Deep Learning for object detection:
fast and accurate results with the YOLO method

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IRMIA Deep Learning Summer School 2022

MINERVA

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Lessons materials

Slides and Google Colab notebook are available on GitHub :

https://github.com/Deyht/IRMIA_2022

Useful commands for shell:

git clone https://github.com/Deyht/IRMIA_2022

git pull

The Jupyter notebook is to open in Google Colab with a GPU reservation.
(The notebook should work on other environment with some adjustments, untested)

All the data will be downloaded and saved in the temporary Colab environment

=> Download locally anything you want to keep on the long term
(for example network saves and figures)

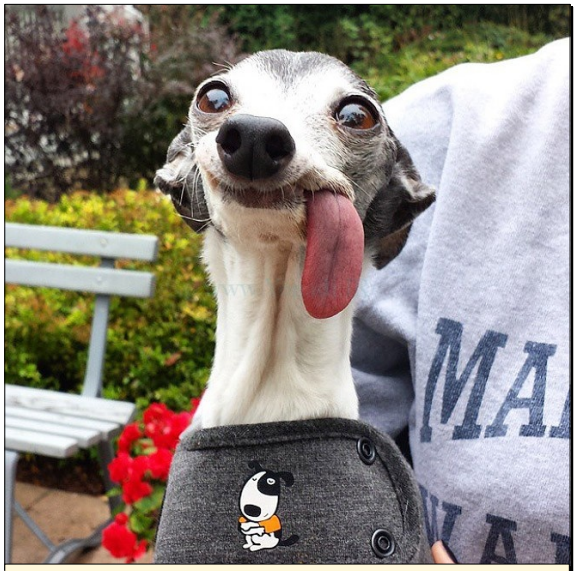
Neural Networks for images

Fully connected networks has shown one weakness

➡ **They are inefficient for handling images !**

- Images are highly dimensional (lots of pixels!)
- They have a very high degree of invariance (mainly translation but also luminosity, color, rotation, ...).

Classical ANN can deal with images by considering each pixel of an image as an individual input but it is STRONGLY inefficient.



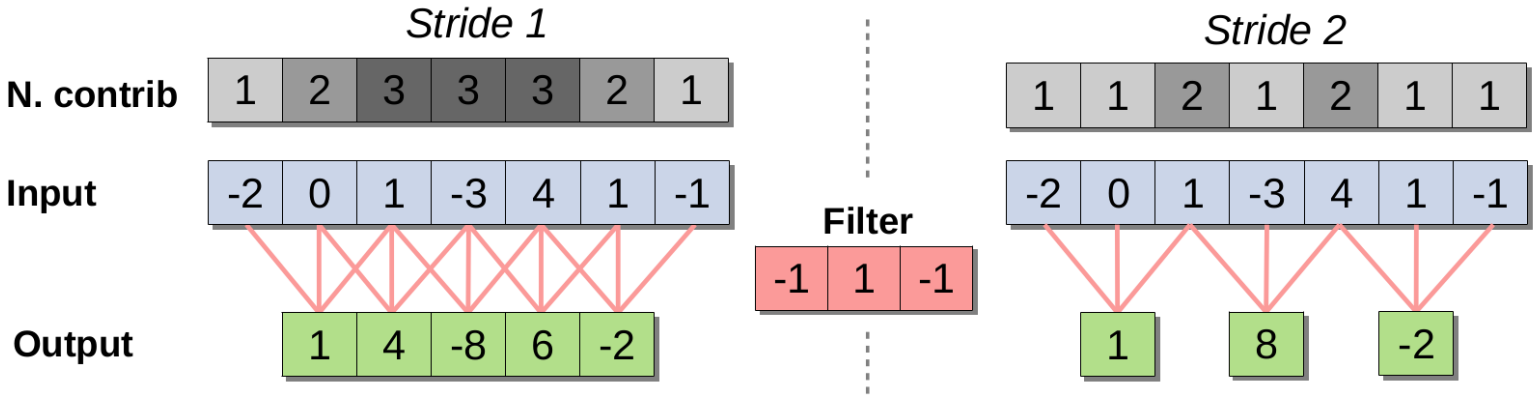
*A **highly dimensional** "dog" with ~0.5 Million pixels. Quite difficult to classify ...*

Driven by the computer vision and pattern recognition community these issues have found a solution in the 90s with:

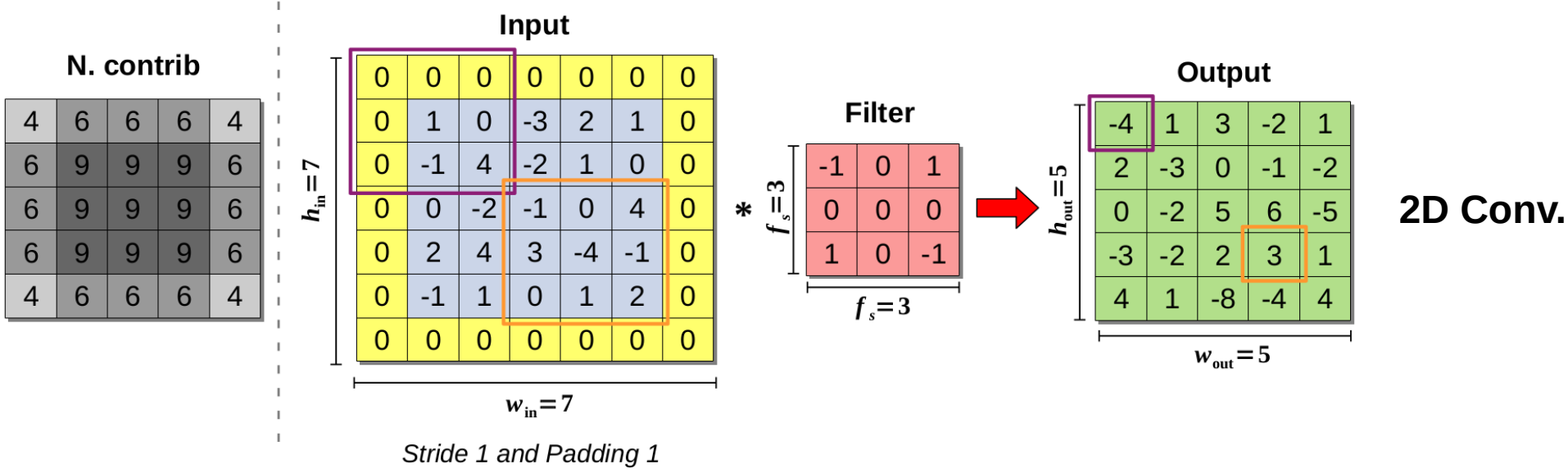
➡ **Convolutional Neural Networks** !

Convolution filter

1D Conv.

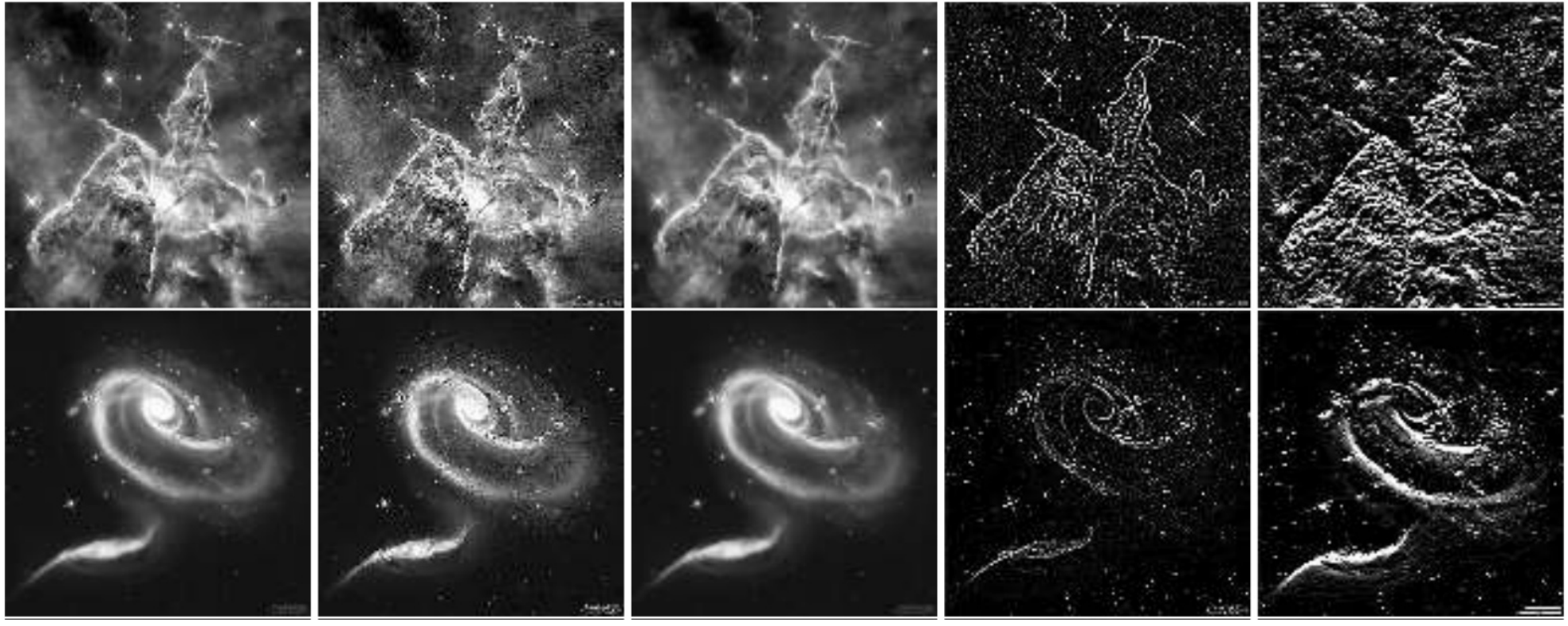


2D Conv.

