$$



https://github.com/vdumoulin

  - Scalar product is applied on each position of the image
  - The result is a matrix giving the presence of kernel's feature on each position of the image

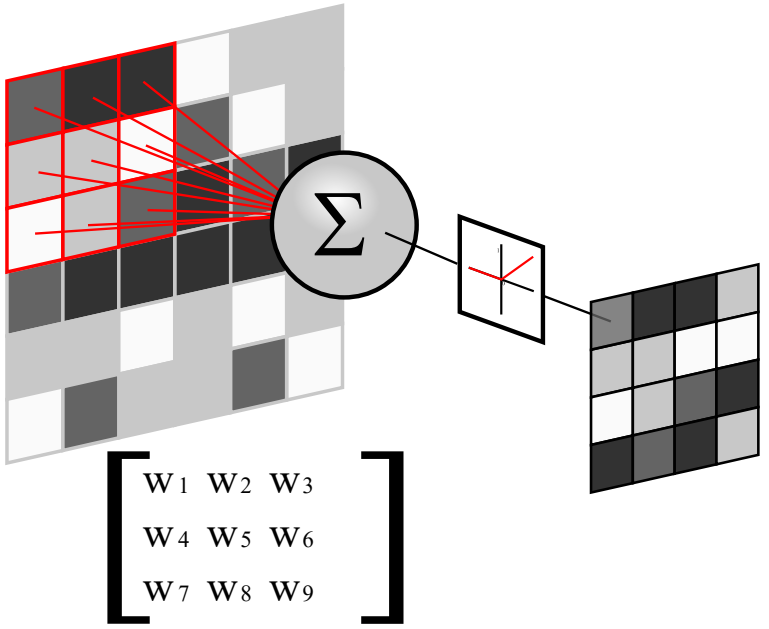
$$\otimes \begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix} =$$



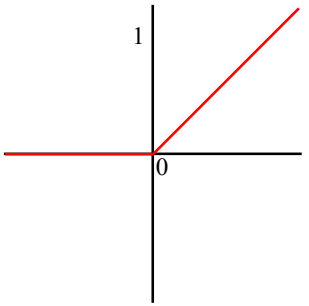
Part II-1 : the deep networks

- **Convolutional neurons**

  - Similar to a formal neuron
    - Input vector X
    - A set of weights W
      → kernel
    - An activation function
    - Reinforcement based on gradient descent



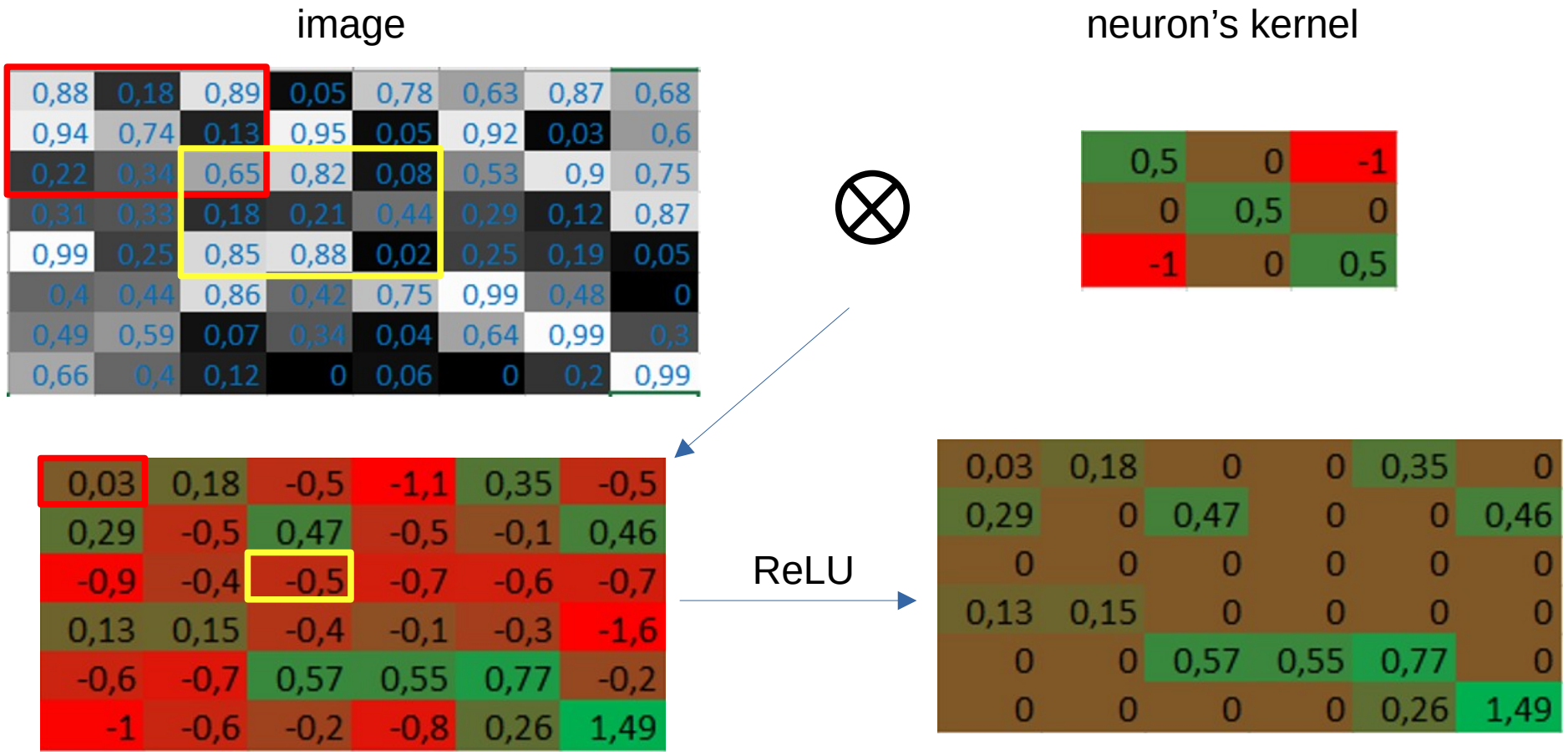
  - Output is an “image”
    - Each pixel p_{xy} is the neuron output at position (x,y)



  - Function RELU is often used : detect the presence of features

Part II-1 : the deep networks

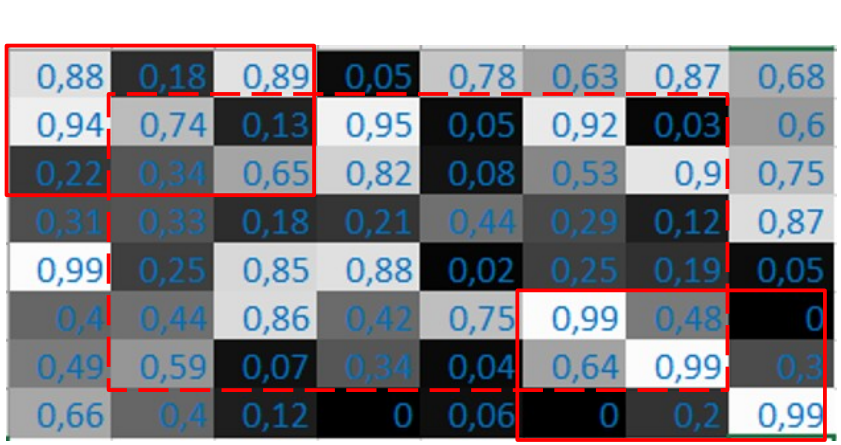
- **Convolutional neurons**

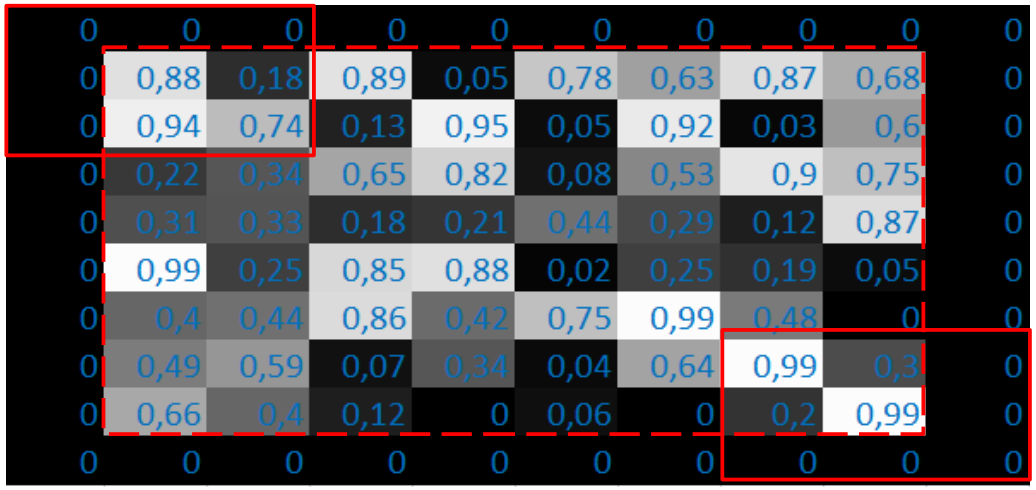


  - We can notice that the output is smaller than the image

Part II-1 : the deep networks

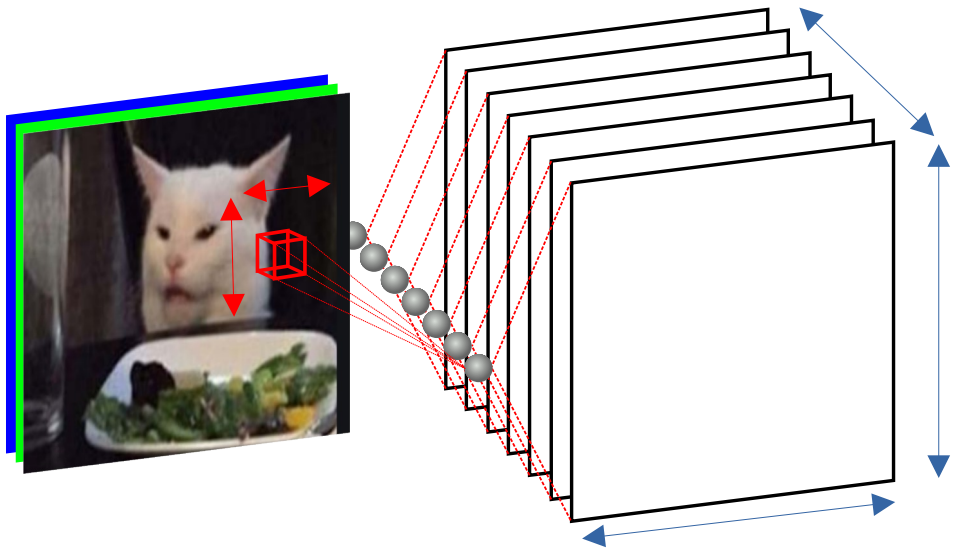
- **Deep Learning**
  - Padding :
    - Pixels with values of 0 are added around the image





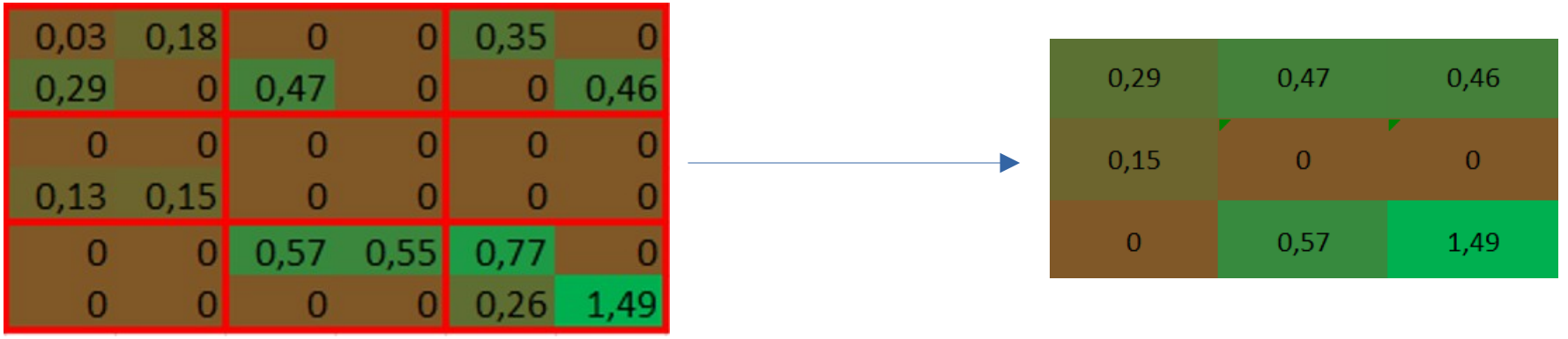
Part II-1 : the deep networks

- **Deep learning**
  - Each neuron of the first layer generate its own convolution image
    - These images are gathered as a unique image with a depth
    - Depth of an image is the number of “layers”
      - A RGB image has a depth of 3
    - The kernel of a neuron has 3 dimensions (width, height and depth) and moves on 2 dimensions on the image



