Module 2 :

Deep Networks

Convolutional Neural Networks

Géraldine Conti, August 2020

Discussion Session

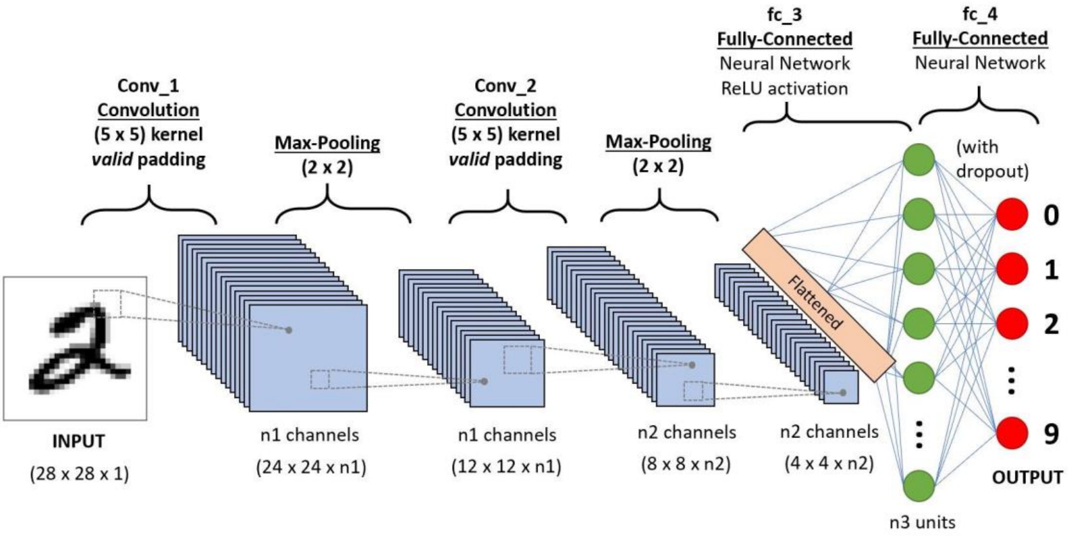
- Review of Notebook 5
    - Vanishing/exploding gradients
    - Xavier/He initializations
    - Leaky ReLU, ELU, SELU
    - Batch normalization
    - Gradient clipping
    - Reusing pretrained layers
    - Faster optimizers
    - Learning rate scheduling
    - Regularization
    - Dropout

Bibliography

- Deep Learning book (Goodfellow, Bengio, Courville)
- Machine Learning @ Stanford (Prof Andrew Ng)
- Hands-On Machine Learning with Scikit-Learn & Tensorflow (Aurélien Géron)

Learning Objectives

- CNN components
- Most important architectures
- Object Detection
- Face Detection



Convolutional Neural Networks

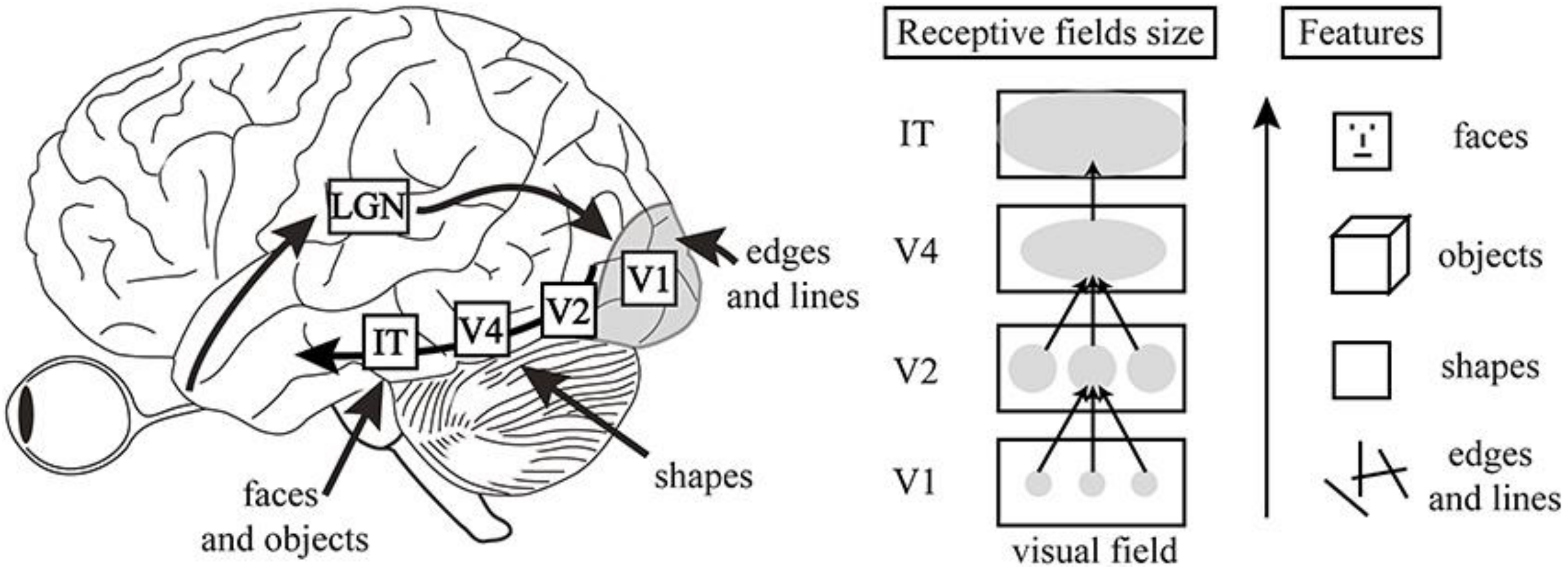
- Convolutional layer
- Padding, stride
- Filters
- Pooling layer