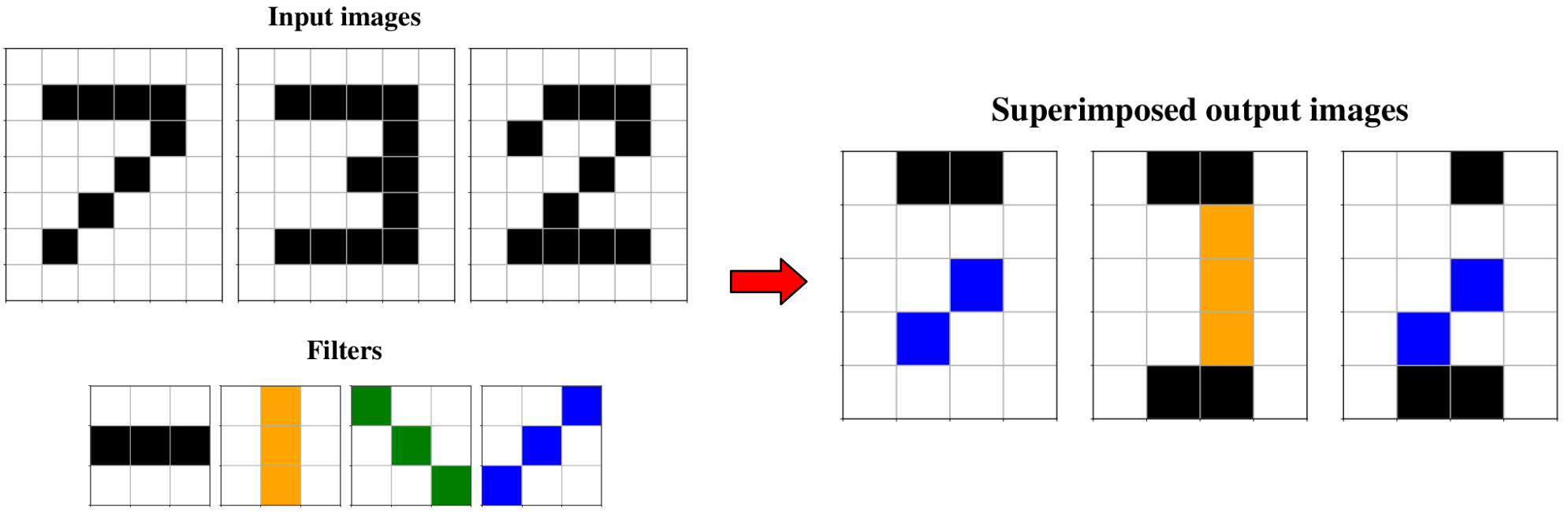


Filter effect examples

No filter	Sharpen	Gaussian blur	Edge detector	Axis elevation
	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	$\frac{1}{16}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	$\begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix}$



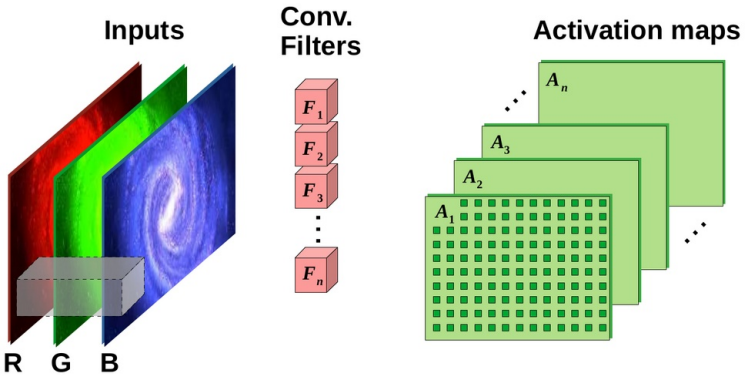
Pattern recognition with several filters



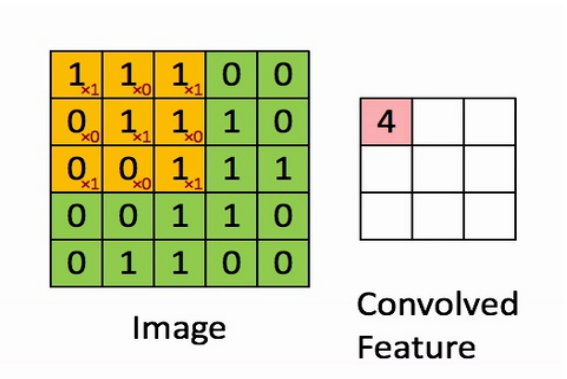
Each filter will produce its own activation map. Combining the information from different activation maps in a new convolutional layer (with a third dimension in the filter corresponding to the number of filters in the previous layer) allow to construct more and more complex patterns.

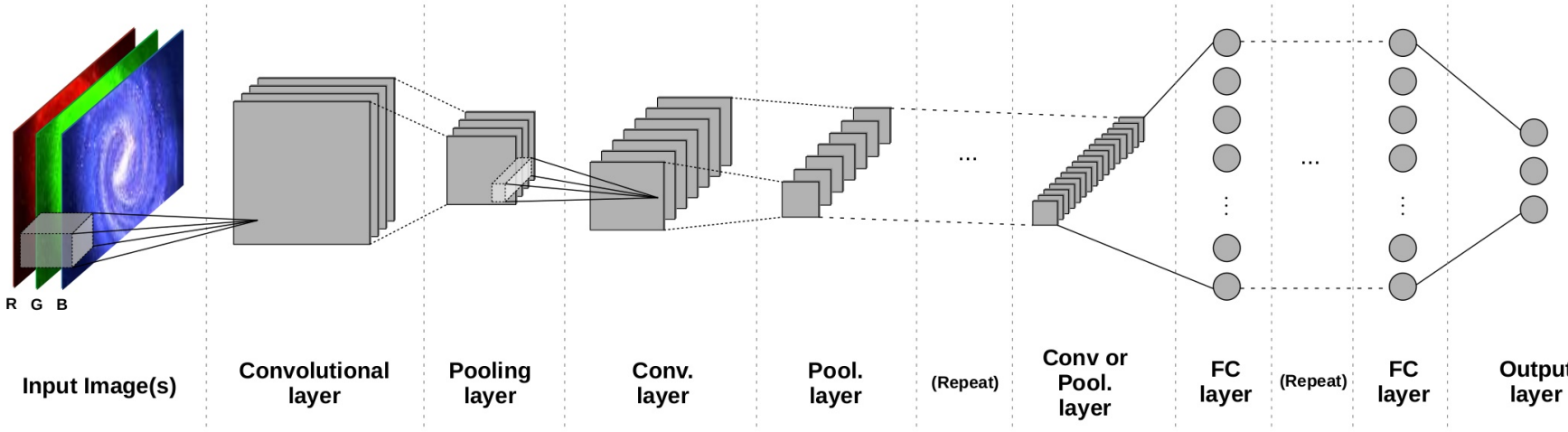
**Here the different activation maps are superimposed using color coding per filter*

