

AI for Astrophysics: Advanced Neural Networks

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**Doctoral course - ED AAIF
2025/2026**

Lessons materials

Slides, exercises, codes, corrections and datasets are **available on GitHub** and will be updated regularly:

http://github.com/Deyht/ML_OSAE_M2

```
git clone https://github.com/Deyht/ML_OSAE_M2  
git pull
```

Or download the repository in zip file

Avoid losing your work on forced pull updates by copying all files from the cloned repository into a working directory!

Do not copy and past content from git-hub pages (lead to format errors).
Use python up to 3.10 but not more recent.

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.



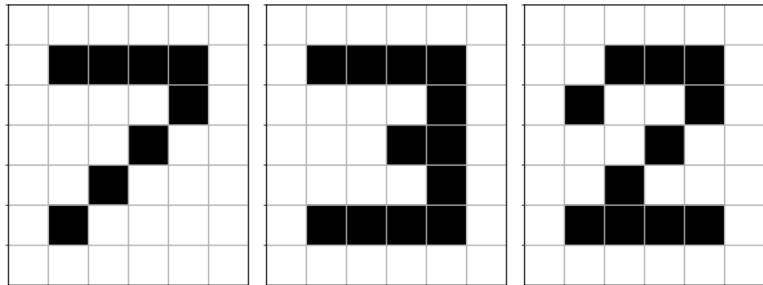
A **highly dimensional** “dog”
with ~0.5 Million pixels.
Quite difficult to classify ...

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

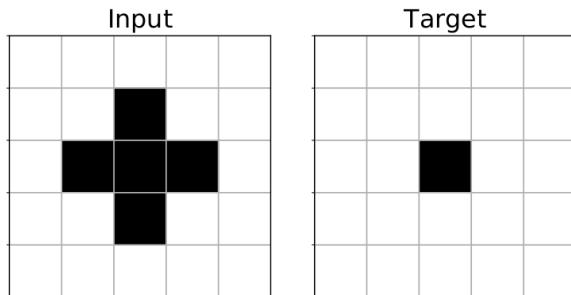
→ **Convolutional Neural Networks !**

Spatially coherent information

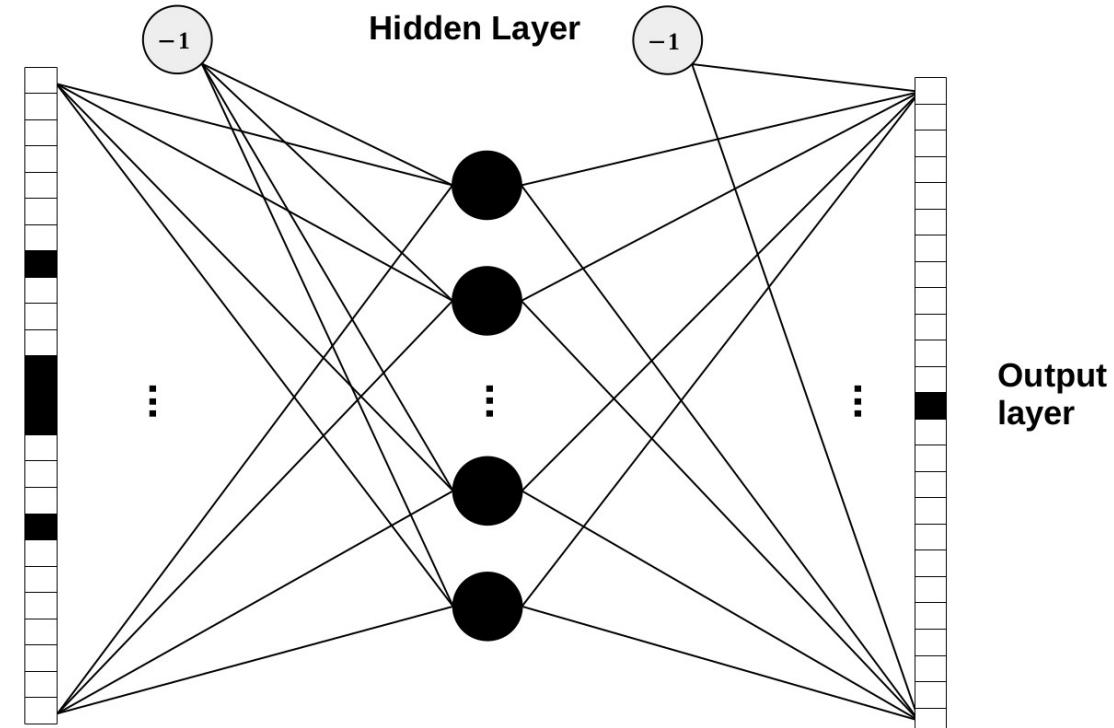
Classical ANN can deal with images by considering *each pixel* of an image *as an individual input* but it is **STRONGLY inefficient**.



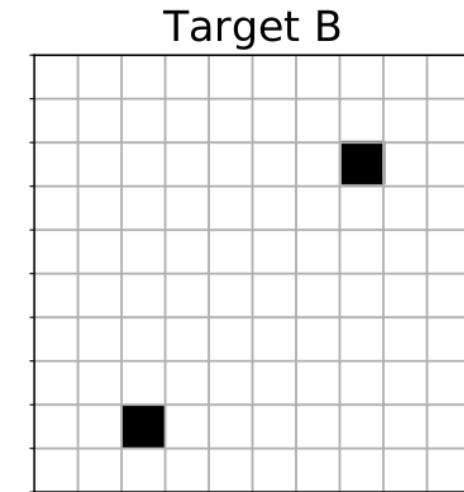
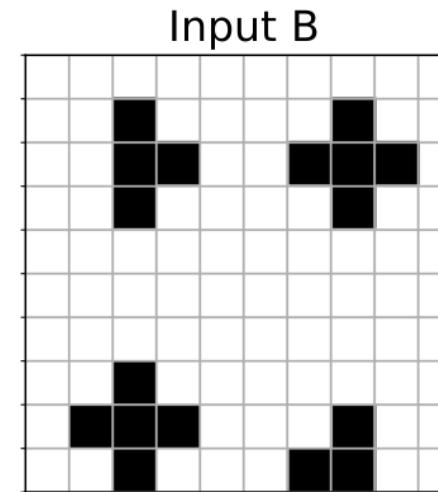
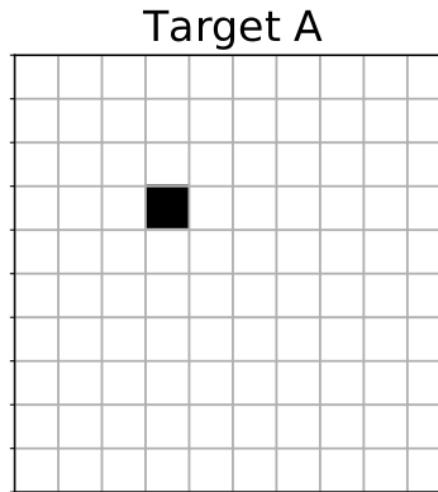
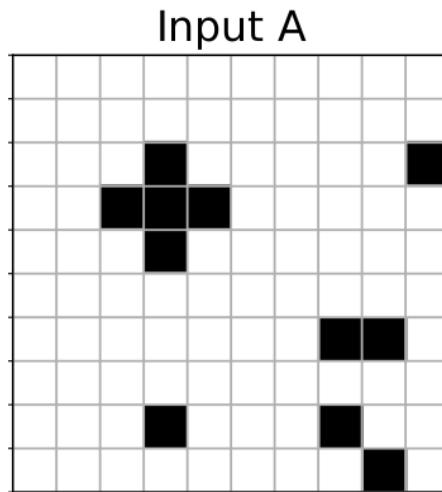
Simple digit representation as a 6×7 binary pixel image



Representation of a simple cross pattern on a 5×5 image as input, and the corresponding localization prediction on an equivalent size output image



Spatially coherent information : Pattern recognition

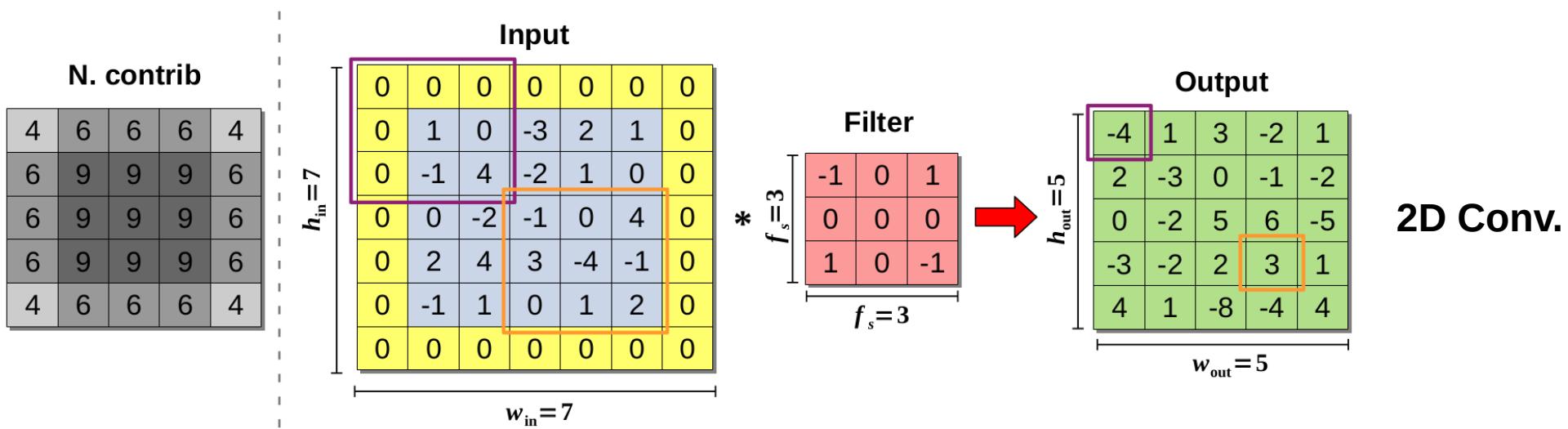
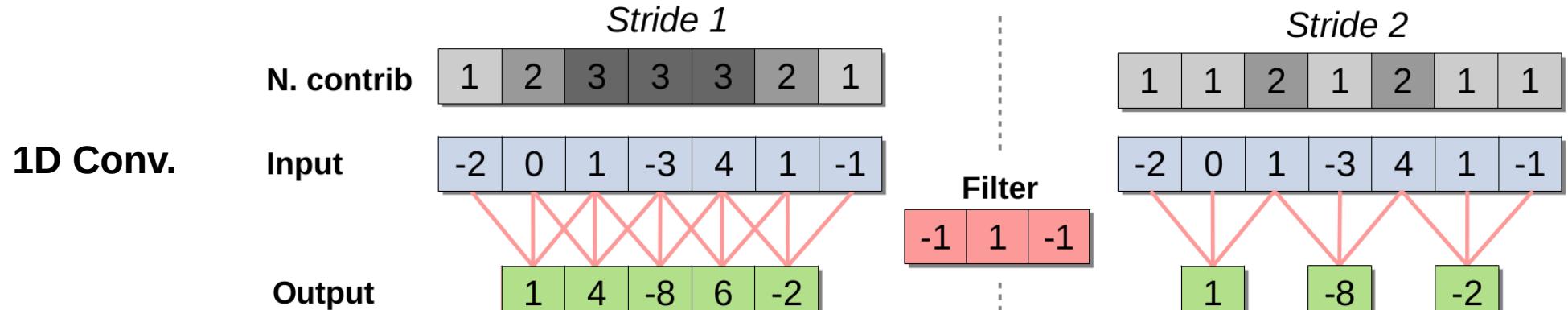


Looking for specific patterns can be automatized by **scanning all the possible positions** in the image.

In contrast, training a fully connected network to do the same task would require learning the presence or non-presence of the pattern at every possible position instead of learning the pattern once and only checking its presence at every position.

How to circumvent this behavior ? → Use **Convolutional layers** !

Convolution filter



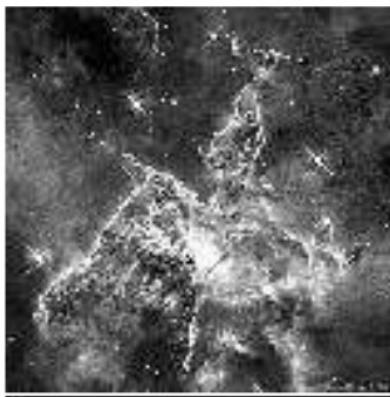
Filter effect examples

No filter



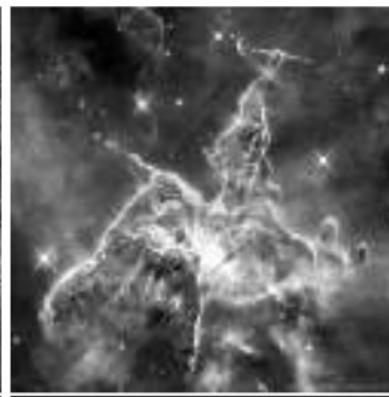
Sharpen

$$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$



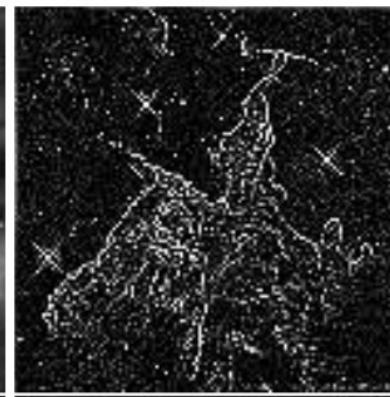
Gaussian blur

$$\frac{1}{16} \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$$



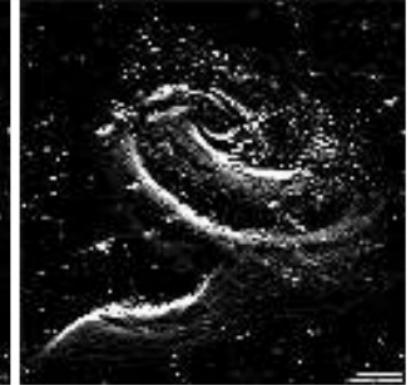
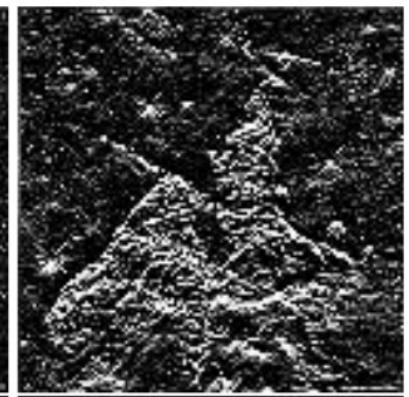
Edge detector

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



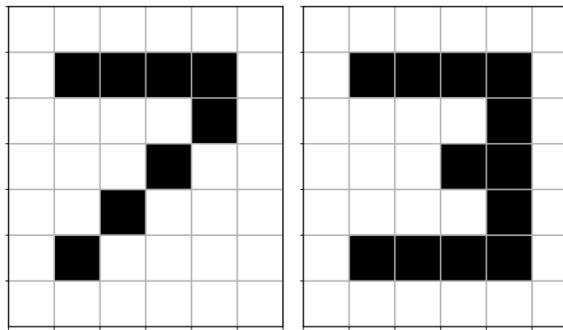
Axis elevation

$$\begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix}$$

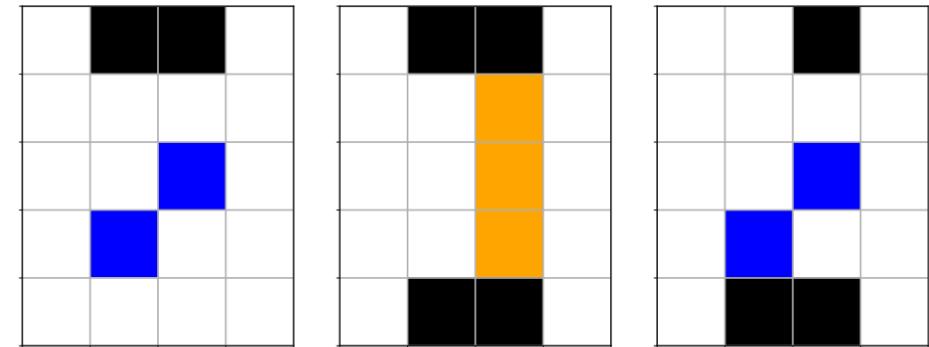


Pattern recognition with several filters

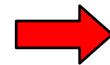
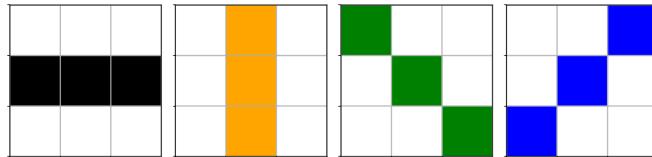
Input images



Superimposed output images



Filters

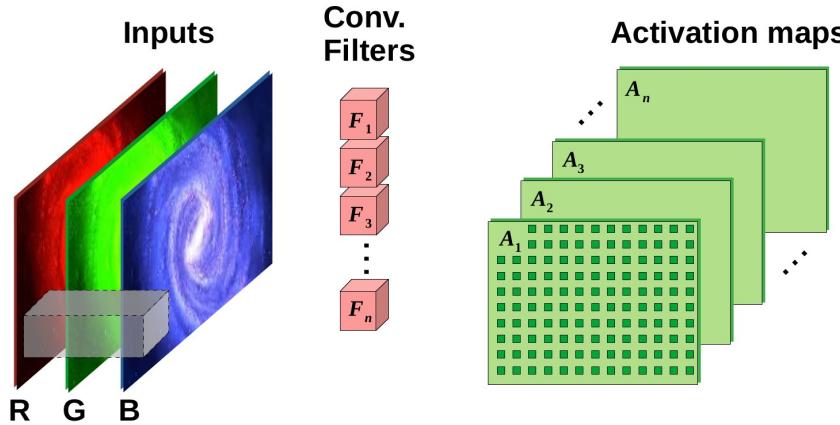


Each filter will produce its own activation map.

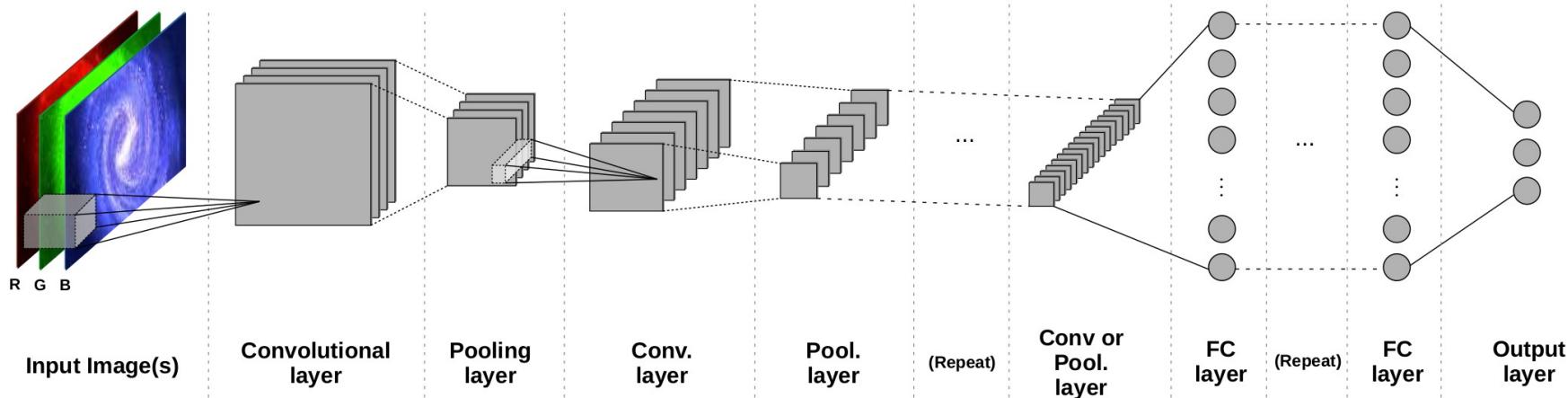
Combining the information from different activation maps allows to **construct more complex patterns**.

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

Convolutional Neural Networks



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

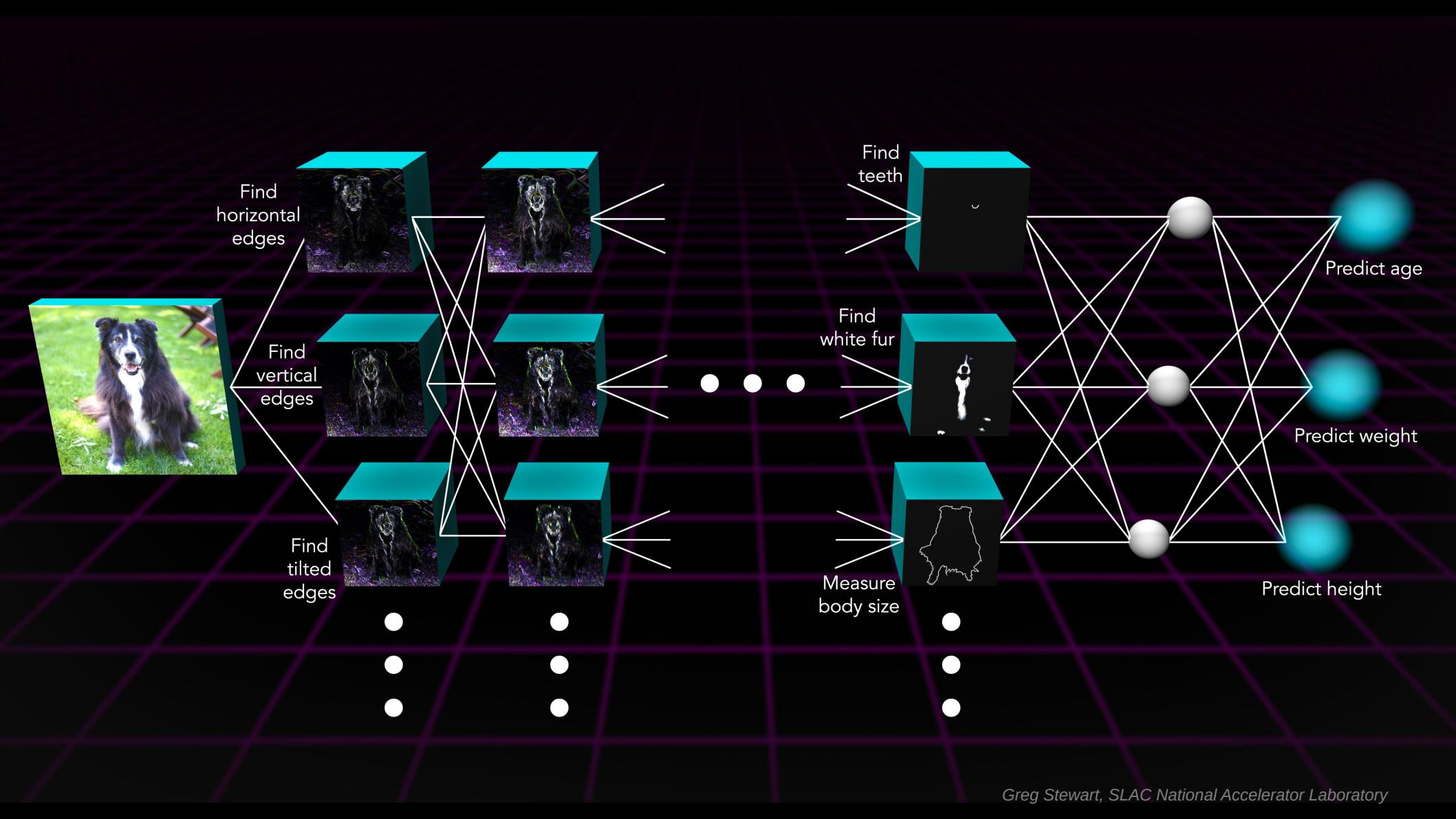


Each filter can be seen as a **single neuron** with one weight per input dimension in the filter.

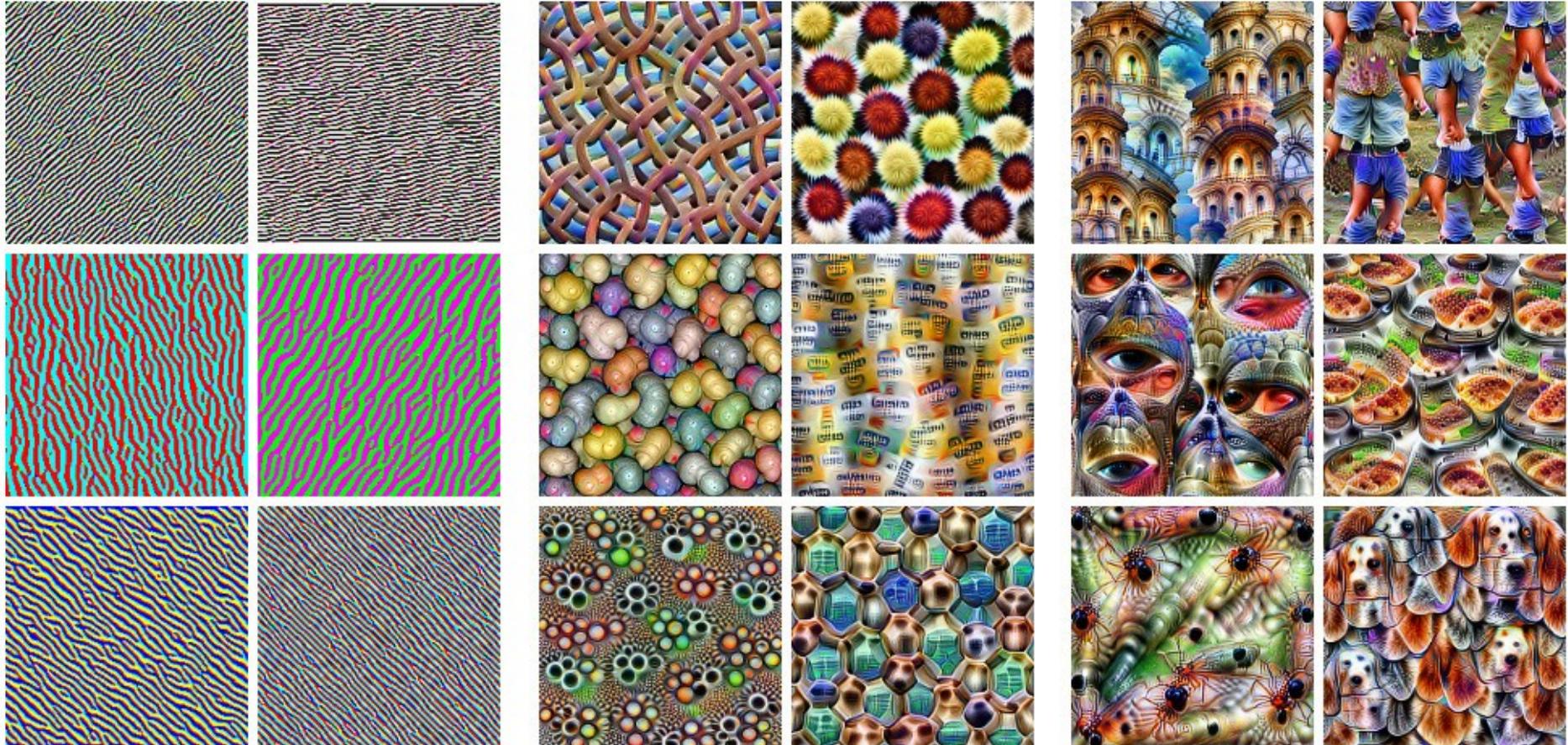
BUT, the same weights are used at every position and the outputs are independent.

→ **Translational equivariance !**

A network made of stacked convolutional layers can be tuned for **Translation invariance**.