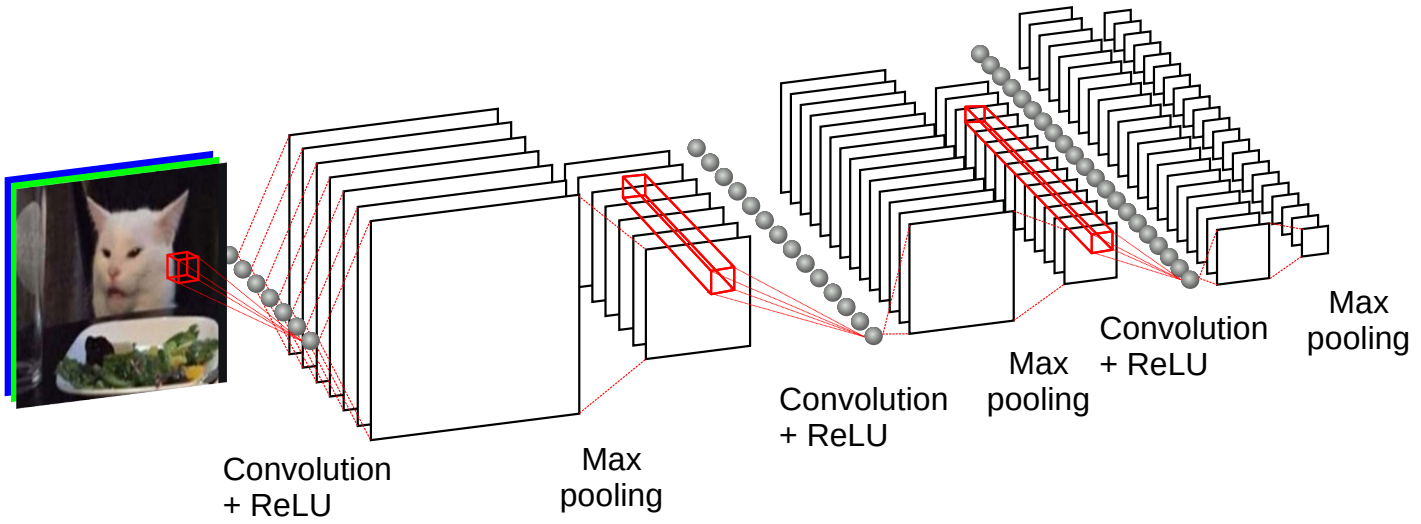
Part II-1 : the deep networks

- **Pooling**
  - As we looks for the presence of features, it is not necessary to keep adjacent pixels with high value
  - Pooling layer :
    - Adjacent pixels are gathered
      - Average pooling → average of the group
      - Max pooling → keep maximum value (most used method)
    - Reduces the number of pixels for next layers



Part II-1 : the deep networks

- **Deep learning**
  - Convolution and pooling layers can be chained
  - We lose spatial information but get information about complex features

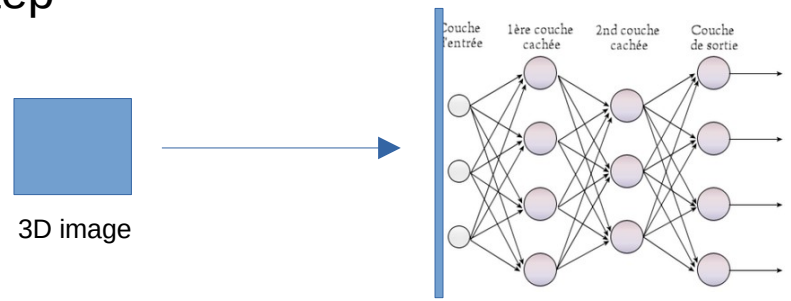


Part II-1 : the deep networks

- **Fully-connectec layers**

  - After several layers, the image looks more like a vector !
    → We thus can use it as input for a ‘normal’ neuronal network

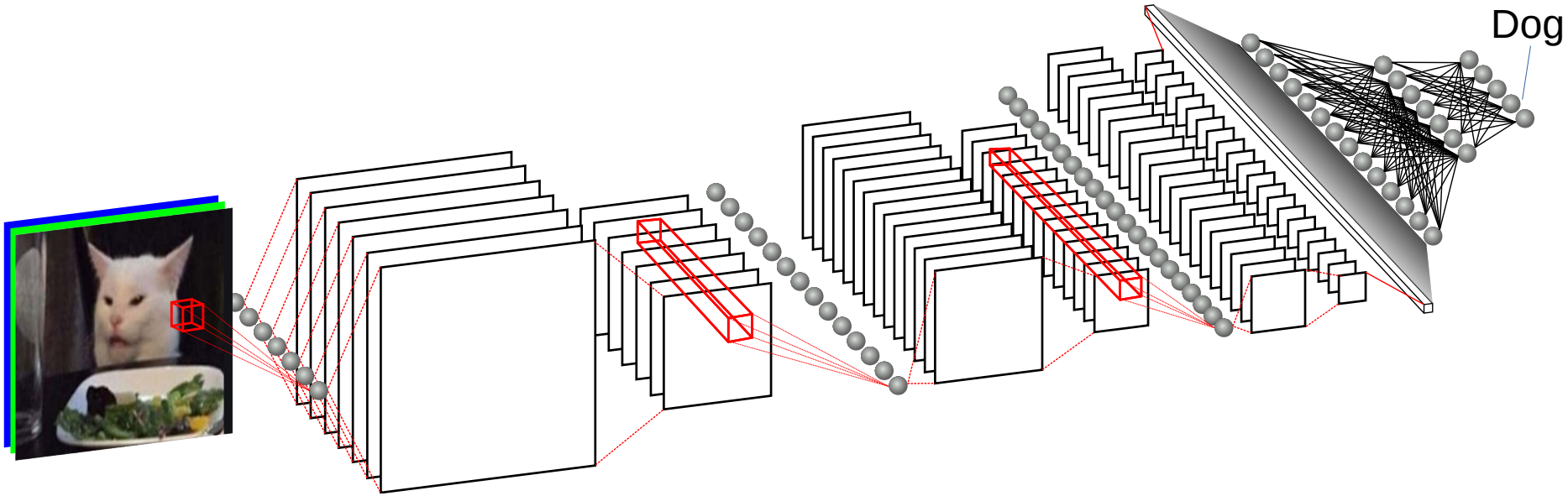
    - Last image is converted to a 1-D vector
      → *flattening* step



    - A neuronal network is then used to “interpret” the feature vector
      → these neuron layers are called *‘fully connected’*

Part II-1 : the deep networks

- **“Classical” architecture of a convolutional deep network**

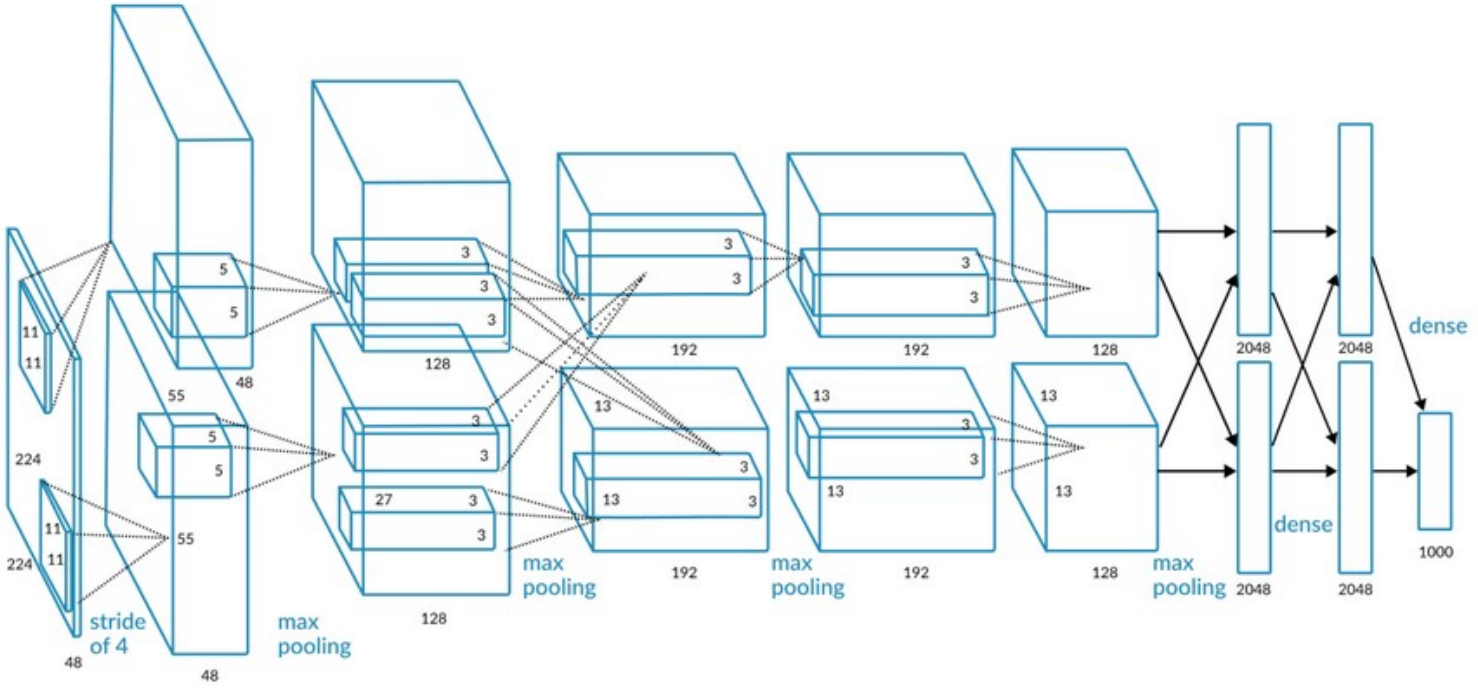


  - convolution + ReLU
  - Pooling
  - convolution + ReLU
  - Pooling
  - …
  - Flattening
  - fully connected layer
  - Output layer

Part II-1 : the deep networks

- **The architecture can be more complex:**

  example : AlphaNet (2012)



Part II-1 : the deep networks

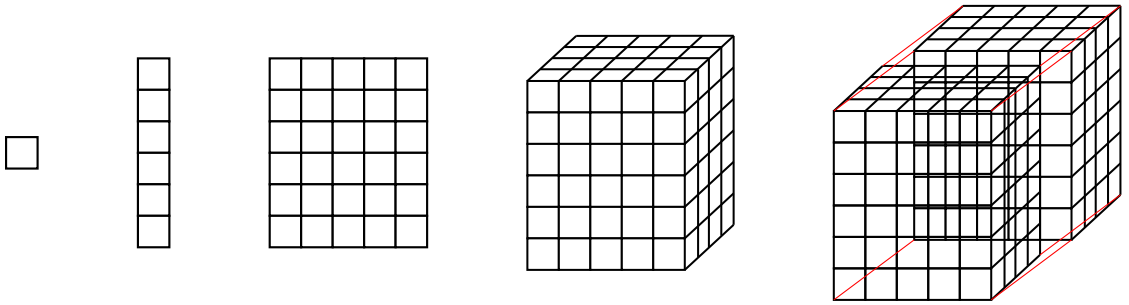
- **Libraries for deep learning model development:**

  - TensorFlow : developed by Google, open-source since 2015, derived from *Disbelief* project (2011)
    - Since 2017, a Lite version was created for embedded systems
  - MXNet : Developed by Apache, can use many languages
  - Caffe
  - Theanos : since 2008
  - Microsoft Cognitive Toolkit : since 2016
  - PyTorch : developed by Facebook, based on Torch

  - Keras : librairy of high level function to easily develop a deep network. Uses Tensorflow or Theanos libraries

Part II-1 : the deep networks

- **TensorFlow**
  - Library dedicated to the manipulation of *tensors*
    - A tensor is a matrix with a given number of dimensions



1D 2D 3D 4D ...

