

# **Machine learning introduction**

## **Part II – Deep Neural Networks**

### **3 - Libraries for Deep Neural Networks : TensorFlow and Keras**

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## Part II-3 : Libraries for deep neural 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 : library of high level function to easily develop a deep network. Uses Tensorflow or Theanos libraries

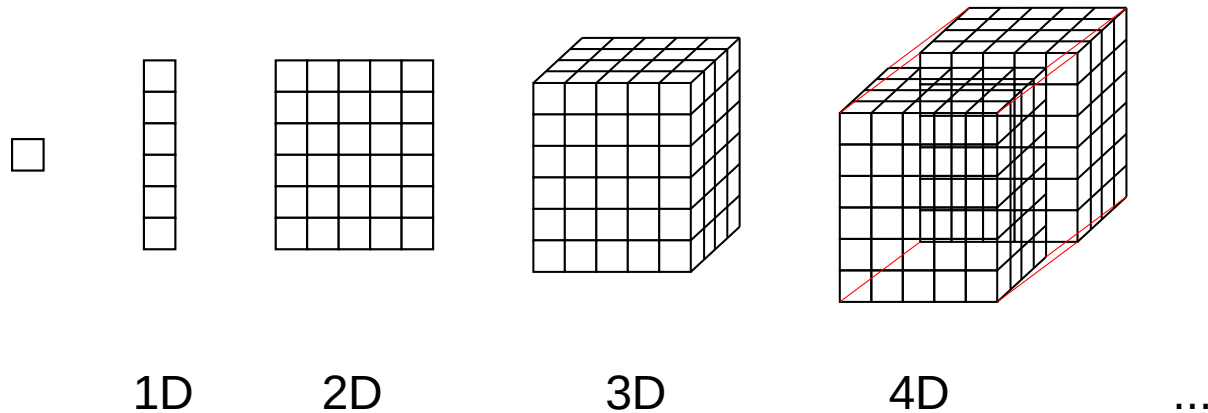


# Part II-3 : Libraries for deep neural networks



- **TensorFlow**

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



- Optimized functions
- Possibility to parallelize on GPU !