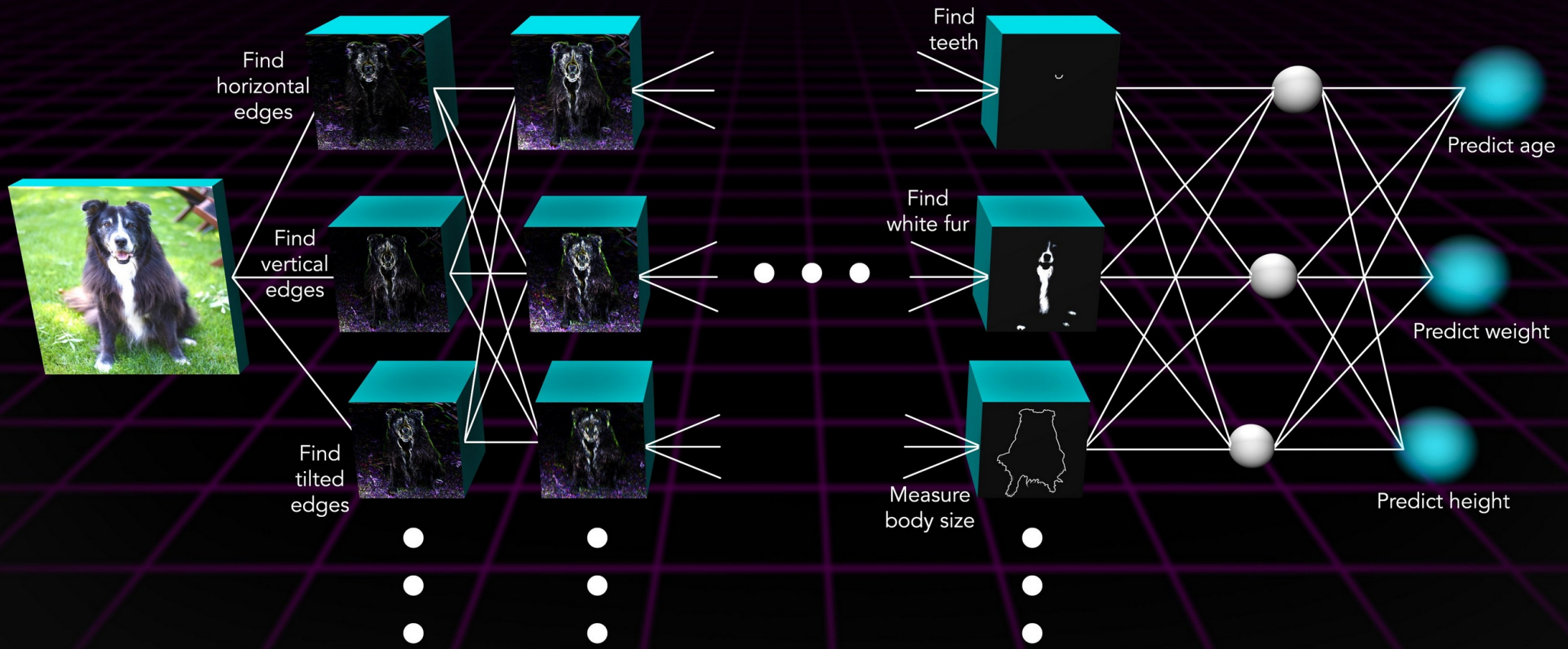
Convolutional Neural Networks



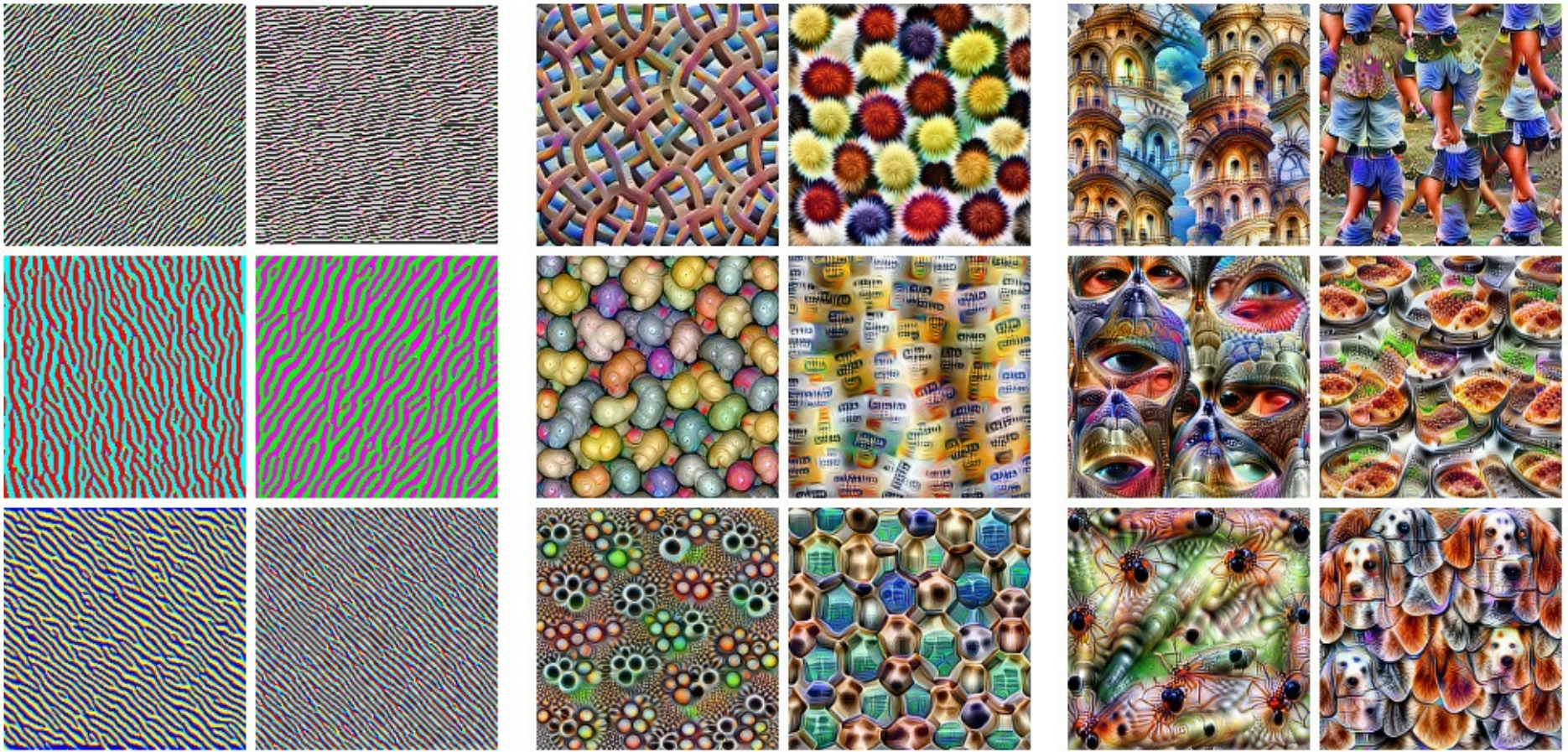
$$g\left(\sum_i X_i \circ W_i\right) = a$$






Find horizontal edges
Find vertical edges
Find tilted edges
Find teeth
Find white fur
Measure body size
Predict age
Predict weight
Predict height

Examples of filter maximization



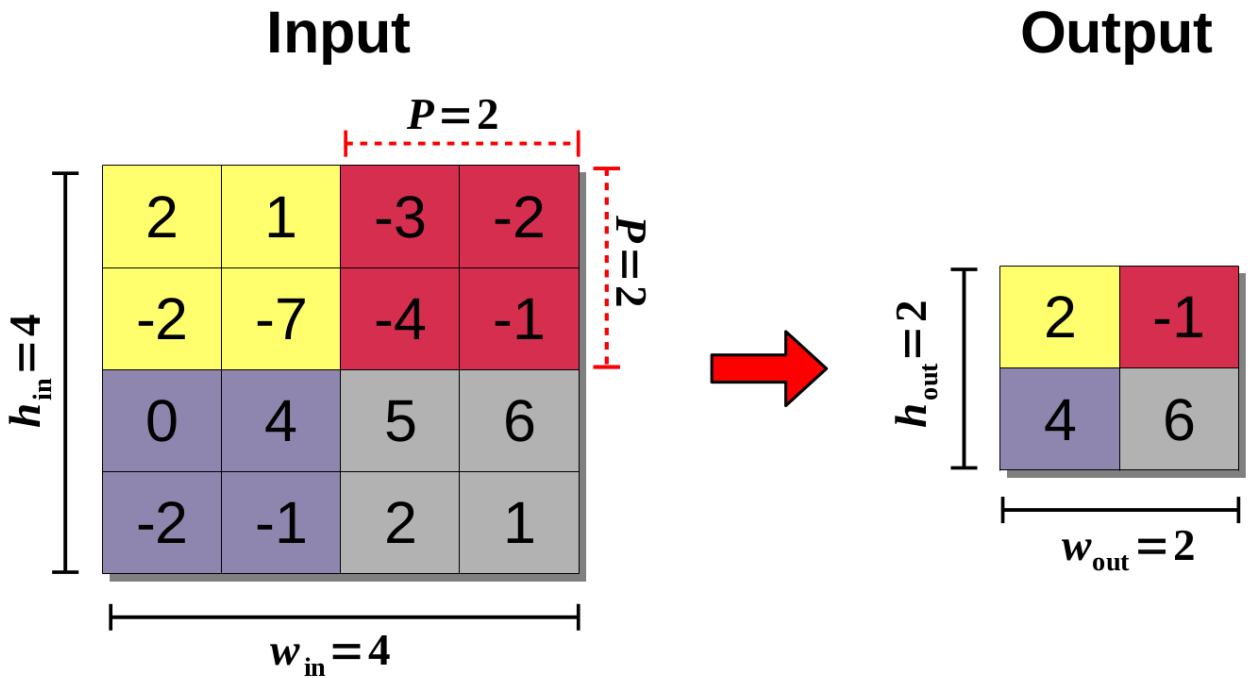
Example of input images that maximize specific filters activation at different depth in a classification network.