Examples of filter maximization



Edges (layer conv2d0)

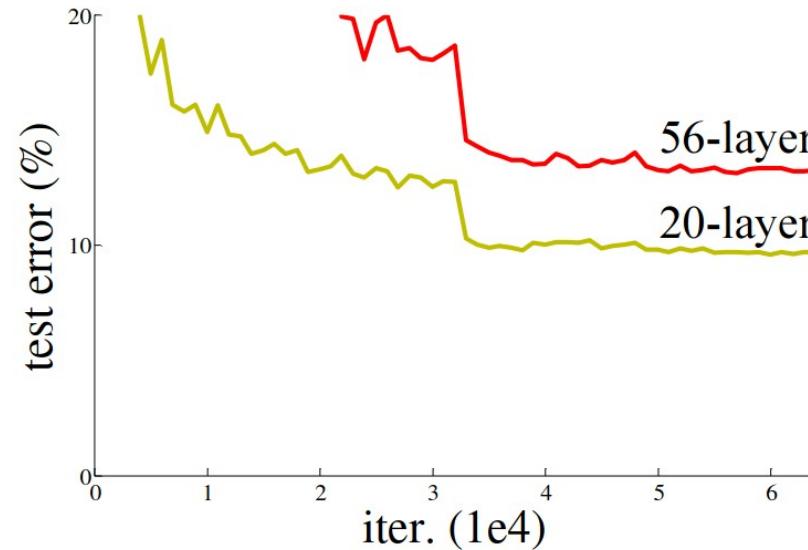
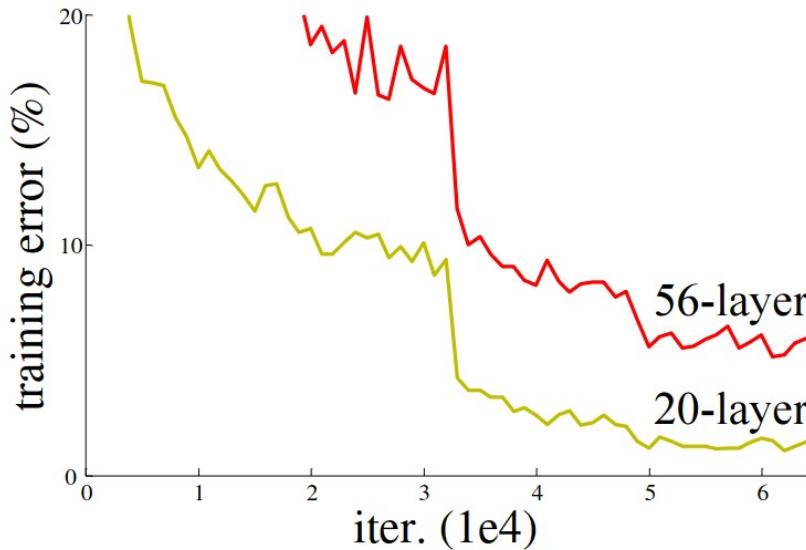
Patterns (layer mixed4a)

Objects (layers mixed4d & mixed4e)

Example of input images that maximize specific filters activation at different depth in a classification network. 11 / 83

Vanishing Gradient Issue

From He et al. 2015



In principle, the deeper the network, the higher its expressivity should be as long as it is trained with enough data. However, it is not the case in practice due to the gradient slowly getting smaller and smaller as it goes through more layers.

Still many approaches can mitigate this issue to construct network with hundreds of layers (e.g., changing the activation or having skip connections between layers that are far away in the network).

The Rectified Linear Unit (ReLU)

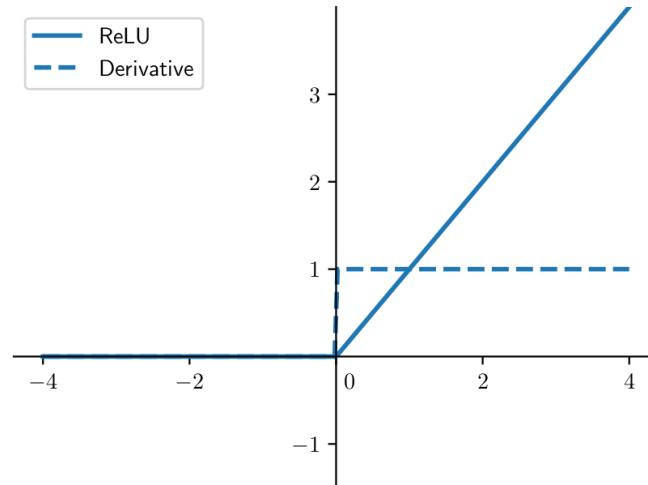
The **ReLU** (or its variance, the leaky-ReLU) has proven **more efficient for CNN**. It preserves a form of non-linearity and its constant derivative reduces **vanishing gradient problems**.

It is scale-invariant, and much faster to compute than other activation functions.

Using this activation, it becomes possible to construct **much deeper networks**.

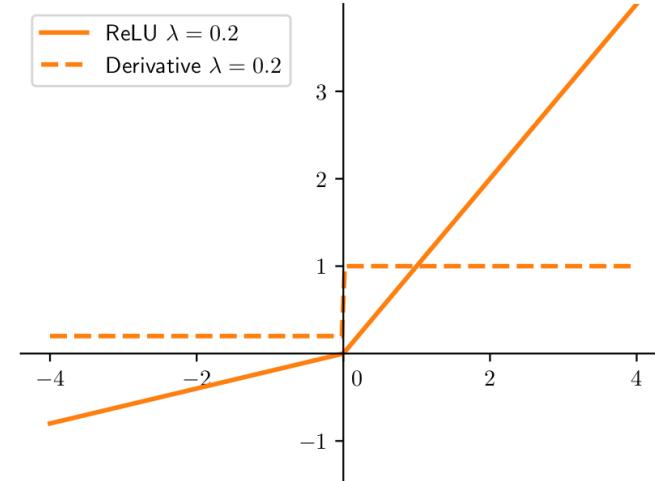
$$a_j = g(h_j) = \begin{cases} h_j & \text{if } h_j \geq 0 \\ 0 & \text{if } h_j < 0 \end{cases}$$

or $a_j = g(h_j) = \max(0, h_j)$



$$a_j = g(h_j) = \begin{cases} h_j & \text{if } h_j \geq 0 \\ \lambda h_j & \text{if } h_j < 0 \end{cases}$$

or $a_j = g(h_j) = \max(0, h_j) + \min(0, \lambda h_j)$



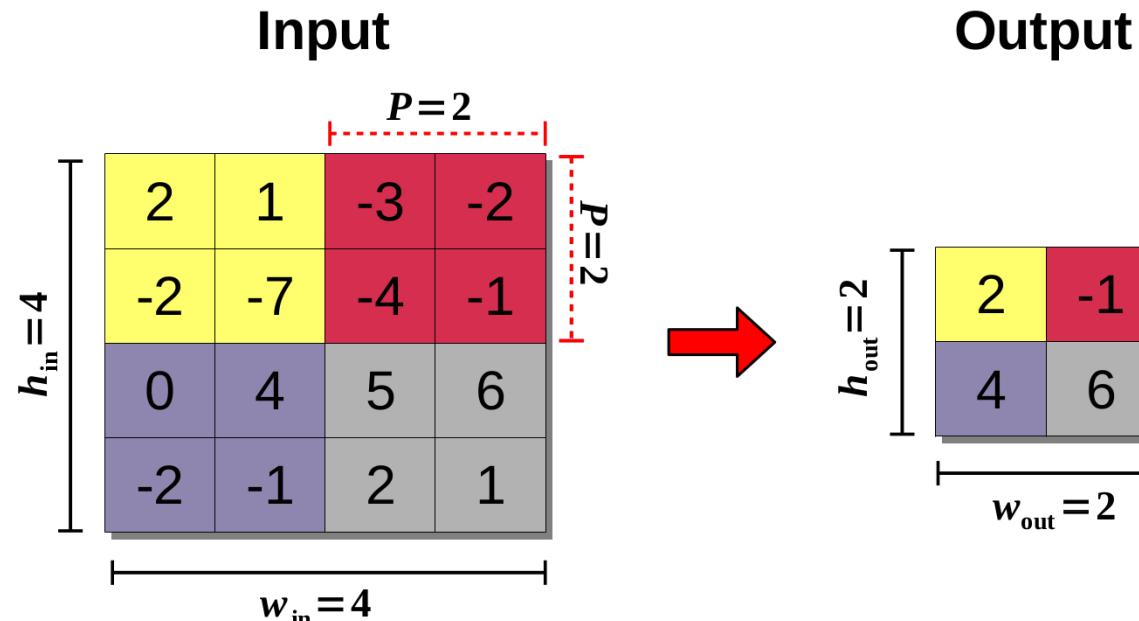
Dimensionality reduction: Pooling

A classical convolution operation is tuned to preserve the spatial dimensionality.

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

For classification tasks, the output layer is often reduced to a dense layer with a few neurons.

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

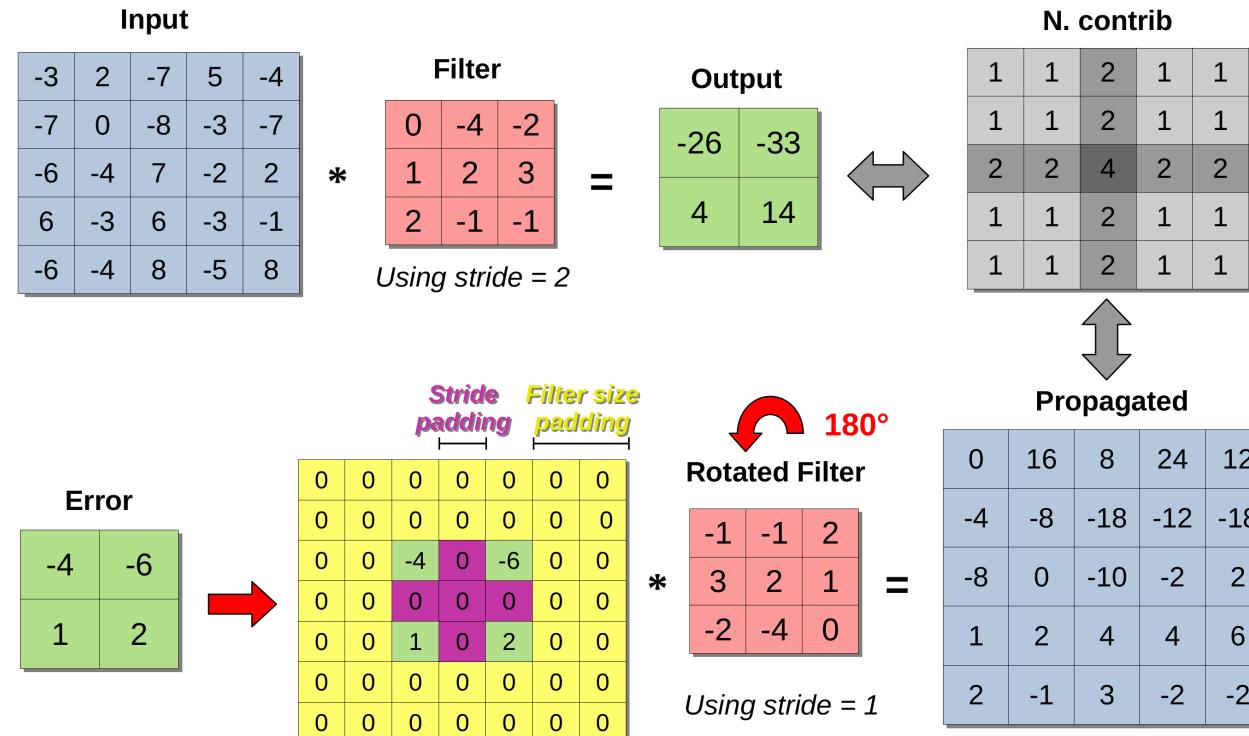


Different pooling methods exist, the most common being **Max-Pooling** and **Average-Pooling**. The pooling size can be modified, but most of the network architectures reduce each spatial dimension by a factor of two.

Learning the filters

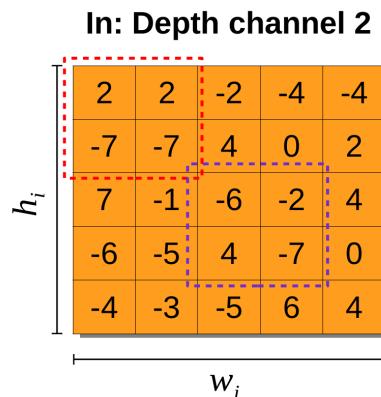
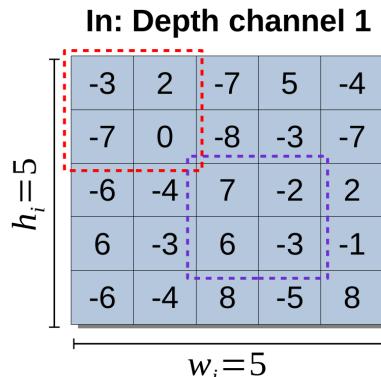
Like fully connected layers, the **convolutional filters** can be learned using **backpropagation** of the error measured at the output layer.

The error is propagated using a **transposed convolution operation**, which can be expressed with a classical convolution operation using simple transformations on specific layer elements.

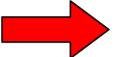


Learning the convolutional filters is often considered to be the definition of “**Deep Learning**”.

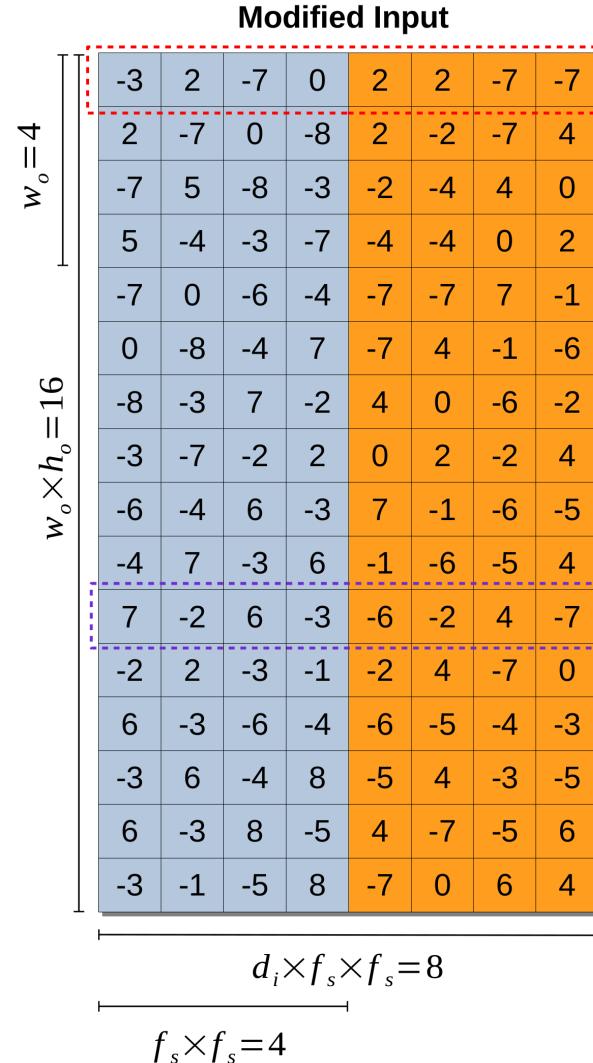
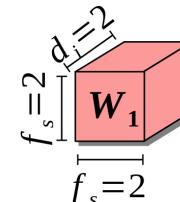
The Im2col transformation



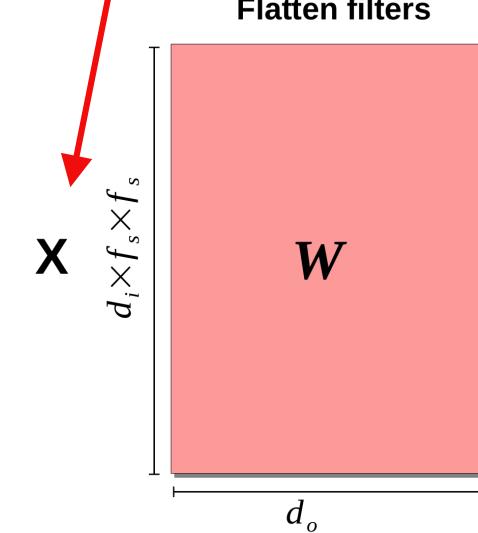
im2col



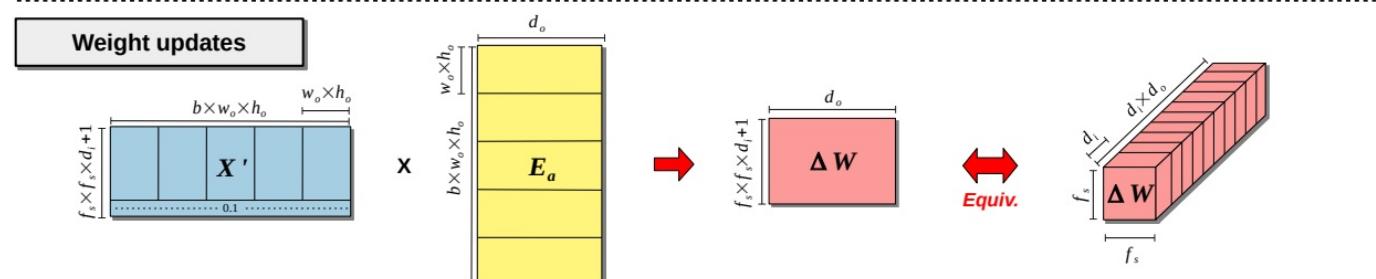
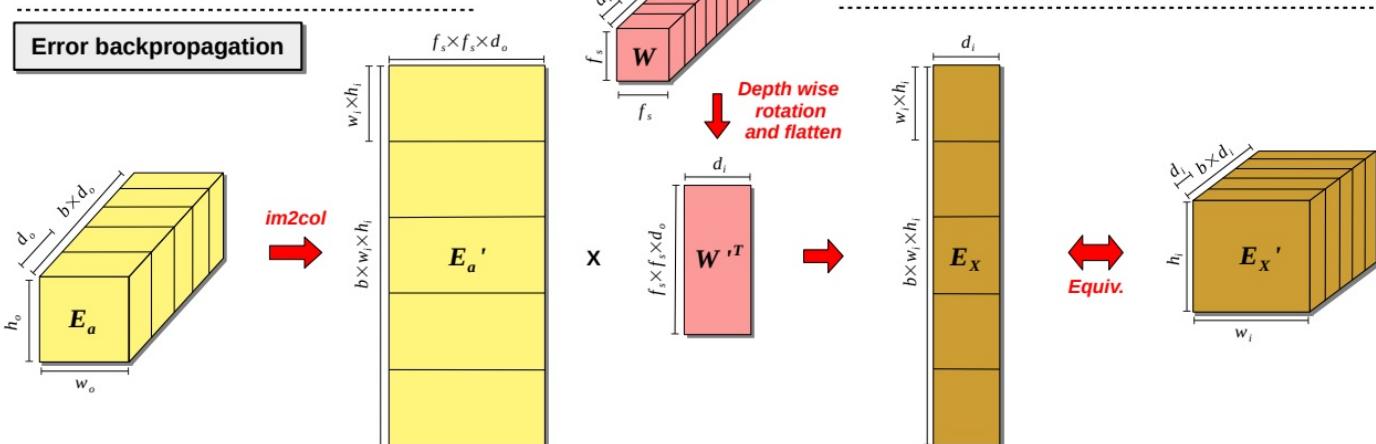
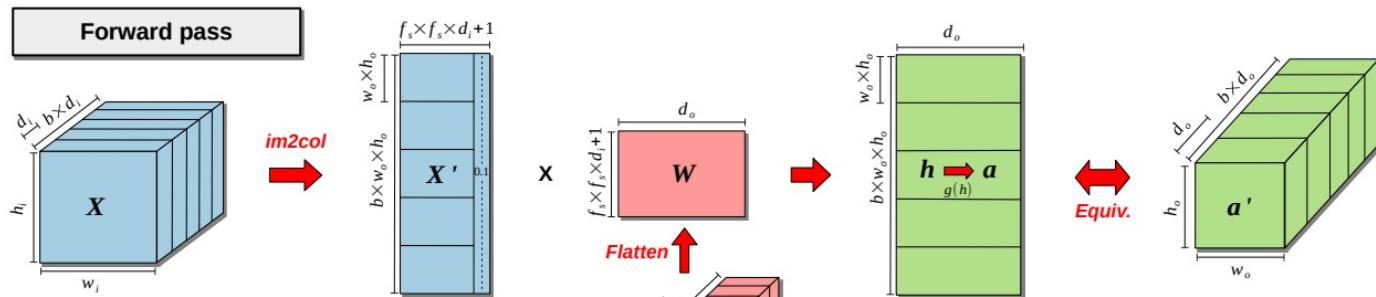
Filter 1



Matrix multiply!



Convolutional layer complete matrix formalism



X Batched Inputs

W Weight filters

a Activation maps

E_a Activation errors

E_x Propagated Input errors

What about computing on GPU?

GPU (Graphical Processing Unit) are massively parallel computing chips dedicated to SIMD like operations (thousands of cores). Most image processing algorithm apply the same transformation to millions of pixels, hence the SIMD formalism.

GPU have the same form factor than CPU but usually come as a dedicated daughter board with their own large cooling system as they can have a much higher power draw than CPU!

GPUs are not suited for all tasks, but for those they were designed for, they pack a huge amount of computing power, which include matrix multiplication!



Nvidia H100 GPU spec-sheet (AI dedicated)

Graphics Processor	
GPU Name:	GH100
Architecture:	Hopper
Foundry:	TSMC
Process Size:	4 nm
Transistors:	80,000 million
Density:	98.3M / mm ²
Die Size:	814 mm ²
Graphics Features	
DirectX:	N/A
OpenGL:	N/A
OpenCL:	3.0
Vulkan:	N/A
CUDA:	9.0
Shader Model:	N/A

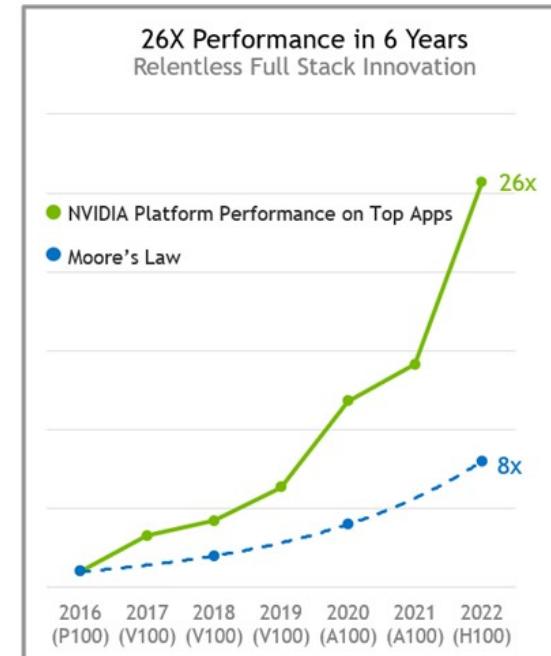
Graphics Card	
Release Date:	Mar 21st, 2023
Generation:	Tesla Hopper (Hxx)
Predecessor:	Tesla Ada
Production:	Active
Bus Interface:	PCIe 5.0 x16
Board Design	
Slot Width:	Dual-slot
Length:	268 mm 10.6 inches
Width:	111 mm 4.4 inches
TDP:	350 W
Suggested PSU:	750 W
Outputs:	No outputs
Power Connectors:	1x 16-pin
Board Number:	P1010 SKU 200

Clock Speeds	
Base Clock:	1095 MHz
Boost Clock:	1755 MHz
Memory Clock:	1593 MHz 3.2 Gbps effective

Memory	
Memory Size:	80 GB
Memory Type:	HBM2e
Memory Bus:	5120 bit
Bandwidth:	2,039 GB/s

Render Config	
Shading Units:	14592
TMUs:	456
ROPs:	24
SM Count:	114
Tensor Cores:	456
L1 Cache:	256 KB (per SM)
L2 Cache:	50 MB

Theoretical Performance	
Pixel Rate:	42.12 GPixel/s
Texture Rate:	800.3 GTexel/s
FP16 (half):	204.9 TFLOPS (4:1)
FP32 (float):	51.22 TFLOPS
FP64 (double):	25.61 TFLOPS (1:2)



From Nvidia

GPU architecture

The GPU is specialized for highly parallel computations and therefore designed such that more transistors are devoted to data processing rather than data caching and flow control. The schematic [Figure 1](#) shows an example distribution of chip resources for a CPU versus a GPU.

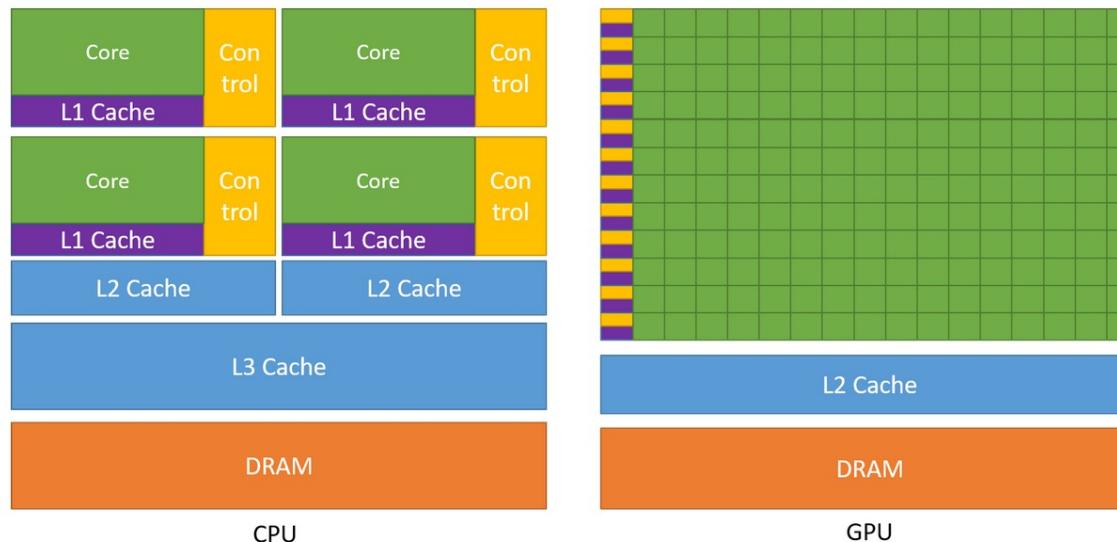
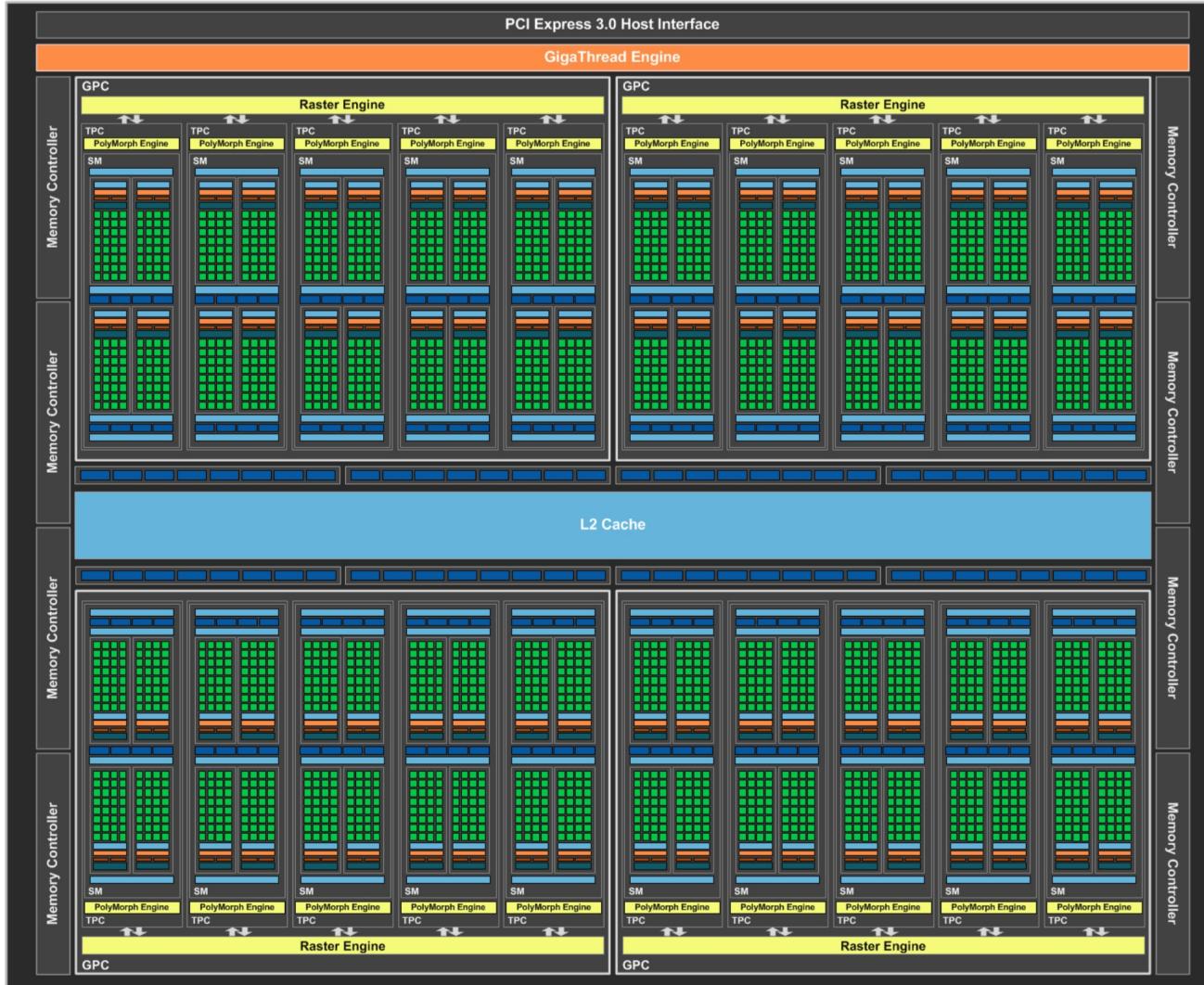


Figure 1: *The GPU Devotes More Transistors to Data Processing*

GPU architecture



Ex. of a GP104 - Tesla P100

The GPU is equipped with a shared “on board” memory. All SM share the same large L2 cache.