# Part II-3 : Libraries for deep neural networks

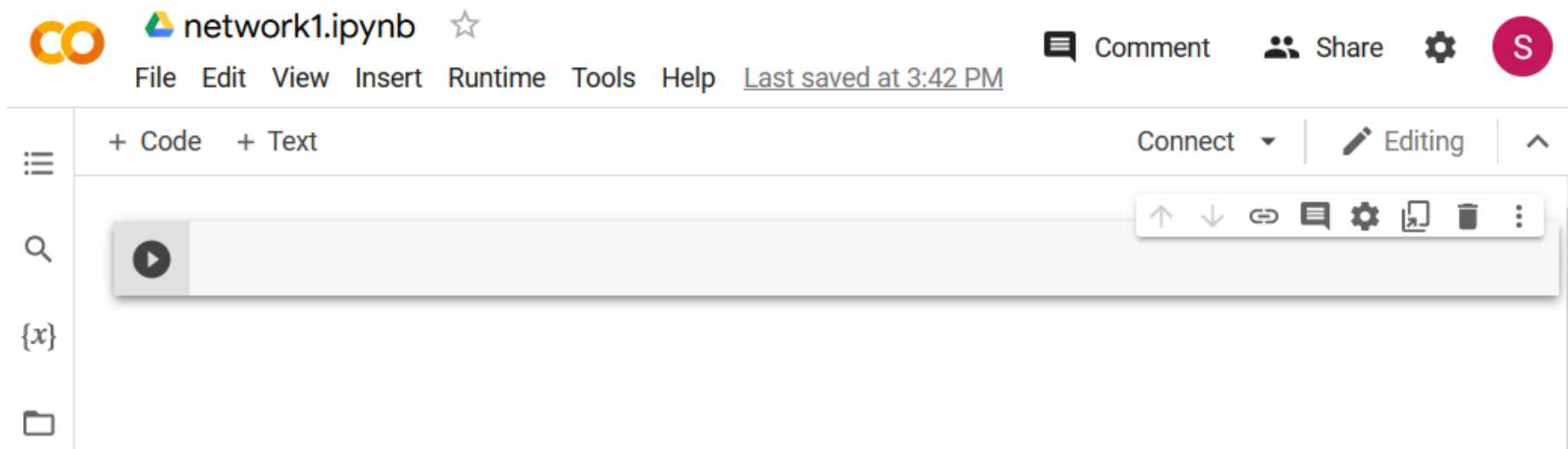


- **Keras**
  - Library of functions exploiting Tensorflow or Theanos
  - Function to:
    - Load a 'common' dataset (ie used for benchmarking)
    - Define the architecture of a network
    - Define learning parameters and loss function
    - Train the network
    - Evaluate the network
    - Exploit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

# Part II-3 : Libraries for deep neural networks



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



## Part II-3 : Libraries for deep neural 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
```

```
import tensorflow as tf

from tensorflow import keras

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

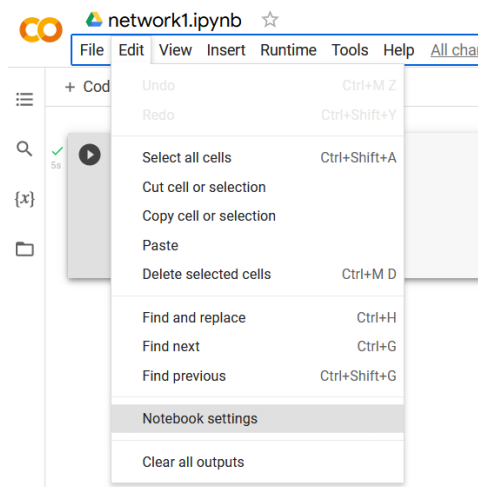
- Tensorflow and Keras for the neural network
  - Pyplot and numpy for image display
- Run the cell to check the imports

# Part II-3 : Libraries for deep neural 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'



## Notebook settings

Hardware accelerator

GPU

To get the most out of Colab, avoid using a GPU unless you need one. [Learn more](#)

☐ Background execution

Want your notebook to keep running even after you close your browser? [Upgrade to Colab Pro+](#)

☐ Omit code cell output when saving this notebook

Cancel

Save


# Part II-3 : Libraries for deep neural networks



- **Using a GPU**

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

Active sessions

Title		Last execution		RAM used	
	network1.ipynb Current session	GPU	0 minutes ago	0.89 GB	<a href="#">TERMINATE</a>

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



# Part II-3 : Libraries for deep neural 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

A screenshot of a Jupyter Notebook cell. The code is as follows:

```
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
```

The output of the cell is displayed at the bottom: `Found GPU at: /device:GPU:0`. On the left side of the code block, there is a green checkmark icon and a small '6s' indicating execution time.

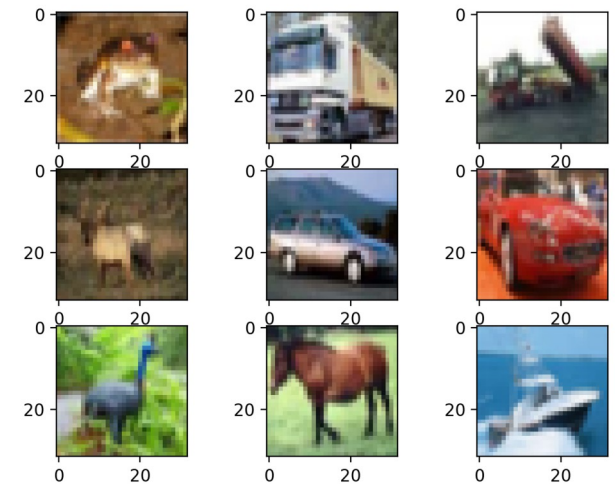
# Part II-3 : Libraries for deep neural networks