Dimensionality reduction: Pooling

A classical convolution operation is parameterized in a way that preserve the spatial dimensionality.

Still, it is most of the time necessary to progressively reduce the “image” size.

One way to reduce the dimensionality it to use Pooling layers !



Different pooling methods exist, the most common being Max-Pooling and Average-Pooling.

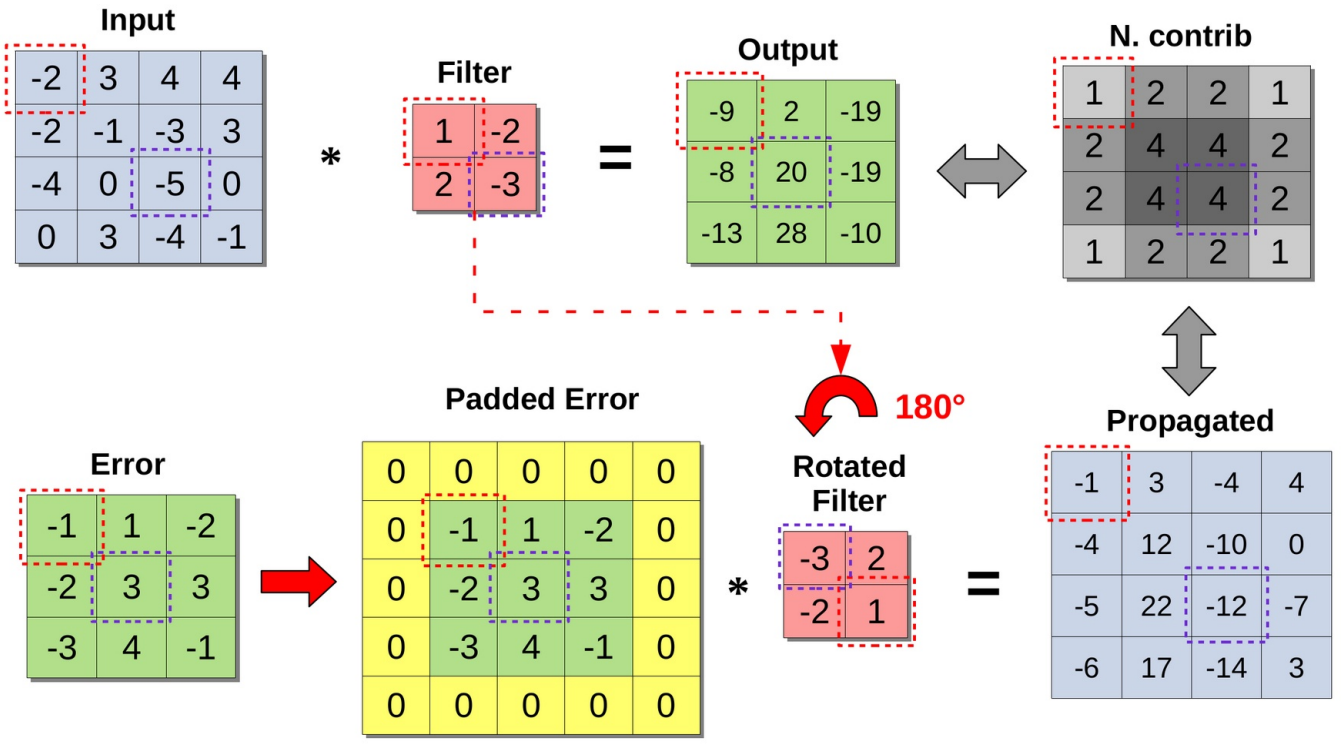
The pooling size can be parametrized, but most of the network architectures reduce each spatial dimension by a factor of two.

Learning the filters

Just like fully connected layers, the convolutional filters can be learned by using backpropagation of the error measured at the output layer.

In practice the error is propagated using a transposed convolution operation, which can be expressed with a classical convolution operation using some simple transformations on specific layer elements.

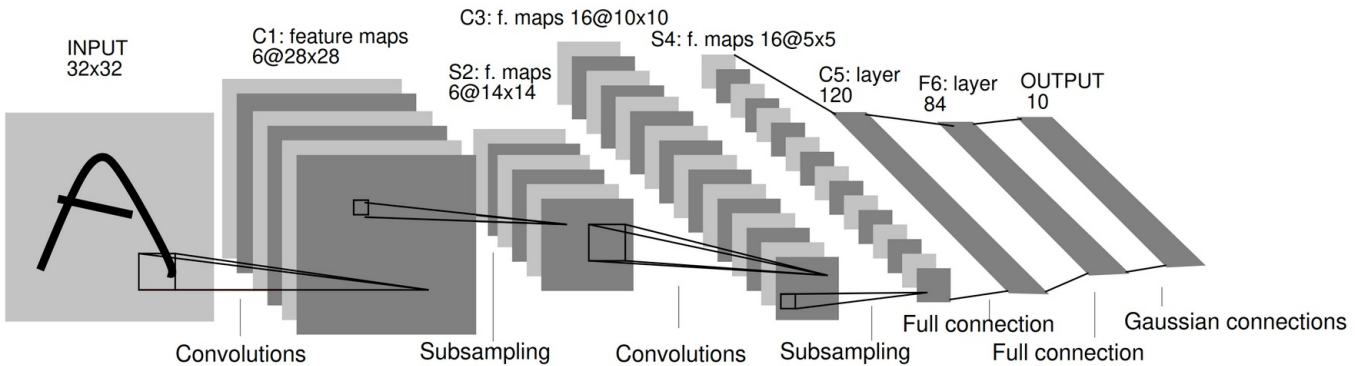
Learning the convolutional filters is the boundary at which most researchers define "**Deep Learning**".

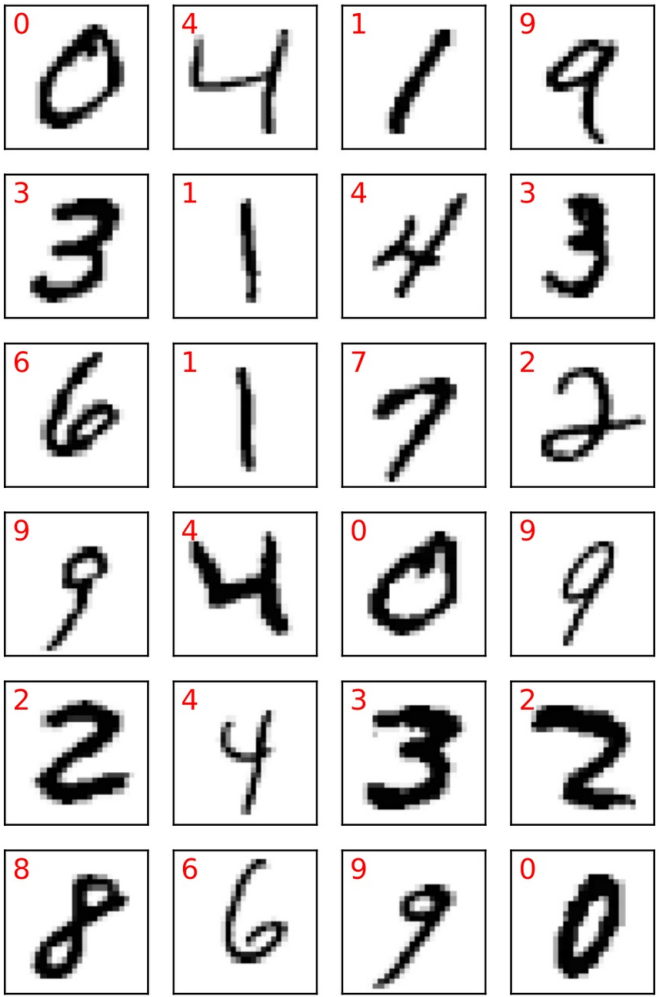


Simple examples: MNIST

The well known **MNIST** (Modified NIST's special dataset) dataset consist of handwritten digits from 500 different writers expressed as 28x28 grayscale images. It is freely accessible in the form of a 60000 image training dataset and a 10000 image test dataset.

Illustration of the LeNet 5 network architecture (from LeCun et al. 2018) for this specific dataset.