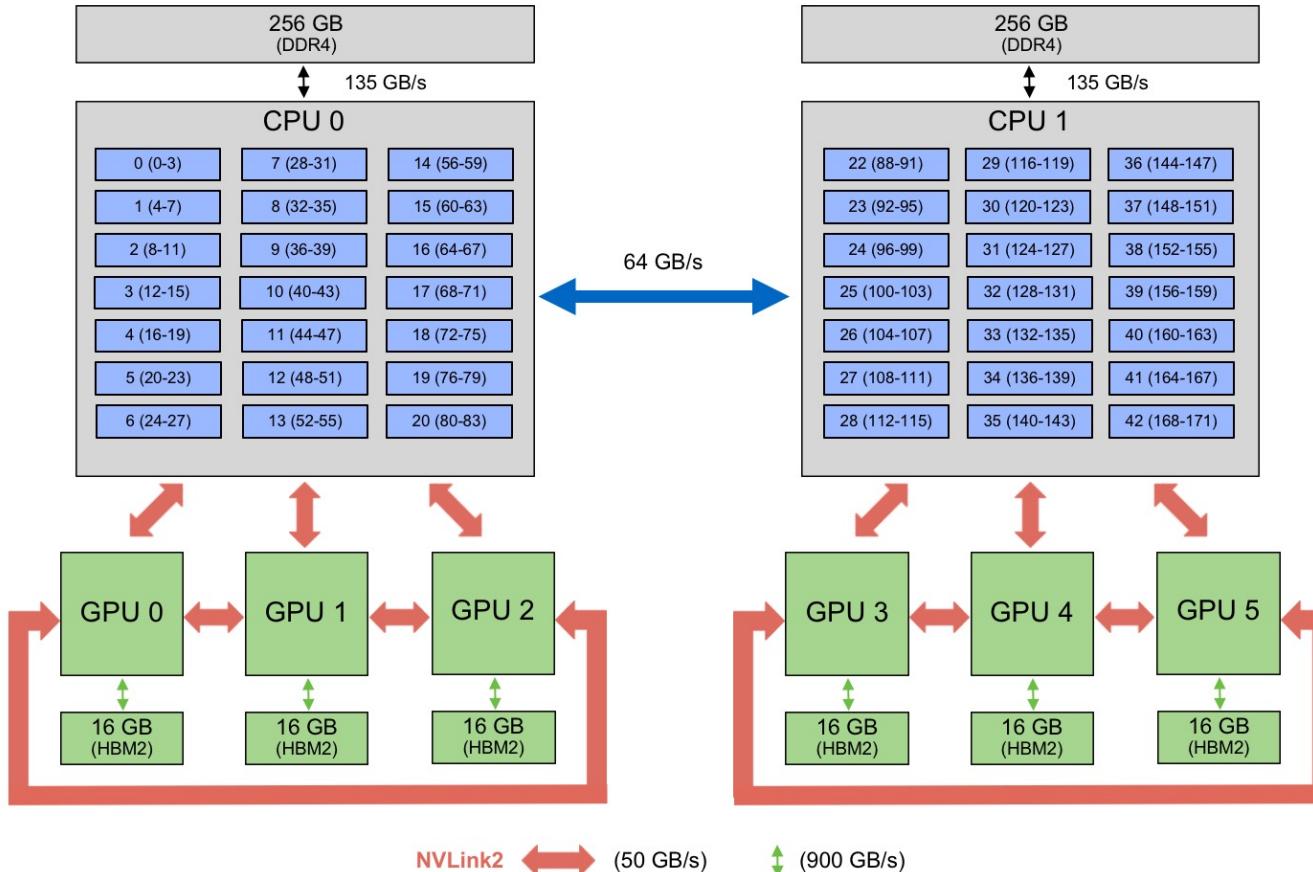
Each SM has a dedicated cache and can launch multiple instruction blocs through multiple warp schedulers.

Inside each SM, there are several CUDA cores and other dedicated compute units.

Distribution in GPU clusters

Summit Node

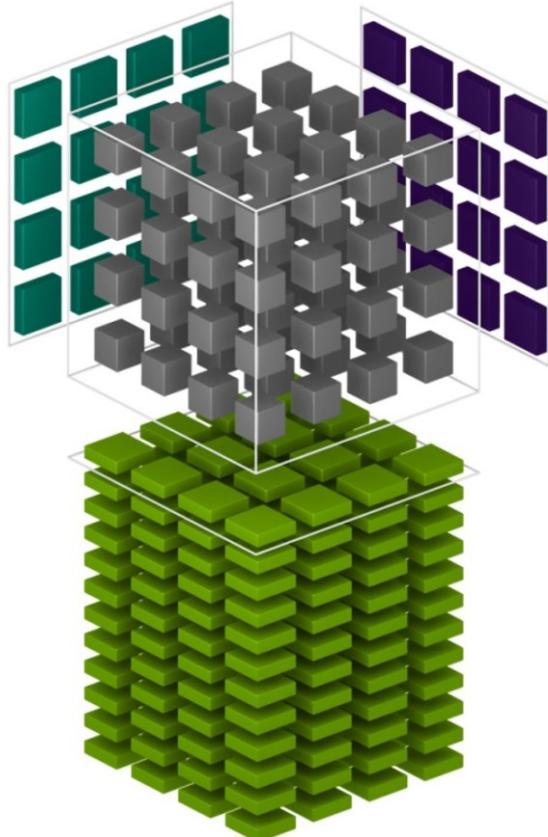
(2) IBM Power9 + (6) NVIDIA Volta V100



Nvidia Tensor Cores

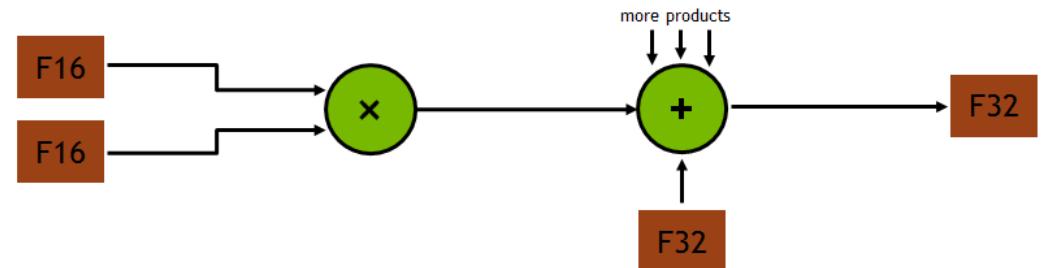
Optimized Warp Matrix Multiply Add (WMMA) instructions !

CuBLAS can be set to used tensor core through the gemmEX function.

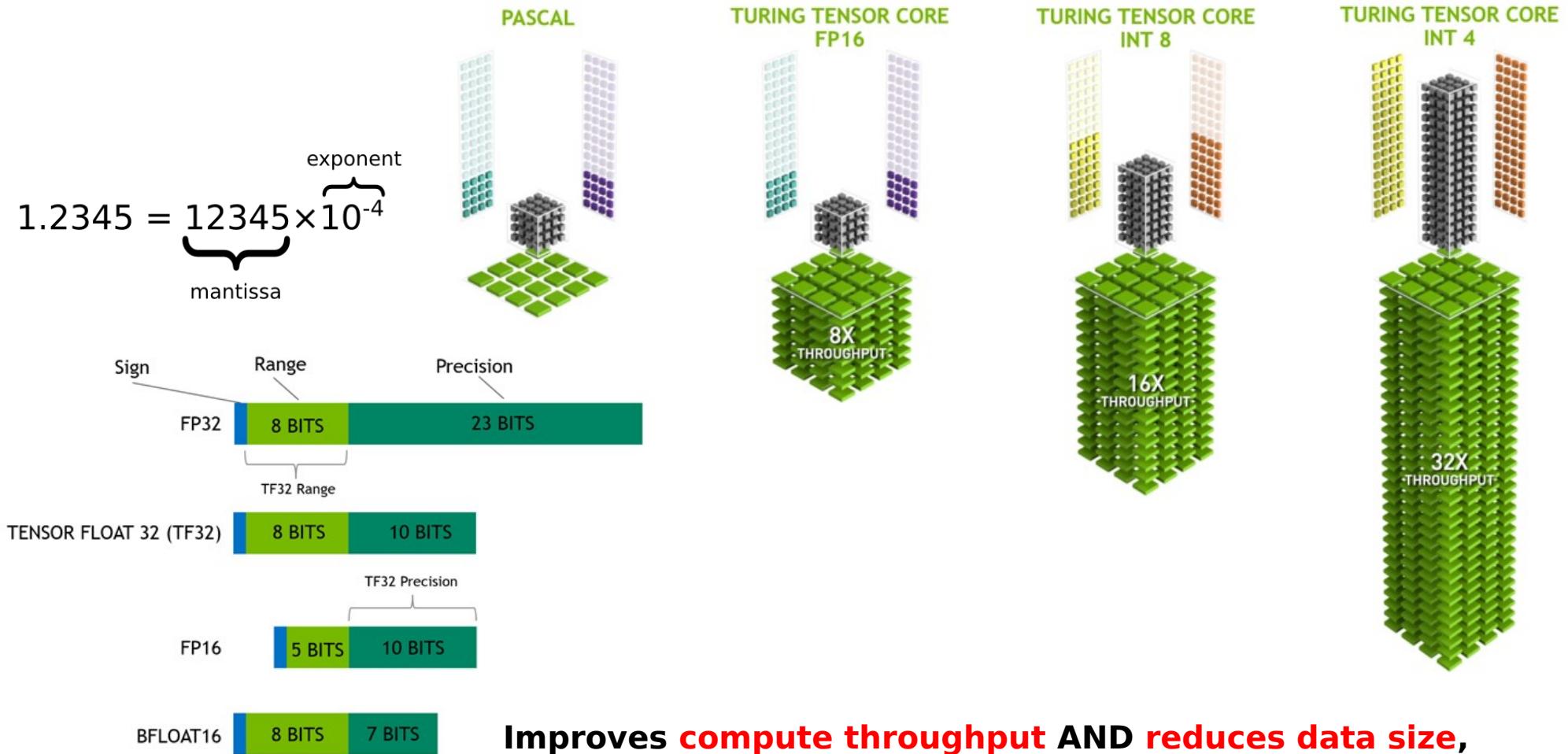


$$D = \left(\begin{array}{cccc} A_{0,0} & A_{0,1} & A_{0,2} & A_{0,3} \\ A_{1,0} & A_{1,1} & A_{1,2} & A_{1,3} \\ A_{2,0} & A_{2,1} & A_{2,2} & A_{2,3} \\ A_{3,0} & A_{3,1} & A_{3,2} & A_{3,3} \end{array} \right) \text{FP16} \times \left(\begin{array}{cccc} B_{0,0} & B_{0,1} & B_{0,2} & B_{0,3} \\ B_{1,0} & B_{1,1} & B_{1,2} & B_{1,3} \\ B_{2,0} & B_{2,1} & B_{2,2} & B_{2,3} \\ B_{3,0} & B_{3,1} & B_{3,2} & B_{3,3} \end{array} \right) \text{FP16} + \left(\begin{array}{cccc} C_{0,0} & C_{0,1} & C_{0,2} & C_{0,3} \\ C_{1,0} & C_{1,1} & C_{1,2} & C_{1,3} \\ C_{2,0} & C_{2,1} & C_{2,2} & C_{2,3} \\ C_{3,0} & C_{3,1} & C_{3,2} & C_{3,3} \end{array} \right) \text{FP16 or FP32}$$

FP16 storage/input Full precision product Sum with FP32 accumulator Convert to FP32 result

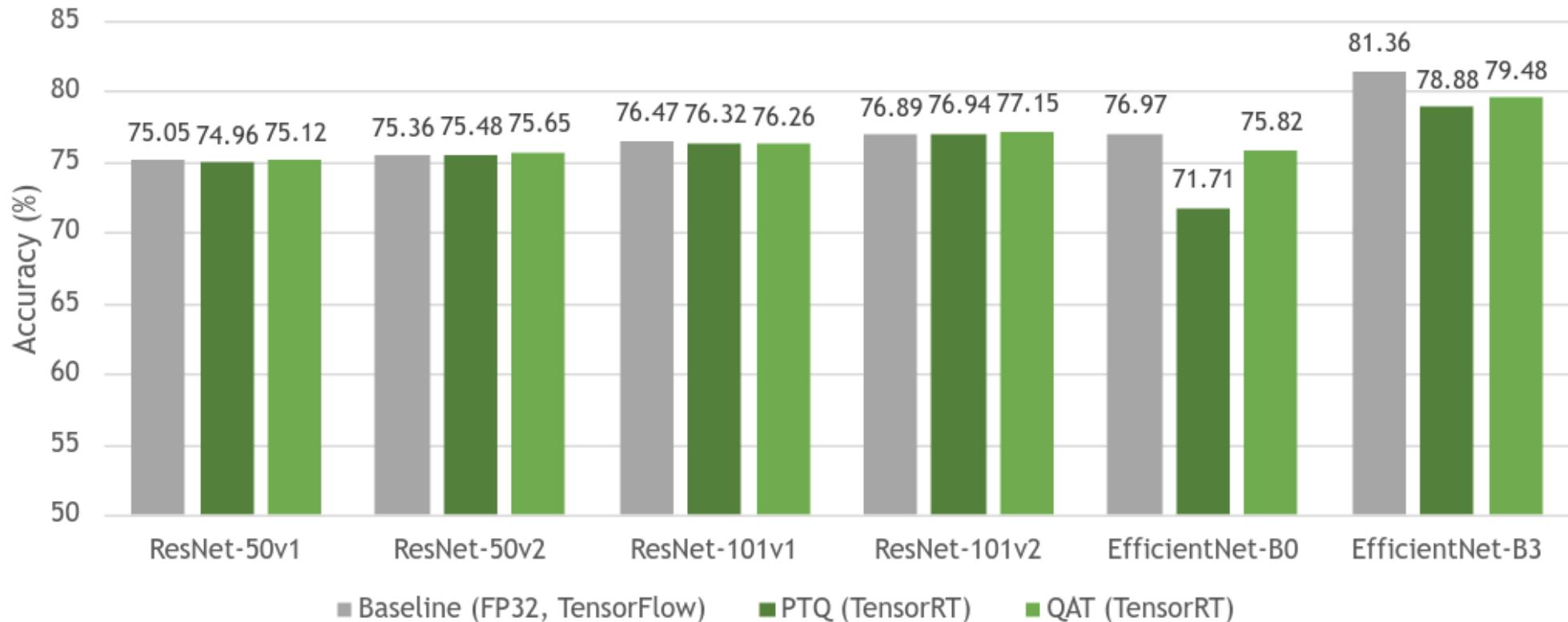


Nvidia Tensor Cores reduced quantization



Quantization effect on AI model accuracy

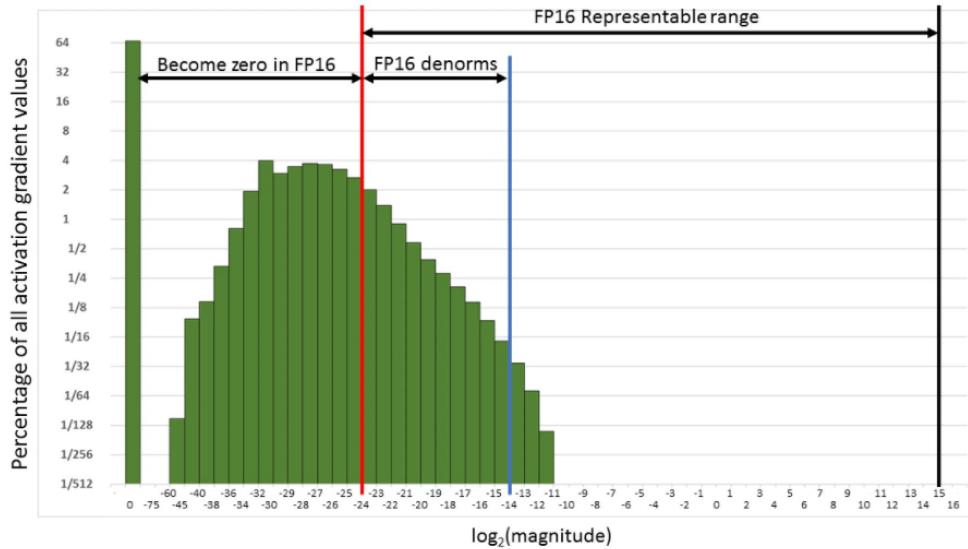
All models quantized to INT8, accuracy for ImageNET-2012



PTQ = Post training quantization

QAT = Quantization aware training

Mixed precision training

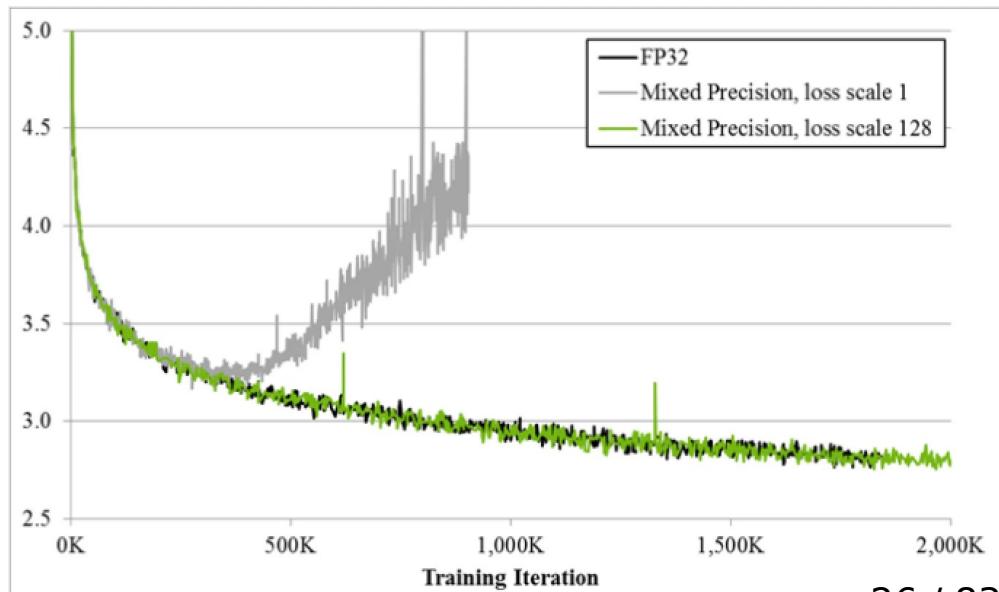


To further reduce this issue, a scaling is applied on the output loss. All propagated values are naturally scaled so they are more likely to be in the proper range.

At weight update time the correction is scaled down by the same factor.

Reduced bit count variables have smaller representable ranges. This can lead to strong gradient vanishing problems.

This problem can first be mitigated by preserving an FP32 copy of the weights for accumulating the updates.



From Nvidia « Mixed precision training »



Development team

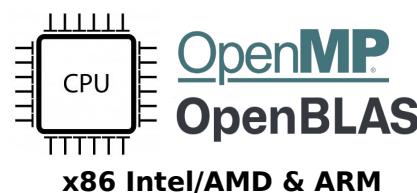


D. Cornu

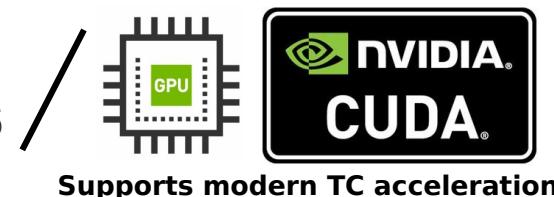
G. Sainton

Convolutional Interactive Artificial Neural Networks by/for Astrophysicists

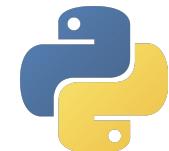
General purpose framework BUT developed for **astronomical applications**



x86 Intel/AMD & ARM



Supports modern TC acceleration



Python interface

Work on a wide variety of hardware from IoT to super-computing facilities



github.com/Deyht/CIANNA

Open source - Apache 2 license

July 24, 2024 (V-1.0.0.0)

Software

Open

Deyht/CIANNA: CIANNA V-1.0

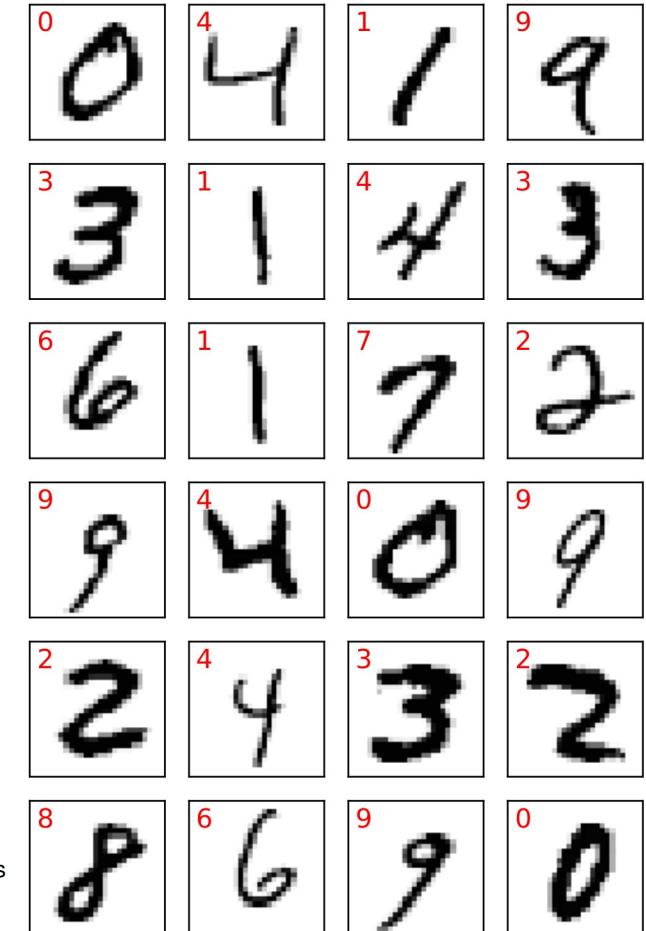
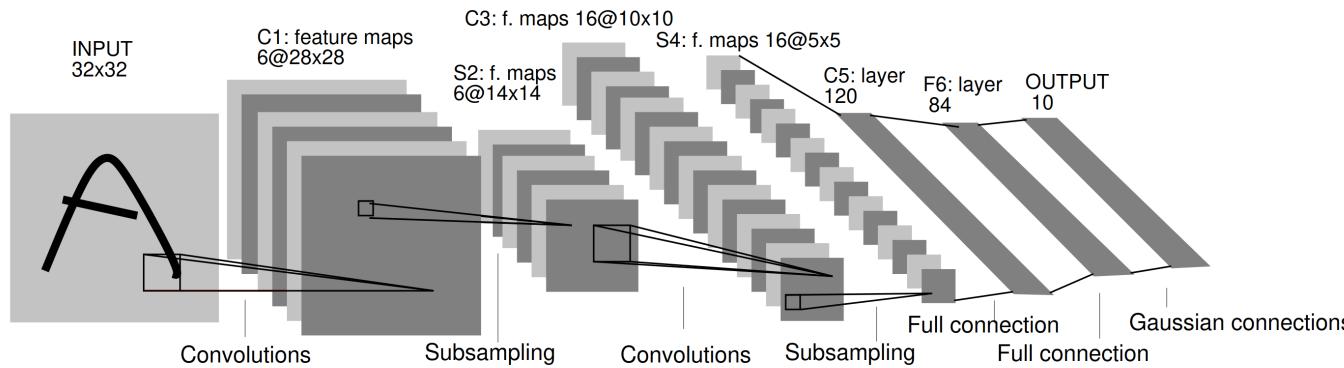
Simple examples: MNIST

The well-known **MNIST** (Modified NIST's special dataset) dataset consists of handwritten digits from 500 different writers expressed as 28x28 grayscale images.

It is freely accessible in the form of a 60000 image training set, 10000 images validation, set and a 10000 image test set.

Very simple CNN architectures can achieve over **99.3 classification accuracy** on this dataset.

LeNet 5 network architecture (from LeCun et al. 1998):



How to use CIANNA for MNIST ?

Example script over MNIST, with an LeNet5 *like* network.

Interface is similar to widely adopted frameworks.

The **full interface documentation** is available on the github repo as a Wiki page listing all available functions with their descriptions.

Several example scripts are provided as Google Colab notebooks.

```
1 #CIANNA initialization
2 cnn.init(in_dim=i_ar([28,28]), in_nb_ch=1, out_dim=10,
3           bias=0.1, b_size=16, comp_meth="C_CUDA",
4           dynamic_load=1, mixed_precision="FP32C_FP32A")
5
6 #Create data subsets (from numpy arrays)
7 cnn.create_dataset("TRAIN", size=60000, input=data_train, target=target_train)
8 cnn.create_dataset("VALID", size=10000, input=data_valid, target=target_valid)
9 cnn.create_dataset("TEST", size=10000, input=data_test, target=target_test)
10
11 #Define the network structure sequentially
12 cnn.conv(f_size=i_ar([5,5]), nb_filters=8 , padding=i_ar([2,2]), activation="RELU")
13 cnn.pool(p_size=i_ar([2,2]), p_type="MAX")
14 cnn.conv(f_size=i_ar([5,5]), nb_filters=16, padding=i_ar([2,2]), activation="RELU")
15 cnn.pool(p_size=i_ar([2,2]), p_type="MAX")
16 cnn.dense(nb_neurons=256, activation="RELU", drop_rate=0.5)
17 cnn.dense(nb_neurons=128, activation="RELU", drop_rate=0.2)
18 cnn.dense(nb_neurons=10, strict_size=1, activation="SMAX")
19
20 #Training loop configuration and launch
21 cnn.train(nb_iter=20, learning_rate=0.004, momentum=0.8, confmat=1, save_every=0)
22
23 #Evaluate network prediction after training
24 cnn.forward(repeat=1, drop_mode="AVG_MODEL")
```

Example results on MNIST

Actual	Predicted										Recall
	C0	C1	C2	C3	C4	C5	C6	C7	C8	C9	
Class	C0	C1	C2	C3	C4	C5	C6	C7	C8	C9	
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%

Practical work:

Reproduce this result using the provided notebooks. Try to modify the architecture (*filter size, #filters, #neurons, batch size, learning rate, etc.*) and estimate the impact of individual changes on the training / inference time and final accuracy.

Data augmentation

From Albumentations



augmentation →



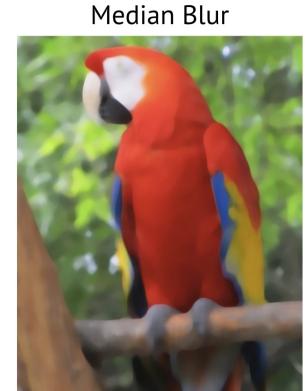
Contrast



Horizontal Flip



Crop



Median Blur



Hue / Saturation / Value



Gamma

Depending on the task, one can choose a set of transforms that do not alter the labeling corresponding to the image (here the class). This allow to increase the coverage of the feature space without the need of new data.