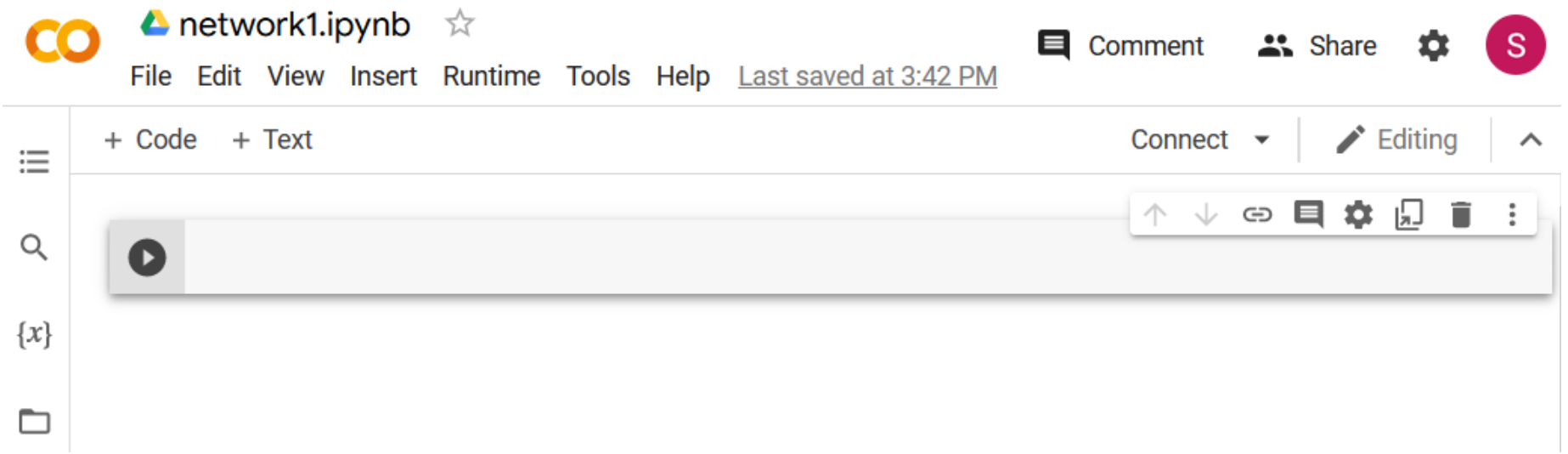
  - Optimized functions
  - Possibility to parallelize on GPU !

Part II-1 : the deep networks

- **Keras**
  - Library of high-level functions exploiting Tensorflow or Theanos
  - Function to:
    - Load a ‘common’ dataset (ie used for benchmarking)
    - Define the architecture of a network
    - Define learning parameters and loss function
    - Train the network
    - Evaluate the network
    - Exploit the network on new data

Part II-1 : the deep networks

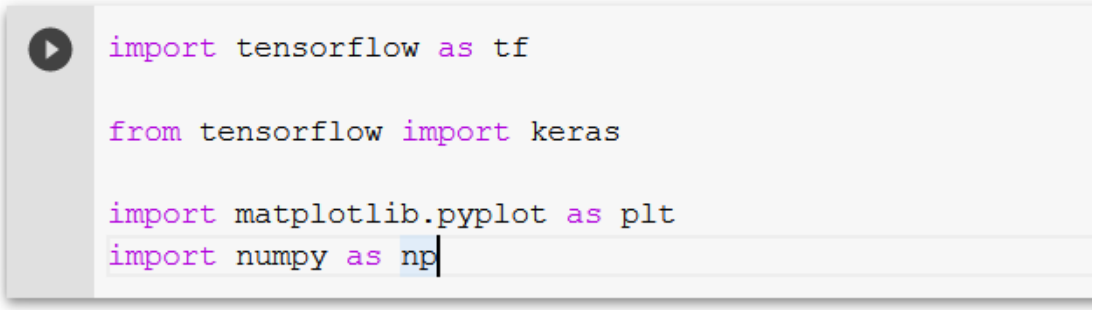
- **Let’s start with Keras : implementing a convolutional network**
  - Open your session in Google Colab
  - Create a new notebook



Github : https://github.com/gaysimon/ARTISAN2022

Part II-1 : the deep networks

- **Let's start with Keras : implementing a convolutional network**
  - In the first cell, import the required libraries



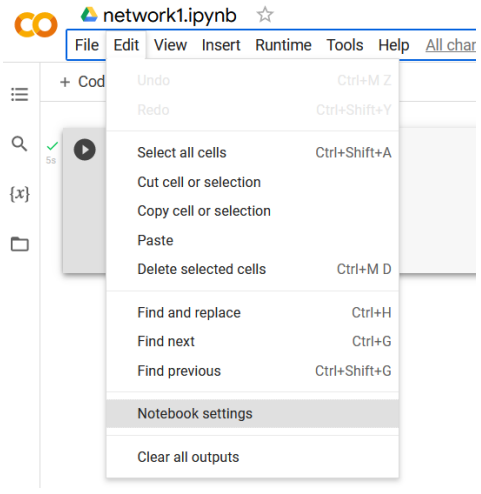

```
import tensorflow as tf

from tensorflow import keras

import matplotlib.pyplot as plt
import numpy as np
```

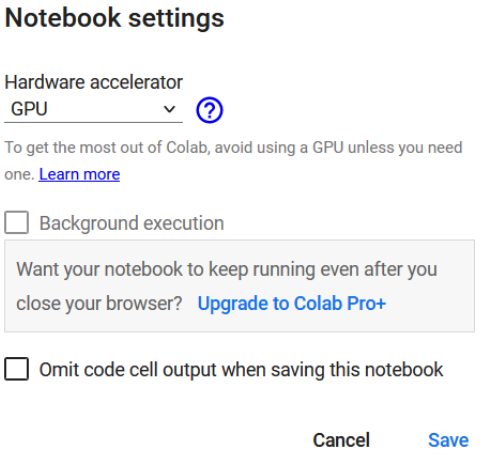
  - Tensorflow and Keras for the neural network
  - Pyplot and numpy for image display

- Run the cell to check the imports

Part II-1 : the deep networks

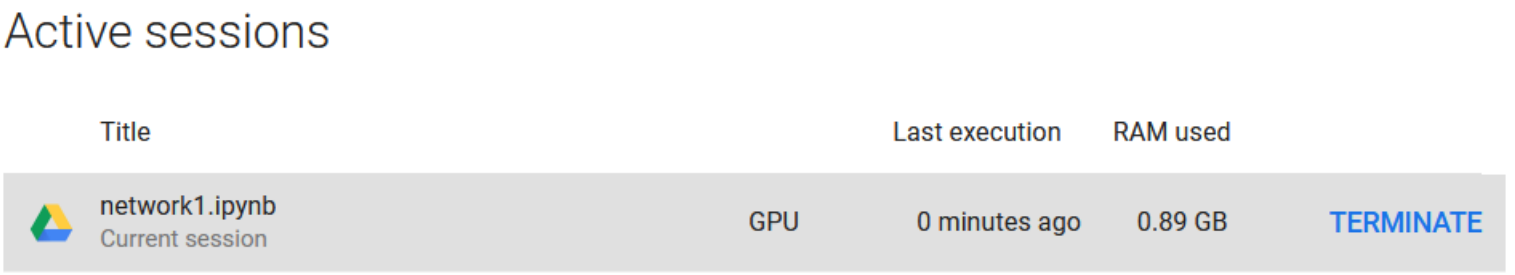
- **Using a GPU**
  - Training a deep neural network requires a huge computational power, and can take several hours to train
  - Hopefully, Tensorflow can parallelize calculations on a GPU
  - Hopefully, Google Colab can provide GPUs
  - Edit → notebook settings, then select ‘GPU’





Part II-1 : the deep networks

- **Using a GPU**
  - DO NOT FORGET to turn off the GPU and stop the session after using it !
    - Runtime → manage sessions



  - Otherwise, Google will reduce your access to GPUs for next sessions !

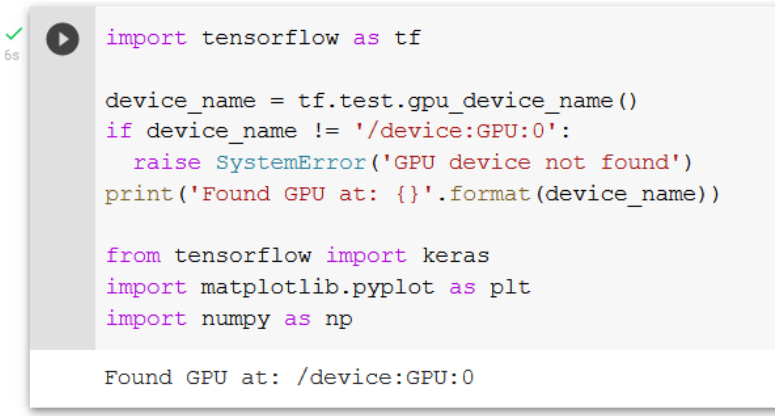
Part II-1 : the deep networks

- **Using a GPU**
  - Then, copy this part of code and paste it just after importing Tensorflow

```
device_name = tf.test.gpu_device_name()
if device_name != '/device:GPU:0':
  raise SystemError('GPU device not found')


print('Found GPU at: {}'.format(device_name))
```

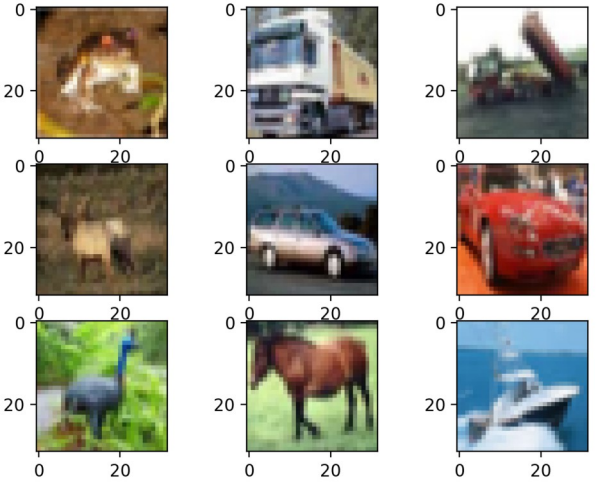
/!\ Python takes indentation into account

- If the message ‘found GPU’ appears, the GPU is ready



Part II-1 : the deep networks

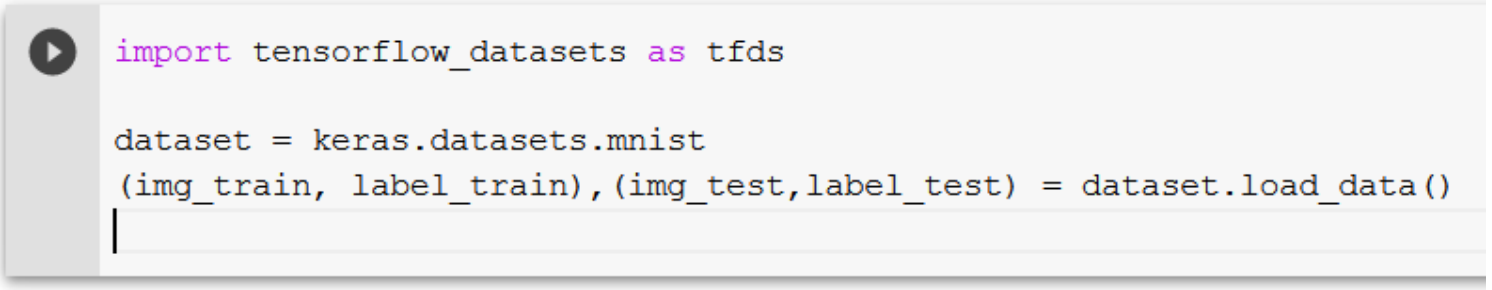
- **Importing a dataset**
  - Keras proposes different common datasets of different types :
    - Boston housing prices (values)
      → *boston_housing*
    - CIFAR-10 (color images of size 32x32)
      → *cifar10*
    - CIFAR-100 (same but with 100 classes)
      → *cifar100*
    - Fashion MNIST (images B&W 28x28)
      → *fashion_mnist*
    - IMDB movie reviews (texts) → *imdb*
    - MNIST (images B&W 28x28) → *mnist*
    - Articles Reuters (texts) → *reuters*



CIFAR-10
(50 000 images)

Part II-1 : the deep networks

- **Importing a dataset**
  - We will use the MNIST dataset
    - Add a new cell in your Colab ('+code')
    - import dataset library
    - Load the MNIST dataset into four matrices



```
import tensorflow_datasets as tfds

dataset = keras.datasets.mnist
(img_train, label_train),(img_test,label_test) = dataset.load_data()
```

```
import tensorflow_datasets as tfds

dataset = keras.datasets.mnist
(img_train, label_train),(img_test,label_test) = dataset.load_data()
```