Simple examples: MNIST

Actual \ Predicted	C0	C1	C2	C3	C4	C5	C6	C7	C8	C9	Recall
C0	976	0	1	0	0	0	1	1	1	0	99.6%
C1	0	1132	1	0	1	0	0	0	1	0	99.7%
C2	1	1	1027	0	1	0	0	1	1	0	99.5%
C3	0	0	1	1004	0	3	0	1	1	0	99.4%
C4	0	0	1	0	972	0	1	0	1	7	99.0%
C5	0	0	0	4	0	886	1	0	0	1	99.3%
C6	3	2	0	0	1	2	949	0	1	0	99.1%
C7	0	2	3	0	0	0	0	1020	1	2	99.2%
C8	0	0	1	1	0	1	1	1	968	1	99.4%
C9	0	0	0	0	3	1	0	4	0	1001	99.2%
Precision	99.6%	99.6%	99.2%	99.5%	99.4%	99.2%	99.6%	99.2%	99.3%	98.9%	99.35%

Obtained using CIANNA with the following architecture
=> I-28.28, C-6.5, P-2, C-16.5, P-2, C-48.3, D-1024_d0.5, D-256_d0.2, D10

All inner layers uses leaky ReLU activation (factor 0.1) and the output uses a Softmax activation.
The batch size is b=64, the learning rate is $\eta=2x10^{-4}$ with a small decay up to $\eta=1x10^{-4}$, and a momentum of $\alpha=0.9$.

The network is trained for 40 epochs.

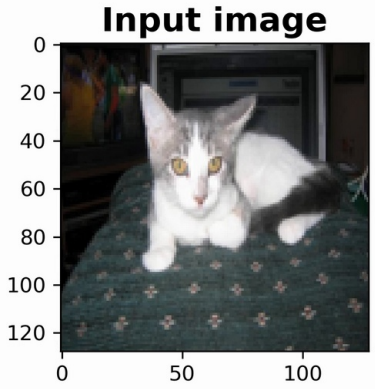
Simple examples: ASIRRA

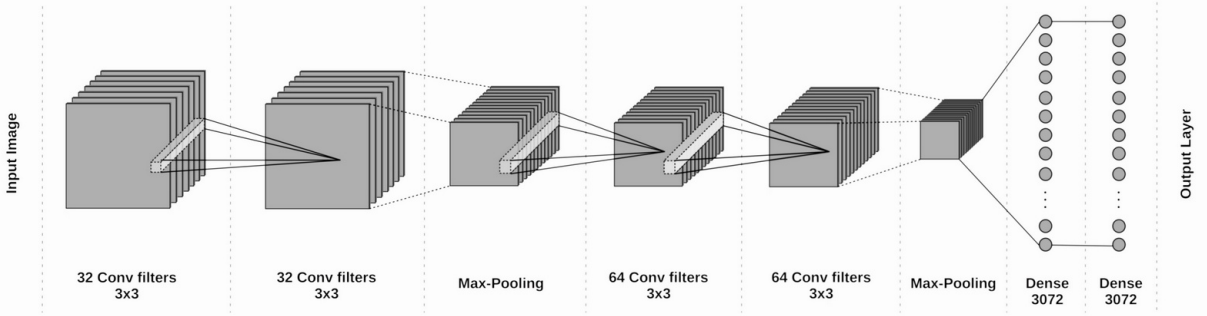
ASIRRA (Animal Species Image Recognition for Restricting Access): 25000 images, 50 % cats, 50 % dogs.

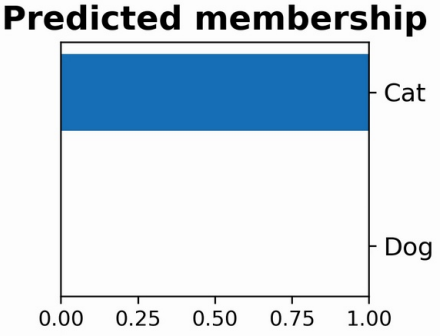
Typical of a **CAPTCHA** task or **HIP** (Human Interactive Proof) because the task is easy and quick for humans.

➡ Nowadays modern CNN tools have more than 90% accuracy on ASIRRA !

Simple examples: ASIRRA








```
Net. forward perf.: 13597.95 items/s
Cumulated error:         0.333725

ConfMat (valid set)
                                 Recall
               925 |         75 |       92.50%
                68 |        932 |       93.20%
Precision :    93.15%      92.55%  Correct : 92.849998%
```

It is possible to obtain good results with relatively small networks (~90% accuracy), while more complex networks can get up to 97-98% accuracy.

Obtained using CIANNA with the following architecture => I-128.128.3, C-32.3, P-2, C-64.3, P-2, C-128.3, P2, C128.3, P2, D-512_d0.2, D2

All inner layers use leaky ReLU activation (factor 0.1) and the output uses a Softmax activation.
The batch size is b=32, the learning rate is $\eta=2x10^{-4}$ with a small decay up to $\eta=5x10^{-5}$, and a momentum of $\alpha=0.8$.

The network is trained for 20 epochs.

“Object detection” types

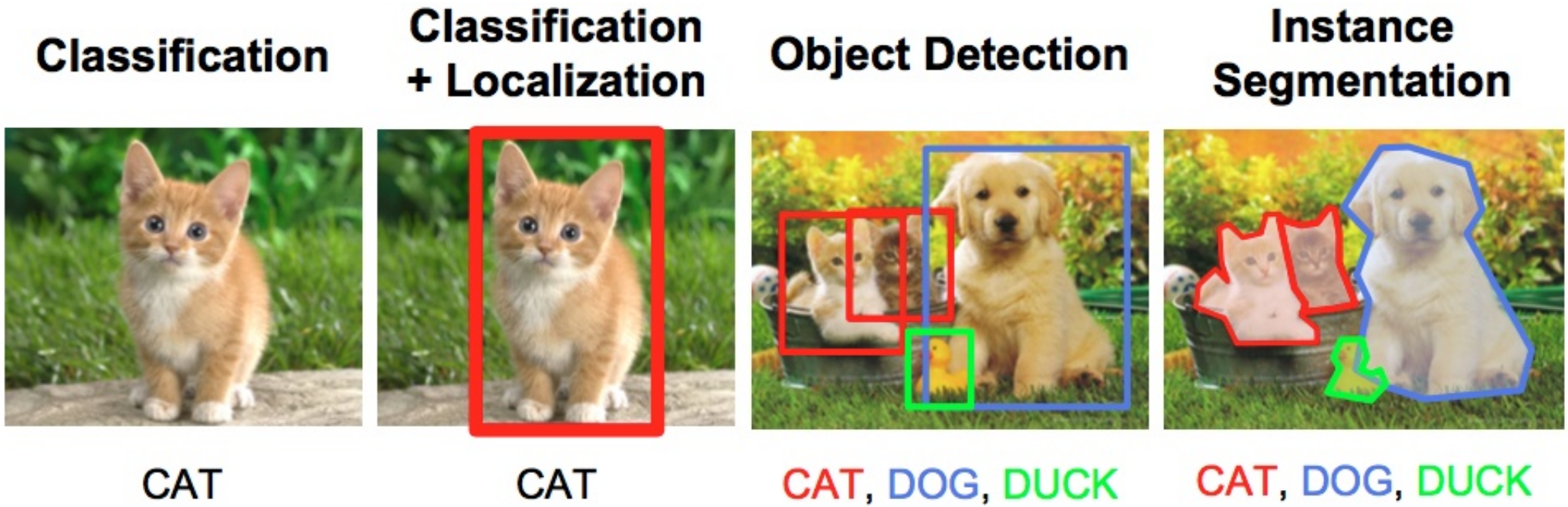


*Image from Stanford Deep Learning course cs224

Our objective : multiple object detection

The PASCAL Visual Object Classes dataset(s)

Standardized image datasets for object class recognition organized in the form of annual challenges from 2005 to 2012

PASCAL2
Pattern Analysis, Statistical Modelling and Computational Learning

http://host.robots.ox.ac.uk/pascal/VOC/index.html

Targets for various “tasks” :

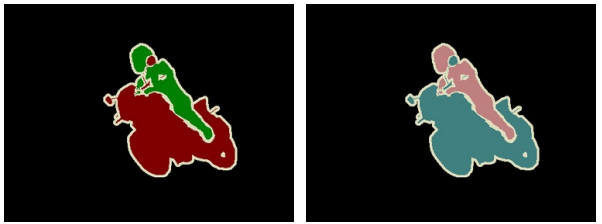
Classification

[Person, Horse]

Detection

List of bounding boxes and their associated class

Segmentation



List of segmentation masks and their associated class

The PASCAL Visual Object Classes dataset(s)

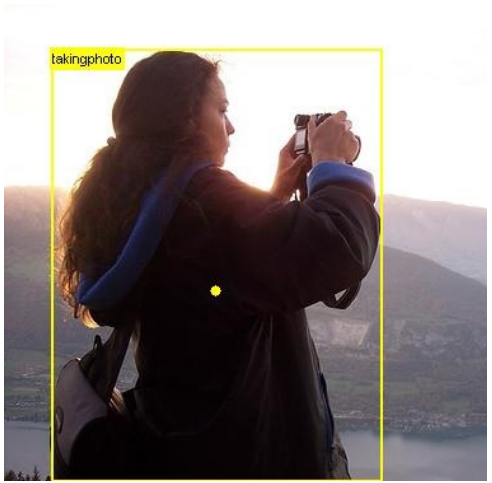
Standardized image datasets for object class recognition organized in the form of annual challenges from 2005 to 2012