- **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-3 : Libraries for deep neural 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-3 : Libraries for deep neural 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  $\rightarrow$  [ 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)
```

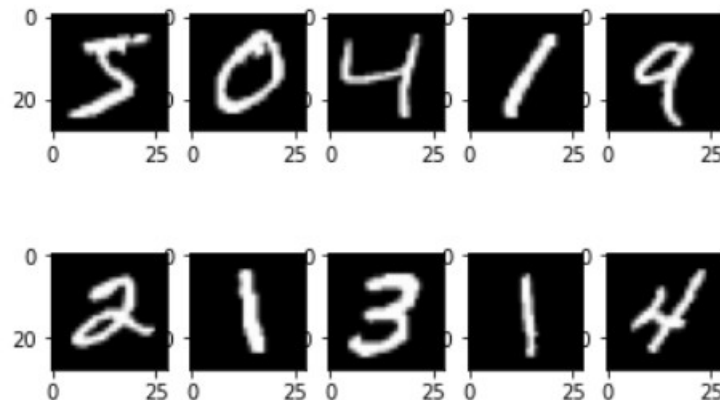
(60000, 28, 28)  
(10000, 28, 28)

# Part II-3 : Libraries for deep neural 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-3 : Libraries for deep neural 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)`

A blue arrow points from the 2D shapes to the 4D shapes, indicating the transformation performed by the code.

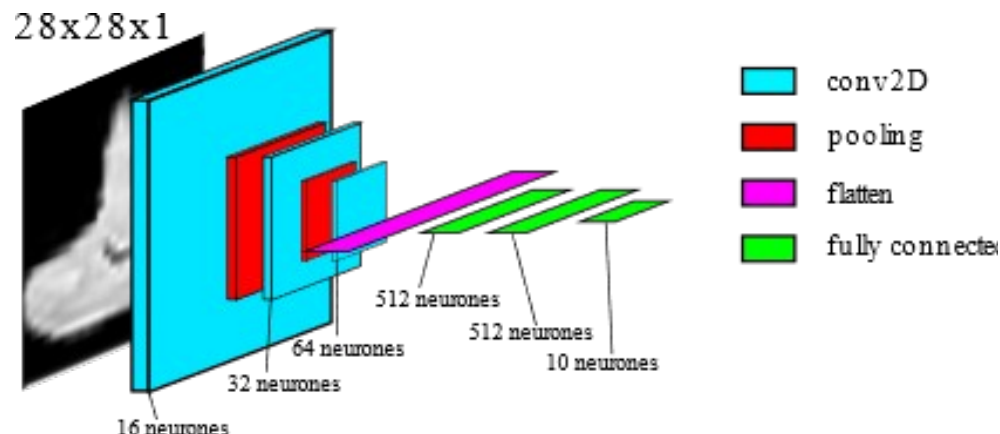
- Now, our images have a depth

## Part II-3 : Libraries for deep neural networks



- **Implementing a convolutional network**

- We will implement this simple network :



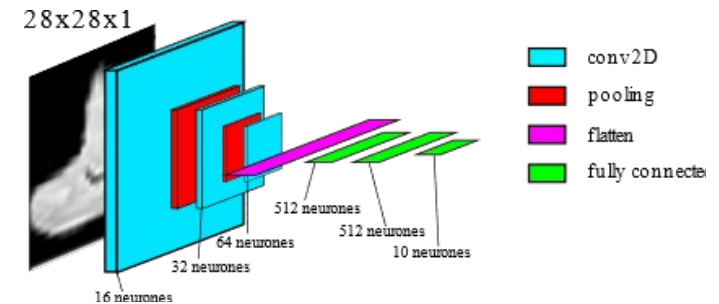
- Create a new Colab cell
  - We start by declaring a Sequential network

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

# Part II-3 : Libraries for deep neural 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()
```