Part II-1 : the deep networks

- **Importing a dataset**
  - The matrices must be converted
    - Images from integer [0,255] to float [0,1]
    - Labels must be converted from a number value to a vector of 10 results (e.g. 3 → [0, 0, 0, 1, 0, 0, 0, 0, 0, 0])
      - Keras proposes a function for that : *to_categorical*

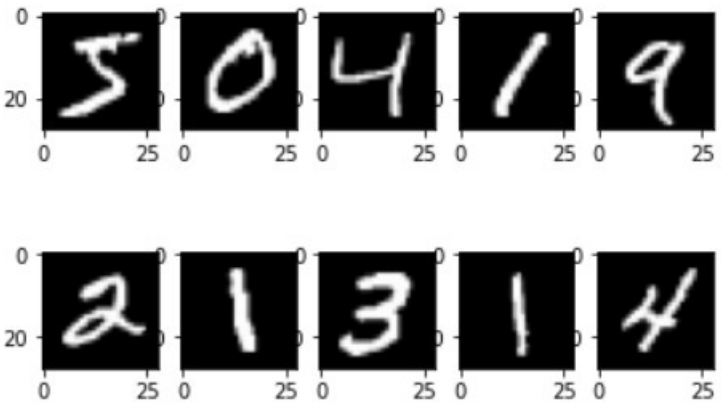
```
import tensorflow_datasets as tfds
from tensorflow.keras.utils import to_categorical

dataset = keras.datasets.mnist
(img_train, label_train),(img_test,label_test) = dataset.load_data()

# convert images into float
img_train=img_train/255.0
img_test=img_test/255.0

output_train=keras.utils.to_categorical(label_train, num_classes=10)
output_test=keras.utils.to_categorical(label_test, num_classes=10)

print(img_train.shape)
print(img_test.shape)
```

```
(60000, 28, 28)
(10000, 28, 28)
```

Part II-1 : the deep networks

- **Importing a dataset**
  - Let’s display a sample of our dataset
    - Add a new colab cell
    - Copy the following code :

```
for i in range(10):
  plt.subplot(2,5,i+1)
  plt.imshow(img_train[i], cmap='gray')

plt.show()
```



Part II-1 : the deep networks

- **Importing a dataset**
  - Problem : the images have 2 dimensions, but our network requires images with a depths !
  - We add a dimension with *numpy's expand* function
    - Add a new colab cell
    - Add these lines :

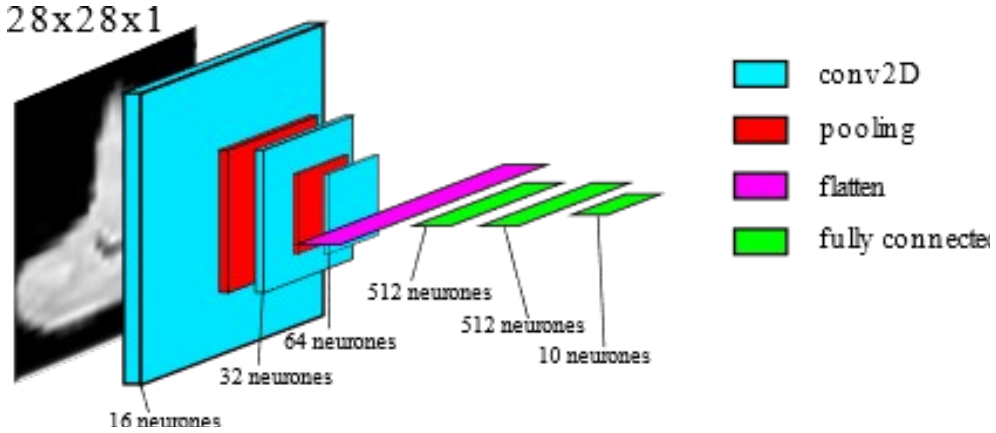
```
img_train = np.expand_dims(img_train,axis=-1)
img_test  = np.expand_dims(img_test, axis=-1)

print(img_train.shape)
print(img_test.shape)
```

```
(60000, 28, 28)        →    (60000, 28, 28, 1)
(10000, 28, 28)             (10000, 28, 28, 1)
```

    - Now, our images have a depth

Part II-1 : the deep networks

- **Implementing a convolutional network**
  - We will implement this simple network :

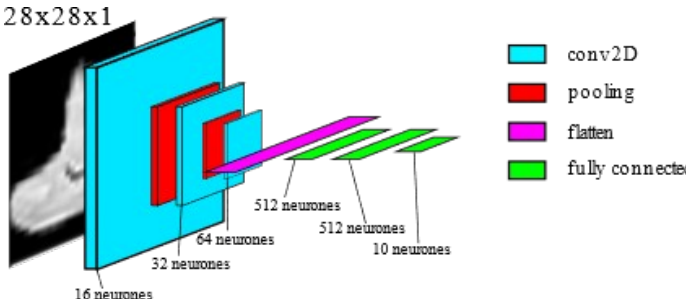


    - Create a new Colab cell
    - We start by declaring a Sequential network

```
model=keras.Sequential()
```

Part II-1 : the deep networks

- **Implementing a convolutional network**
  - We then add layers :
    - A first layer of convolutional neurons
      - Input images of size 28x28
      - 16 neurons
      - Convolution kernel of size 3x3
      - Padding
      - A ReLU activation function
    - A max pooling layer with groups of size 2x2

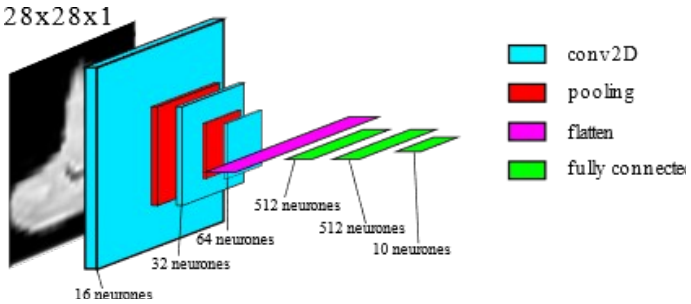



```
model=keras.Sequential()

model.add(keras.layers.Conv2D(input_shape=(28,28,1), filters=16, kernel_size=(3,3), padding="same", activation="relu"))
model.add(keras.layers.MaxPool2D(pool_size=(2,2), strides=(2,2)))
```


```
model=keras.Sequential()

model.add(keras.layers.Conv2D(input_shape=(28,28,1), filters=16, kernel_size=(3,3), padding="same", activation="relu"))
model.add(keras.layers.MaxPool2D(pool_size=(2,2), strides=(2,2)))
```

Part II-1 : the deep networks

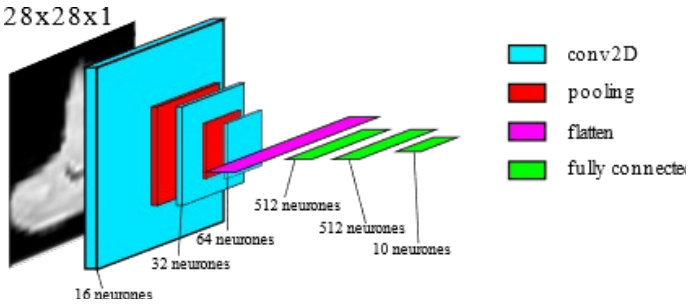
- **Implementing a convolutional network**
  - We then add layers :
    - A new convolutional layer (32 neurons)
    - A new max pooling
    - A last convolutional layer (64 neurons)




```
model=keras.Sequential()

model.add(keras.layers.Conv2D(input_shape=(28,28,1), filters=16, kernel_size=(3,3), padding="same", activation="relu"))
model.add(keras.layers.MaxPool2D(pool_size=(2,2), strides=(2,2)))

model.add(keras.layers.Conv2D(filters=32, kernel_size=(3,3), padding="same", activation="relu"))
model.add(keras.layers.MaxPool2D(pool_size=(2,2),strides=(2,2)))

model.add(keras.layers.Conv2D(filters=64, kernel_size=(3,3), padding="same", activation="relu"))
```

Part II-1 : the deep networks

- **Implementing a convolutional network**
  - We then add the fully connected part :
    - A flatten layer
    - 2 fully connected layers of 512 neurons
    - An output fully connected layer of 10 neurons (softmax function)

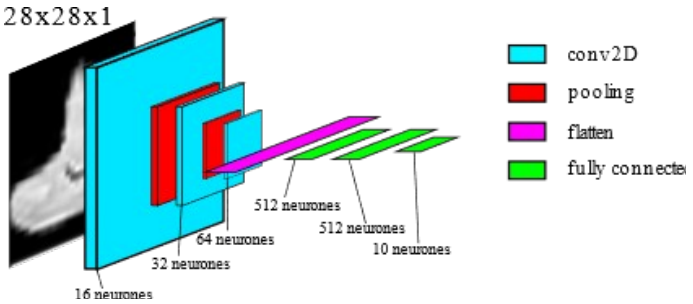



```
[ ]
    model=keras.Sequential()

    model.add(keras.layers.Conv2D(input_shape=(28,28,1), filters=16, kernel_size=(3,3), padding="same", activation="relu"))
    model.add(keras.layers.MaxPool2D(pool_size=(2,2), strides=(2,2)))
    model.add(keras.layers.Conv2D(filters=32, kernel_size=(3,3), padding="same", activation="relu"))
    model.add(keras.layers.MaxPool2D(pool_size=(2,2),strides=(2,2)))
    model.add(keras.layers.Conv2D(filters=64, kernel_size=(3,3), padding="same", activation="relu"))


    model.add(keras.layers.Flatten( ))

    model.add(keras.layers.Dense(units=512,activation="relu"))
    model.add(keras.layers.Dense(units=512,activation="relu"))

    model.add(keras.layers.Dense(units=10, activation="softmax"))
```

```
model.add(keras.layers.Flatten( ))

model.add(keras.layers.Dense(units=512,activation="relu"))
model.add(keras.layers.Dense(units=512,activation="relu"))

model.add(keras.layers.Dense(units=10, activation="softmax"))
```

Part II-1 : the deep networks

- **Implementing a convolutional network**
  - The model architecture can be displayed with ***model.summary()***




```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 28, 28, 16)        160

 max_pooling2d (MaxPooling2D  (None, 14, 14, 16)       0
 )

 conv2d_1 (Conv2D)           (None, 14, 14, 32)        4640

 max_pooling2d_1 (MaxPooling  (None, 7, 7, 32)         0
 2D)

 conv2d_2 (Conv2D)           (None, 7, 7, 64)          18496

 flatten (Flatten)           (None, 3136)              0

 dense (Dense)               (None, 512)               1606144

 dense_1 (Dense)             (None, 512)               262656

 dense_2 (Dense)             (None, 10)                5130

=================================================================
Total params: 1,897,226
Trainable params: 1,897,226
Non-trainable params: 0
_________________________________________________________________
```

Part II-1 : the deep networks

- **Keras :** some important types of layers (with <u>some</u> important parameters) :
  - **tf.keras.layers.Dense**(
    units, → number of neurons in the layer
    activation=None, → activation function
    use_bias=True, → use a bias or not
)
  - **tf.keras.layers.Conv2D**(note : versions 1D and 3D also exist
    filters, → number of neurons
    kernel_size, → size of kernel
    strides=(1, 1), → displacement (steps) of kernel
    padding="valid", → padding when *"same"*
    activation=None, → activation function
    use_bias=True, → use a bias or not
)
  - **tf.keras.layers.MaxPooling2D(**
    pool_size=(2, 2), → pooling reduction
    strides=None, → ‘movements’
    padding="valid"
)

- Some activation functions: relu, sigmoid, softmax, tanh, …
- Complete list of 100+ types of layers on: https://keras.io/api/layers/

Part II-1 : the deep networks

- **Keras :** construction of a network model
  - A sequential model can also be defined as a vector of layers:

```
model = Sequential( [
        Conv2D(input_shape=(224,224,3), filters=64, kernel_size=(3,3), padding="same", activation="relu"),
        Conv2D(filters=64,kernel_size=(3,3), padding="same", activation="relu"),
        MaxPool2D(pool_size=(2,2), strides=(2,2)), …
] )
```

  - Another method: functionnal model
    - Layers are created separately and connected

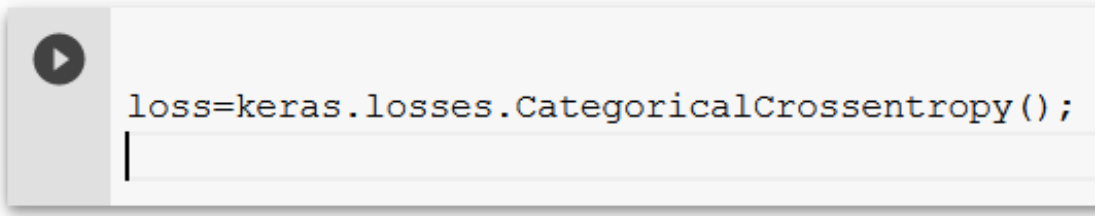
```
input_layer = Input(shape=(28,28,1))
conv1 = Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=(32,32,1))(input_layer)
conv2 = Conv2D(64, (3, 3), activation='relu', input_shape=(32,32,1))(input_layer)
merge = concatenate([conv1, conv2])
flatten = Flatten( )(merge)
output_layer = Dense(num_classes, activation='softmax')(flatten)
model = Model(inputs=input_layer, outputs=output_layer)
```

    - Allows defining non sequential models (fusion, split...)