Introduction

- Convolutional Neural Networks (CNNs) emerged from the study for the brain's visual cortex
- Used in image recognition since the 1980s
  - Milestone (1998) with LeNet-5 architecture (LeCun)
- Huge improvements in the last few years due to :
  - Increased computational power
  - Amount of available training data
  - Tricks for training deep nets
- Everywhere: image search services, self-driving cars, automatic video classification, voice recognition, natural language processing,…

Visual Cortex

- Nobel prize in physiology (1981) : many neurons in the visual cortex react only to visual stimuli located in a limited region of the visual field (local receptive field)
  - Receptive fields overlap and tile the whole visual field

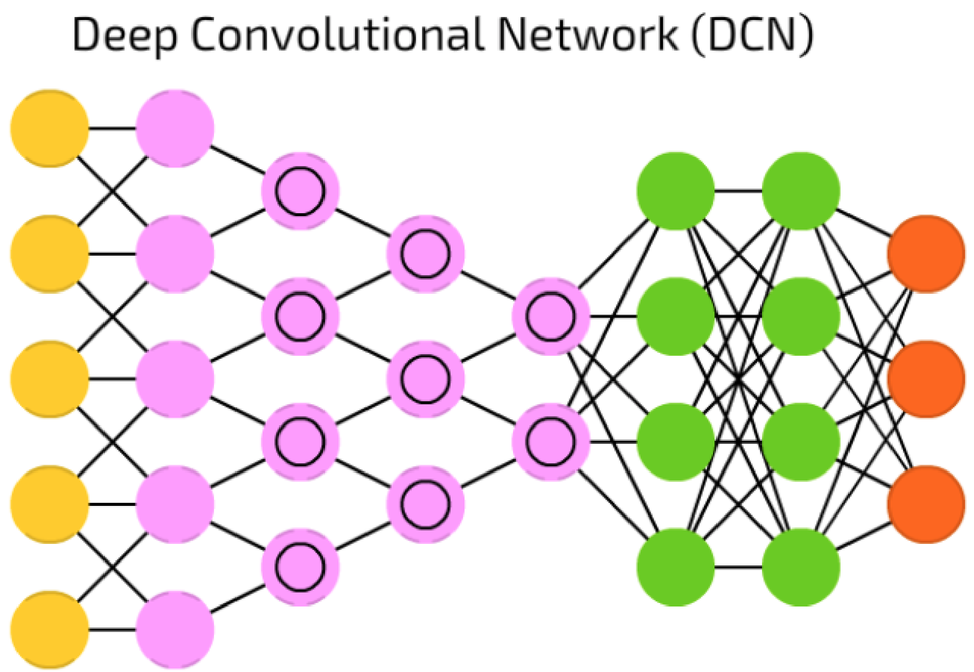


- Some neurons (with same receptive field) react to different line orientations (horizontal lines, lines with angle,…)

- Some neurons have larger receptive fields and react to more complex patterns : idea that higher-level neurons are based on the outputs of neighboring lower-level neurons

CNN

- inspired by the organization of the animal visual cortex



- **Convolutional and pooling cells** introduced in LeNet-5
    - used to process and simplify input data
    - weight sharing between *local regions*

Use cases

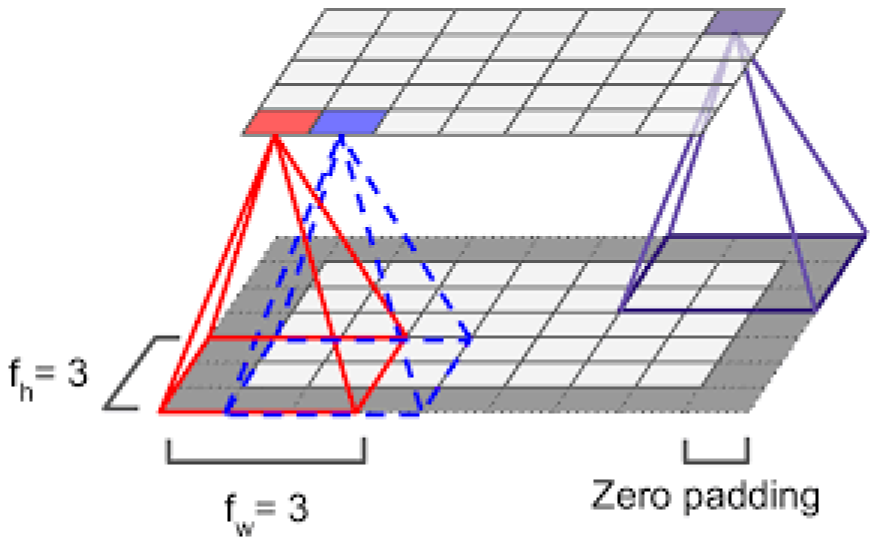
- well suited for computer vision tasks
  - Image classification
  - Object detection