Augmentation does not solve all the dataset size issues, it usually **cannot create new contexts** nor it can generate features that are simply missing in the original dataset.

More advanced image classification

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

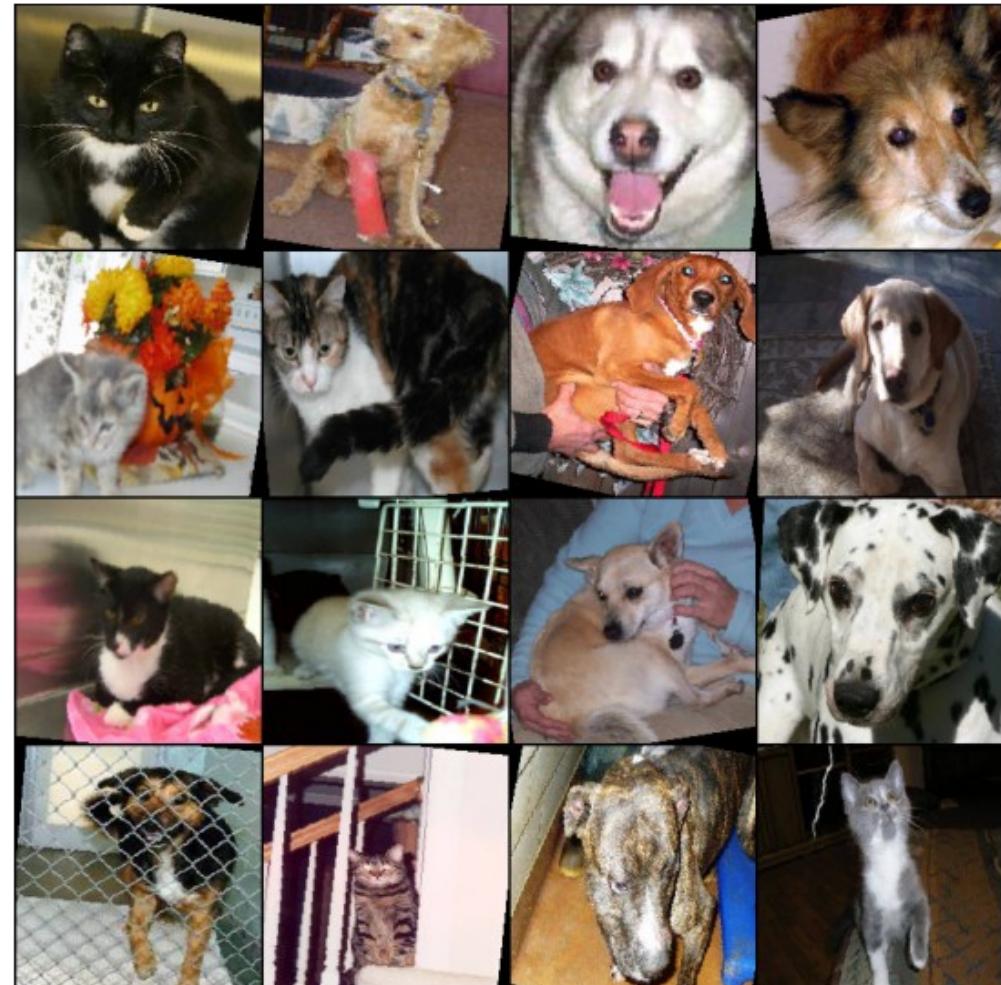
Typical of a **CAPTCHA** task or **HIP** (Human Interactive Proof) because the task is easy and quick for humans.

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

We can generate standardize and augmented images from the dataset using dynamic image augmentation.

Practical work:

Using the provided dataset and data loading script, implement a CNN (with either framework) for this classification. Explore the architectures, hyperparameters, and augmentation setups by yourself and try to optimize the prediction result.



A more complex task, the CIFAR-10 dataset

airplane



automobile



bird



cat



deer



dog



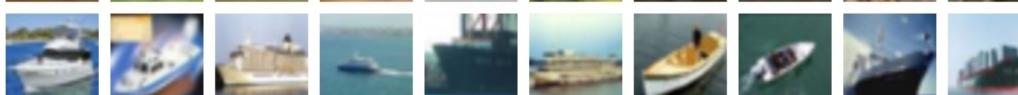
frog



horse



ship



truck



60000 images of 32x32 pixels labeled into 10 classes.

50000 images for training and 10000 for testing.

Modern methods can reach 97% accuracy on this dataset.

The lower resolution combined to the increase in number of classes and image context make it a more difficult task to solve than for ASIRRA.

Practical work:

Do the same work you've done for ASIRRA on this new dataset. Try to identify the key differences between the dataset and explore how it affects the optimal architecture.

1D CNN for spectra

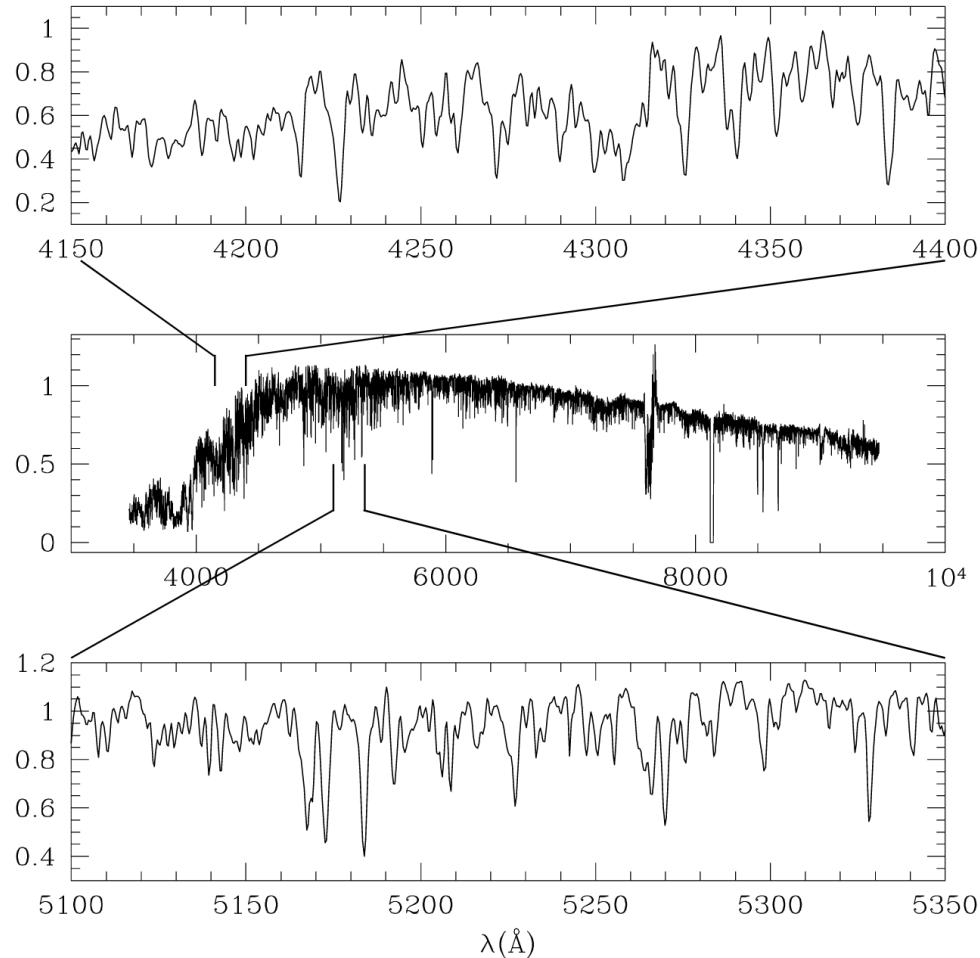
A spectra is a continuous **1D data structure** decomposed into many frequency bins.

Like an image it can exhibit recurrent patterns that could be search in a **translation equivariant** way.

Practical work:

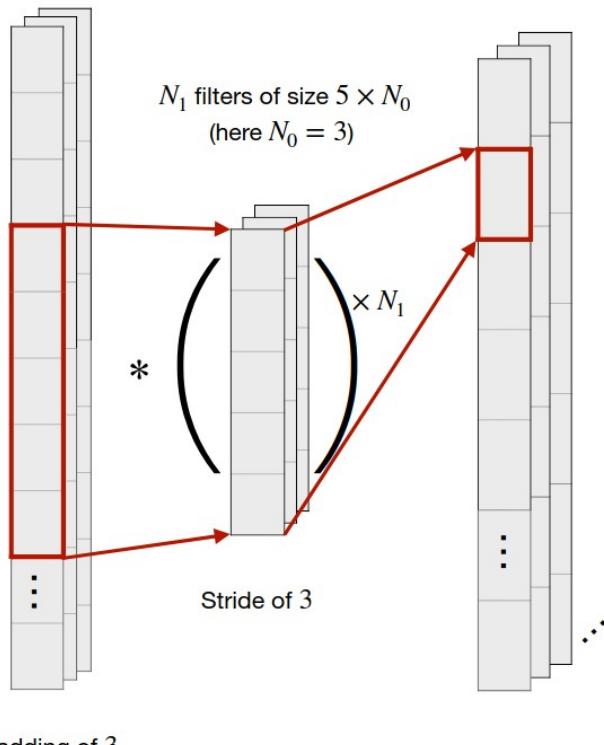
Using the stellar spectra dataset from the Perceptron and MLP parts of the course, build a 1D CNN that performs the classification. As before, a notebook is provided as a starting point.

As the number of frequency bins is much higher than in a typical image, you might need to use larger filters and to reduce the convoluted dimensionality more aggressively.



1D CNN for spectra

Input : 35,000 spectral
dimension \times 3 normalizations



N_1 Features maps
of dimension D_1

N_{14} Features maps
of dimension D_{14}

Flattened maps of
dimension $= N_{14} \times D_{14}$

From Kessler et al. 2025 (in prep)

Output layer of 20 neurons

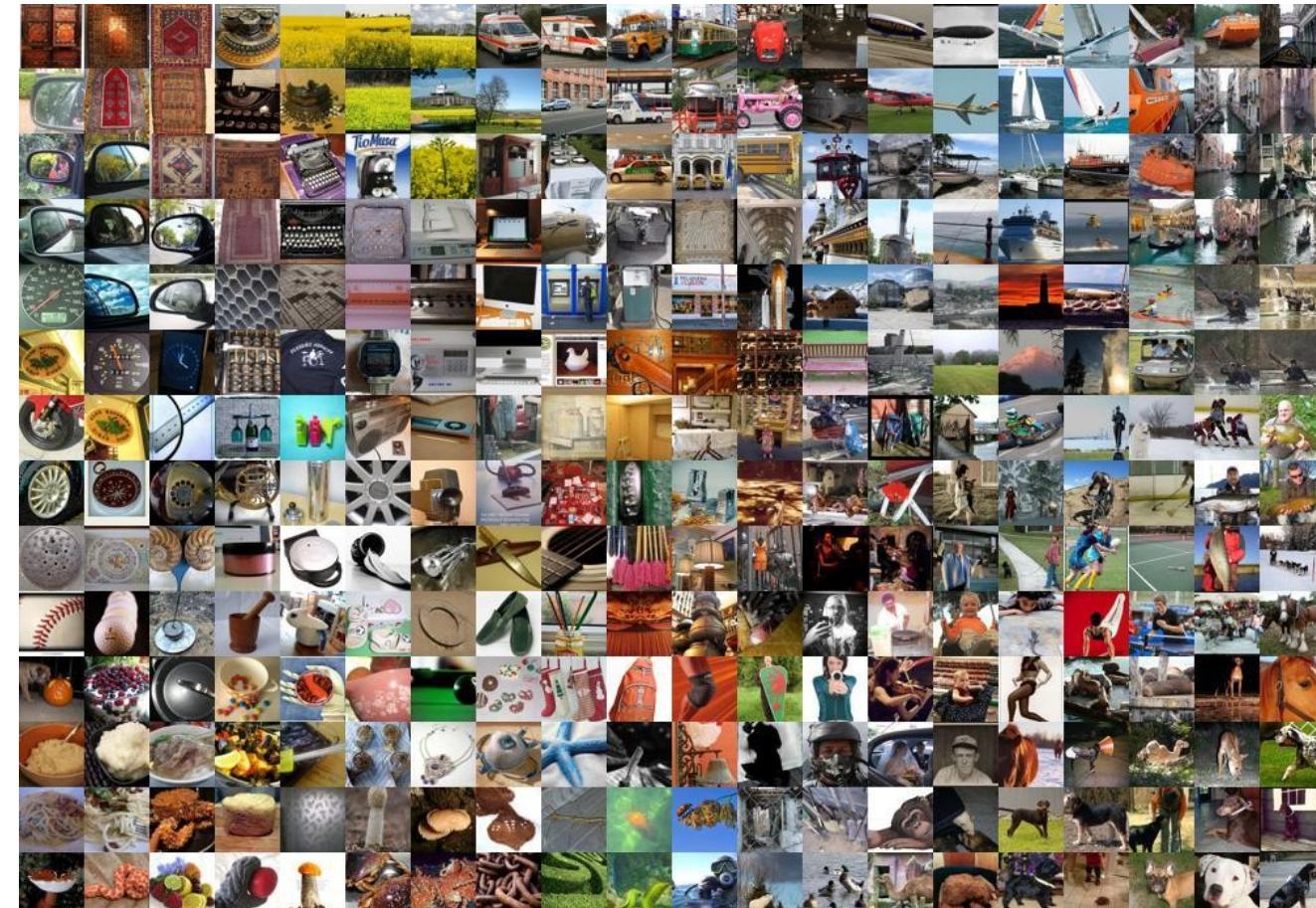
Example of target

0.08	a(CH ₂ OH) ₂	0
0.99	C ₂ H ₃ CN	1
0.10	C ₂ H ₅ CN	0
0.98	C ₂ H ₅ OH	1
0.09	NH ₂ CN	0

0
1
0
1
0

Fig. 5. Scheme of the ANN architecture. Filters are applied to the input data to convolve the information and produce features maps. This operation is done for each of the convolutional layers. Dense layers then combine the extracted features and learn how to label the spectra depending on the provided target. The output layer is composed of one neuron per class giving a score between 0 and 1 independent between each other.

The canonical ImageNet-2012 dataset



ImageNet is a famous dataset as it is large and diverse enough to pre-train large models for a large variety of applications (classification, generation, detection, etc.)

- 1,281,167 training images (150 GB)
- 50,000 validation images
- 100,000 test images,
- Each image is associated with one of 1000 possible classes.

Images are of variable resolution with an average around 500x400.

Practical work:

This dataset is way too heavy for training a model during the course. Use the provided script to run a pre-trained model, identify its architecture and visualize some results. You can try apply it to your own images.

The canonical ImageNet-2012 dataset

Result over ImageNet using a darknet-19 backbone, **91.7 Top5 Accuracy** over the 1000 classes, at a 448p resolution. The network run at 740 ips on an RTX 4090.



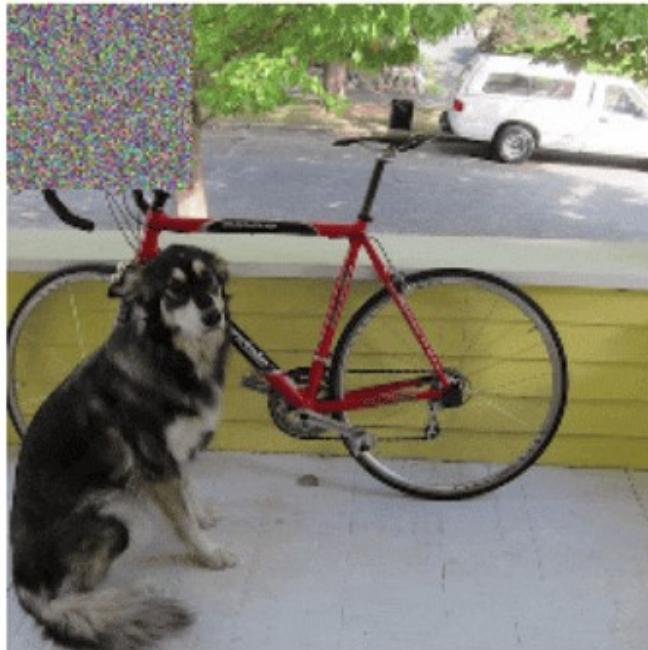
Explaining a model decision with occlusion analysis

An **occlusion analysis** is done by replacing a portion of the image by noise and measuring the impact it has on the model prediction. An occlusion map can be created by repeating moving the occlusion window over the original image.

Allow to identify **image features** that contribute positively or negatively to a given prediction.

Here the occlusion map is done with the ImageNet trained model for the « malamute » class.

Occulted input image



Pred difference map



The Galaxy Zoo 2 dataset

Morphological classification of galaxies



In GZ1 Volunteers classified images of SDSS galaxies as belonging to one of six categories - **elliptical, clockwise spiral, anticlockwise spiral, edge-on, star/don't know, or merger**. GZ2 extends the original classifications for a subsample of the brightest and largest galaxies, measuring more detailed morphological features. This includes **galactic bars, spiral arm and pitch angle, bulges, edge-on galaxies, relative ellipticities, and many others**.

There are **243434 images** in total, all resized to a 424x424 resolution. Images are composed so the main object is centered and a part of the environment is visible. This implies that the FoV of each image is different. For simplicity, we will use cropped and resized images that are more zoomed in toward the object and resized to either a 64x64 or a 128x128 image resolution.

Details on the classification process can be found in Hart et al. 2016

GZ2 DL classification

The catalog contains the debiased answer to each question for every object in the dataset.

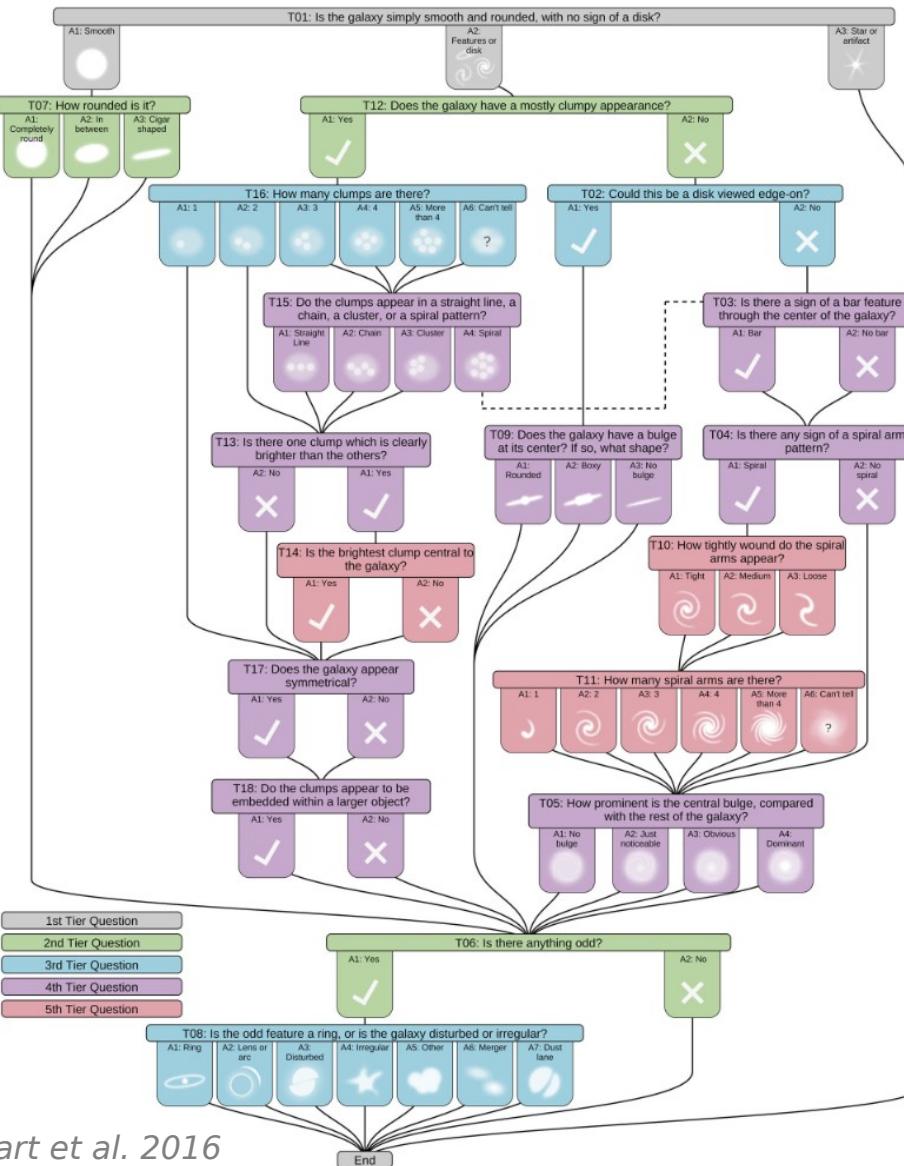
Two approaches:

- 1) Try to reproduce only the E, S, SB classification
 - it is relatively balanced
 - low class count
 - Not very representative of the task

- 2) Try to reproduce the result of all the Txx steps
 - Some classes will have a low example count
 - Output can't be mutually exclusive, logistic output required, but we can re-normalize mutually exclusive answers "a posteriori".
 - more representative of the initial labeling process
 - The debiased probability could be used as a non binary target!

Practical work:

Two notebooks are provided corresponding to both strategies. Try to adapt the ASIRRA architecture to this problem.



Object detection



“Object detection” types

*Image from Stanford Deep Learning course cs224

Classification



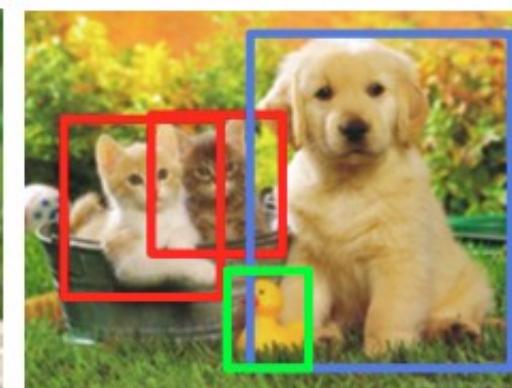
CAT

Classification + Localization



CAT

Object Detection



CAT, DOG, DUCK

Instance Segmentation

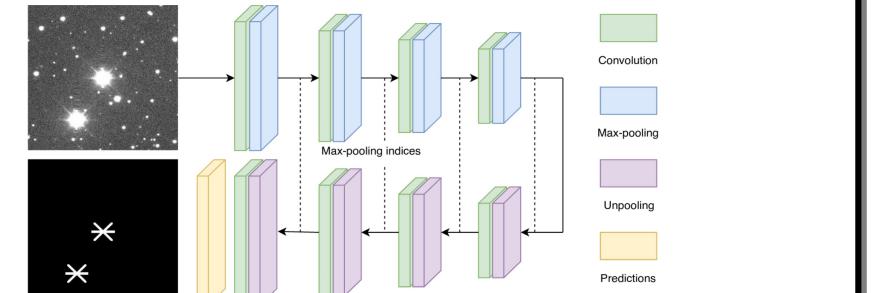


CAT, DOG, DUCK

CNN architectures for object detection

U-Nets

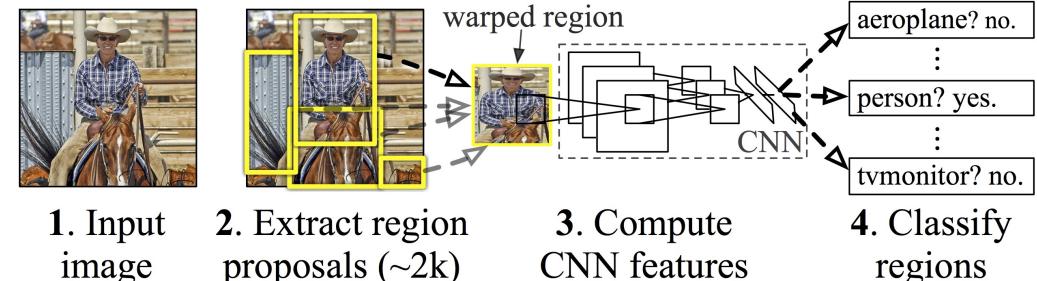
Pros: segmentation maps, shallow latent space, ...



Region-based

Methods : R-CNN (Fast and Faster), SPP-net, Mask R-CNN, ...

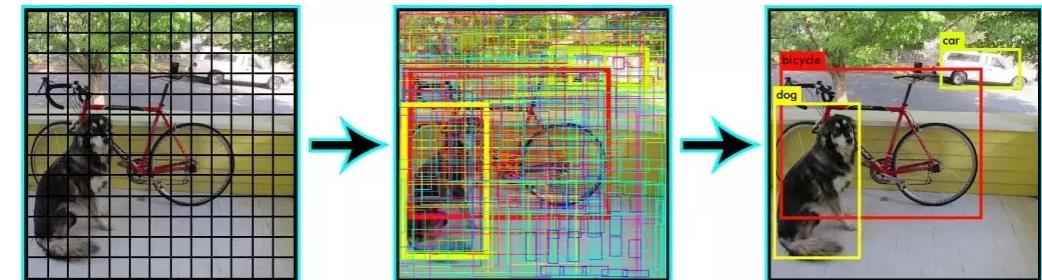
Pros: Best accuracy, ...



Regression-based

Methods : SSD (Single Shot Detector), YOLO (You Only Look Once), ...

Pros: Very Fast, straightforward architecture,...



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



Targets for various “tasks” :

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

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



Targets for various “tasks” :

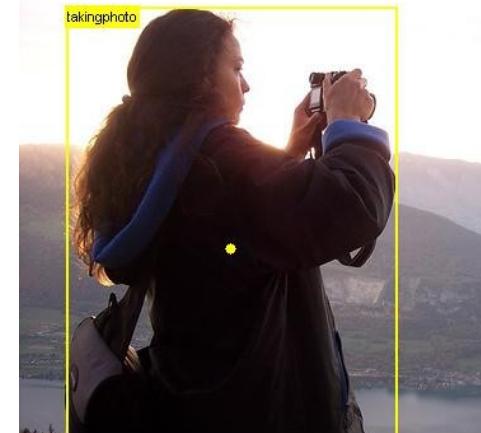
<http://host.robots.ox.ac.uk/pascal/VOC/index.html>

Boxless Action



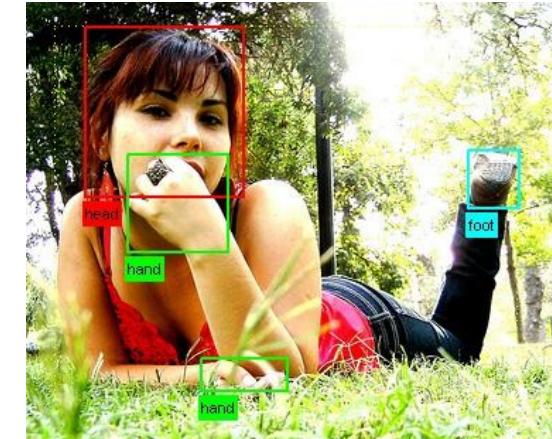
A single reference point and the associated action

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

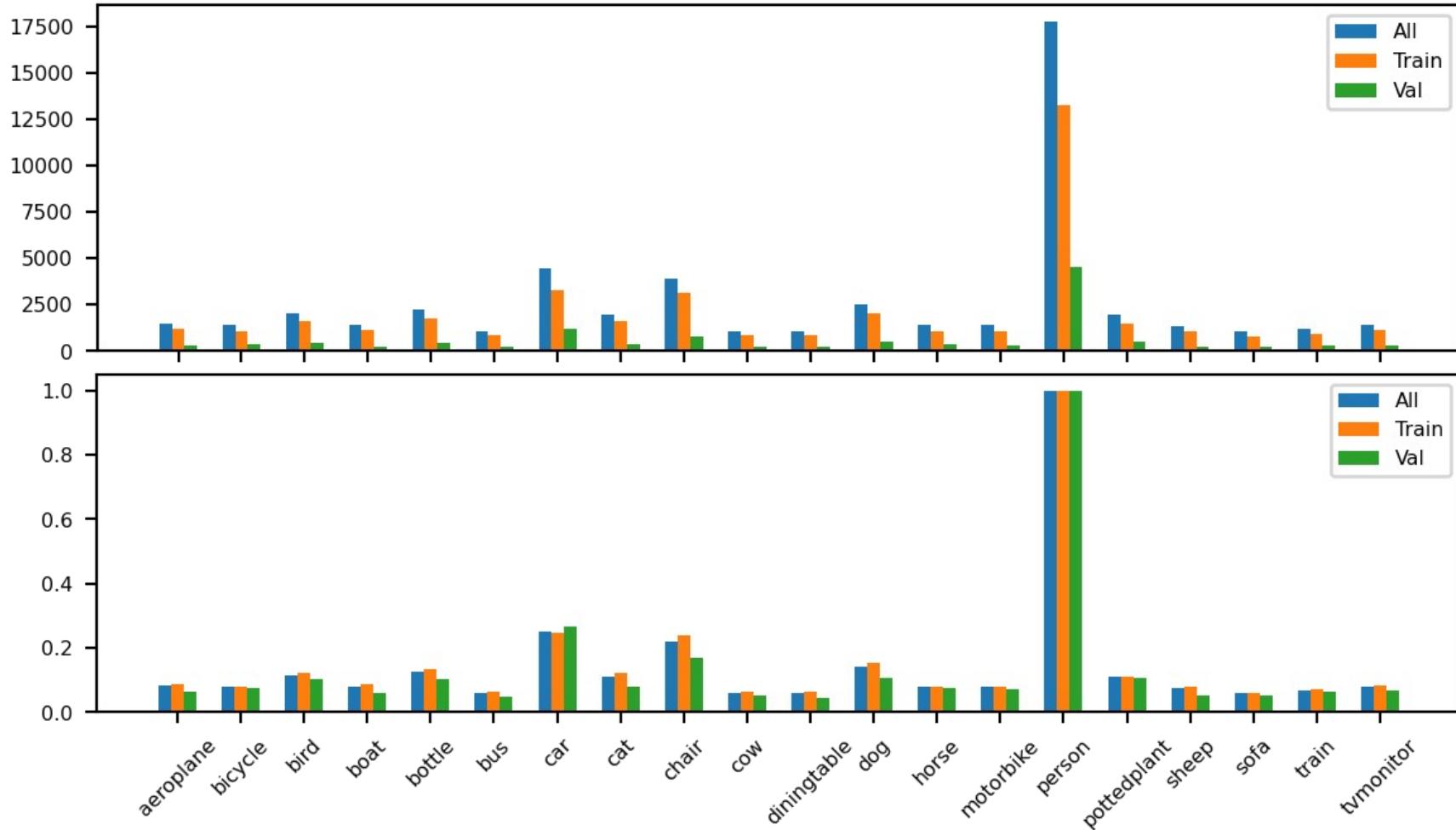
The data from 2007 and 2012 can be combined to obtain a larger dataset of 21503 images, containing 52090 objects.