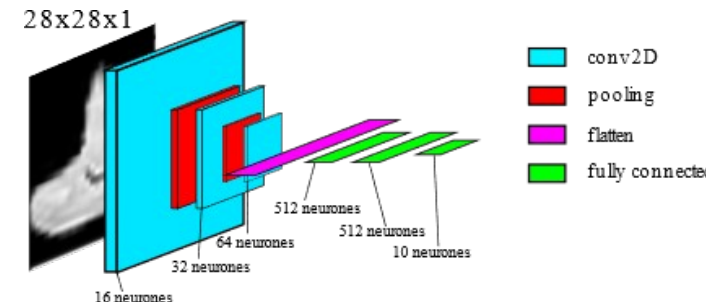
```
model.add(keras.layers.Conv2D(input_shape=(28,28,1), filters=16, kernel_size=(3,3), padding="same", activation="relu"))  
model.add(keras.layers.MaxPool2D(pool_size=(2,2), strides=(2,2)))
```



# Part II-3 : Libraries for deep neural 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)))

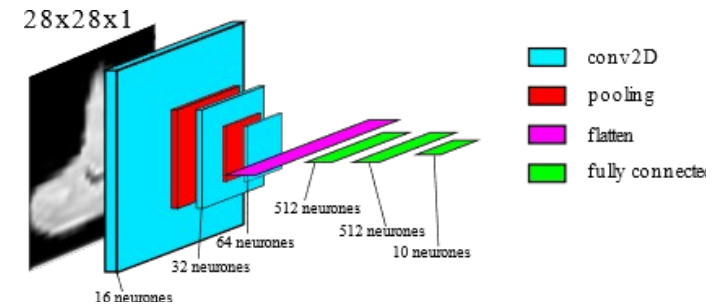
model.add(keras.layers.Conv2D(filters=32, kernel_size=(3,3), padding="same", activation="relu"))
model.add(keras.layers.MaxPool2D(pool_size=(2,2),strides=(2,2)))

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

# Part II-3 : Libraries for deep neural 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-3 : Libraries for deep neural networks

- Implementing a convolutional network

- The model architecture can be displayed with

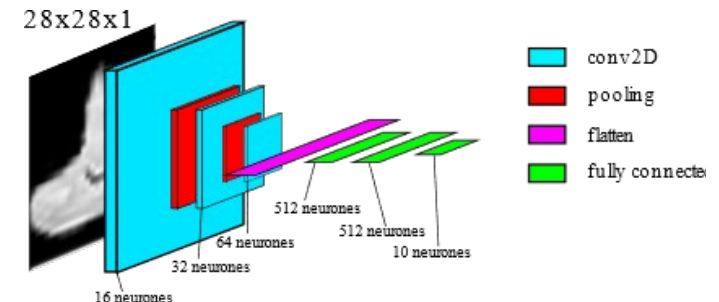
***model.summary()***

```
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 (MaxPooling2D)	(None, 7, 7, 32)	0
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-3 : Libraries for deep neural networks



- **Keras** : some important types of layers (with some important parameters) :

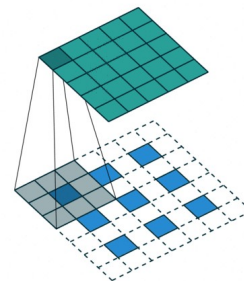
- **tf.keras.layers.Dense**(  
    *units*,  
    *activation=None*,  
    *use\_bias=True*,  
    )  
    → number of neurons in the layer  
    → activation function  
    → use a bias or not
- **tf.keras.layers.Conv2D**(  
    *filters*,  
    *kernel\_size*,  
    *strides=(1, 1)*,  
    *padding="valid"*,  
    *activation=None*,  
    *use\_bias=True*,  
    )  
    note : versions 1D and 3D also exist  
    → number of neurons  
    → size of kernel  
    → displacement (steps) of kernel  
    → padding when "same"  
    → activation function  
    → use a bias or not

- Some activation functions: relu, sigmoid, softmax, tanh, ...

# Part II-3 : Libraries for deep neural networks



- **Keras** : Some important types of layers :
  - **tf.keras.layers.MaxPooling2D**(  
    pool\_size=(2, 2),  
    strides=None,  
    padding="valid"  
)  
→ pooling reduction  
→ 'movements'
  - **tf.keras.layers.UpSampling2D**(  
    size=(2, 2),  
    interpolation="nearest"  
)  
→ unpooling 'inflation'  
→ "nearest" or "bilinear"
  - **tf.keras.layers.Conv2DTranspose**(  
    filters,  
    kernel\_size,  
    strides=(1, 1),  
    padding="valid",  
    activation=None,  
    use\_bias=True,  
)  
→ number of output images (depth)  
→ kernel size  
→ adds 0 between pixels  
    equivalent to a 'bed of nails'
- Complete list of 100+ types of layers on: <https://keras.io/api/layers/>



# Part II-3 : Libraries for deep neural 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: fonctionnal 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-3 : Libraries for deep neural networks

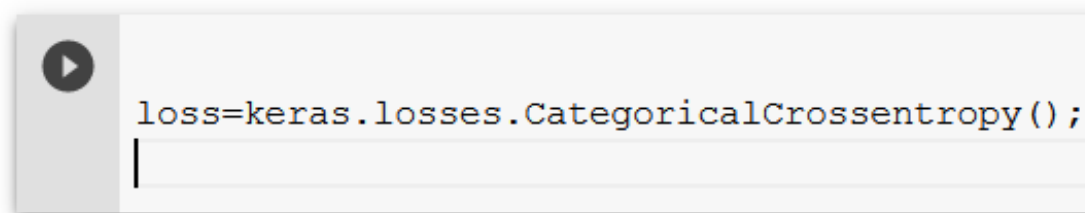


- **Learning parameters**

- 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* :  $E = (y - \hat{y})^2$
- ... and dozens of other available functions : <https://keras.io/api/losses>
- In a new Colab cell, add :

A screenshot of a Google Colab code cell. It has a grey background with a play button icon on the left. The code text is in a monospaced font, showing the first line of the Keras loss function definition.

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

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

## Part II-3 : Libraries for deep neural 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, Adadelata, 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-3 : Libraries for deep neural 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-3 : Libraries for deep neural 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-3 : Libraries for deep neural 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]
```