Part II-1 : the deep networks

- **Learning parameters**
  - After constructing the network, we have to define
    - The loss function (error measure to optimize)
    - The optimization function (weight update algorithm)
  - With a softmax activation function, we will use the CategoricalCrossentropy loss function !

    Other loss functions :
    - *MeanSquaredError :* $E = (r – y)^2$
    - … and dozens of other available functions : https://keras.io/api/losses
  - In a new Colab cell, add :




```
loss=keras.losses.CategoricalCrossentropy();
```

Part II-1 : the deep networks

- **Learning parameters**
  - The optimization function is the function that reinforce neurons' weights
    - The SGD is the gradient descent presented previously
    - Other more optimized function adapt the learning rate to reduce learning time
      - Adam, Adadelta, Nadam, Ftrl… (see https://keras.io/api/optimizers/)

    - We select Adam optimizer, with a learning rate of 0.001 :

```
loss=keras.losses.CategoricalCrossentropy();
optim=keras.optimizers.Adam(learning_rate=0.001)
```

optim=keras.optimizers.Adam(learning_rate=0.001)

Part II-1 : the deep networks

- **Finalizing the network**
  - Finally, the network is compiled : the neuron reinforcement functions are defined according to the network architecture and selected loss and optimization functions :

```
loss=keras.losses.CategoricalCrossentropy();
optim=keras.optimizers.Adam(learning_rate=0.001)

model.compile(loss=loss, optimizer=optim, metrics=["accuracy"])
```

model.compile(loss=loss, optimizer=optim, metrics=["accuracy"])

  - Run the cell : if no error message appears, the network is ready !

Part II-1 : the deep networks

- **Training the network**
  - Keras takes care of everything with function *fit*
    - Parameters:
      - The training data and label
      - The size of batches (number of data learned simultaneously)
      - The number of epoches
      - The level of details to display
    - In a new cell, write :

```
model.fit(img_train, output_train, batch_size=16, epochs=10, verbose=2)
```

```
Epoch 1/10
3750/3750 - 13s - loss: 0.1175 - accuracy: 0.9638 - 13s/epoch - 3ms/step
Epoch 2/10
3750/3750 - 10s - loss: 0.0502 - accuracy: 0.9848 - 10s/epoch - 3ms/step
```

    - The learning process can takes several minutes...

Part II-1 : the deep networks

- **Evaluating/Exploiting the network**
  - Keras takes care of everything (again) :
    - Function evaluate (works in a same way than fit)

```
model.evaluate(img_test, output_test, batch_size=16, verbose=2)
```

```
625/625 - 1s - loss: 0.0703 - accuracy: 0.9884 - 1s/epoch - 2ms/step
[0.07027573138475418, 0.9883999824523926]
```

< 1,2 %

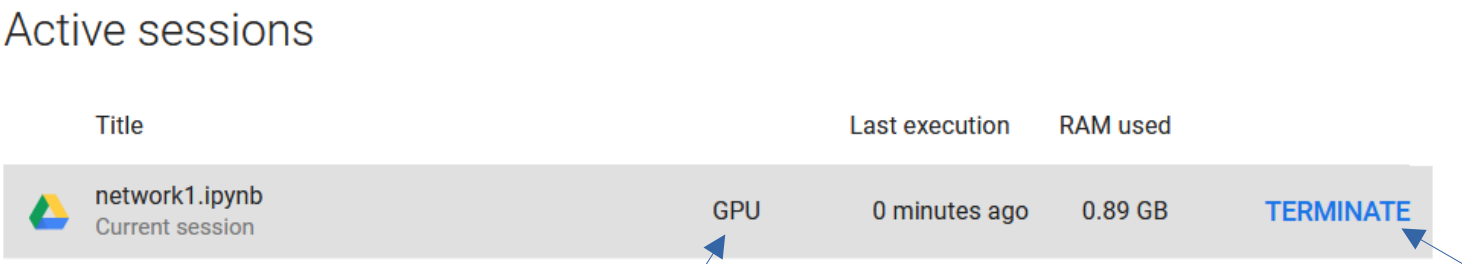
    - An image can be used as parameter to get a prediction :

```
print(label_test[0:1])

model(img_test[0:1,:,:])
```

```
[7]
<tf.Tensor: shape=(1, 10), dtype=float32, numpy=
array([[1.1164599e-26, 2.6863731e-18, 2.3253600e-17, 1.2962786e-17,
        2.5873384e-16, 5.7846084e-20, 1.6555734e-36, 1.0000000e+00,
        1.5967833e-22, 9.6893570e-12]], dtype=float32)>
```

Part II-1 : the deep networks

- Save your colab
- **Do not forget to disable the GPU and stop the session !**



Edit → notebook settings, then select ‘none’

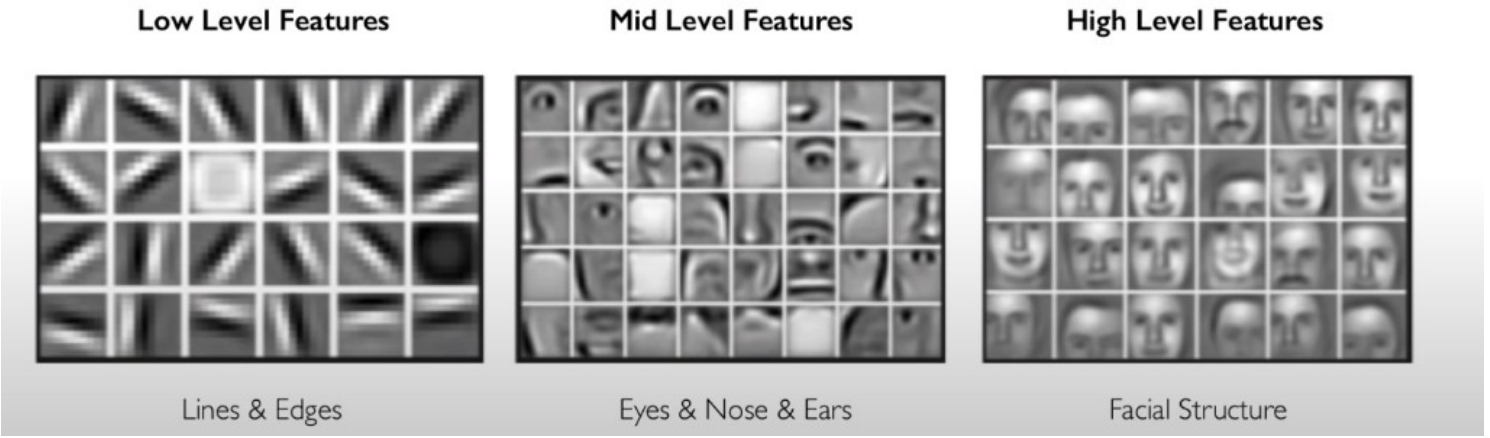
- **Note to go further :** there is a dataset similar to MNIST :
  - dataset = keras.datasets.**fashion_mnist**
  - You can try to improve your model to get the best accuracy

Training a deep network: the question of the dataset

Part II-1 : the deep networks

- **Training a deep network**

  - The more layers of neurons there are, the larger the learning dataset must be
    - A deep network may require a dataset of tens, even hundreds thousand images (or other kind of data)
  - Do we need a huge dataset for each new problem ?
  - For two similar problems, features defined by lowest layers are similar !

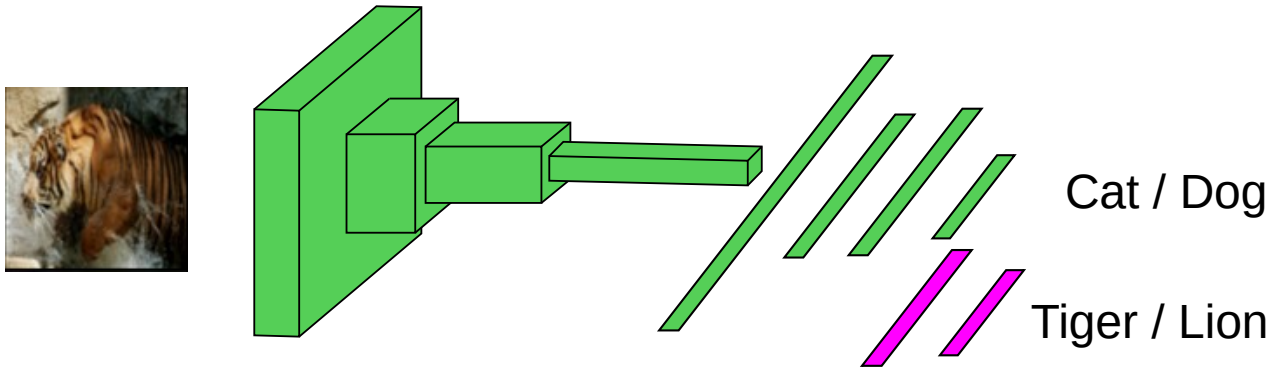


Part II-1 : the deep networks

- **Training a deep network**
  - For similar problem, it is possible to re-use low layers of an existing trained network

    → Principle of **transfer learning**

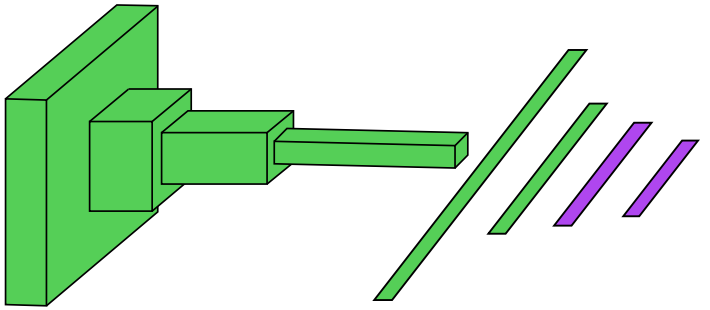
  - We can use a network trained on a similar problem
  - We then replace last layers of the network with new layers



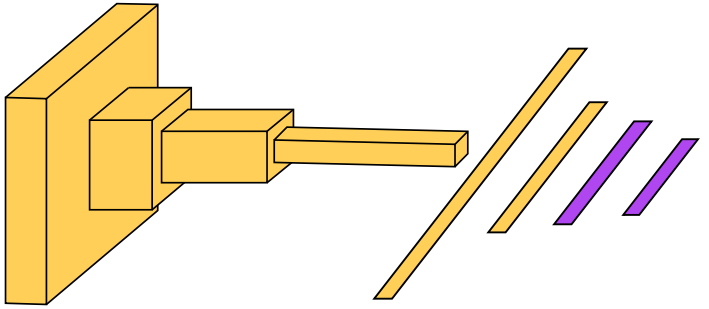
  - The number of layers to replace depends on problems similarities and available dataset's size

Part II-1 : the deep networks

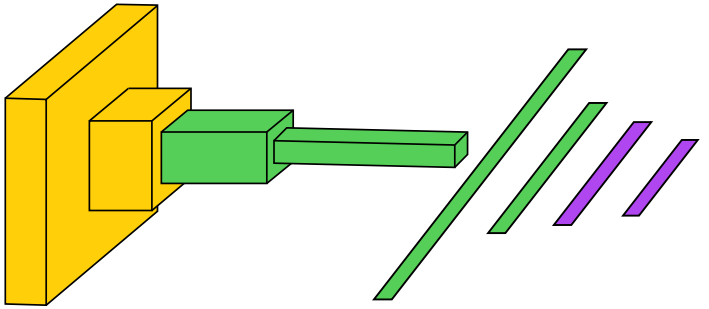
- **Transfer Learning**
  - Fine tuning: last layers (often fully connected part) are replaced with new initialized layers
    - Faster learning with less examples
    - Low level features can adapt to the new problem
    - Still requires a large dataset