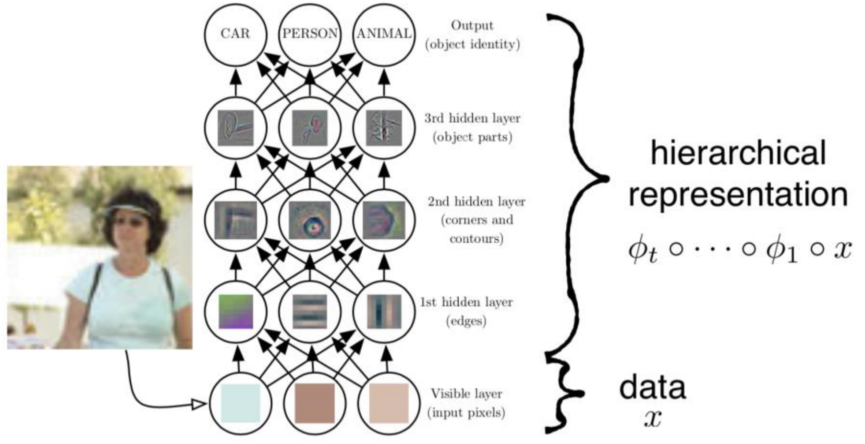
- More generally, specialized Neural Network for data arranged on a grid
  - Images
  - DNA sequences
  - …

	A	C	G	T	W	S	M	K	R	Y	B	D	H	V	N	Z
A	1	0	0	0	1/2	0	1/2	0	1/2	0	0	1/3	1/3	1/3	1/4	0
C	0	1	0	0	0	1/2	1/2	0	0	1/2	1/3	0	1/3	1/3	1/4	0
G	0	0	1	0	0	1/2	0	1/2	1/2	0	1/3	1/3	0	1/3	1/4	0
T	0	0	0	1	1/2	0	0	1/2	0	1/2	1/3	1/3	1/3	0	1/4	0

Convolutional Layer (CONV)

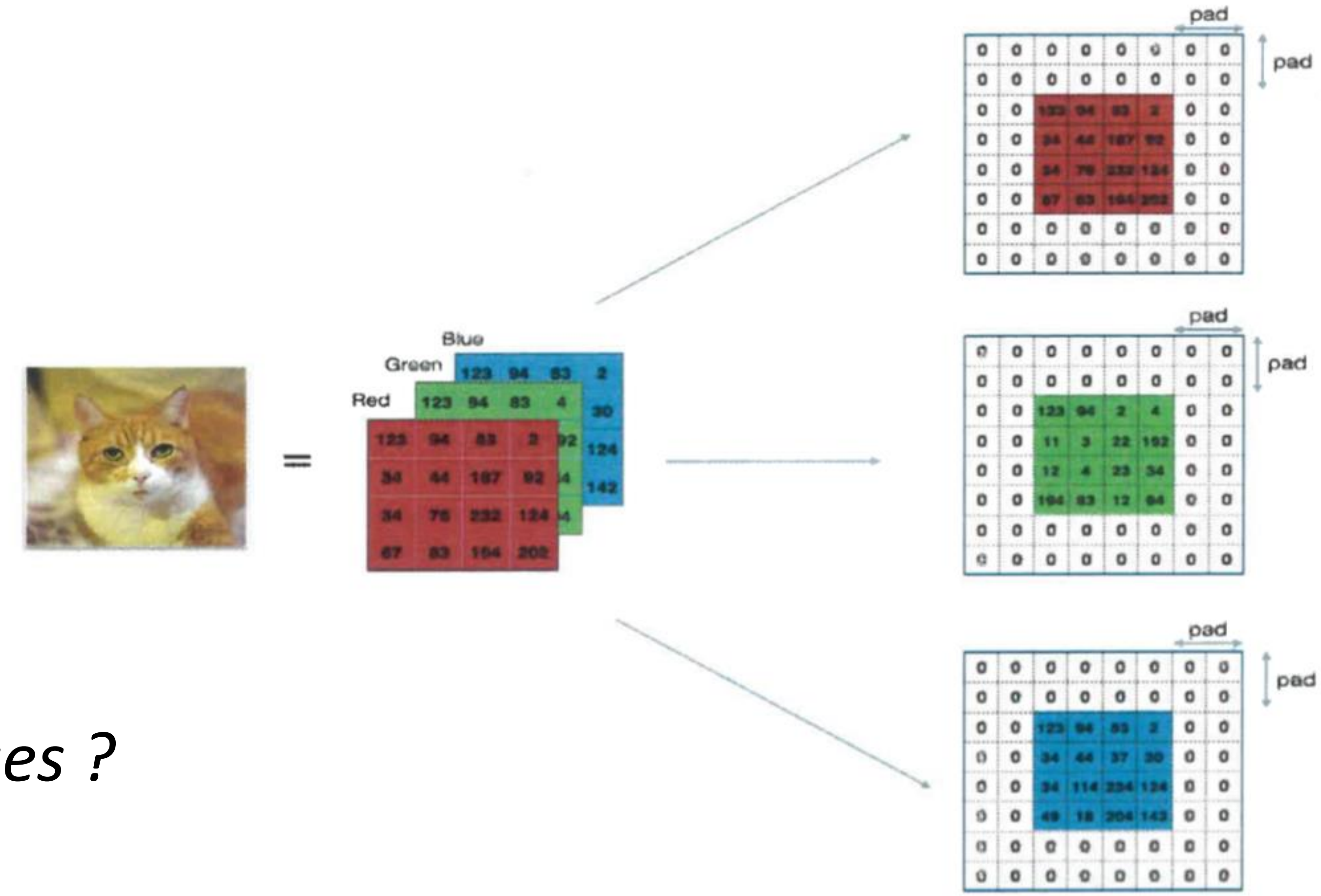
- Neurons in the 1st convolutional layer are not connected to every single pixel in the input image, but only to pixels in their receptive fields
- Neurons in the 2nd layer are connected only to neurons located within a small rectangle in the first layer
- Low-level features in the first hidden layer, higher-level features in the next hidden layer,…