< 0.12 %

- 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-3 : Libraries for deep neural networks



- **Next network**

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

Active sessions

Title		Last execution	RAM used	
 network1.ipynb Current session	GPU	0 minutes ago	0.89 GB	<a href="#">TERMINATE</a>

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

# Part II-3 : Libraries for deep neural networks



- **A true deep neural network !**
  - New way to build a dataset
  - Transfert learning from an existing network
  - Goal : recognize a cat from a dog
- Create a new Colab Notebook, enable GPU, and copy the imports

A screenshot of a Google Colab notebook interface. The top bar shows the Colab logo, the notebook name 'deep1.ipynb', and a star icon. Below this is a menu bar with 'File', 'Edit', 'View', 'Insert', 'Runtime', 'Tools', and 'Help'. The main area has a toolbar with '+ Code' and '+ Text' buttons. On the left, there are icons for a menu, search, a green checkmark, a variable '{x}', and a folder. The code cell is active, showing Python code to check for a GPU and import libraries. The output at the bottom shows 'Found GPU at: /device:GPU:0'.

```
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-3 : Libraries for deep neural 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
```

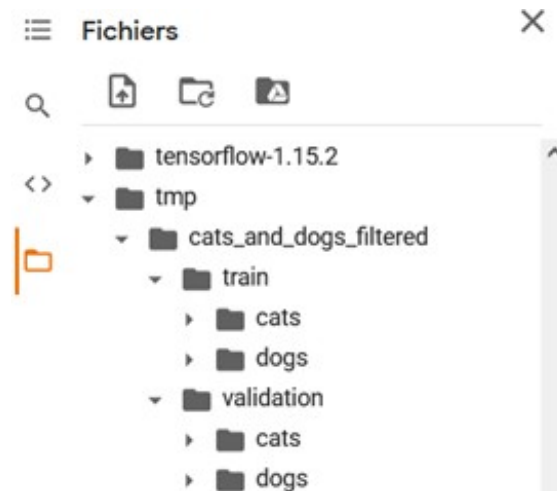
```
import os  
import zipfile  
  
local_zip = '/tmp/cats_and_dogs_filtered.zip'  
zip_ref = zipfile.ZipFile(local_zip, 'r')  
zip_ref.extractall('/tmp')  
zip_ref.close()  
  
train_dir = '/tmp/cats_and_dogs_filtered/train'  
test_dir = '/tmp/cats_and_dogs_filtered/validation'
```