  - Feature extraction: last layers are replaced and remaining layers are frozen
    - Fast learning with few examples
    - Resulting network is not always efficient



  - Partial Fine tuning: olast layers are replaces, but only lowest layers are frozen
    - Good compromise between above methods
    - Low level features are more ‘universal’



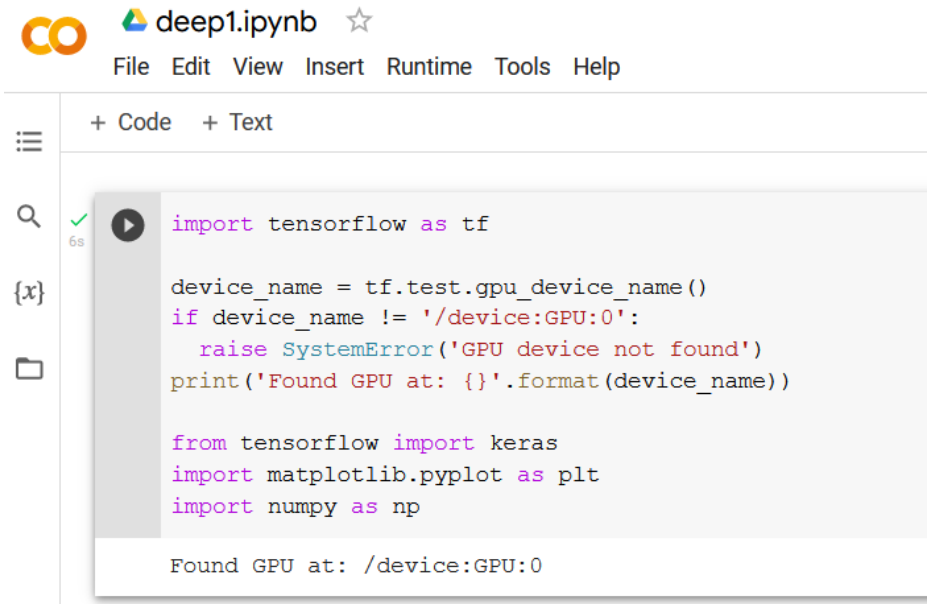
Part II-1 : the deep networks

- **Transfer Learning**
  - **Several well-trained open-source networks are proposed for transfer learning :**
    - AlexNet : architecture used for ILSVRC 2012
    - VGGnet : one of most versatile. Uses 16 convolution layers
    - GoogleNet : winner of ILSVRC 2014, uses 22 convolution layers
    - ResNet : winner of ILSVRC 2015 (with an error ratio of 3,57 %, it is more efficiant than human participants!), uses 152 convolution layers

Part II-1 : the deep networks

- **Let's implement a true deep neural network !**
  - New way to build a dataset
  - Transfer learning from an existing network
  - Goal : recognize a cat from a dog

  - Create a new Colab Notebook, enable GPU, and copy the imports




```
import tensorflow as tf

device_name = tf.test.gpu_device_name()
if device_name != '/device:GPU:0':
  raise SystemError('GPU device not found')
print('Found GPU at: {}'.format(device_name))

from tensorflow import keras
import matplotlib.pyplot as plt
import numpy as np
```

Part II-1 : the deep networks

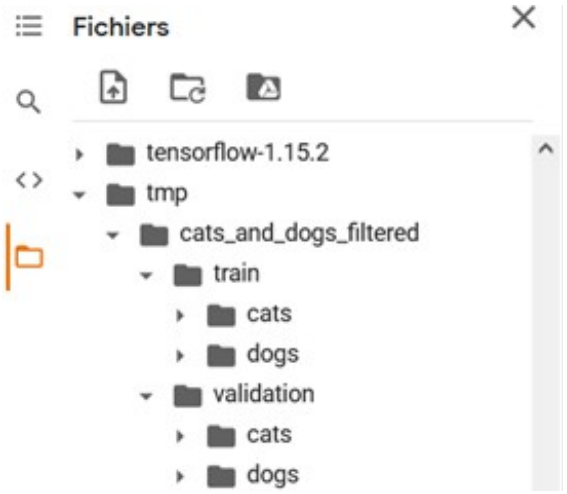
- **The dataset**
  - We will download a set of images and unzip them in different folders
  - Copy and paste these code lines in two different colab cells, and execute them :

```
!wget --no-check-certificate \
    https://storage.googleapis.com/mledu-datasets/cats_and_dogs_filtered.zip \
    -O /tmp/cats_and_dogs_filtered.zip
```

```
import os
import zipfile

local_zip = '/tmp/cats_and_dogs_filtered.zip'
zip_ref = zipfile.ZipFile(local_zip, 'r')
zip_ref.extractall('/tmp')
zip_ref.close()

train_dir = '/tmp/cats_and_dogs_filtered/train'
test_dir = '/tmp/cats_and_dogs_filtered/validation'
```

Part II-1 : the deep networks

- **The dataset**
  - The images are stored in a specific folder tree



  - Keras proposes an object that can browse this kind of folder tree to feed a neural network for training or evaluating it :
    - The ***ImageDataGenerator***

Part II-1 : the deep networks

- **The dataset**
  - In a new Colab cell, we write the image generator :

```
trainDataGenerator = keras.preprocessing.image.ImageDataGenerator(rescale=1./255)
trainData = trainDataGenerator.flow_from_directory(directory=train_dir, target_size=(224,224))

testDataGenerator = keras.preprocessing.image.ImageDataGenerator(rescale=1./255)
testData = testDataGenerator.flow_from_directory(directory=test_dir, target_size=(224,224))
```

```
Found 2000 images belonging to 2 classes.
Found 1000 images belonging to 2 classes.
```

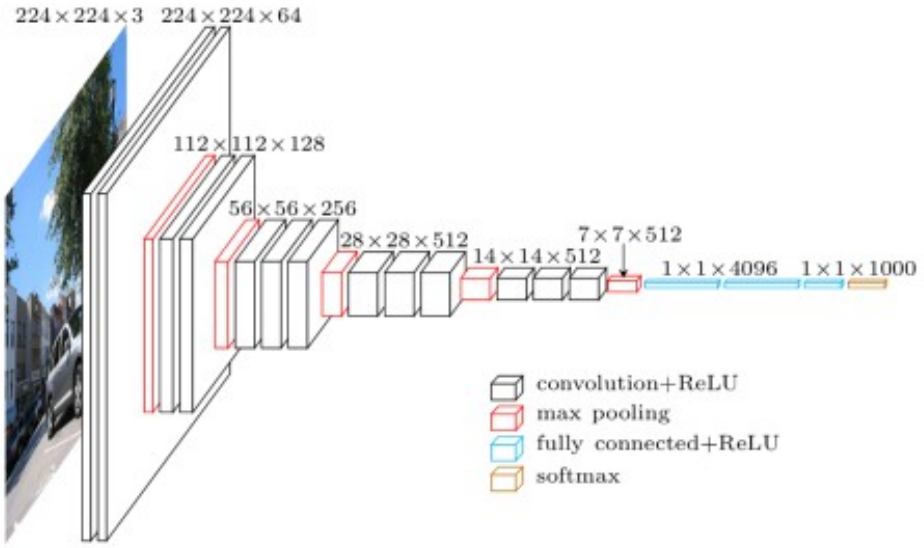
  - Then, we load the VGG16 network

```
VGG16= keras.applications.VGG16(weights="imagenet")

VGG16.summary()
```

Part II-1 : the deep networks

- **The VGG16 network**
  - We cannot train a network with so many parameters

```
=================================================
Total params: 138,357,544
Trainable params: 138,357,544
Non-trainable params: 0
_________________________________________________
```



  - Especially with such a small dataset !
  - Hopefully, the VGG16 network was trained with multiple animals (including cats ans dogs) : the lowest layers may recognize pertinent features

- Note : VGG16 was trained during multiple days on high-end GPUs with *imageNet* dataset (>1M labeled images)

Part II-1 : the deep networks

- **The VGG16 network**
  - The VGG16 network, as proposed by Keras, can be loaded without the fully connected part
    - Parameter include_top can be set to False
    - Parameter weights='imagenet' allows loading weight obtained with imagenet dataset (10M+ images)
  - Add a new Colab cell and paste this :

```
base_VGG16= keras.applications.VGG16(weights="imagenet", include_top=False, input_shape=(224,224,3))
base_VGG16.summary()
```

  - Observe where the network is cut :
    - As the flatten layer is not included, other convolutional layers can be added

Part II-1 : the deep networks

- **The VGG16 network**
  - We freeze the weights of the network (in a new Colab cell) :

```
base_VGG16.trainable=False

base_VGG16.summary()
```

```
=================================================
Total params: 14,714,688
Trainable params: 0
Non-trainable params: 14,714,688
_________________________________________________
```

Part II-1 : the deep networks

- **The VGG16 network**
  - The VGG16 part is then used as a layer for our network
  - We then add the fully connected part using a flatten layer, a fully connected layer with 50 neurons and an output flatten layer with 2 neurons

```
model=keras.models.Sequential()
model.add(base_VGG16)

model.add(keras.layers.Flatten())
model.add(keras.layers.Dense(50, activation="relu"))
model.add(keras.layers.Dense(2, activation="softmax"))

model.summary()
```

```
=================================================
Total params: 15,969,240
Trainable params: 1,254,552
Non-trainable params: 14,714,688
_________________________________________________
```

Part II-1 : the deep networks

- **The VGG16 network**
  - The network is compiled with Categorical_Crossentropy and Adam functions

```
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
```

  - And trained using the data generator that provides both data and labels

```
model.fit(trainData, epochs=5, batch_size=32)
```

```
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

model.fit(trainData, epochs=5, batch_size=32)
```

```
Epoch 1/5
19/63 [========>.....................] - ETA: 6s - loss: 0.8847 - accuracy: 0.7105
```

Part II-1 : the deep networks

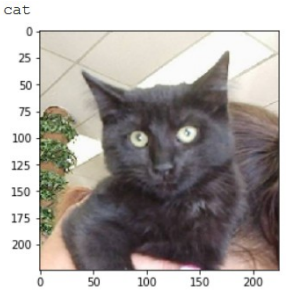
- **The VGG16 network**
  - The network can then be evaluated :

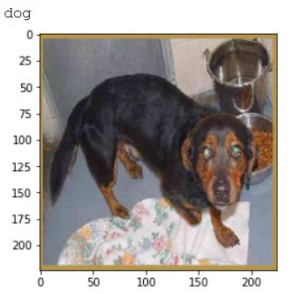
```
model.evaluate(testData, batch_size=32, verbose=2)
```

```
32/32 - 6s - loss: 0.2513 - accuracy: 0.9080 - 6s/epoch - 186ms/step
[0.2513466775417328, 0.9079999923706055]
```

  - The following code allows testing an image :

```
test_cats_files = os.listdir(test_dir+"/cats")
test_dogs_files = os.listdir(test_dir+"/dogs")

img = keras.preprocessing.image.load_img(test_dir+"/cats/"+test_cats_files[8],target_size=(224,224))
#img = keras.preprocessing.image.load_img(test_dir+"/dogs/"+test_dogs_files[8],target_size=(224,224))
img = np.asarray(img)
plt.imshow(img)
img = np.expand_dims(img, axis=0)

prediction=model.predict(img)

if prediction.argmax()==0: print("cat")
else : print("dog")
```





Part II-1 : the deep networks

- **Applications**
  - Question : is it possible to recreate the image from the feature vector ?
    - Successive convolution generate an information loss
    - The feature vector only contains a fraction of image information
    - New layers to reverse convolutional layer’s processing
      - De-pooling
      - transposed convolution

Part II-1 : the deep networks

- **Image reconstruction**
  - De-Pooling :
    - Nearest neighbor

0,29	0,47	0,46
0,15	0	0
0	0,57	1,49

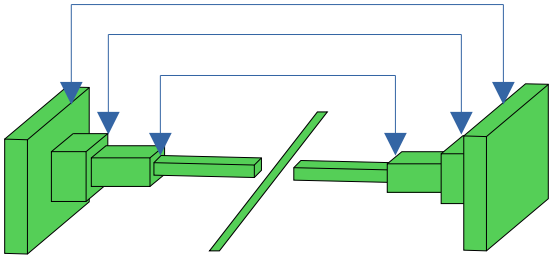
0,29	0,29	0,47	0,47	0,46	0,46
0,29	0,29	0,47	0,47	0,46	0,46
0,15	0,15	0	0	0	0
0,15	0,15	0	0	0	0
0	0	0,57	0,57	1,49	1,49
0	0	0,57	0,57	1,49	1,49