Padding

- Adds zeros around the border of an image

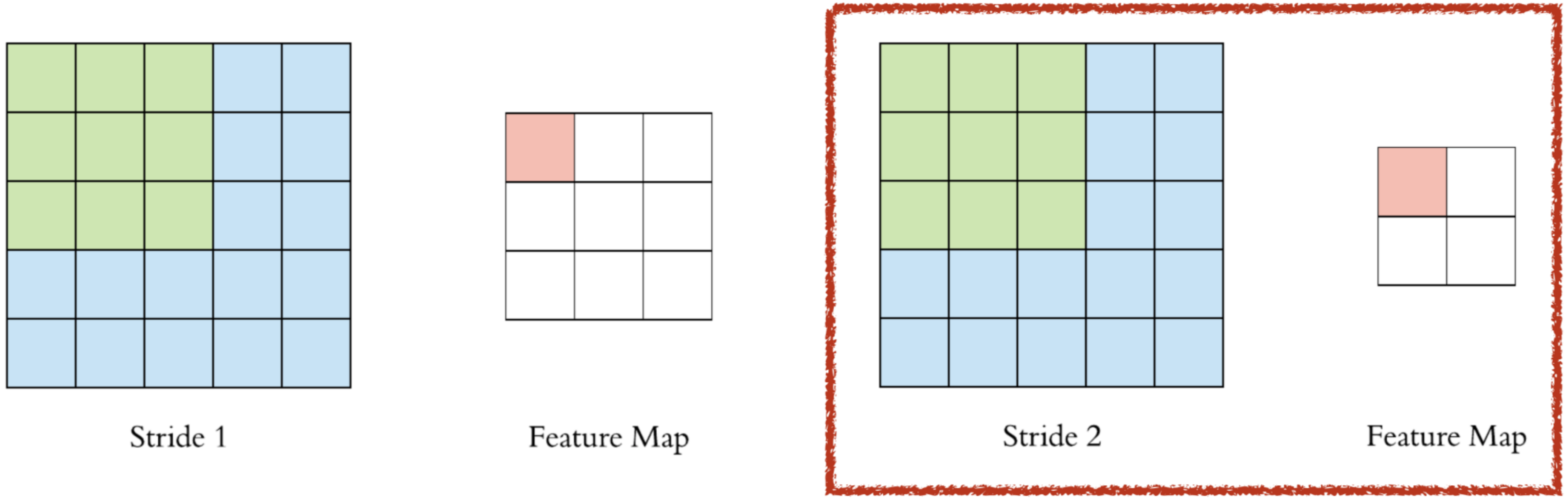


Use cases ?

Stride

- By how much you move the filter

- Use cases :
  - Connect a large input layer to a much smaller layer by spacing out the receptive fields (reduce dimensionality)



increasing stride from 1 to 2

Filters

- Also called convolutional kernels
- used to detect features
- Examples :
  - Vertical filter : neurons using these weights will ignore everything in their receptive field except for the central vertical line
  - Idem for a horizontal filter