PASCAL2
Pattern Analysis, Statistical Modelling and Computational Learning

Targets for various “tasks” :

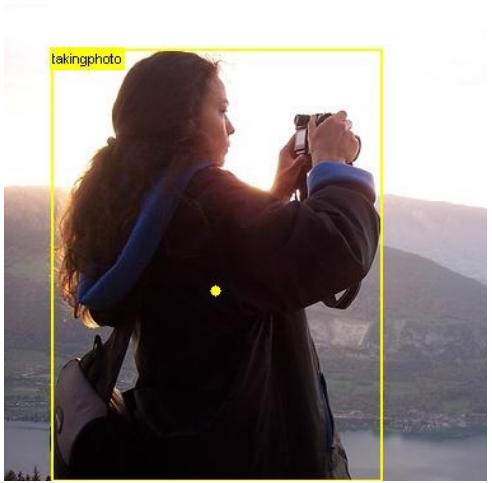
http://host.robots.ox.ac.uk/pascal/VOC/index.html

Boxless Action



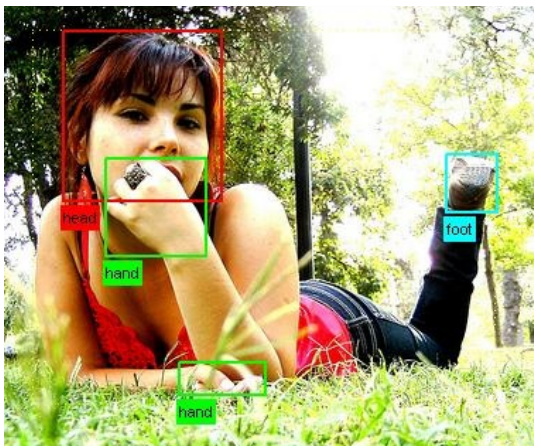
A single reference point and the associated action

Action



List of person boxes and their associated action

Person Layout



List of bounding boxes corresponding to body parts

Pascal detection task
Dataset construction and properties

VOC – 2005 : Standalone data
1578 Train (and 1293 Test) annotated images, detection task with 4 classes

VOC – 2006 : Standalone data
5618 Train (and 2686 Test) annotated images, detection task with 10 classes

VOC – 2007 : Standalone data
5011 Train (and 4952 Test) annotated images, detection task with 20 classes

VOC - 2012 : incremental from 2008 to 2012
11540 Train annotated images (test set hidden), detection task with 20 classes

One can **combine the Train and Test data from 2007 with the Train data from 2012** to obtain a larger training dataset of **21503 images, containing 52090 objects**

Total	plane	bicycle	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	m-bike	person	p-plant	sheep	sofa	train	tv
52090	1456	1401	2064	1403	2233	1035	4468	1951	3908	1091	1030	2514	1420	1377	17784	1967	1312	1053	1207	1416

Practical objectives for the course

Switching to practice with the Google Colab notebook !

Introduction

- Get the Google Colab environment working
- Get the Pascal VOC data and visualize it
- Install and understand the CIANNA Deep Learning framework

Using a combination of the data from Pascal VOC 2007 and 2012:

A - Training a simple classifier using object cutouts

B - Training a sliding window detector

C - Training a dedicated YOLO object detector

CIANNA

Convolutional Interactive Artificial Neural Networks by/for Astrophysicists

General purpose framework (like Keras, PyTorch, ...)
BUT developed for **astronomical applications**

github.com/Deyht/CIANNA
Open source – Apache 2 license

CPU OpenMP OpenBLAS
x86 Intel/AMD & ARM

GPU NVIDIA CUDA
5 dernière générations

Custom YOLO implementation

Activation **Cost** **Association**

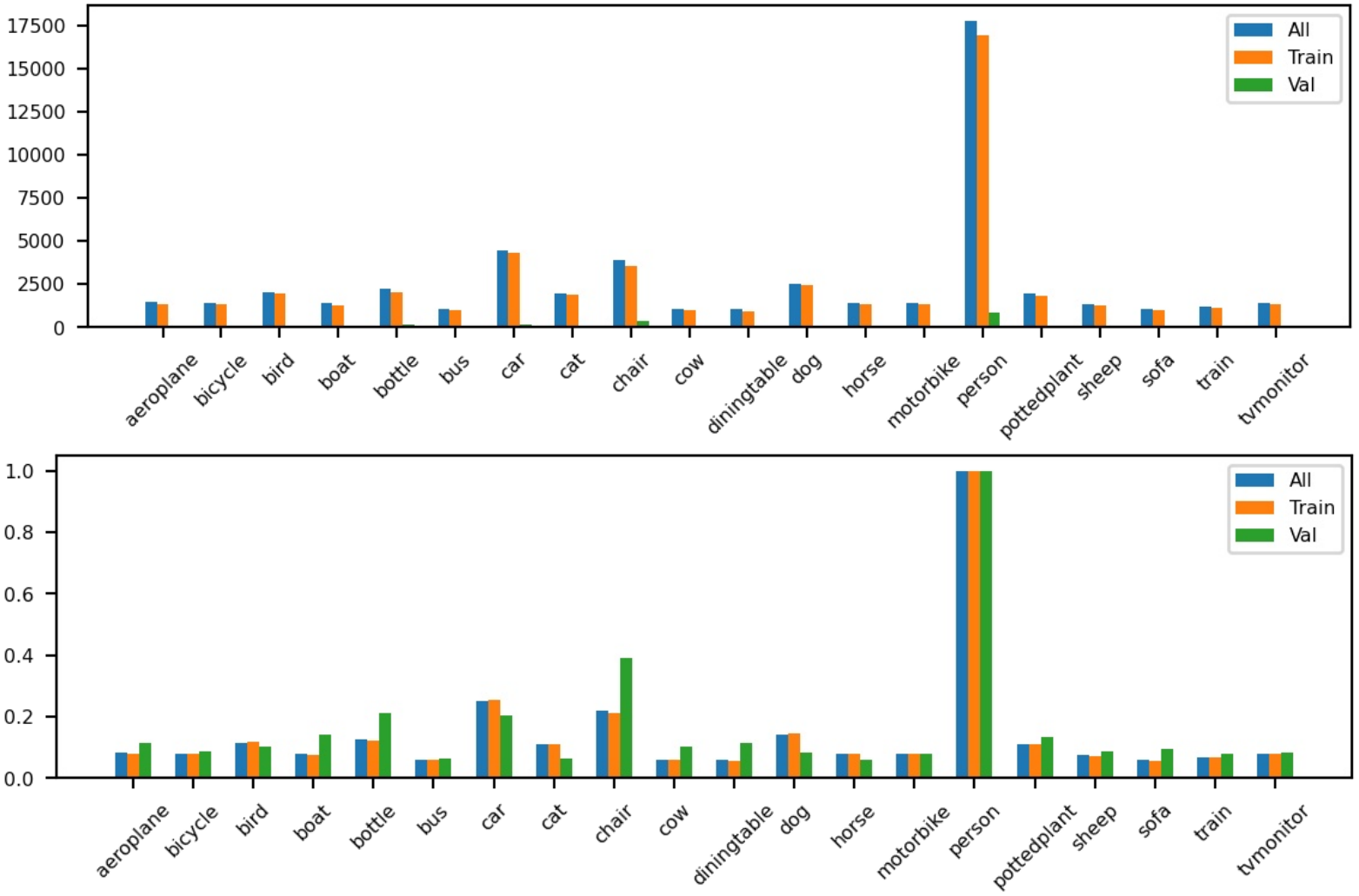
And specificities : supplementary parameters per box, cascading loss, custom NMS process, ...