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

Training dataset summary statistics

Training dataset = Train 2007 + Train 2012

Valid/Test dataset = Test 2007



Training dataset summary statistics

All the images are made square and resized to 288x288 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.

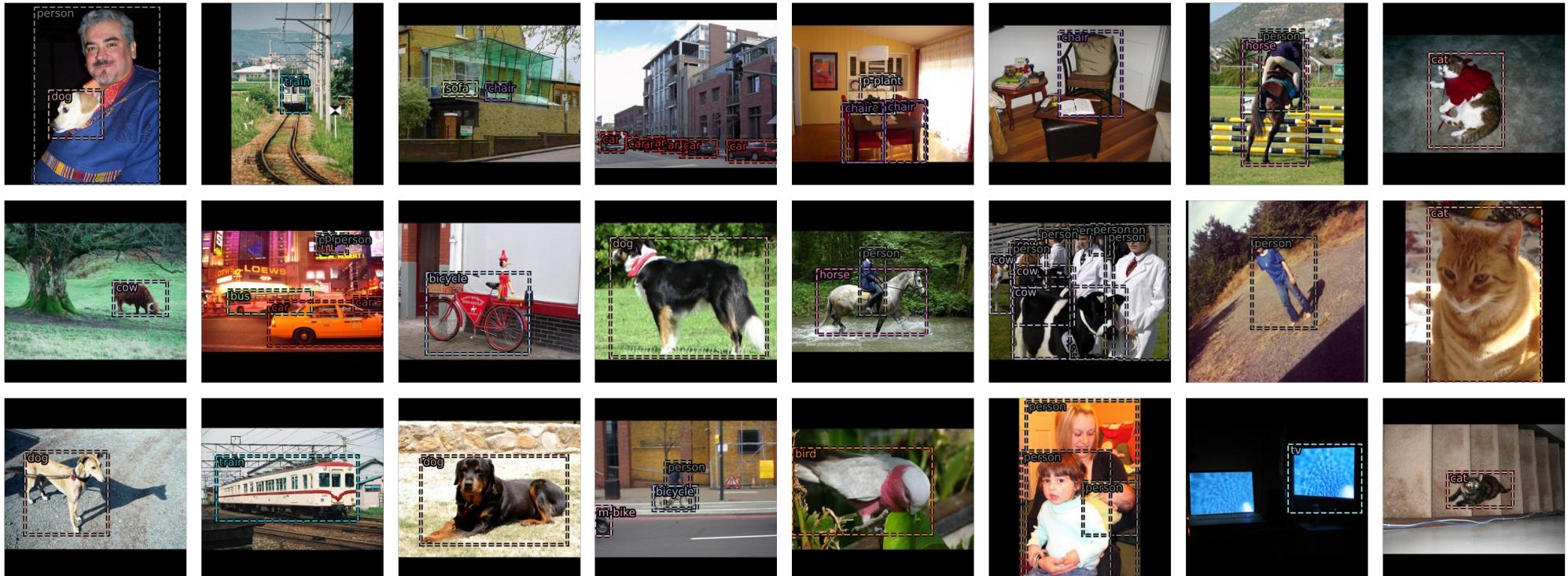


table	dog	horse	m-bike	person	p-plant	sheep	sofa	train	tv
plane	bicycle	bird	boat	bottle	bus	car	cat	chair	cow

Simple classifier using object cutouts

We define a classifier with an **input dim. of 128x128**, and an **output dim. of 20** (number of classes) using **Softmax** activation. The 4952 Test 2007 images are kept untouched for validation.

The training images are dynamically generated using the **Albumentations library**

- Pick a random image in the training set
- Pick a random target box in the image and perform a **cutout and rescale**
- Apply augmentation (Flip, color, contrast, translate, rotate, etc.)

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

Some examples of training images:



Simple classifier using object cutouts

Possible network architecture

```
cnn.conv(f_size=i_ar([3,3]), nb_filters=16 , 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=32 , 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=64 , 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=1024, padding=i_ar([1,1]), activation="RELU")
cnn.conv(f_size=i_ar([3,3]), nb_filters=1024, padding=i_ar([1,1]), activation="RELU")
cnn.conv(f_size=i_ar([1,1]), nb_filters=nb_class, padding=i_ar([0,0]), activation="LIN")
cnn.pool(p_size=i_ar([1,1]), p_global=1, p_type="AVG", activation="SMAX")
```

Confusion matrix on the validation set for the pre-trained network at epoch 300 :

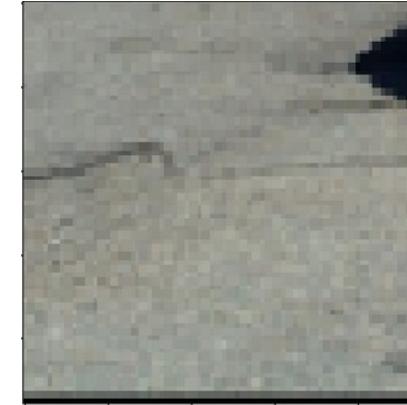
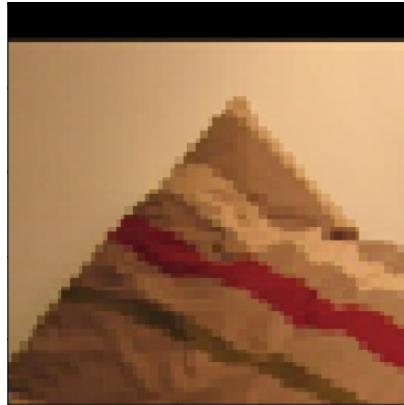
ConfMat																				Recall	
93	0	3	3	0	0	1	0	0	0	1	0	0	0	0	3	0	0	0	3	86.92%	
0	133	0	1	1	1	0	0	4	0	0	0	0	0	0	8	8	0	0	0	85.26%	
3	1	154	1	3	0	4	6	1	5	0	3	5	2	12	3	2	0	1	0	74.76%	
4	2	2	92	0	0	2	0	0	0	1	0	2	1	1	1	0	0	4	0	82.14%	
0	0	0	1	99	0	1	0	4	0	0	4	0	0	22	3	0	1	0	1	71.74%	
2	1	0	4	0	77	8	0	0	0	0	0	0	0	0	0	0	0	7	0	77.78%	
8	2	0	4	1	9	404	0	4	0	1	1	0	0	4	4	1	0	2	2	90.18%	
0	0	5	0	1	0	1	117	4	0	0	19	2	0	13	1	4	2	1	0	68.82%	
0	3	2	1	0	0	1	0	261	0	14	0	1	1	30	3	1	19	6	2	75.65%	
0	0	1	0	0	0	0	0	1	2	49	0	9	11	0	2	0	8	0	0	59.04%	
0	1	0	4	1	0	3	0	4	0	77	0	1	0	4	1	0	4	3	0	74.76%	
0	1	4	0	0	0	0	23	1	9	0	159	16	0	24	1	3	3	0	0	65.16%	
1	0	3	0	0	0	0	0	0	1	3	1	5	132	0	14	0	3	0	0	80.98%	
1	4	0	0	1	0	5	0	0	0	1	1	0	114	14	0	0	0	0	0	80.85%	
0	13	10	6	12	2	6	4	24	1	5	14	13	13	1685	0	0	11	4	1	92.38%	
0	1	5	0	2	0	3	1	7	0	2	0	0	0	3	158	0	0	2	0	85.87%	
0	0	2	0	0	0	0	3	1	12	0	14	2	0	0	73	0	0	0	0	67.59%	
1	1	0	1	0	0	3	2	8	1	3	2	1	0	17	0	0	72	3	0	62.61%	
1	2	1	3	0	1	0	0	0	0	0	0	0	0	2	0	0	0	125	1	91.91%	
0	0	0	1	1	1	0	0	6	0	1	1	0	0	4	2	0	0	2	99	83.90%	
Prec.	81.58%	80.61%	80.21%	75.41%	81.15%	84.62%	91.40%	74.52%	78.61%	61.25%	72.64%	68.53%	70.59%	78.62%	90.45%	90.80%	77.66%	63.16%	76.69%	94.29% Acc	83.83%

Adding a background class

To be used as a detector our classifier must be able to predict an empty case

- 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**
 - **20% of the time, 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 too small → stop the process and use an empty (zero) input instead

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



The performance of this new classifier should be similar with ~94% recall on background examples

Using the new classifier as a sliding window detector

The sliding window principle

Classifier = identify individual objects relatively centered

Can be used as a **sliding window detector**:

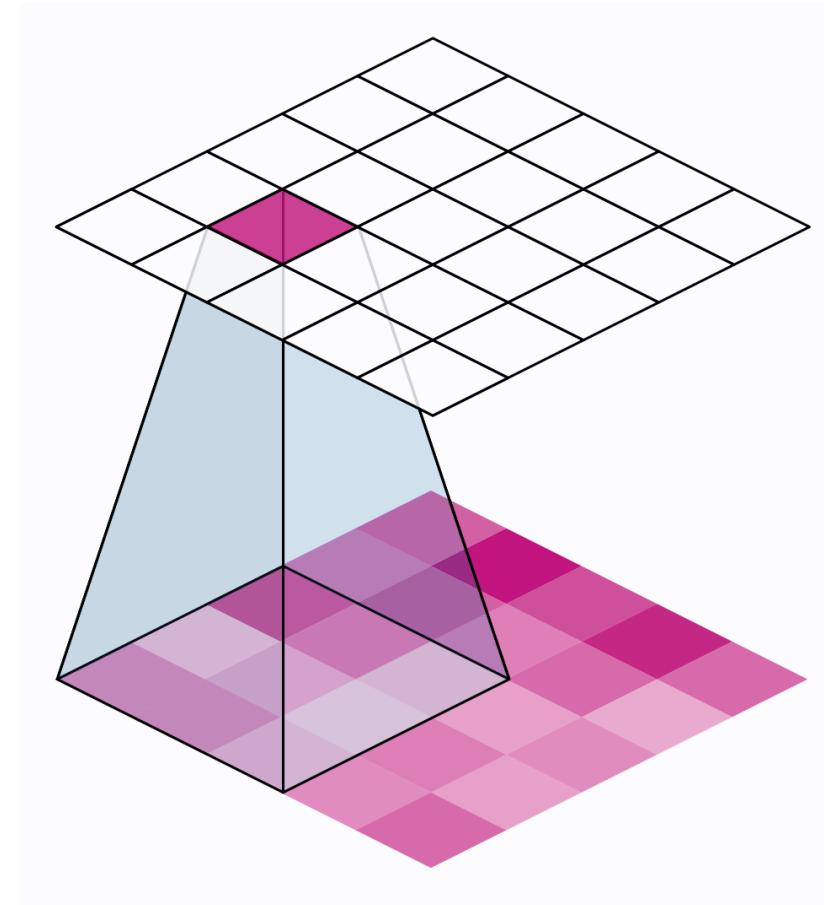
- Split a larger image in “chunks”
- Overlapping Chunks for more « centered » objects

**Process similar to a convolution,
with Classifier ≈ Filter**

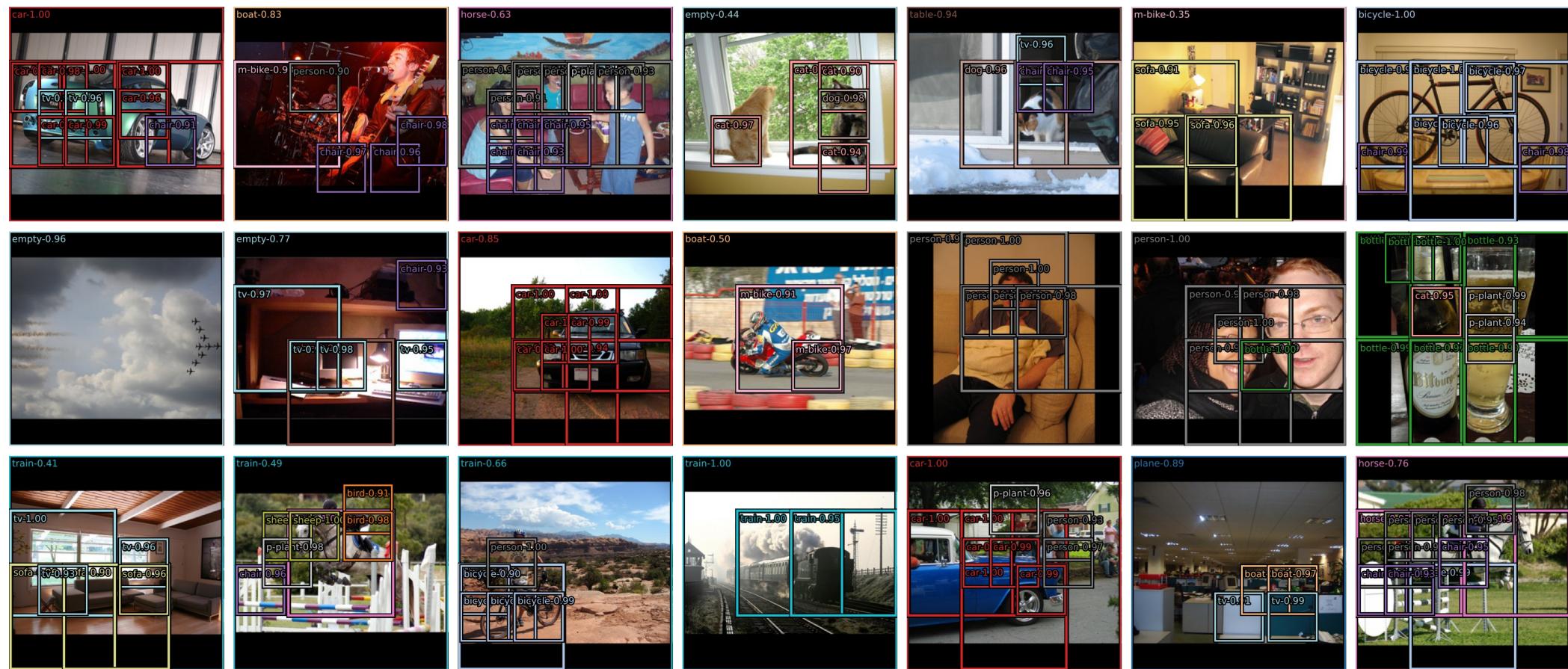
- Using multiple window sizes increases the chance of a proper cutout for objects of various sizes

In the present case we use **3 window sizes** [288, 144, 72] with a respective stride of [0, 72, 36].

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



Training a sliding window detector

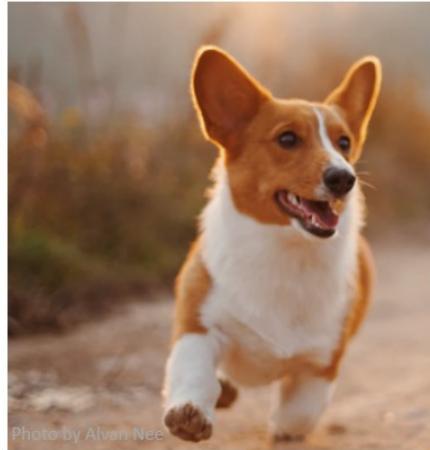


Questions : How to filter overlapping detection ? How to evaluate prediction performance ?

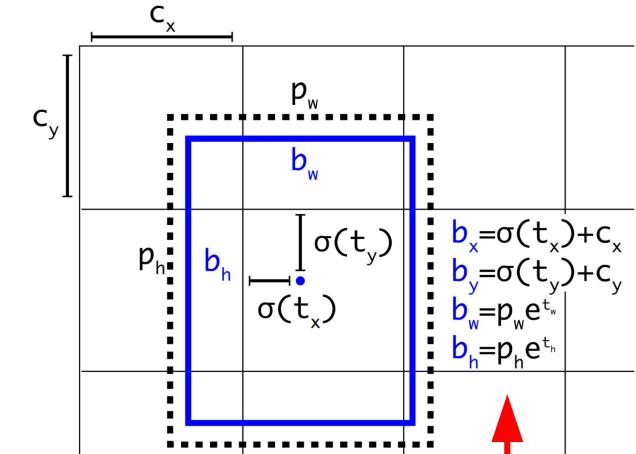
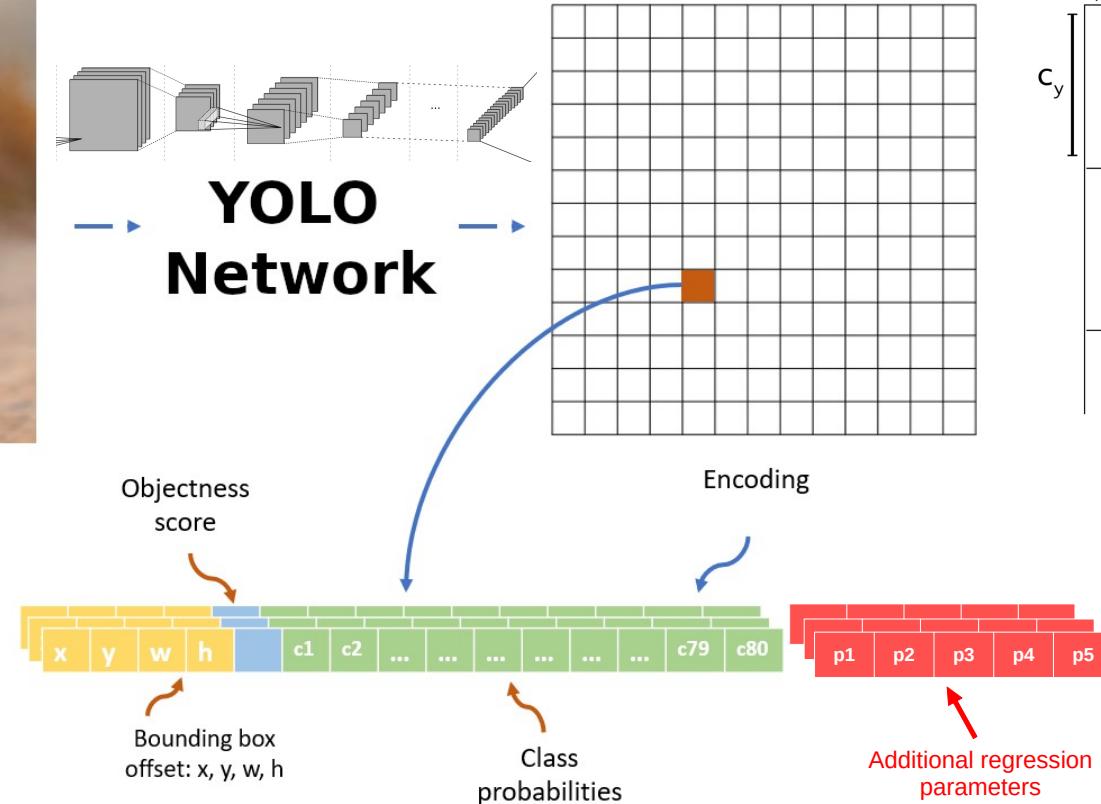
The You Only Look Once (YOLO) detector

Originally introduced in Redmon et al. 2015 (V1), 2016 (V2), 2018 (V3)

*Images from [blog post](#) and Redmon papers



Pre-processing Image

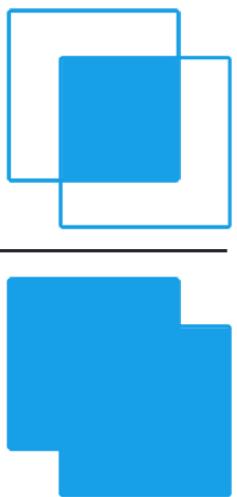


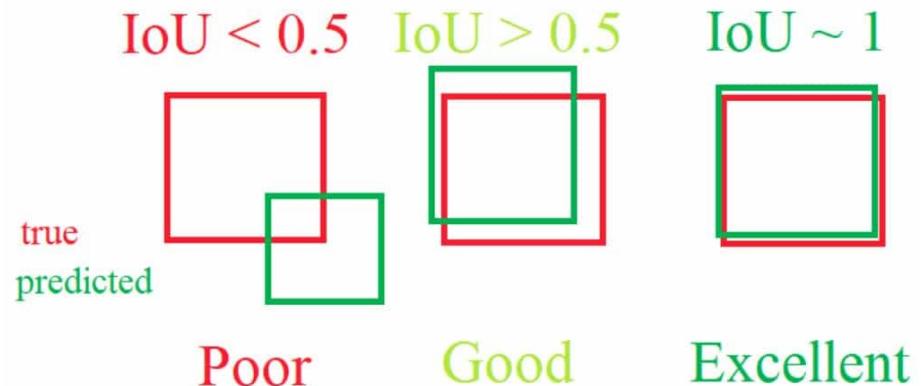
Box size
priors

The last layer is conv. = the boxes « share » weights spatially.

The output is a 3D cube encoding all possible boxes on the output grid.

How to estimate box « correctness » ?

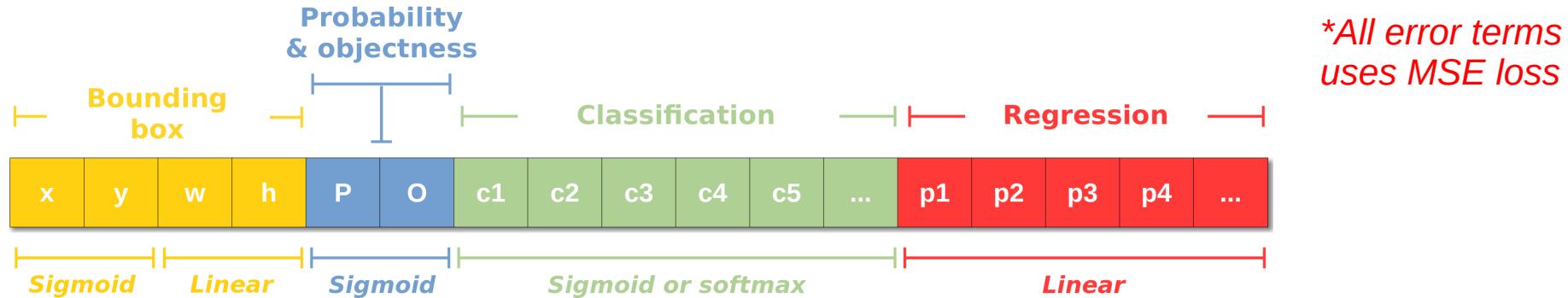
$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$




For each box the network will predict an “objectness” score defined as:

$$Pr(\text{object}) * IOU(b, \text{object}) = \sigma(t_o)$$

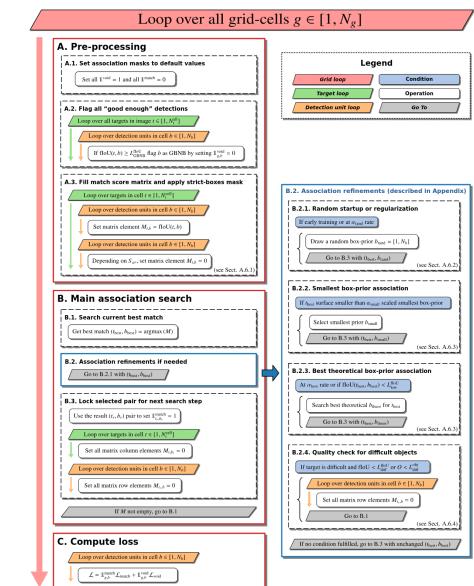
The YOLO activation/ association process



Simplified Training procedure:

- For each target, find the corresponding grid element
- Search for the best predicted box in this grid element
- Exclude “good but not best” boxes (using an IoU threshold)
- For the best box only :**
 - Update the position and size
 - Update objectness with target probability of 1
 - Update parameters and class according to targets
- For all the predictions with no associated target, update only the objectness with a target 0

*See the full association function in Cornu et al 2024



The YOLO activation / Loss function

$$\mathcal{L} = \sum_{i=0}^{N_g} \sum_{j=0}^{N_b} \mathbb{1}_{ij}^{\text{match}} \left(\lambda_{\text{pos}} \left[(o_{ij}^x - \hat{o}_{ij}^x)^2 + (o_{ij}^y - \hat{o}_{ij}^y)^2 \right] \right.$$

$$+ \lambda_{\text{size}} \left[(o_{ij}^w - \hat{o}_{ij}^w)^2 + (o_{ij}^h - \hat{o}_{ij}^h)^2 \right]$$

$$+ \lambda_{\text{class}} \mathbb{1}_{ij}^C \sum_k^{N_C} \left(-\hat{C}_{ij}^k \log(C_{ij}^k) \right)$$

$$+ \lambda_{\text{param}} \mathbb{1}_{ij}^p \sum_k^{N_p} \gamma^k \left(p_{ij}^k - \hat{p}_{ij}^k \right)^2$$

$$+ \lambda_{\text{prob}} \mathbb{1}_{ij}^P \left(P_{ij} - 1 \right)^2$$

$$\left. + \lambda_{\text{obj}} \mathbb{1}_{ij}^O \left(O_{ij} - \text{IoU}_{ij} \right)^2 \right)$$

$$+ \sum_{i=0}^{N_g} \sum_{j=0}^{N_b} \mathbb{1}_{ij}^{\text{void}} \lambda_{\text{void}}^j \left(\lambda_{\text{prob}} \left(P_{ij} - 0 \right)^2 + \lambda_{\text{obj}} \left(O_{ij} - 0 \right)^2 \right).$$

/!\ No error term for
« Good but not best » boxes

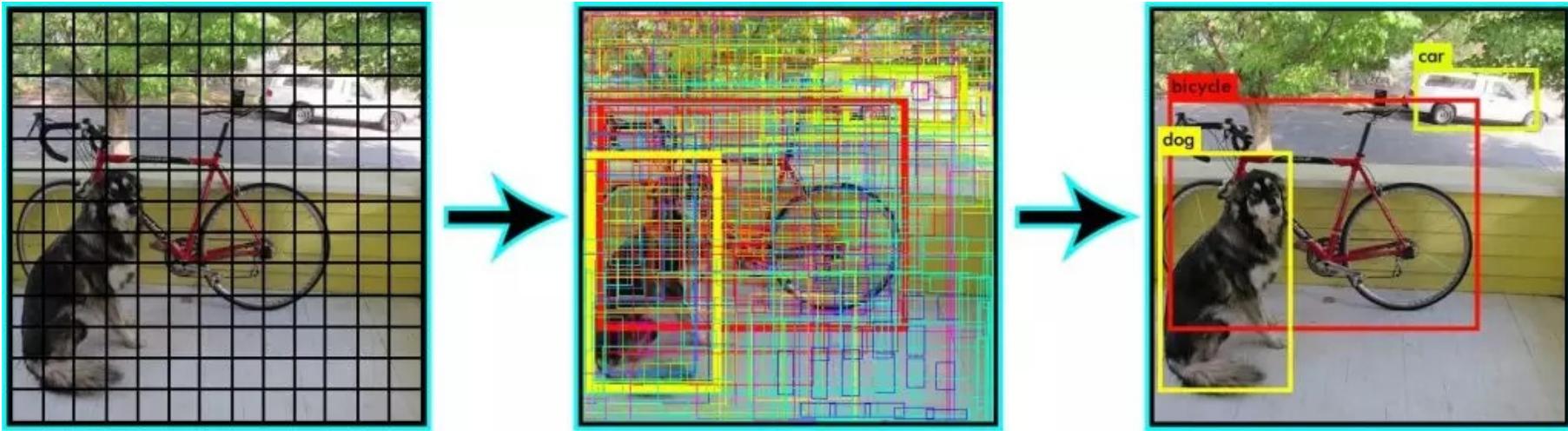
Only for the best box
corresponding to each target



Only for background (no
match) predicted boxes

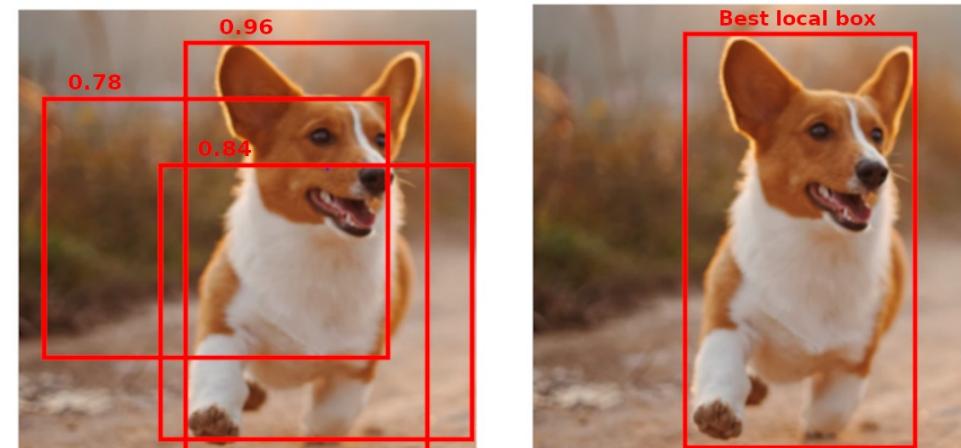
Post-processing: Non Max Suppression

Due to the fixed size nature of its output layer, a YOLO network always predict all the possible boxes



1) Most probable boxes are kept using a threshold in objectness

2) NMS takes the most probable box and removes overlapping ones based on an IoU threshold. Repeat.