1	0	-1
1	0	-1
1	0	-1

Vertical

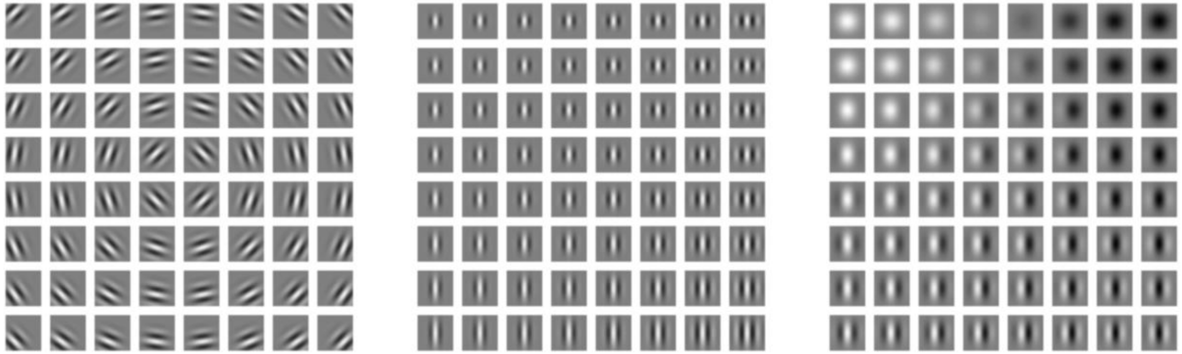
1	1	1
0	0	0
-1	-1	-1

Horizontal

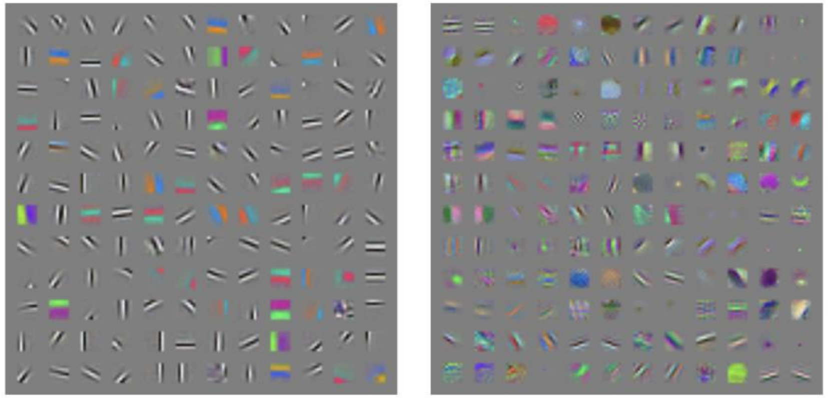
Kernel Initialization

- With random weights

- With hand-designed features

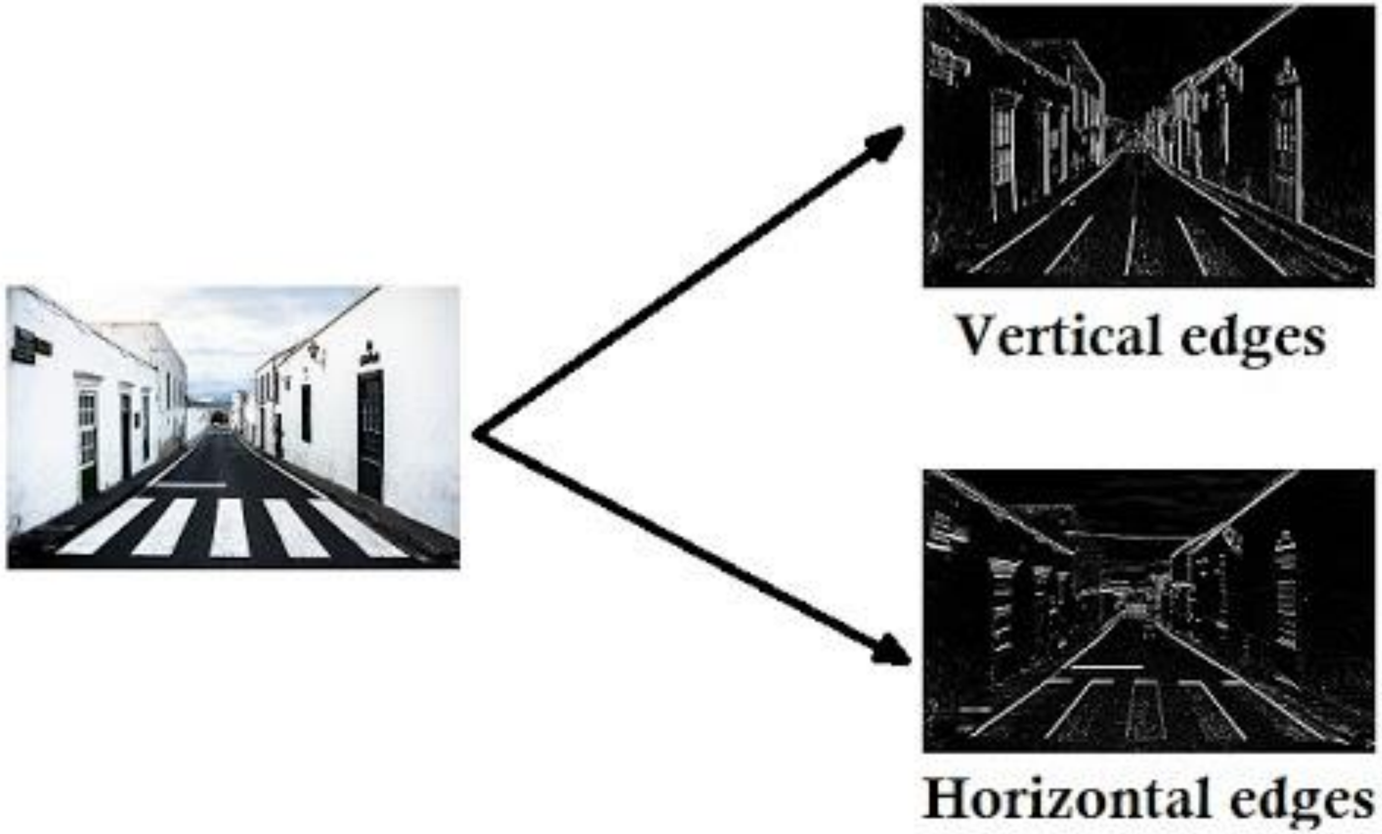


- With unsupervised learning algorithms (eg. apply K-means clustering to patches, then use centroids as kernels)