Full user interface

Successfully deployed on

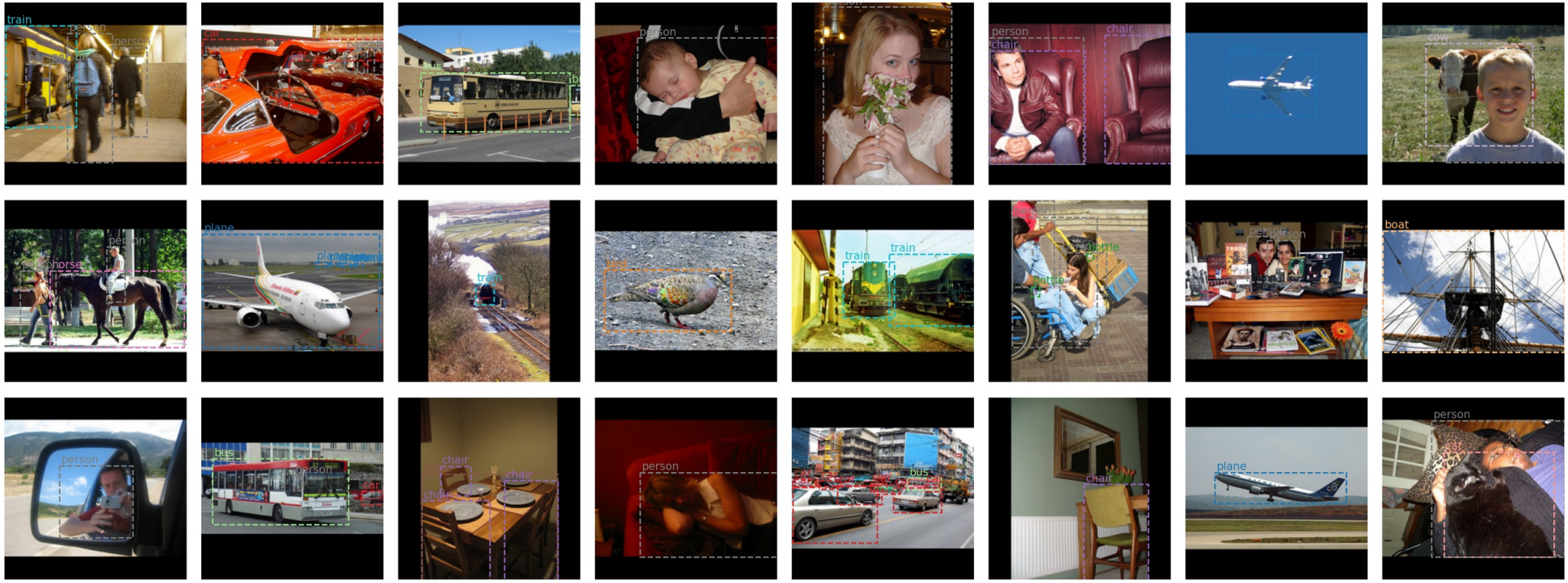
- **Laptops / Workstation**
- **Local compute serveurs**
- **Mesocenteurs**
- **Large computing facilities**

Training dataset summary statistics



Training dataset summary statistics

All the images are made square and resized to 224x224 pixels, using uint8 encoding.
The resulting dataset is saved in a binary format for use over all the applications in the notebook.
Target bounding boxes are encoded in a specific format for CIANNA, and also saved as binary.



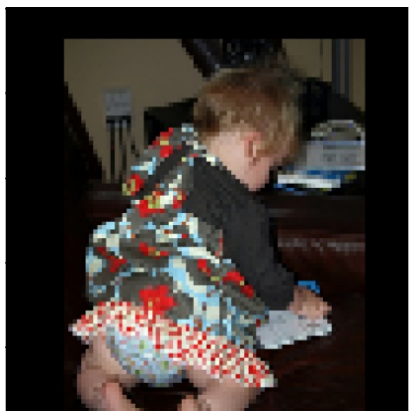
A - Simple classifier using object cutouts

We define a classifier with an **input dim. of 96x96**, and an **output dim. of 20** (number of classes) using Softmax activation. 1000 original images are kept apart for validation.

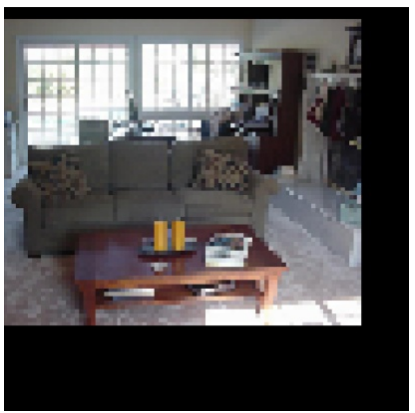
The training images dynamically generated as followed

- Pick a random image in training set
- Pick a random target box in the image
- Apply simple augmentation (zoom, and translate)
- Cutout the augmented region and rescale it the input size

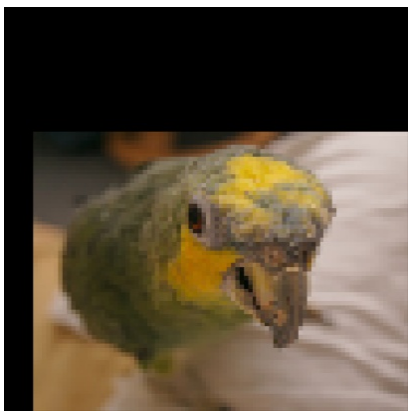
The validation images correspond to all the objects in the validation set with no augmentation



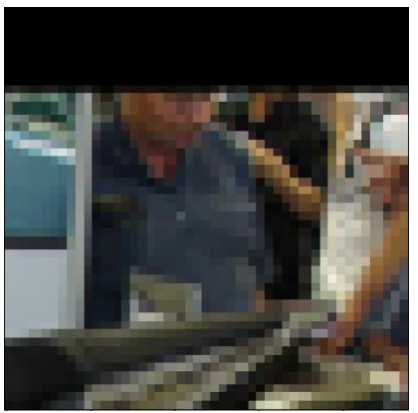
[person]



[sofa]



[bird]



[person]

A - Simple classifier using object cutouts

Suggested network architecture :

```
cnn.conv(f_size=i_ar([3,3]), nb_filters=48, padding=i_ar([1,1]), activation="RELU")
cnn.pool(p_size=i_ar([2,2]), p_type="MAX")
cnn.conv(f_size=i_ar([3,3]), nb_filters=96, padding=i_ar([1,1]), activation="RELU")
cnn.pool(p_size=i_ar([2,2]), p_type="MAX")
cnn.conv(f_size=i_ar([3,3]), nb_filters=128, padding=i_ar([1,1]), activation="RELU")
cnn.pool(p_size=i_ar([2,2]), p_type="MAX")
cnn.conv(f_size=i_ar([3,3]), nb_filters=256, padding=i_ar([1,1]), activation="RELU")
cnn.pool(p_size=i_ar([2,2]), p_type="MAX")
cnn.conv(f_size=i_ar([3,3]), nb_filters=512, padding=i_ar([1,1]), activation="RELU")
cnn.conv(f_size=i_ar([3,3]), nb_filters=512, padding=i_ar([1,1]), activation="RELU")
cnn.dense(nb_neurons=1024, activation="RELU", drop_rate=0.4)
cnn.dense(nb_neurons=512, activation="RELU")
cnn.dense(nb_neurons=nb_class, activation="SMAX")
```

Confusion matrix on the validation set at epoch 1100 :

ConfMat (valid set)

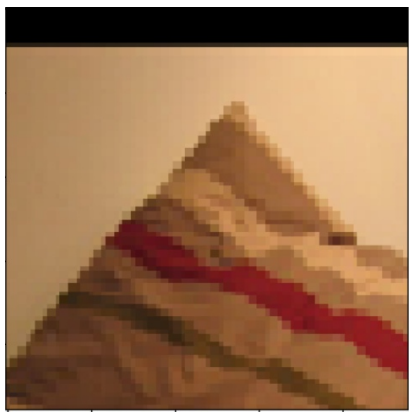
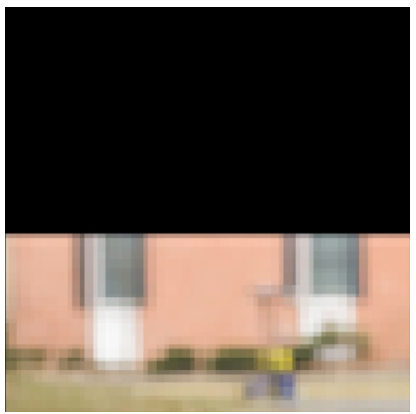
																					Recall
	68	1	2	7	0	3	10	1	1	0	0	1	0	1	3	0	0	0	0	1	68.69%
	2	24	3	0	3	0	4	1	7	1	0	6	0	6	15	2	0	0	1	1	31.58%
	3	0	61	1	0	0	0	3	0	1	0	5	0	0	6	1	1	0	0	9	67.03%
	9	2	4	74	0	3	8	0	0	0	0	3	0	1	6	1	0	0	2	9	60.66%
	1	0	1	2	106	0	2	2	9	0	0	2	0	1	40	5	0	0	0	13	57.61%
	1	0	0	2	1	39	8	0	1	1	0	0	0	0	1	0	0	0	2	0	69.64%
	0	1	0	2	1	5	136	1	3	0	0	0	0	1	12	2	0	2	1	10	76.84%
	0	0	0	0	0	0	1	29	0	0	0	18	0	0	2	2	0	1	0	2	52.73%
	0	6	6	1	14	2	8	4	186	0	3	2	0	0	45	4	1	10	2	35	54.87%
	0	0	0	0	2	0	0	1	2	50	0	8	5	0	12	1	8	0	0	0	56.18%
	0	0	3	0	0	0	1	4	15	0	42	3	0	0	21	3	0	5	0	4	41.58%
	0	0	0	0	0	0	1	13	0	0	0	42	2	1	5	1	5	0	0	2	58.33%
	0	1	1	0	0	0	0	1	2	14	0	7	17	0	5	0	3	0	1	1	32.08%
	0	2	2	0	0	0	7	0	1	0	0	4	0	37	12	0	1	0	1	2	53.62%
	1	3	7	0	15	0	6	7	17	1	0	21	1	12	768	1	0	1	1	7	88.17%
	0	2	2	0	5	0	1	0	2	0	0	0	0	0	23	76	0	0	0	4	65.52%
	0	0	0	0	5	0	0	0	0	8	0	4	2	0	3	0	52	0	0	1	69.33%
	0	0	0	4	2	0	2	2	14	0	2	2	1	0	17	1	0	29	0	5	34.52%
	3	0	0	3	0	3	5	0	2	0	0	0	0	0	3	1	0	2	44	4	62.86%
	0	0	0	0	0	0	0	0	1	0	0	1	0	0	6	0	0	0	0	3	84.51%
	0	0	0	1	0	0	1	2	6	1	0	0	0	0	4	1	1	1	3	0	95.80%
Precision	77.27%	57.14%	66.30%	76.29%	68.83%	70.91%	67.66%	40.85%	69.14%	64.94%	89.36%	32.56%	60.71%	61.67%	76.11%	74.51%	72.22%	56.86%	75.86%	78.95%	80.91%	Acc	71.78%