Post-processing: Non Max Suppression

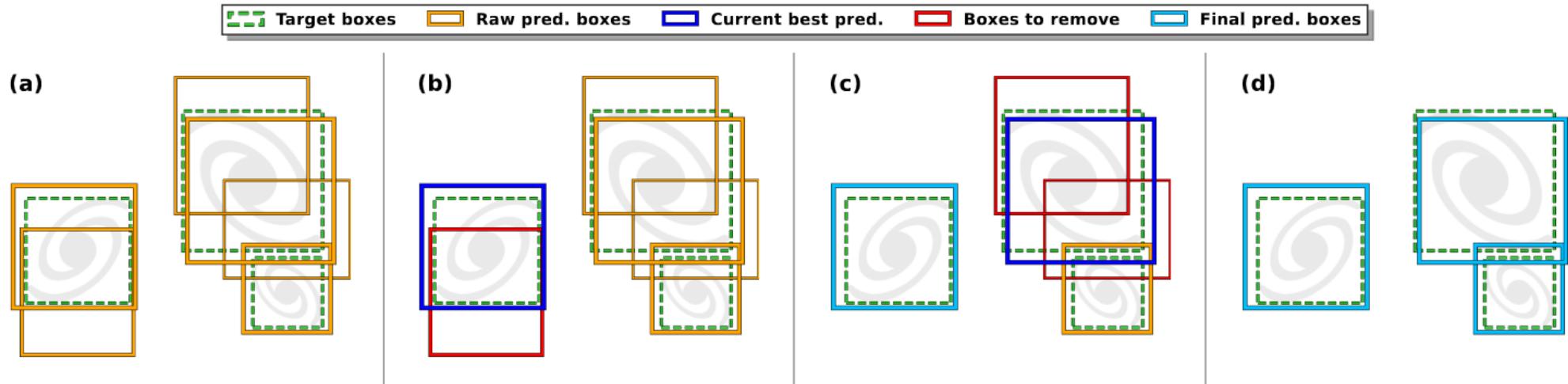
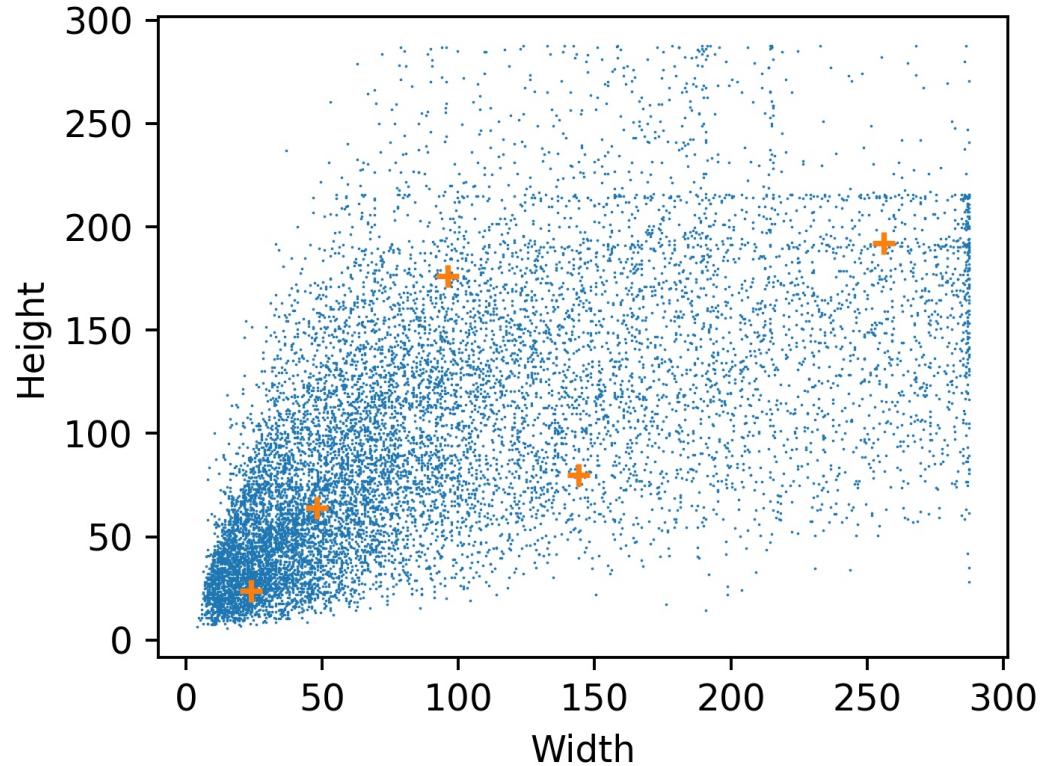
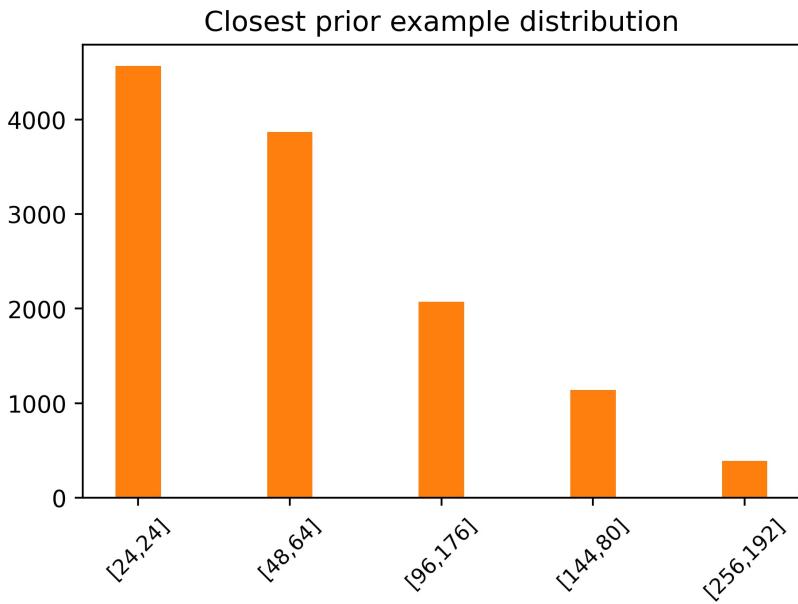


Fig. 5: Illustration of the NMS process in a given image. The dashed boxes are the target, and the solid boxes are the predictions. The line widths of the boxes are scaled on their respective objectness score. The colors indicate the state of the box in the NMS process at different steps. Frame (a) represents the targets and the raw network predictions that remain after the objectness filtering. Frames (b) and (c) represent two successive steps of the NMS process with a different best current box. Frame (d) represents the remaining boxes after completion of the NMS.

Training a YOLO network on PASCAL VOC

Input dimension: 288x288
Spatial reduction factor: 32
→ **Output grid:** 9x9



Based on testset box size distribution
Nb priors: 5
[24,24];[48,64];[96,176];[144,80];[256,192]

Training a YOLO network on PASCAL VOC

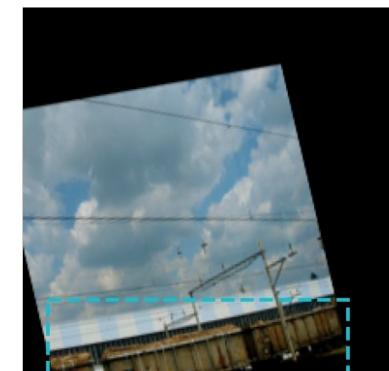
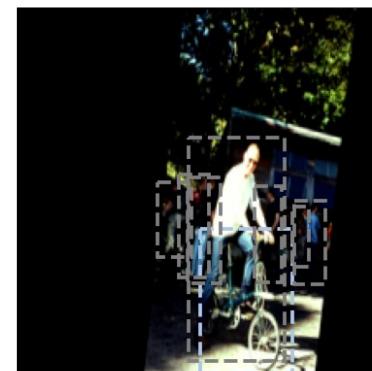
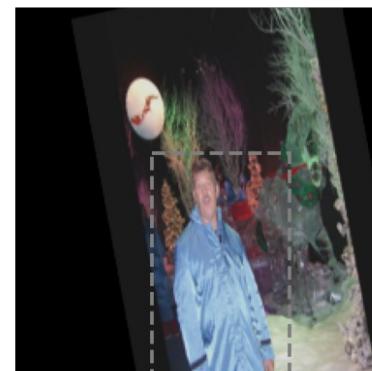
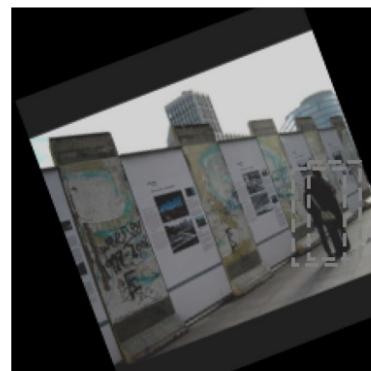
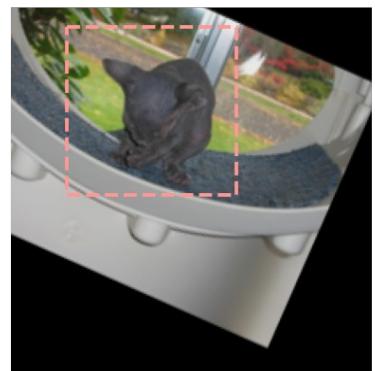
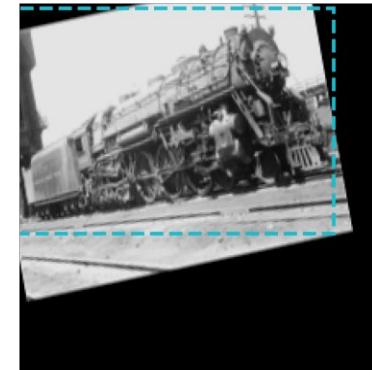
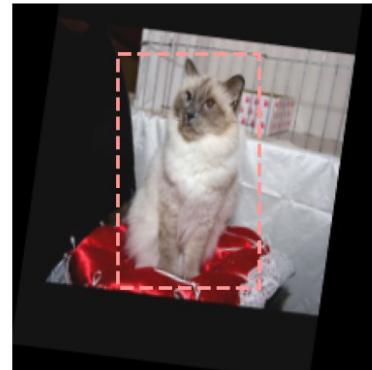
Possible network architecture

```
cnn.conv(f_size=i_ar([3,3]), nb_filters=24, 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=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=256, padding=i_ar([1,1]), activation="RELU")
cnn.conv(f_size=i_ar([3,3]), nb_filters=256, padding=i_ar([1,1]), activation="RELU")
cnn.conv(f_size=i_ar([1,1]), nb_filters=512, padding=i_ar([0,0]), activation="RELU", drop_rate=0.1)
cnn.conv(f_size=i_ar([1,1]), nb_filters=nb_yolo_filters, padding=i_ar([0,0]), activation="YOLO")
```

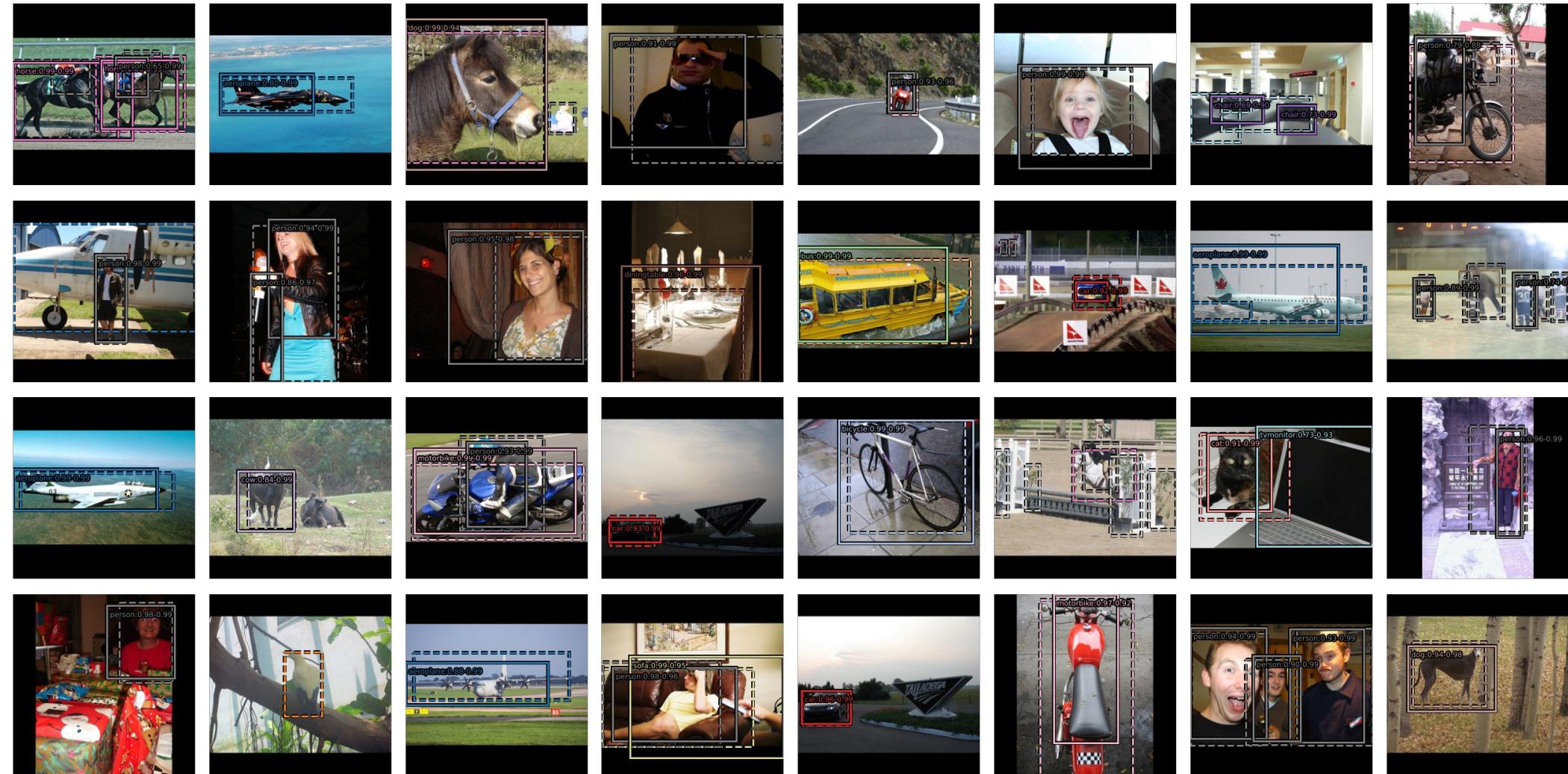
Inspired by the YOLO-Light V2 and Tiny-Yolo V2 architectures

Training a YOLO network on PASCAL VOC

Advanced data augmentation



Training a YOLO network on PASCAL VOC

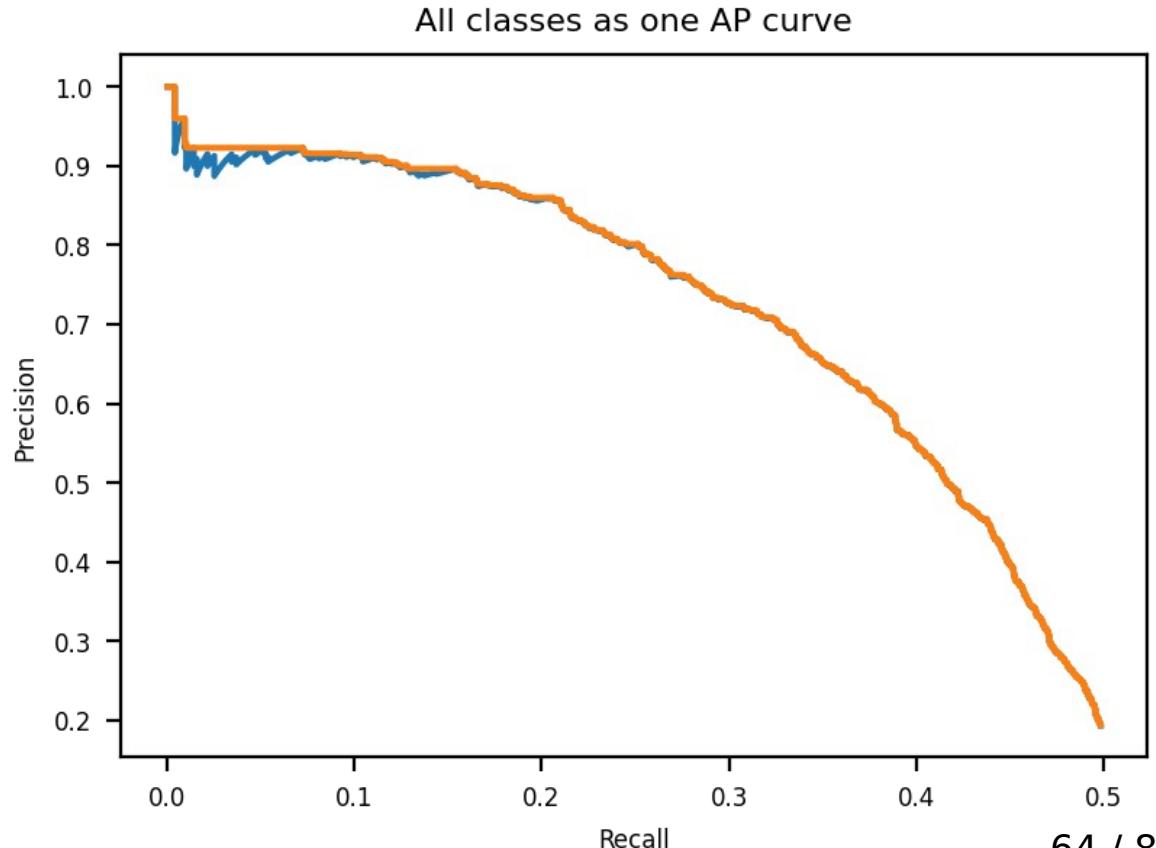


Detection performance metric

Match if $\text{IoU} > V$ between prediction and target → Usually $V = 0.5$

The precision-recall curve

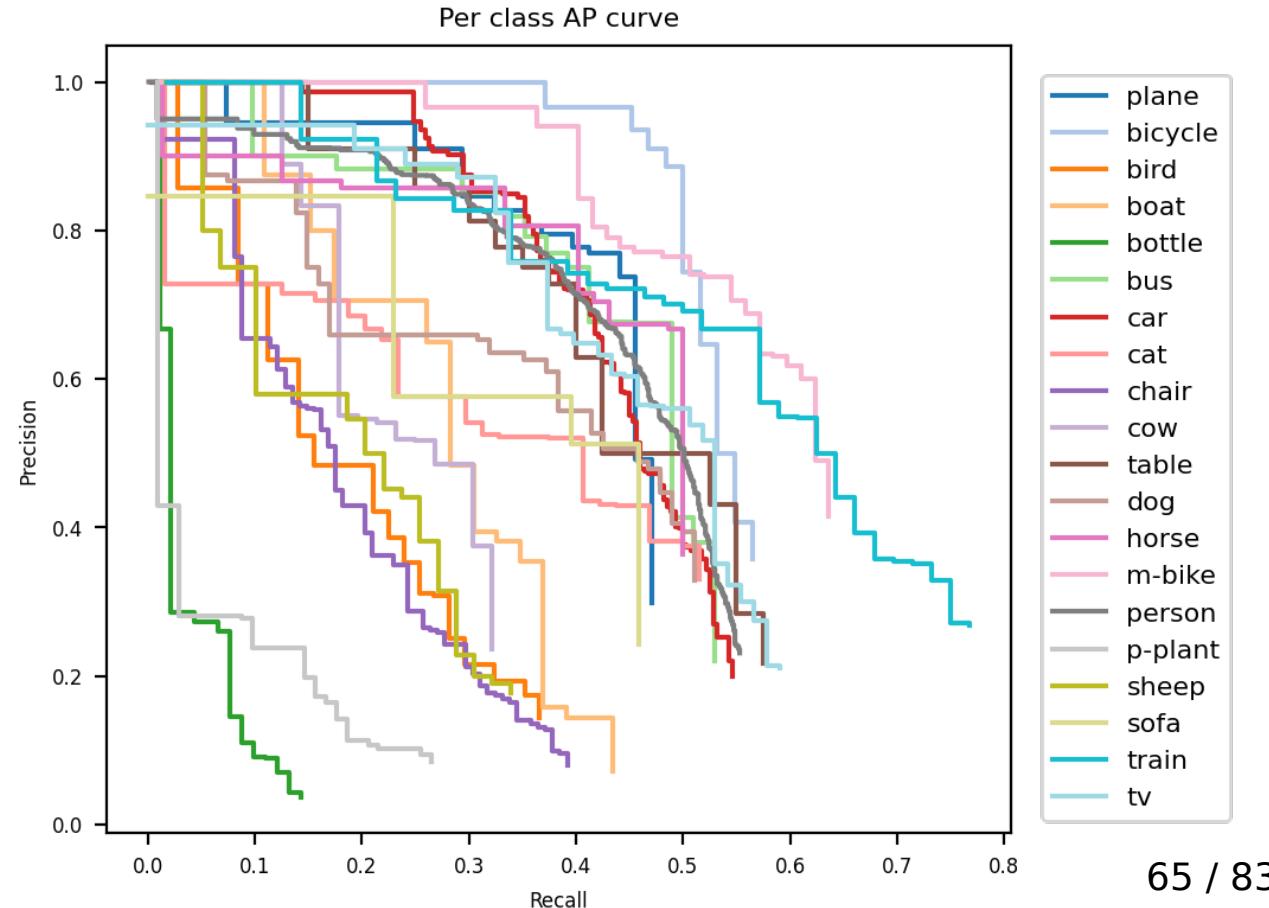
- Predictions are sorted by score
- For each data point, compute the precision and recall using all the predictions that are scored higher, using **IoU@0.5** and correct classification as “True” criteria
- The curve is then smoothed so it can only monotonically decrease (precision is always equal to its maximum value for any higher recall)
- The area under the curve defines the global metric called:
Averaged-Precision AP@50



Per class AP and Mean AP

Each class gets its own Recall-Precision curve and AP score.
The final metric is the **mean of the AP values**.

Here mAP@50 ~ 32%

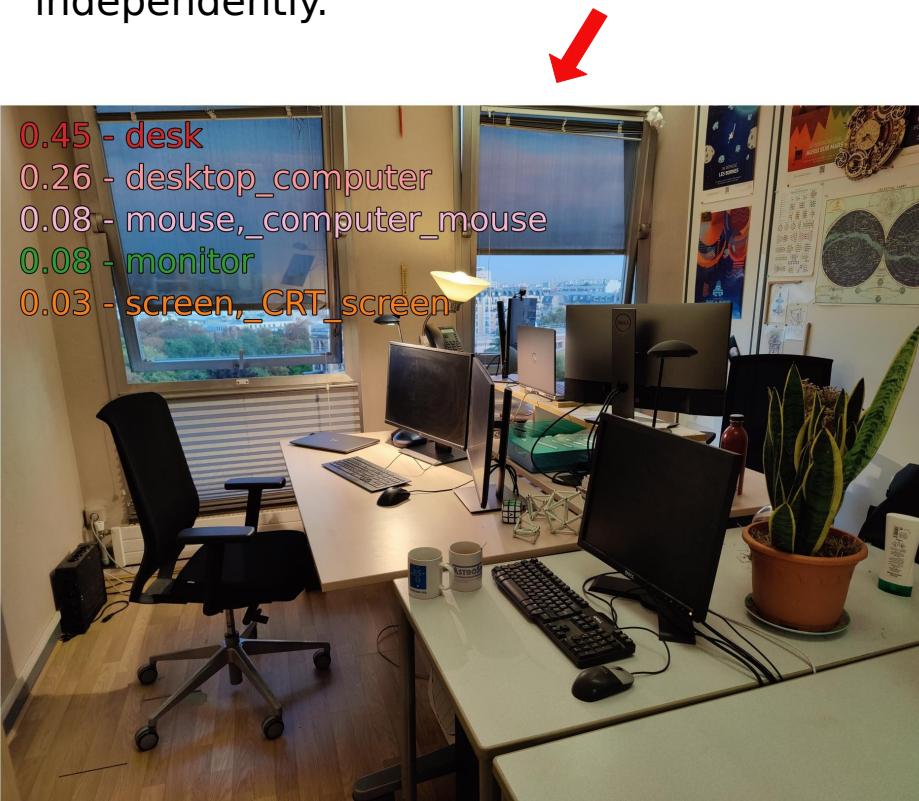


Warning: definition of AP and mAP
might change depending on the
challenge or dataset

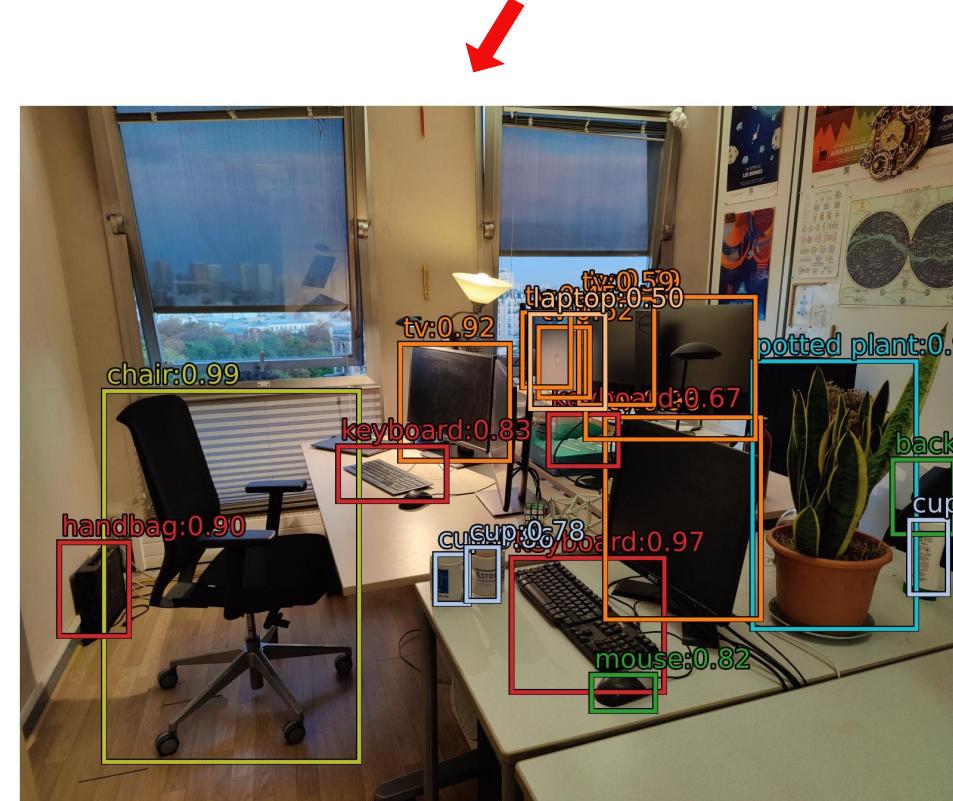
More advanced YOLO detection

In the CIANNA git repository (<https://github.com/Deyht/CIANNA>), we provide several detection models using the custom YOLO-CIANNA method with backbone very similar to the darknet-19 architecture and applied to several datasets.