## Part II-3 : Libraries for deep neural 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-3 : Libraries for deep neural 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()
```



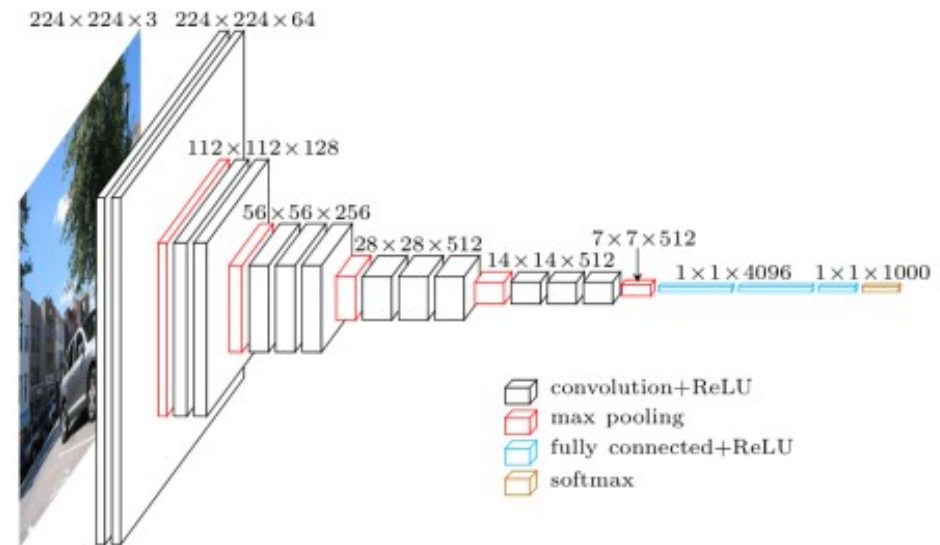
## Part II-3 : Libraries for deep neural networks



- **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
=====
```



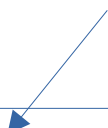
- Especially with such a small dataset !
  - Hopefully, the VGG16 network was trained with multiple animals (including cats and dogs) : the lowest layers may recognize pertinent features
- Note : VGG16 was trained during multiple days on high-end GPUs with *imageNet* dataset (>1M labeled images)

## Part II-3 : Libraries for deep neural 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-3 : Libraries for deep neural 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-3 : Libraries for deep neural 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  
=====
```

A blue arrow points from the right side of the slide towards the line 'Trainable params: 1,254,552'.

## Part II-3 : Libraries for deep neural 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-3 : Libraries for deep neural networks



- **The VGG16 network**

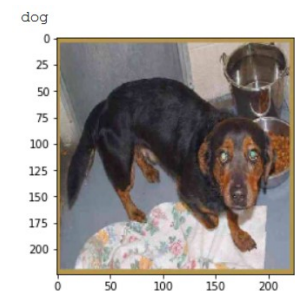
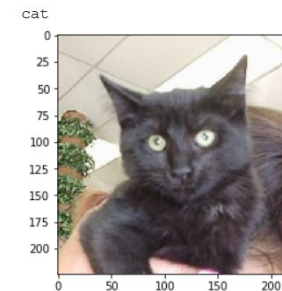
- The network can then be evaluated :

```
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")
```



# Conclusion

- Deep learning is a recent domain...
  - ... but already shows impressive results and achievements
  - Deep learning can still be improved on many aspects, and there is still a great margin for improvements
  - A neuronal network however remains a classifier algorithm, unable to understand or interpret data that it generates, and cannot generate more than what was in training dataset.
- 
- There are other forms of AI, such as reinforcement learning and developmental robotics/learning, that try to interact with an environment to overcome these limitations...
    - ... But this is another story !