    - Bed of nails

0,29	0	0,47	0	0,46	0
0	0	0	0	0	0
0,15	0	0	0	0	0
0	0	0	0	0	0
0	0	0,57	0	1,49	0
0	0	0	0	0	0

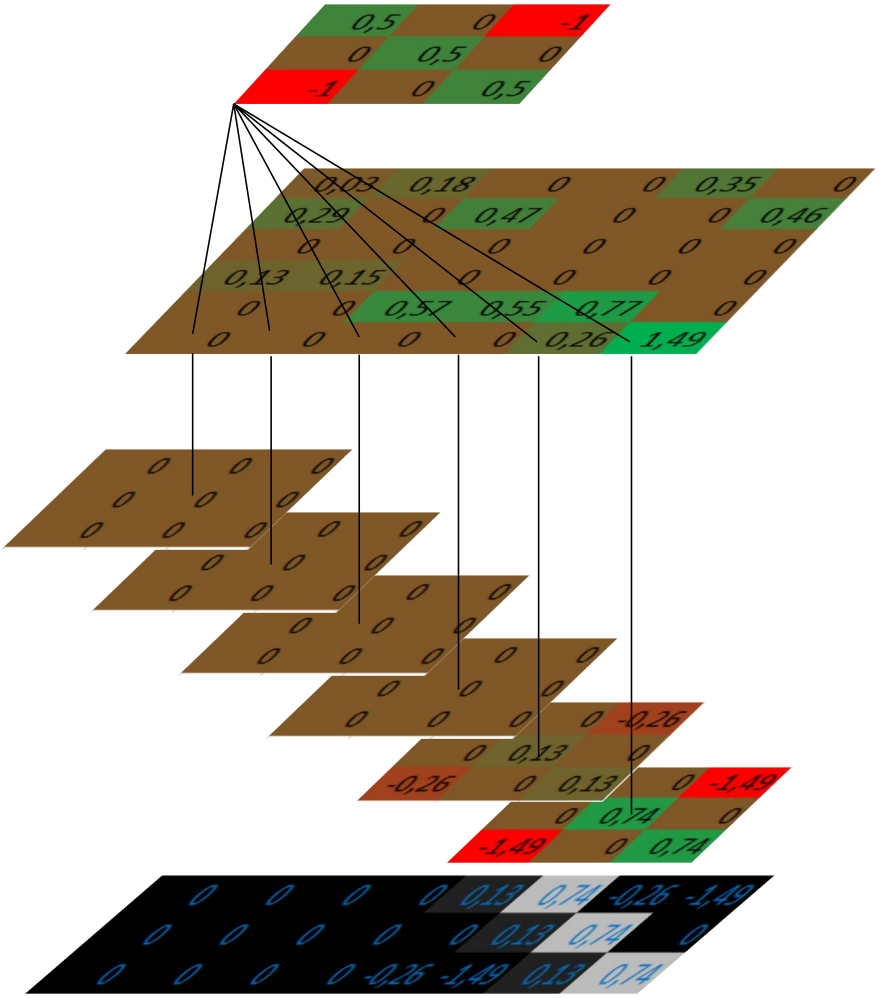
    - Max UnPooling

      → use the mirror pooling layer to define which pixel get the value



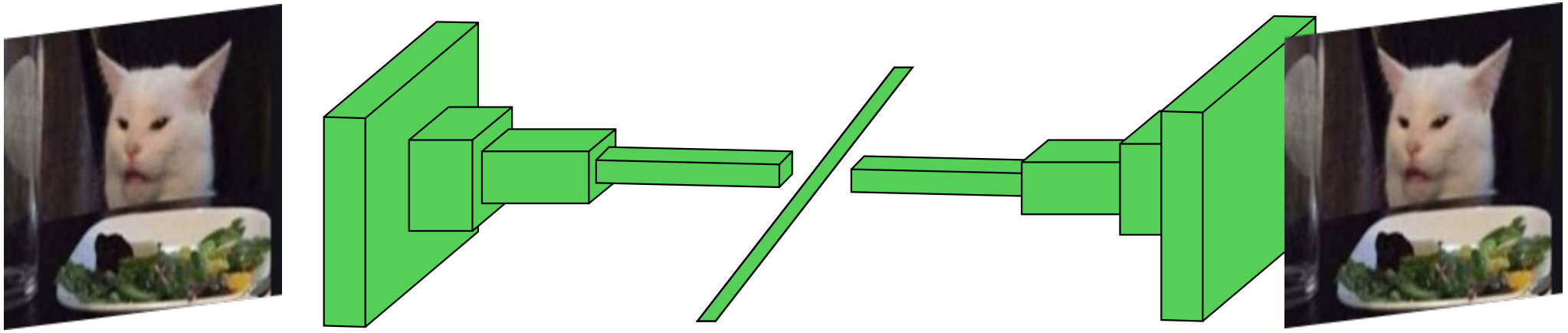
Part II-1 : the deep networks

- **Image Reconstruction**
  - Transposed Convolution:
    - Principle of convolution is ‘reversed’
    - Output image is the sum of kernel weighted by convolution image values



Part II-1 : the deep networks

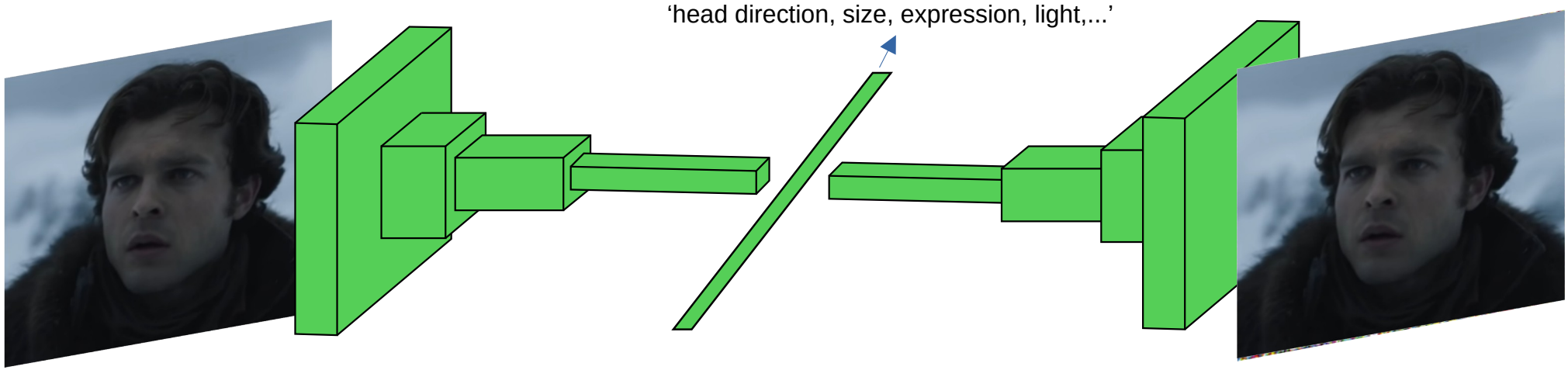
- **Image reconstruction**
  - The fully-connected part is replaced by a ‘mirror’ version of the network



  - Input image is used as expected result ($E = | Img_{ref} – Img_{gen} |^2$)
  - First part encodes the information: ‘encoder’ network
  - Second part ‘decode’ the feature vector to reconstruct the image: ‘decoder’ network
    - Decoder learns to generate textures, edges… from feature description
  - Very efficient way to de-noise an image

Part II-1 : the deep networks

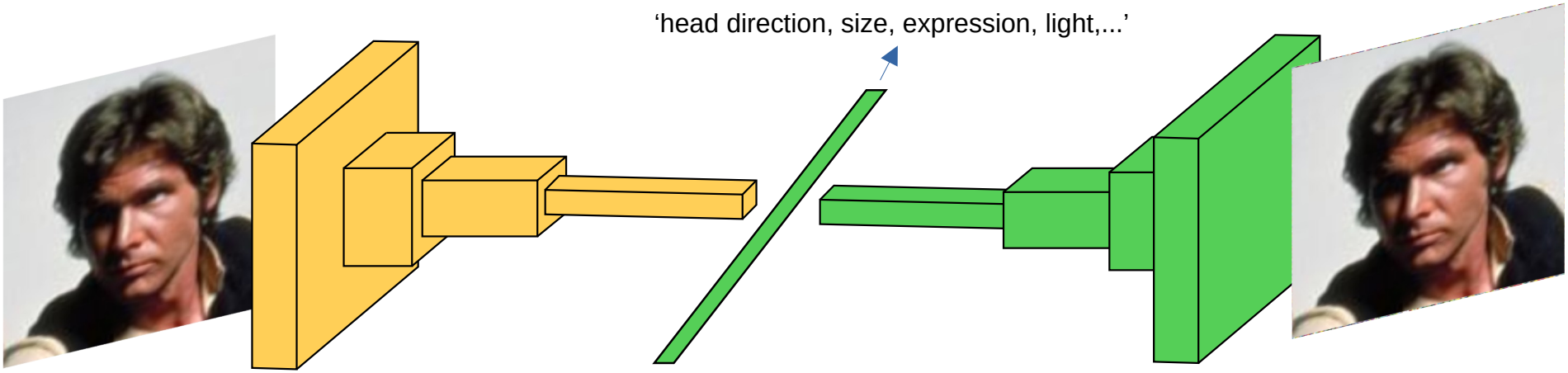
- **Image reconstruction**
  - The network ‘learns’ to define minimal information
  - Let’s train the network on images of a specific face



  - The network will learn to encode minimum data to reconstruct the face
    - Head orientation and size, facial expression… (implicitly)
    - The decoder learns to reconstruct the image with these features

Part II-1 : the deep networks

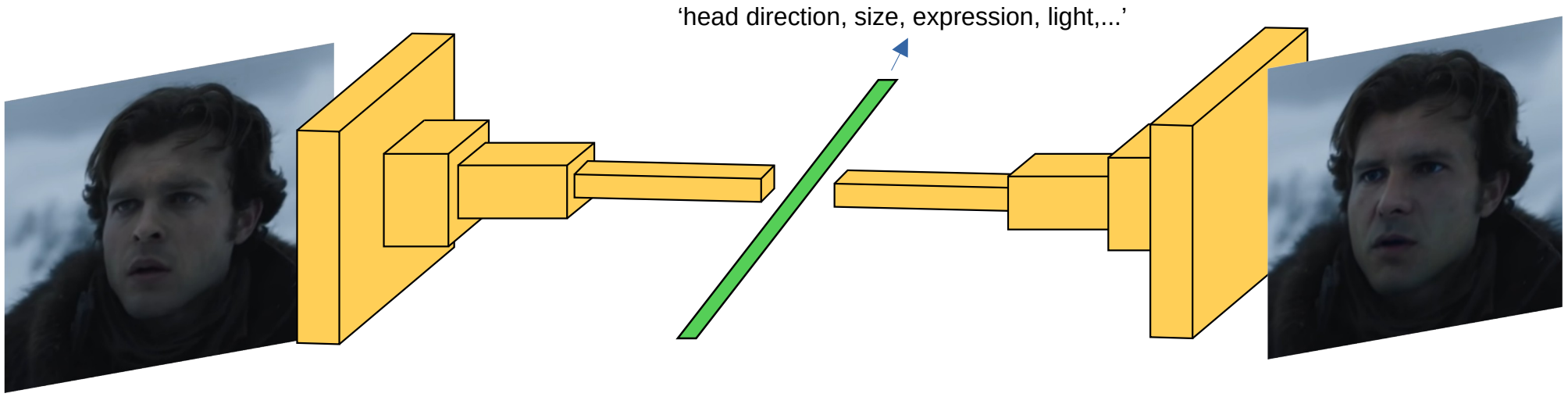
- **Image reconstruction**
  - The encoder’s weights are frozen
  - Decoder is reinitialized and trained with another face



  - The encoder will provide feature vectors in a similar way
  - But the decoder must learn to generate this face from features

Part II-1 : the deep networks

- **Image reconstruction**
  - We now froze the whole network
  - An image of first face is presented to the network
    - The encoder extracts features from this face
    - The decoder will generate an image of the second face from these features