B - Training a sliding window detector

We just slightly modify the previous classifier

- We add a new “background / empty” class, raising the output dimension to 21
- When generating data
  - ➞ **80% of the time, generate an image and class as before**
  - ➞ **Generate a “background / empty” example**
    a) Pick a random image, and define a starting *size*
    b) Randomly select a position in the image and define a box around it using *size*
    c) Check if box overlap a target : If no accept the box and rescale it, if yes retry random position
    d) If the box is rejected X times, reduce *size* and retry X times
    e) If *size* become two small, stop the process and use an empty (zero) input instead

The validation is enriched with “selected” background examples using the validation images

The performance of this new classifier should be similar with ~95% recall on background examples

B - Training a sliding window detector

The sliding window principle

Our classifier is trained to identify individual objects relatively centered in the input image.

To use it as a **sliding window detector**, one can split a larger image on “chunks” that each goes through the network.

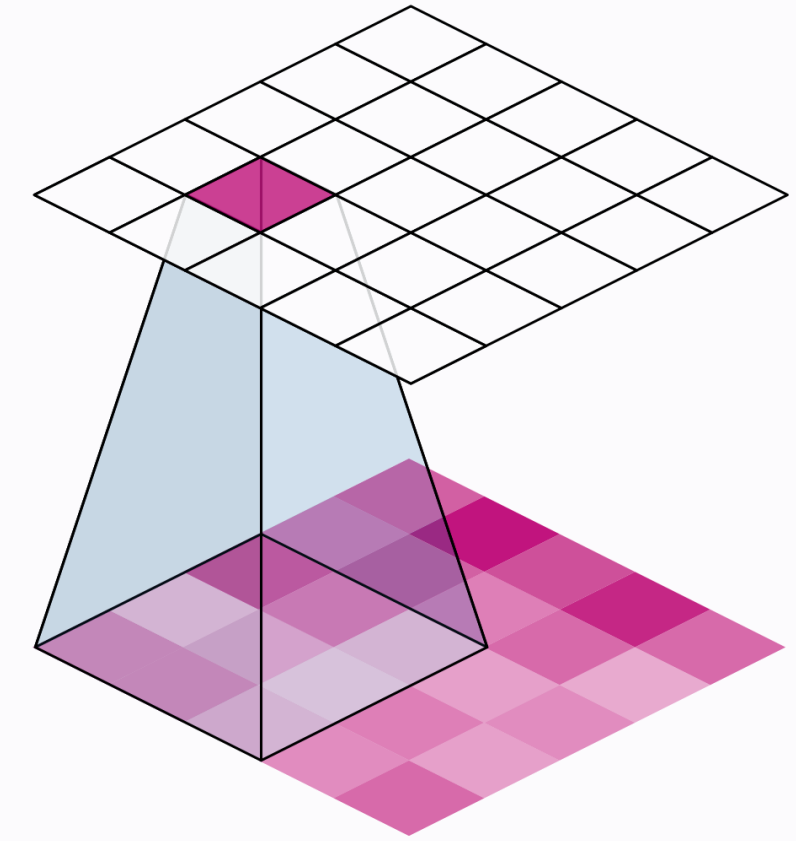
To increase the chance of the object to be centered on the “input window”, each chunks **partially overlap each others**.

This all process is similar to a convolution, with the filter being the classifier

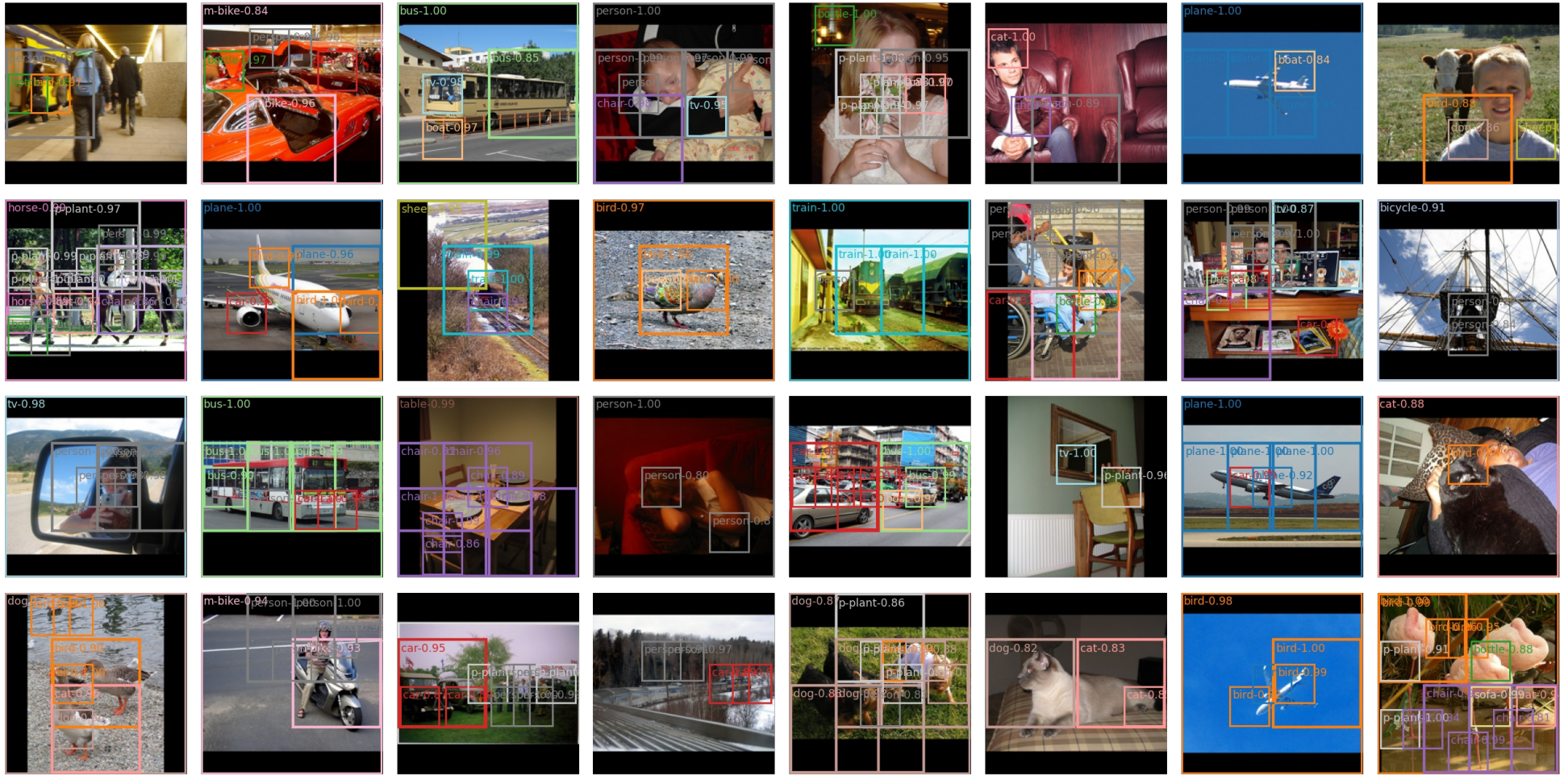
To improve prediction across scales, one can use several window sizes (each time rescale to the classifier input size) in order to detect larger and small objects in the image.

In the present case we use **3 window sizes** [224, 112,56] with a respective stride of [0, 56, 28].

This leads to a number of « chunk » par size of [1, 9, 49], corresponding to grids of [1x1, 3x3, 7x7].



B - Training a sliding window detector



Questions : How to filter overlapping detections ? How to evaluate prediction performance ?