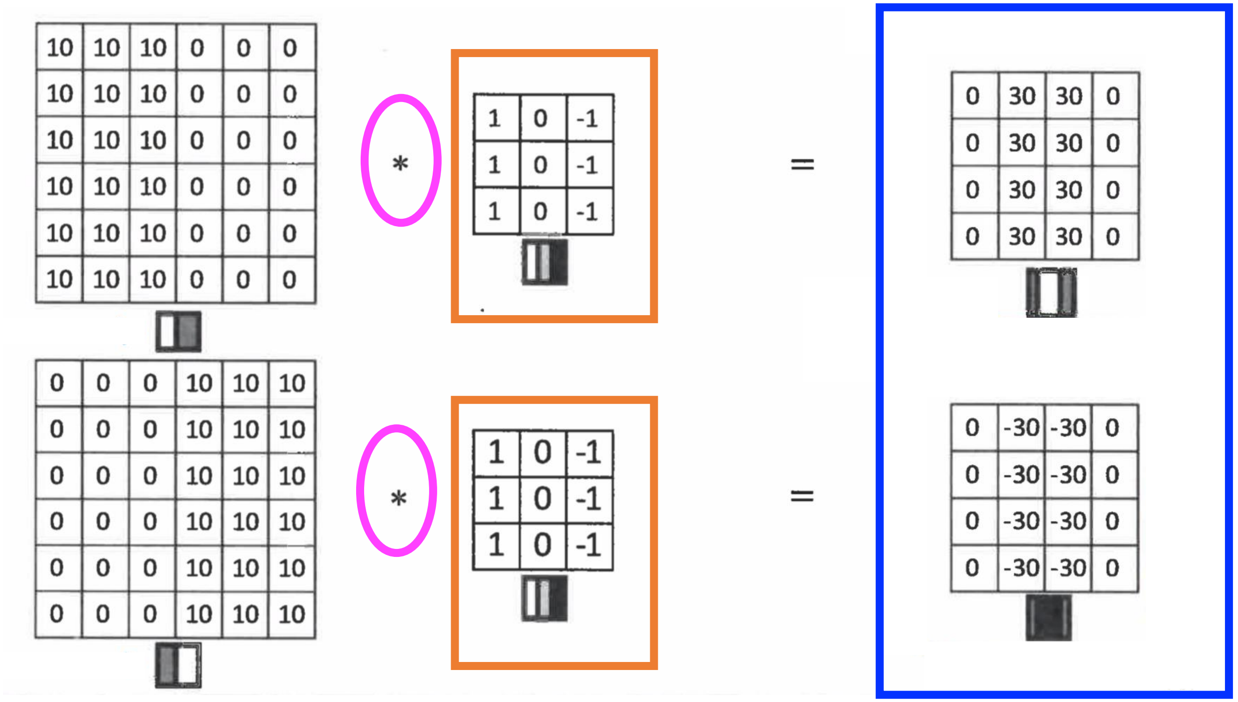


Feature Map

- A full layer of neurons using the same filter gives a feature map highlighting the areas in an image that are most similar to the filter



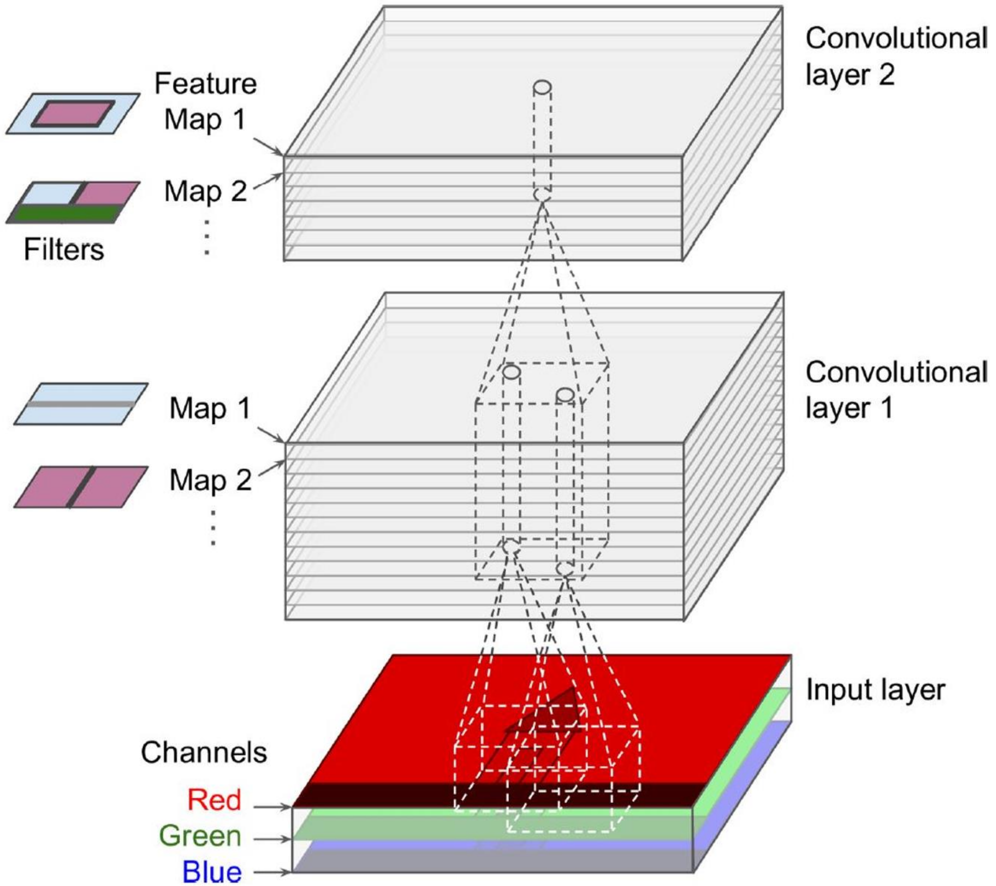
Convolution



$n \times n$ image $\quad f \times f$ filter $\quad \text{out} = n - f + 1$

Stacking Multiple Feature Maps

- Each convolutional layer composed of several feature maps of equal sizes
- Within one feature map, all neurons share the same parameters (weights and bias term)