The model is pre-trained on **ImageNet** and then trained on the PASCAL and **COCO** datasets independently.

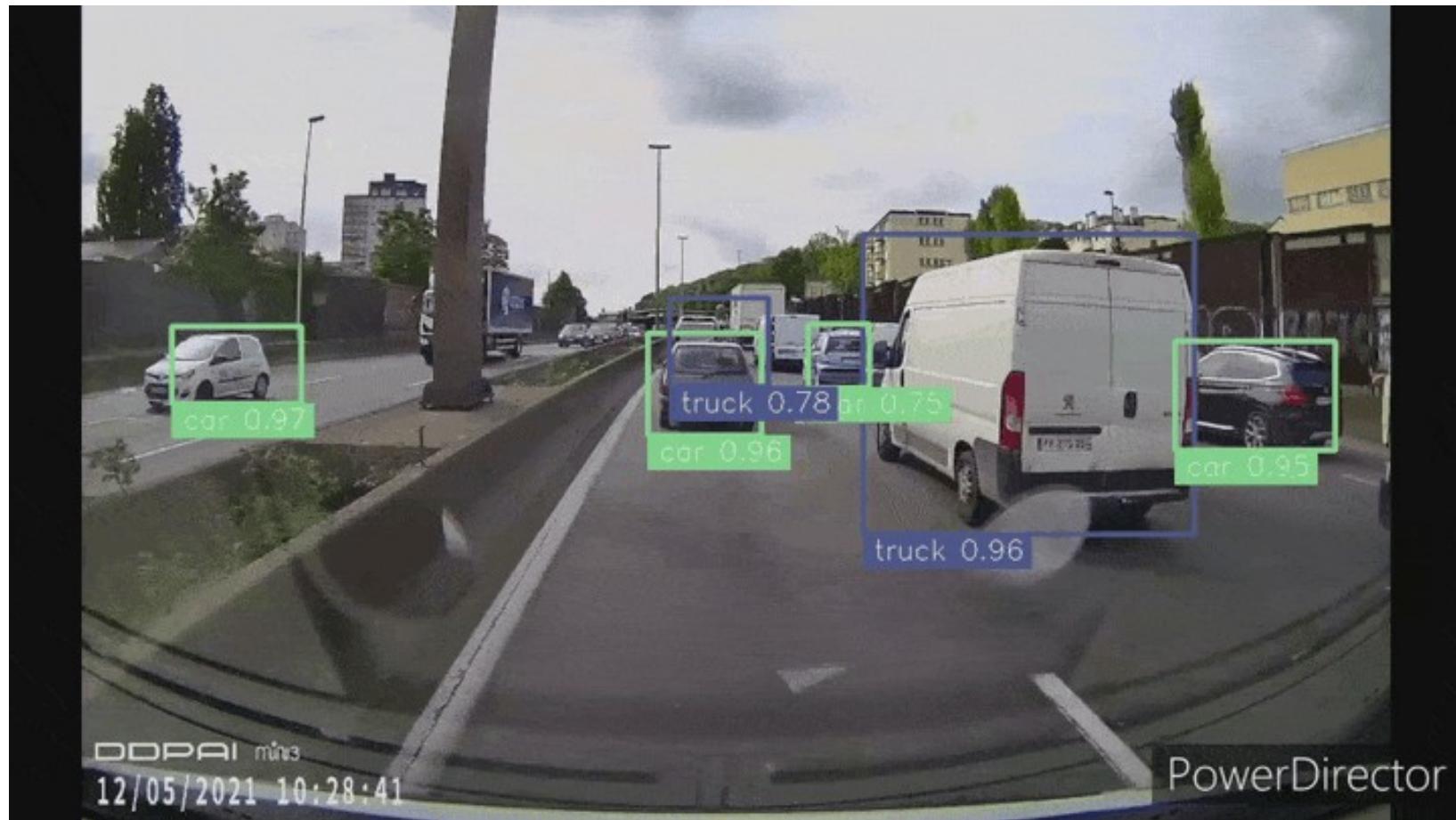


0.45 - desk
0.26 - desktop_computer
0.08 - mouse,_computer_mouse
0.08 - monitor
0.03 - screen,_CRT_screen



Results from a YOLO network trained on COCO

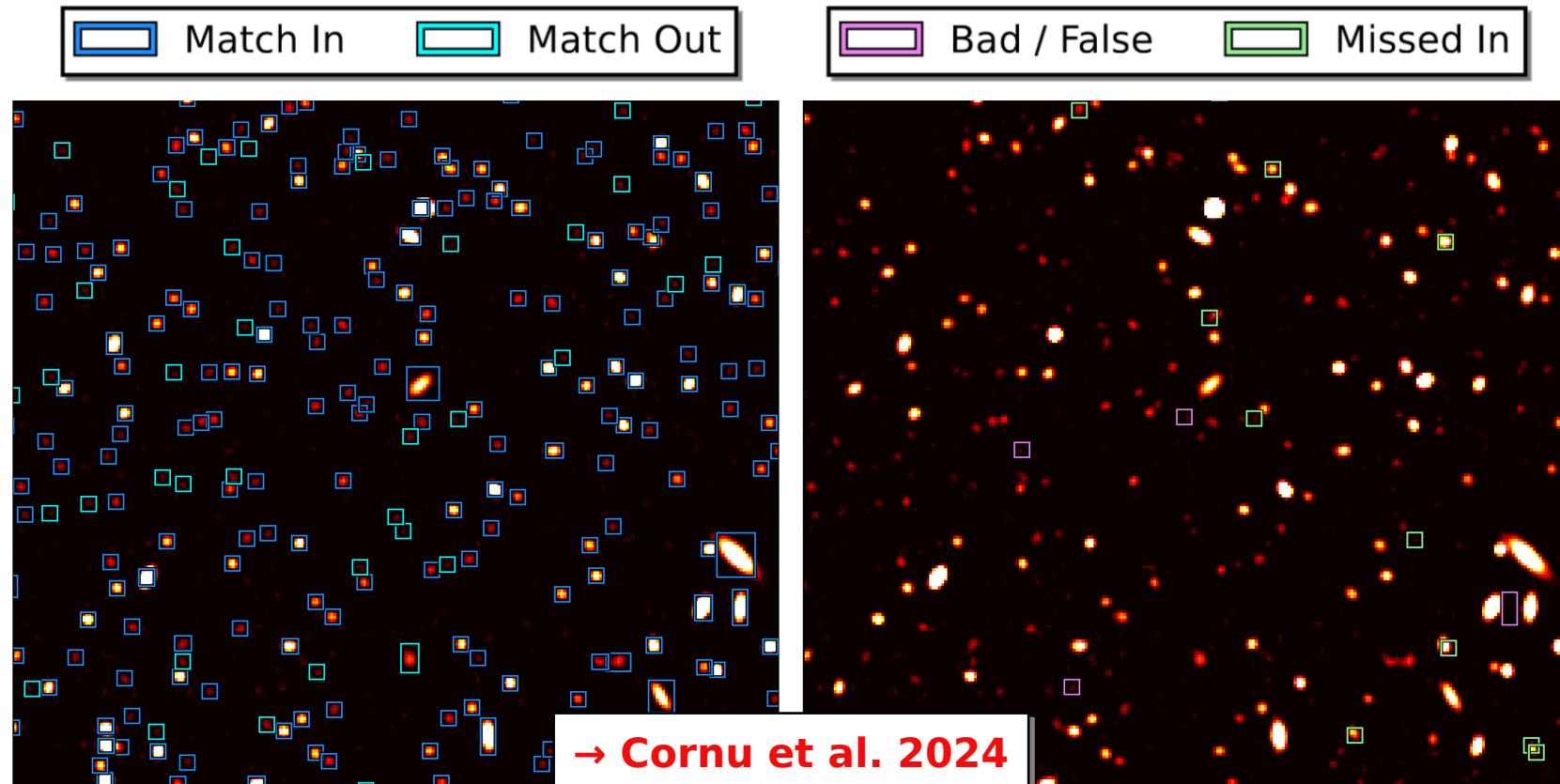
Result using a YOLO detector with a darknet-19 “like” backbone. 40.1 mAP over the 1000 classes, at a 416p resolution. The network run at 690 ips on an RTX 4090.



YOLO-CIANNA for galaxy detection - SKAO SDC1

Simulated continuum observation at 560 MHz for 1000h integration time with SKA

Objective: detect (Ra, Dec) and characterize (Flux, Bmaj, Bmin, PA, ...) the sources

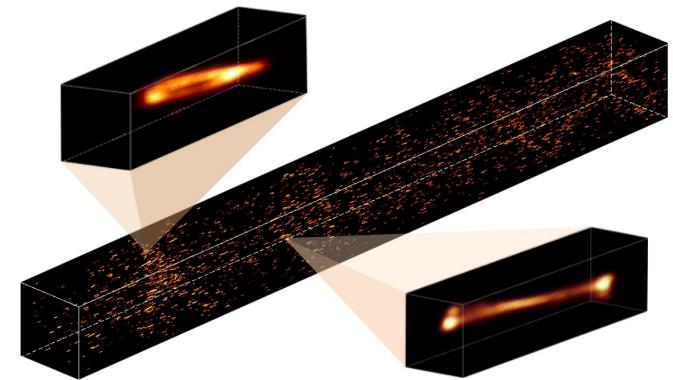


Fast (~ 130 Mpix/s - RTX 4090) and light network (17 layers, 13M param)

YOLO-CIANNA for galaxy detection - SKAO SDC2

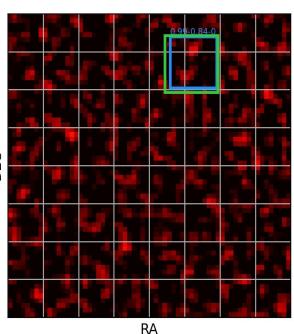
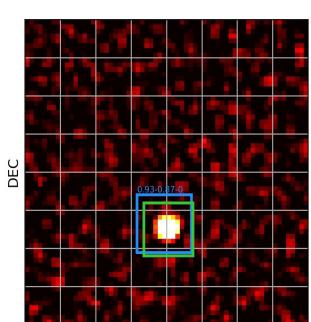
Simulated HI cube for 2000h integration time with SKA

Objective: detect (Ra, Dec, Freq) and characterize (Line flux, HI size, PA, I) the sources

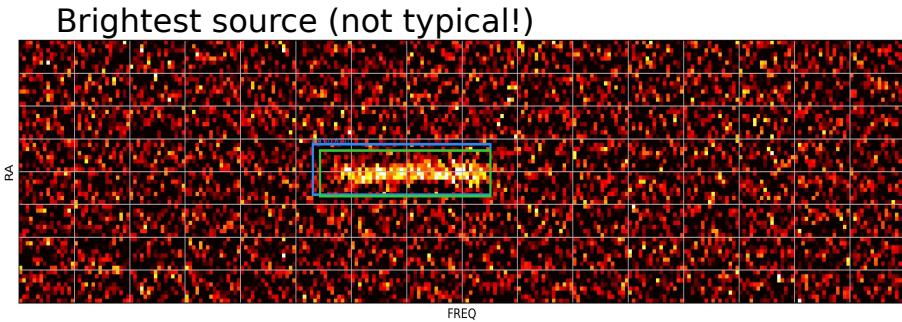


→ Harley et al. 2023
→ Cornu et al. 2025

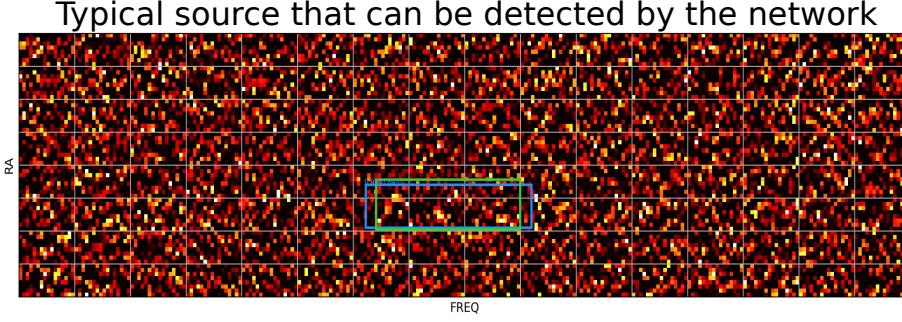
True boxes vs Predicted boxes



Brightest source (not typical!)



Typical source that can be detected by the network



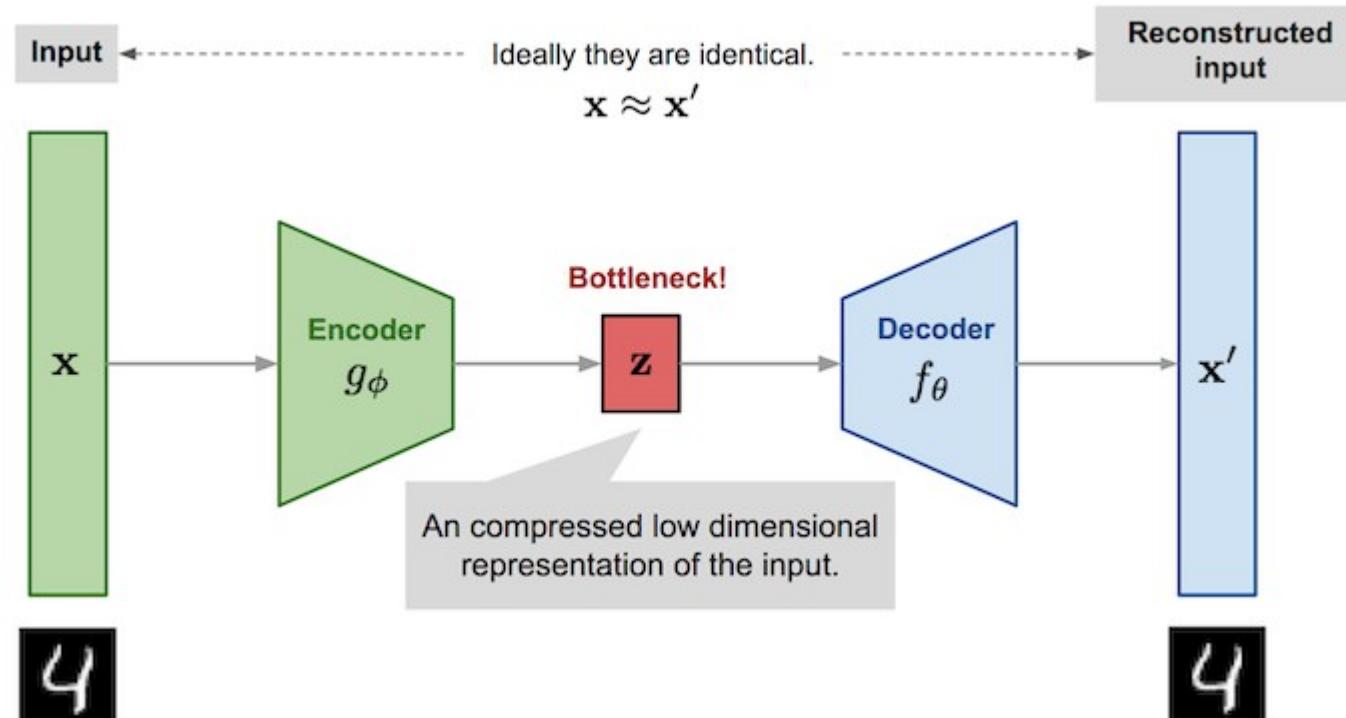
*averaged over 20 channels in FREQ and 20 pixels in DEC respectively

Fully 3D, fast (~120 Mpix/s - RTX 4090) and light network (23 layers, 4M param)

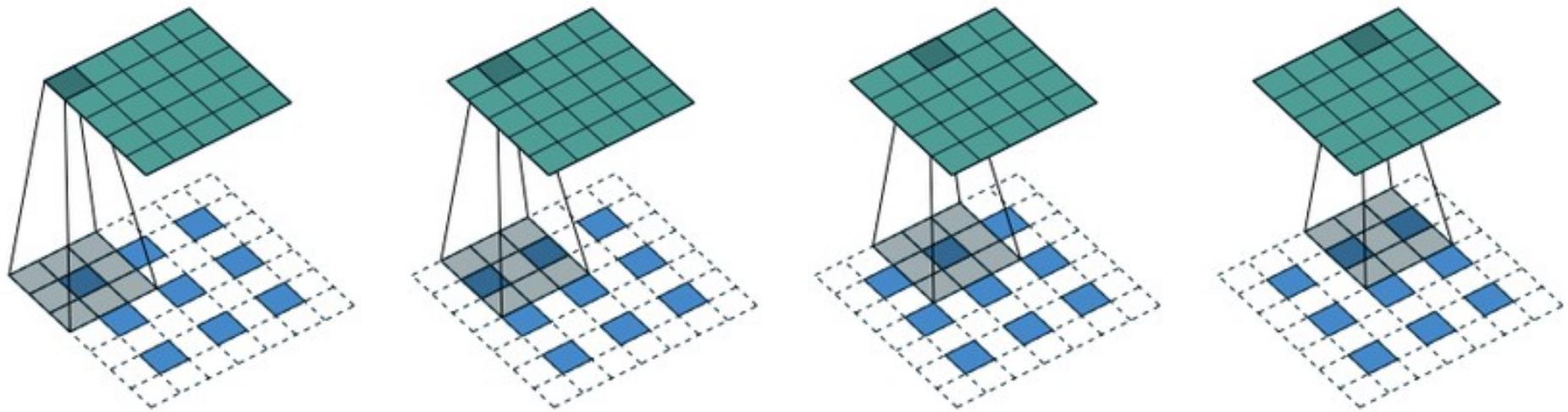
Self-supervised training with Auto-Encoders

AE networks aims to **reconstruct their input (self-supervised learning)**. They are composed of an **encoder** that compresses the information up to a **latent space**, and of a **decoder** that reconstructs the input from the latent representation.

AE are used for denoising, data compression, and even data generation.



Transposed convolution for upsampling



To upsample the activation maps of a given layer, the common approach is transposed convolution.

By adding an **internal padding between elements of the activation maps and then doing a classical convolution**, we obtain output maps that are larger than the input ones.

→ *This is the operation used when backpropagating the gradient through layers with a stride >1*

This structure allows the construction of **expanding decodeurs** that are employed in many architectures.

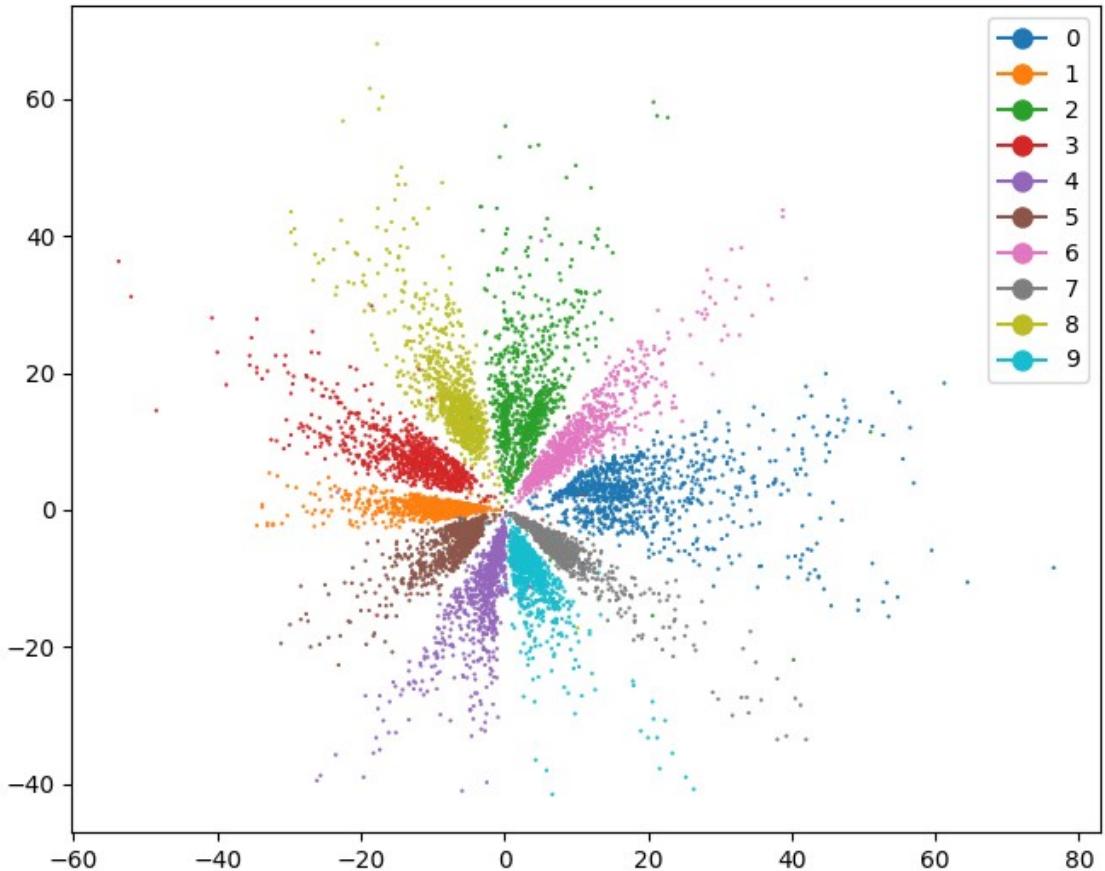
Visualizing the latent space

After the AE is trained, we can use the **encoder on labeled data** to visualize their distribution **in the latent space**.

AE are very similar to PCA in their principle but can separate more complex objects thank to the learned non-linearity allowed by the network structure.

AE can be used for data generation by selecting new points in the latent space and using the decoder to generated the associated image.

Most modern applications use Variational AE in order to produce more compact and distinct distributions in the latent space, which also improve the realism of generated images when drawing in between class distribution in the latent space.



Generated digits from an MNIST AutoEncoder



Generated using a regular sampling in polar coordinates in the latent space from last slide.

Practical work:

Using the provided starting notebook, create an AE architecture on the MNIST dataset.

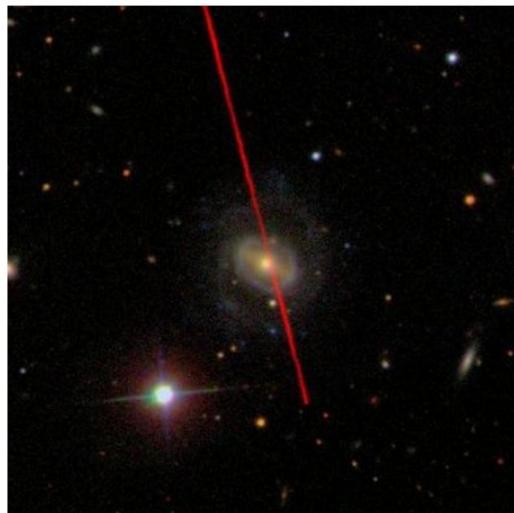
You will evaluate the performance of your reconstruction, visualize the latent space, and use it to generate new digits like above.

Advanced:

→ How could you reduce class confusion in the latent space ?

Semi-supervised recommendation rating

Example with Astronomaly

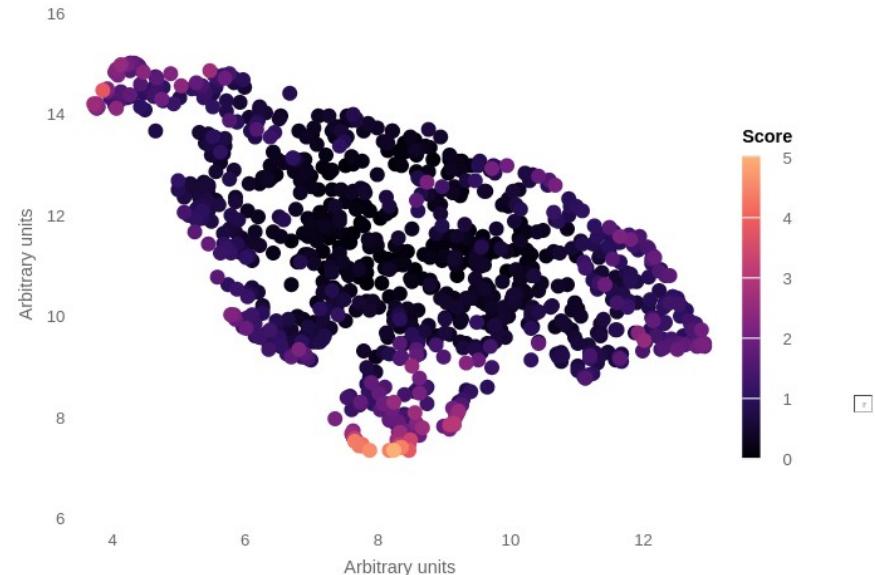


0



Index in list

701930



HOW INTERESTING IS THIS OBJECT?