- Principle of deep fake

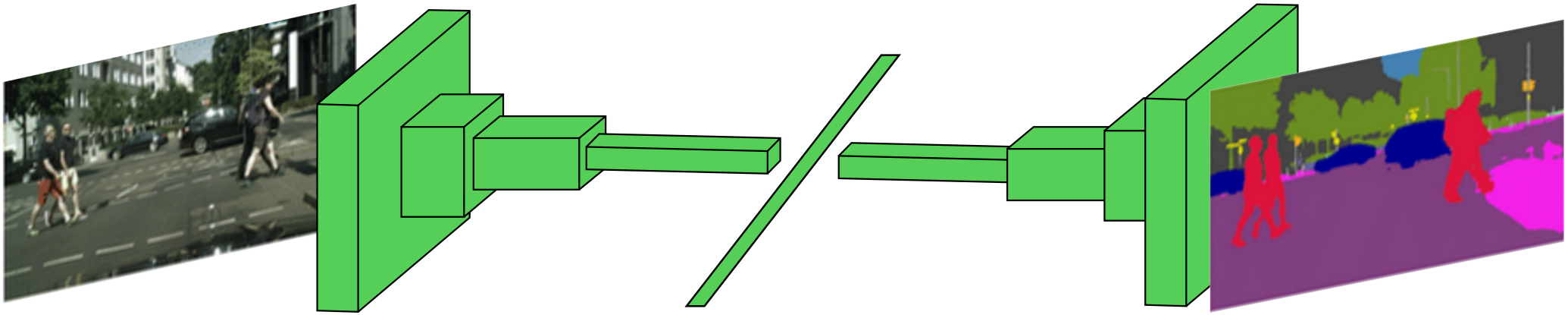
Part II-1 : the deep networks

- **Image reconstruction**

Harrison Ford in Solo: A Star Wars Story (Shamook)

Part II-1 : the deep networks

- **Fully-convolutional networks**
  - We can also use other type of images as output
  - Example : Mask-RCNN
    - The network is trained on images, with hand-labeled mask images

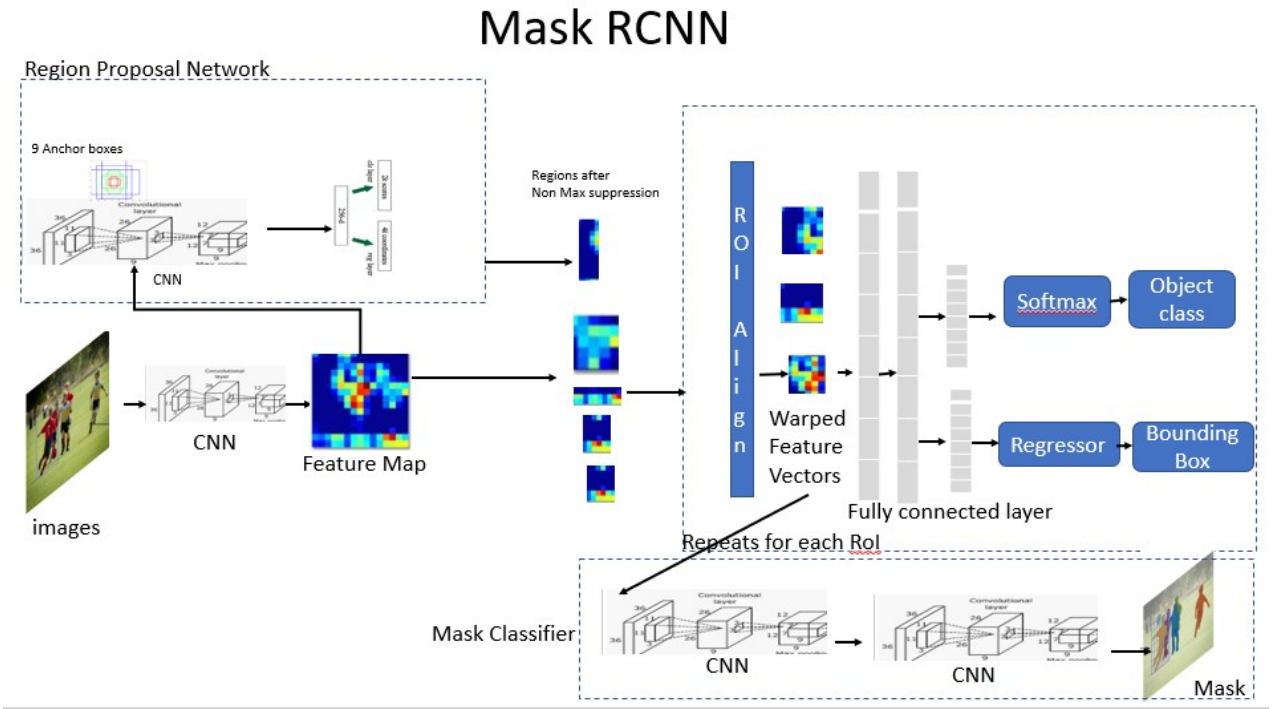


  -

Part II-1 : the deep networks

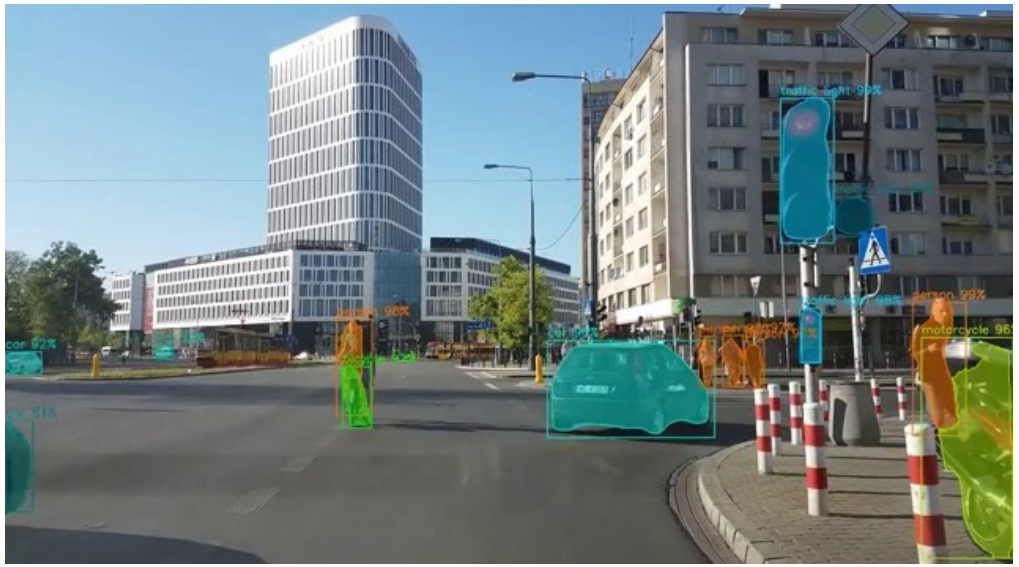
- **Fully-convolutional network**
  - Mask-RCNN : in practice, a little more complex
    - Detection of objects in the image

      → extraction of region of interest containing objects
    - Detection pixel by pixel to generate a mask



Part II-1 : the deep networks

- **Fully-convolutional network**
  - Mask-RCNN, trained on dataset COCO (Common Objects in COntext)



Training a deep network: bias and security

Part II-1 : the deep networks

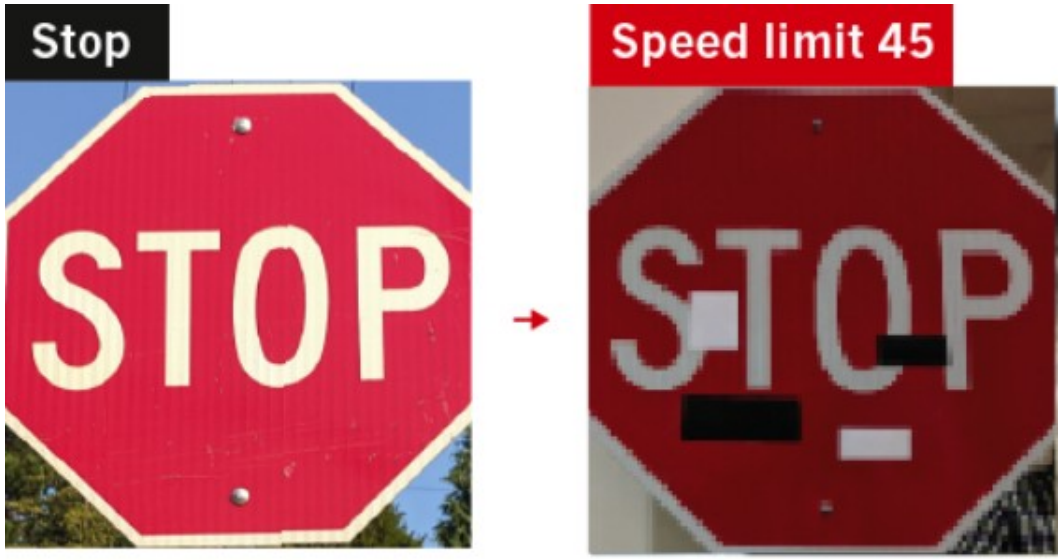
- **The dataset bias**
  - Training a deep network requires a huge number of examples
    - Gathering a large number of example can be difficult, leading to statistical bias in the collected samples
    - Neural networks are very sensitive to statistical bias in datasets and will use ANY regularity they can found to minimize errors
      - Example : a network defining the age of a person uses the size of ears
    - These bias may generate serious issues
      - In 2014, Amazon used a deep network to analyze applicants' resume
      - This network massively rejected women's resume
      - The network was trained on resumes collected during 10 past years, most of them were from men...

Part II-1 : the deep networks

- **The dataset bias**
  - Example de biais :
    - Network trained to recognize wolves from husky
    - High success ratio
    - But some (obvious) errors !
  - After analyzing features, it appeared that the network only detect snow on the background !
    - In the dataset, a large majority of wolf pictures have snow in the background

Part II-1 : the deep networks

- **Security**
  - Training a network with a biased dataset not only reduce its reliability, but also makes it more vulnerable to attacks



Part II-1 : the deep networks

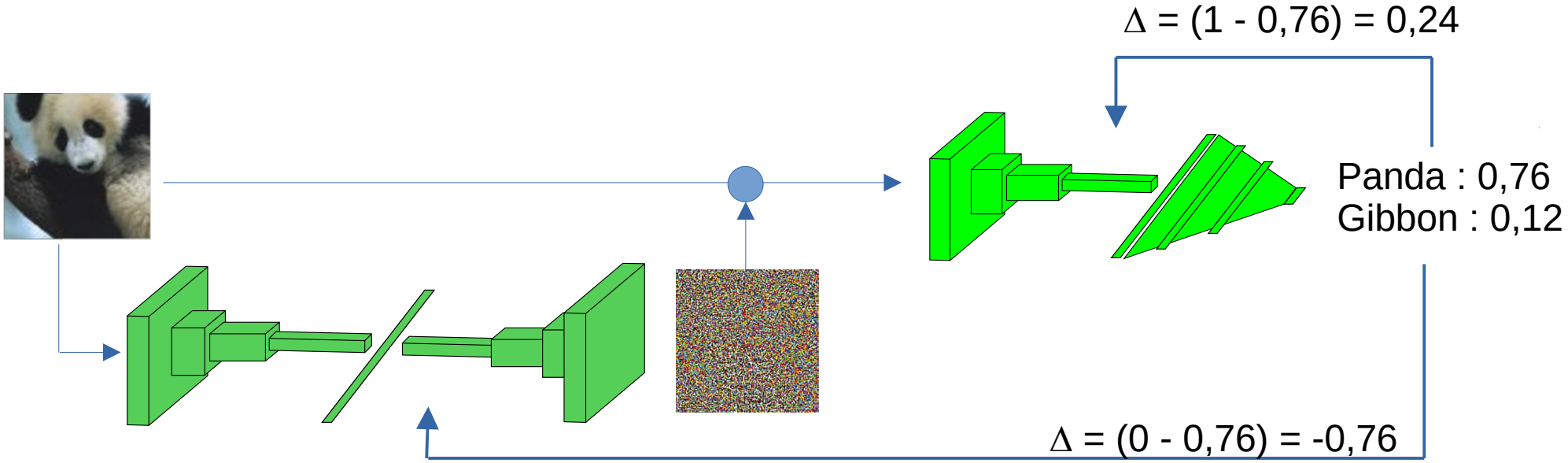
- **Security**
  - It is also possible to ‘manipulate’ the network to modify its output

  - The added noise disrupted low level features, which also interfere with higher level features, and thus, changed the result.
  - How this variation was created ?

Part II-1 : the deep networks

- **Manipulating a network**

  - A ‘normal’ deep network recognize animals on images
  - An encoder-decoder network is added to generate a ‘noise image’ that is added to the initial image
  - The success of second network is related to the failure of first network



  - If the two networks learn simultaneously, they have antagonist objectives !