- Parameters : $\boxed{\text{(filter width * filter height * filter depth +1) * filter number}}$

Exercise

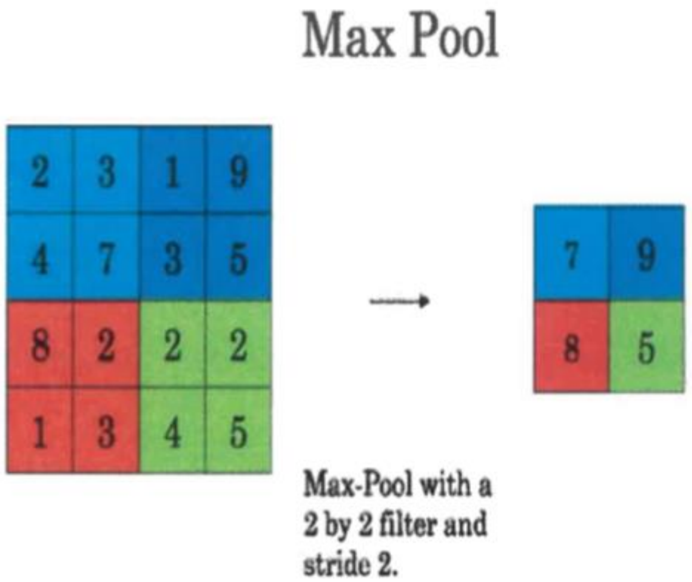
- 300x300 RGB image, how many parameters does a hidden layer have (incl. bias) in the following cases:

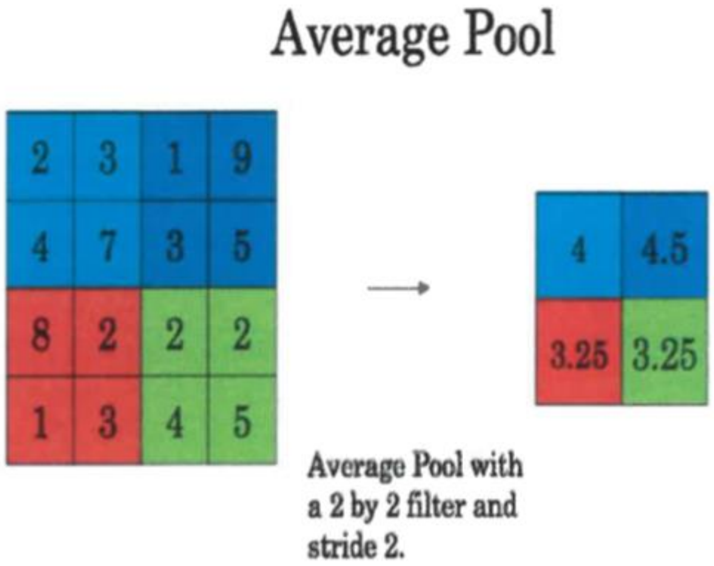
a) Hidden layer with 100 neurons, each fully connected to the input (*no convolution*)