0

1

2

3

4

5

Raw anomaly s... ▾



Show unlabelled objects first

DELETE LABELS

RETRAIN

Scoring method to sort by

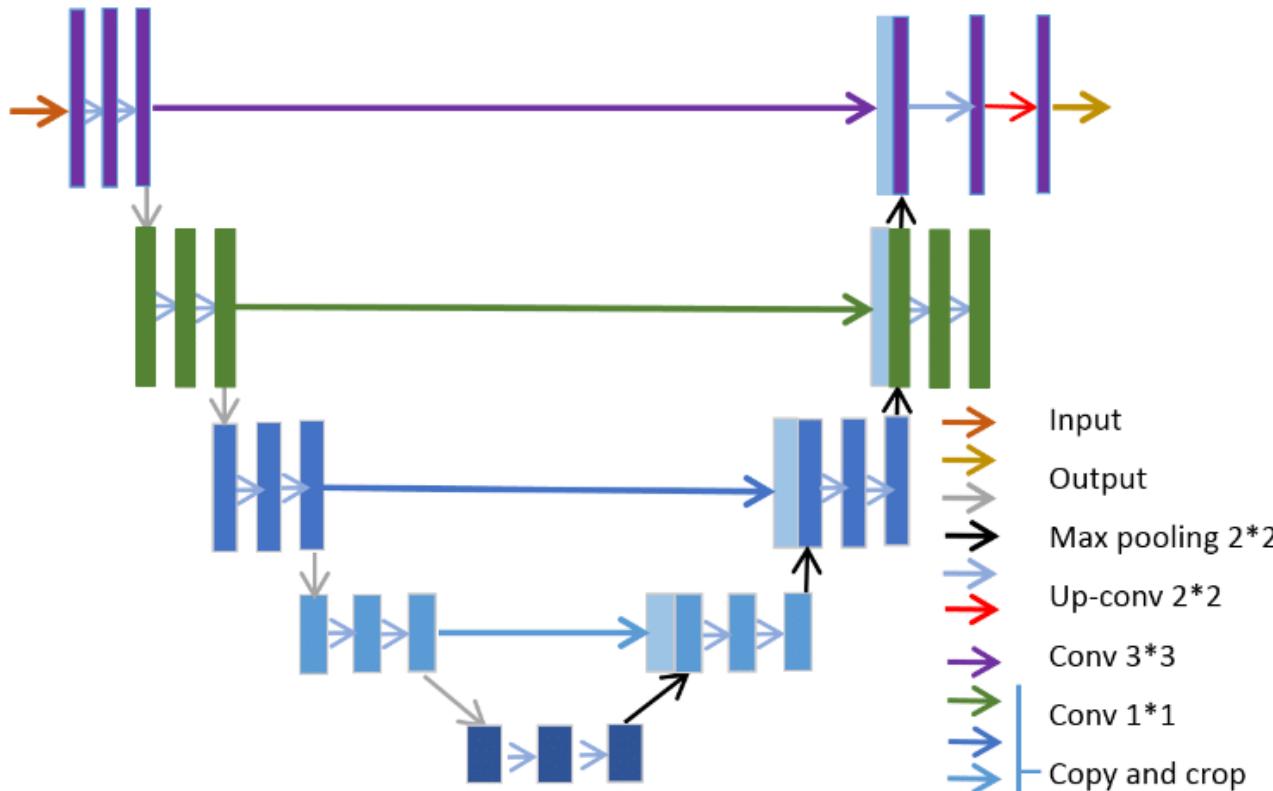
Raw anomaly score

Scoring method to colour by

Shortcut connections and the U-Net architecture

Shortcut/skip connections (or concatenate connections) are used to **adjunct the activation maps of a given layer to another layer** with the same spatial dimensions.

They are mostly used to pass high resolution maps from early stages of the network to later stage, usually from an encoder part to a decoder part like in the U-Net architecture.

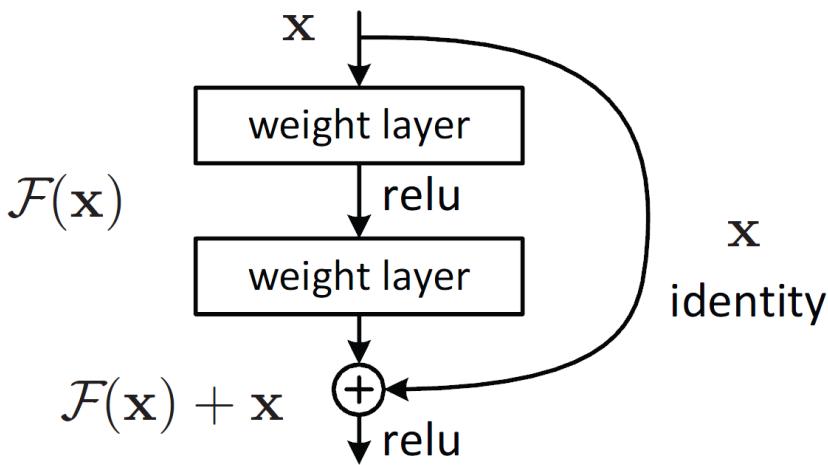


During training, the gradient flows both to the direct previous layer and through the shortcut connection. At the origin of the shortcut the two gradients are summed.

Using shortcut connections **reduce the vanishing gradient issue** as the gradient can flow directly to upper parts of the network. This principle can be used to construct deeper networks!

This type of architecture can be used for many application, for example denoising, image segmentation, or image generation, and it can be trained in a supervised or self-supervise way depending on the application.

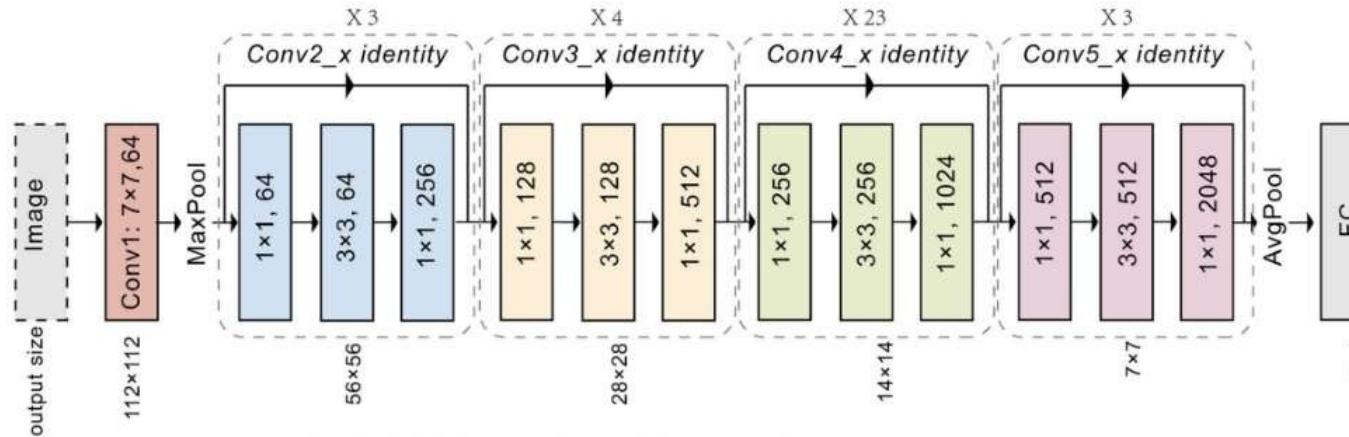
Very deep networks: Residual connections



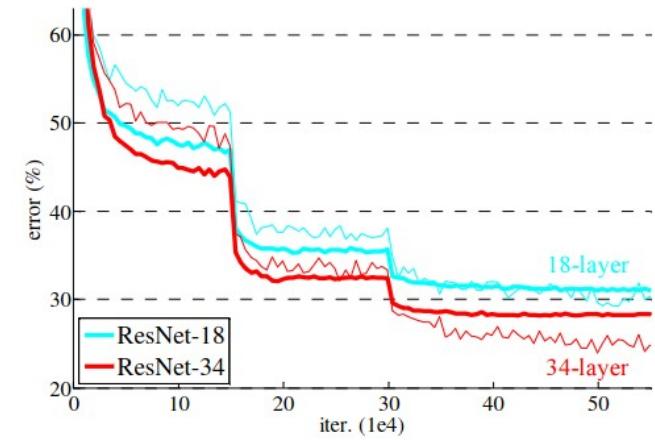
Residual connections are a specific type of shortcut connection where the feature maps of two distant layers are added element wise.

By construction, it means that an identity mapping flows through the residual connection and that all layers in between are tasked to learn a residue to add to this identity.

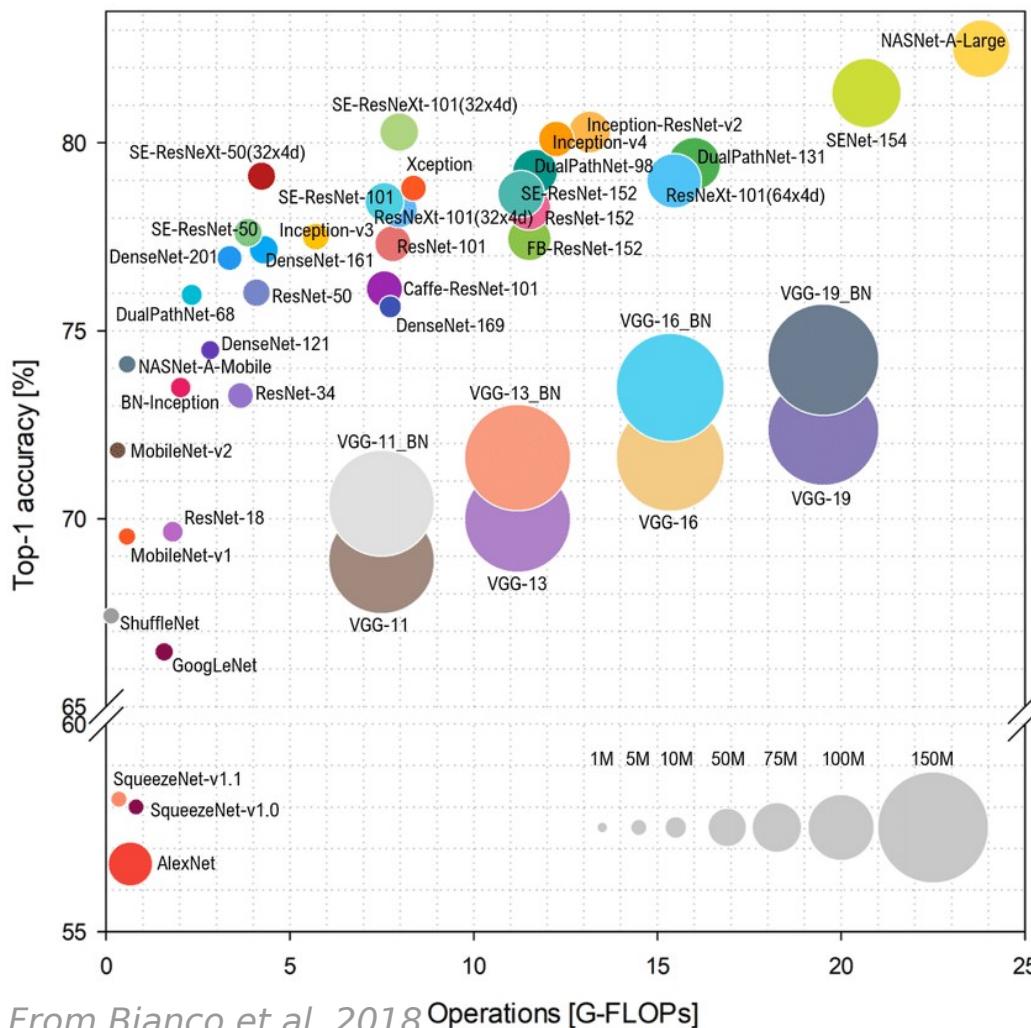
Residual connections are the main innovation that allowed the construction of networks with **hundreds of layers** without suffering from the vanishing gradient effect (Res-Net).



From He et al. 2015



Green AI vs Red AI



← Obtained from Image-Net 2012

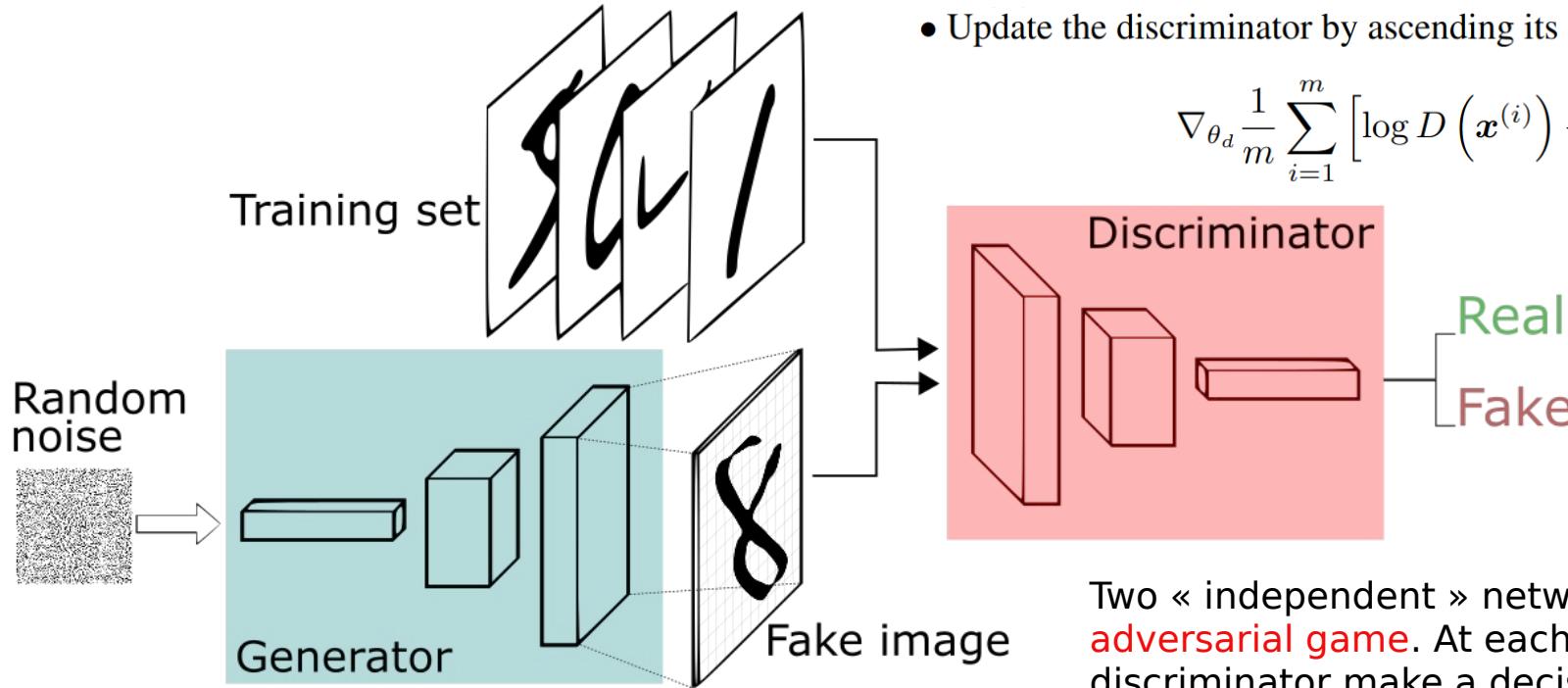
There is a **clear relation between accuracy and compute cost and model size**.

Finding efficient models that reach high accuracy is usually possible but more difficult to design and train.

Exploring architectures and training procedures require computing time !!

- When optimizing **a single prediction**, the total impact is mostly dominated by training time. (e.g., simulation based inference in research). Therefore optimizing the architecture might be irrelevant, or counter-productive.
→ Problem: High accuracy result obtained this way encourage the use of sub-optimized model structures!
- When the model is planned to be **deployed** optimization is way more important as **any % gained in efficiency scale with the size of the user base!**

Generative Adversarial Networks



- Update the discriminator by ascending its stochastic gradient:

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^m \left[\log D(\mathbf{x}^{(i)}) + \log (1 - D(G(\mathbf{z}^{(i)}))) \right].$$

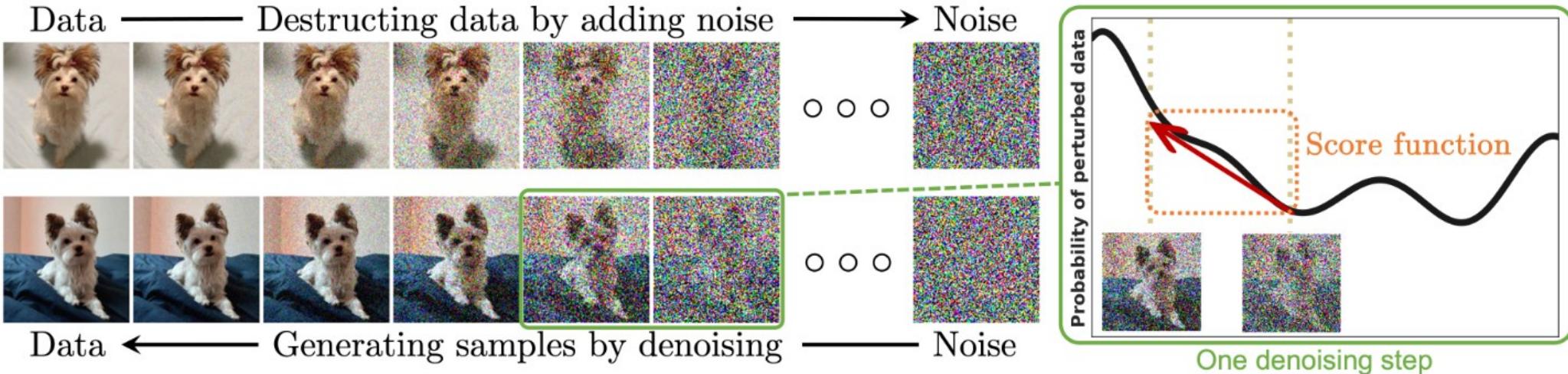
Two « independent » networks plays a **min-max adversarial game**. At each training step the discriminator make a decision that can then be used to motivate the update of the generator so it can fool the discriminator.

GANs comes in many flavors and can be used to perform a wide variety of tasks.

GANs can generate very convincing images, but they are usually considered more difficult to train than other generative approaches like diffusion models.

Denoising Diffusion Probabilistic models

From Yang et al. 2022



Denoising diffusion models have revolutionized the world of AI image generation. It is the technic behind most modern AI generator you have encountered.

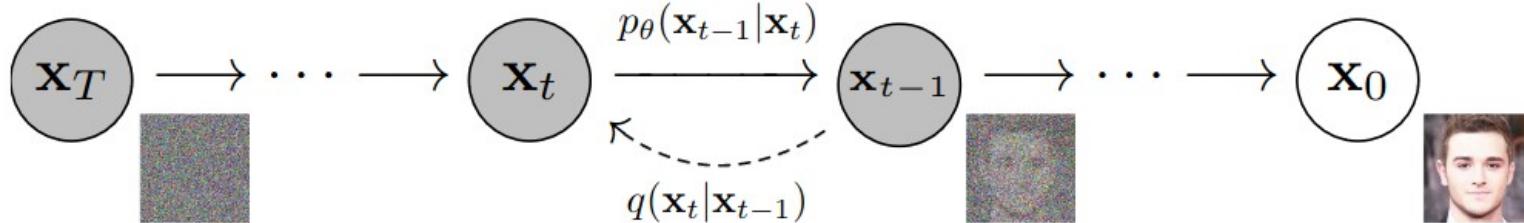
Training a network to denoise an image with no prior information about its content is a special case of **self supervised learning**. The very simplicity of this task makes it suitable for almost any dataset, and it will automatically preserve the inherent diversity (or entropy) of the training database (in contrast with GAN that can collapse to a restrained parameter space).

A DDPM can be built from any denoising network architecture, e.g., U-Net or transformers.

With this approach it is possible to train very large models that can be used as foundation models pour other more specific tasks.

Denoising Diffusion Probabilistic models

From Ho et al. 2020



The forward process (diffusion process) is fixed to a Markov Chain that gradually adds Gaussian noise to the data based on a beta variance schedule.

$$q(\mathbf{x}_{1:T}|\mathbf{x}_0) := \prod_{t=1}^T q(\mathbf{x}_t|\mathbf{x}_{t-1}), \quad q(\mathbf{x}_t|\mathbf{x}_{t-1}) := \mathcal{N}(\mathbf{x}_t; \sqrt{1 - \beta_t}\mathbf{x}_{t-1}, \beta_t\mathbf{I})$$

The reverse process is a Markov Chain with learned Gaussian transitions.

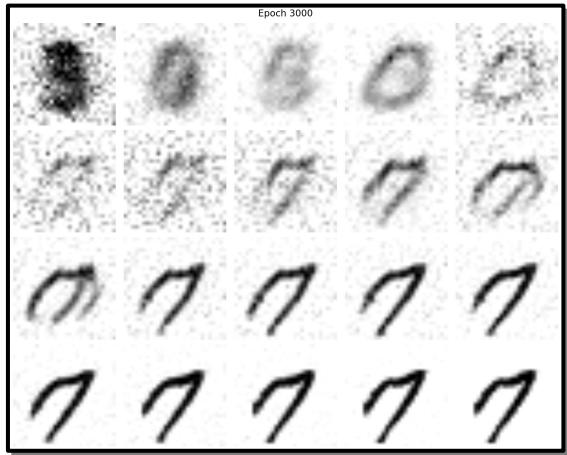
$$p_\theta(\mathbf{x}_{0:T}) := p(\mathbf{x}_T) \prod_{t=1}^T p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t), \quad p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t) := \mathcal{N}(\mathbf{x}_{t-1}; \boldsymbol{\mu}_\theta(\mathbf{x}_t, t), \boldsymbol{\Sigma}_\theta(\mathbf{x}_t, t))$$

In practice you can use the following relation in both cases:

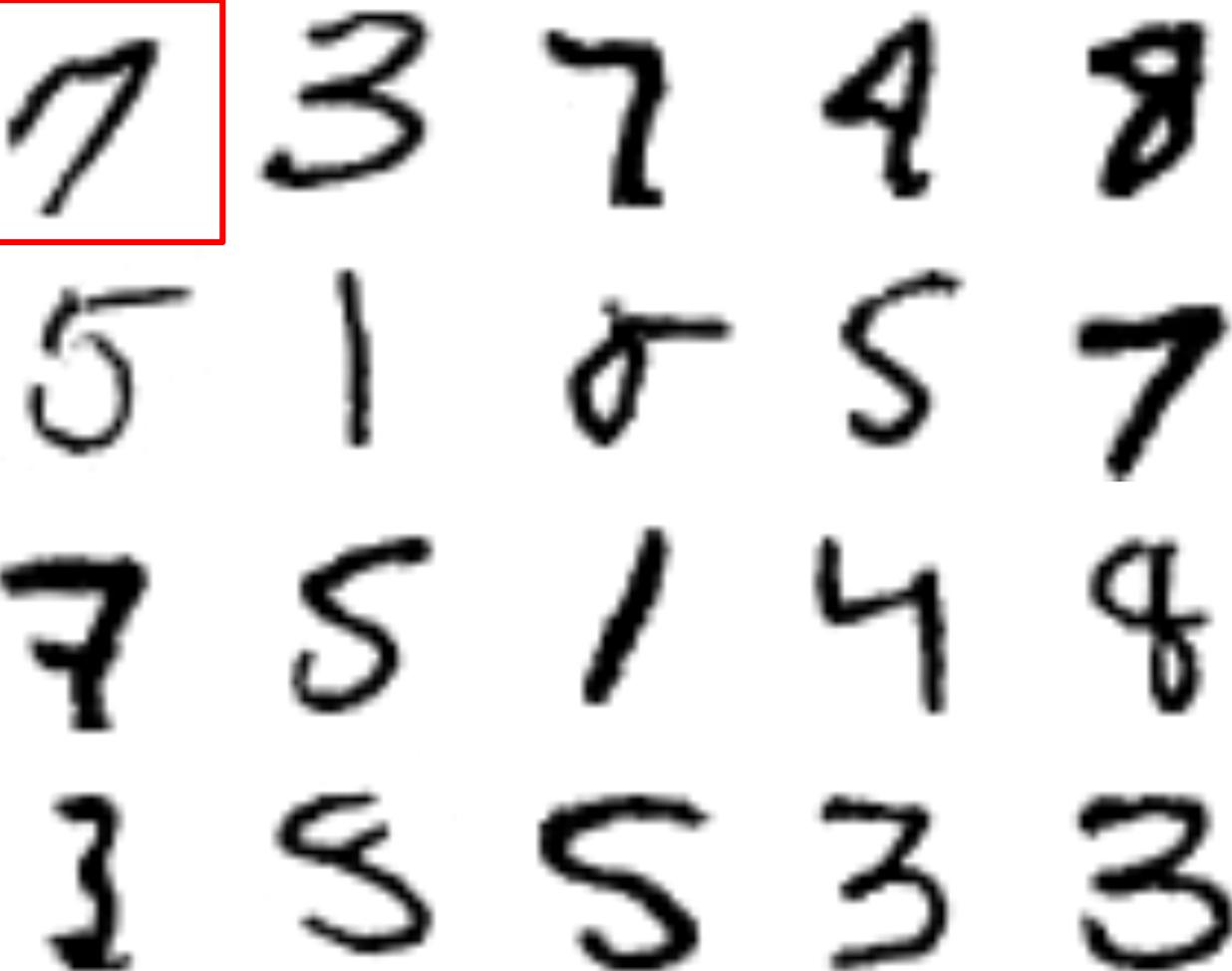
$$\mathbf{x}_t = \sqrt{\bar{\alpha}_t}\mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t}\boldsymbol{\epsilon}$$

With $\rightarrow \alpha_t := 1 - \beta_t$ and $\bar{\alpha}_t := \prod_{s=0}^t \alpha_s$ $\boldsymbol{\epsilon} \sim \mathcal{N}(0, \mathbf{I})$

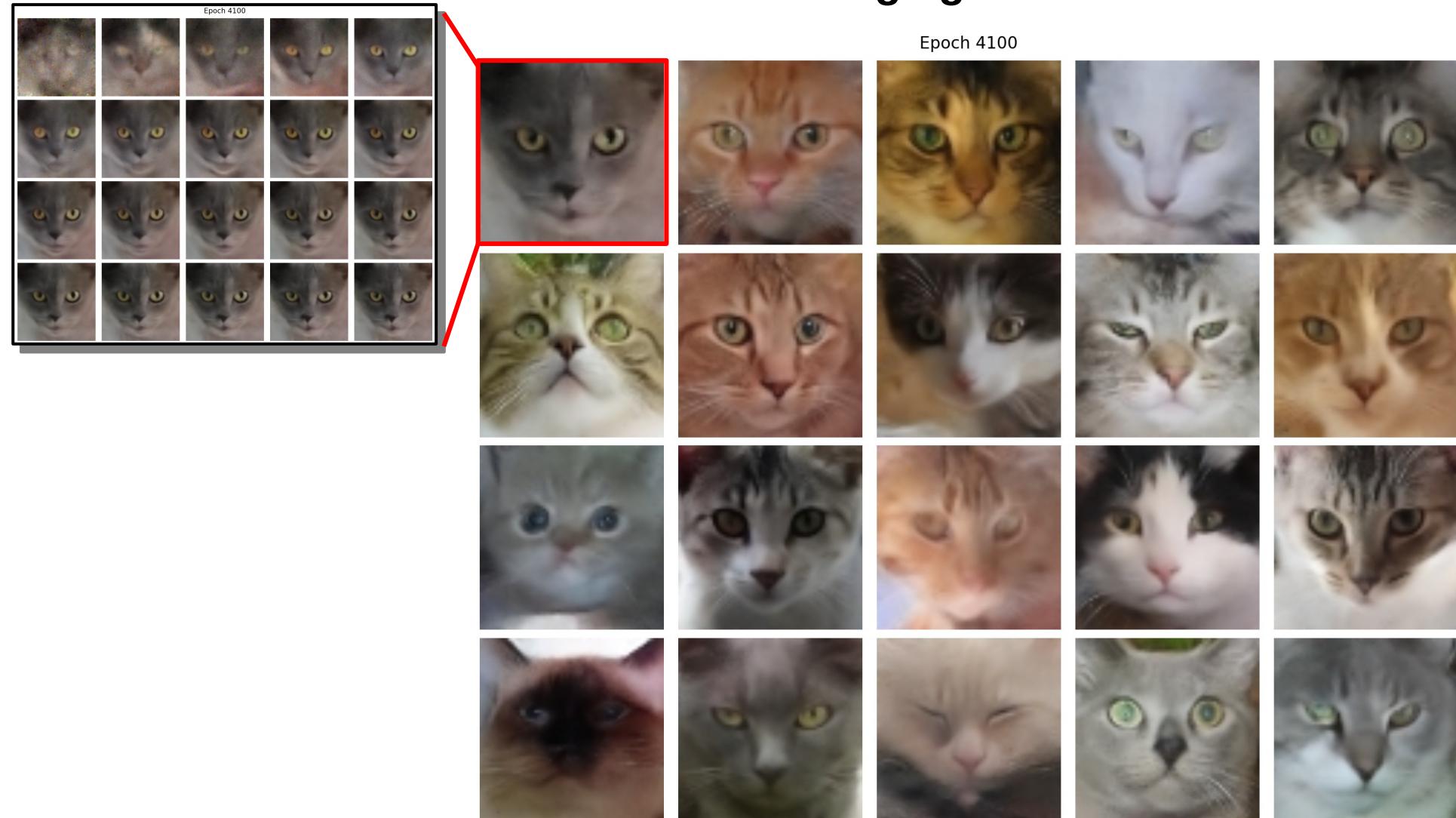
DDPM: MNIST Image generation



Epoch 3000



DDPM: Cat faces Image generation



DDPM: GZ2 SDSS image generation