b) Hidden *convolution* layer with 100 filters that are each 5x5

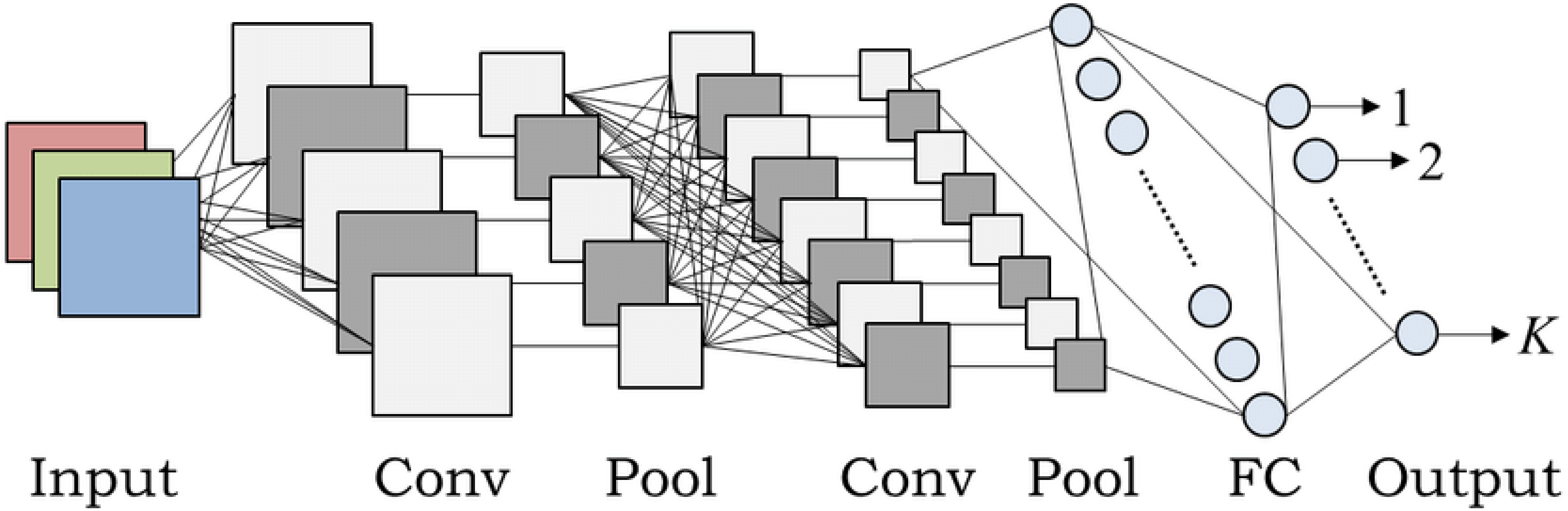
Pooling Layer

- Goal is to subsample the input image
  - Reduce the computational load, memory usage, number of parameters (hence overfitting)
- Neurons connected to the outputs of a limited number of neurons in the previous layer located within a small rectangular receptive field
- Pooling neuron has no weights, it aggregates the inputs with an aggregation function (max, mean)





CNN Architectures



- Stack a few CONV layers (each one followed by ReLU), then a POOL layer, then few CONV layers (+ReLU), then POOL layer, …
- Image gets smaller and smaller, but also deeper and deeper (with more feature maps) due to the CONV layers
- At the top of the stack, a regular feedforward NN is added with a few fully connected layers (+ReLU)
- Final output is the prediction (softmax giving class probabilities)

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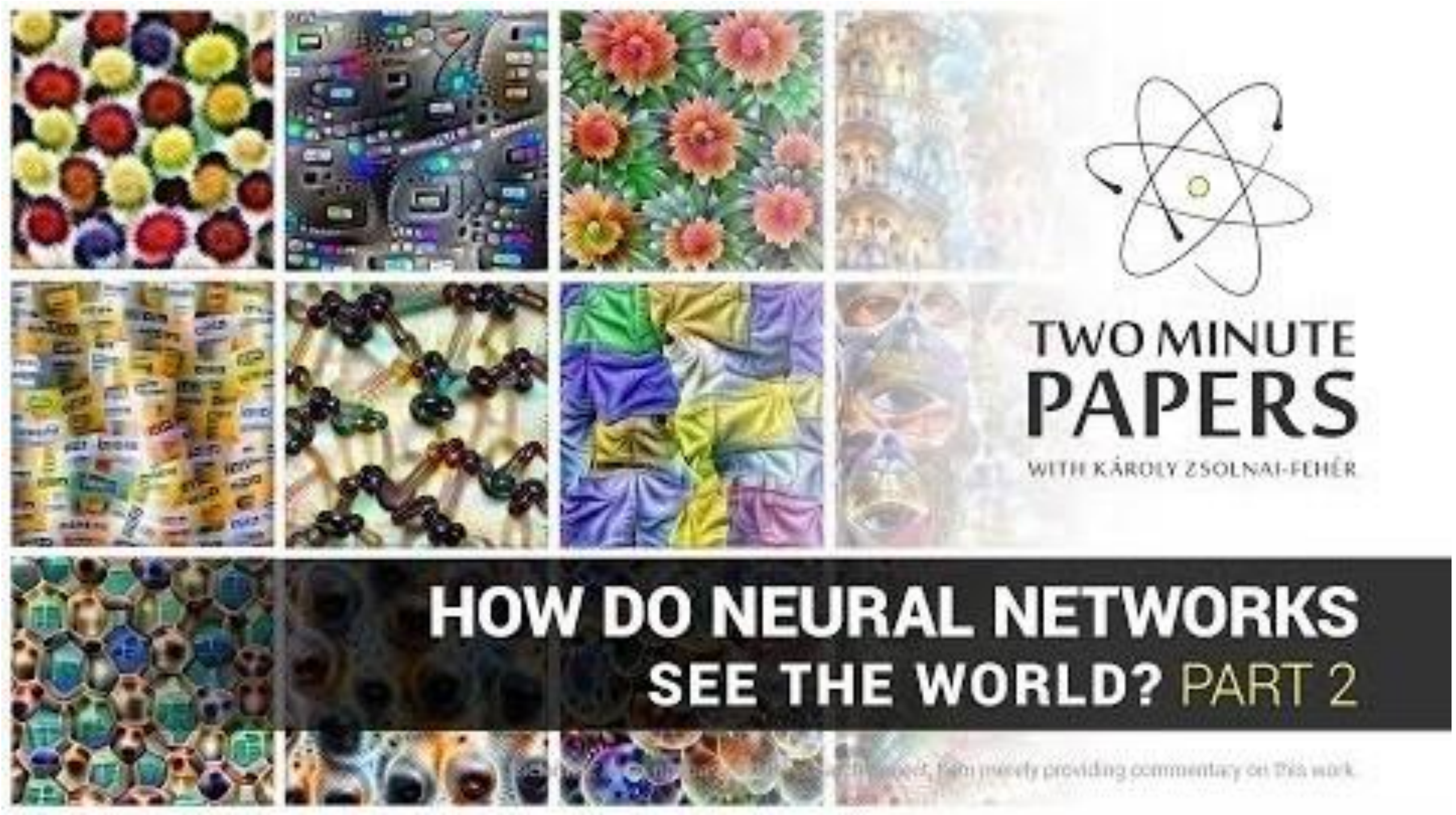
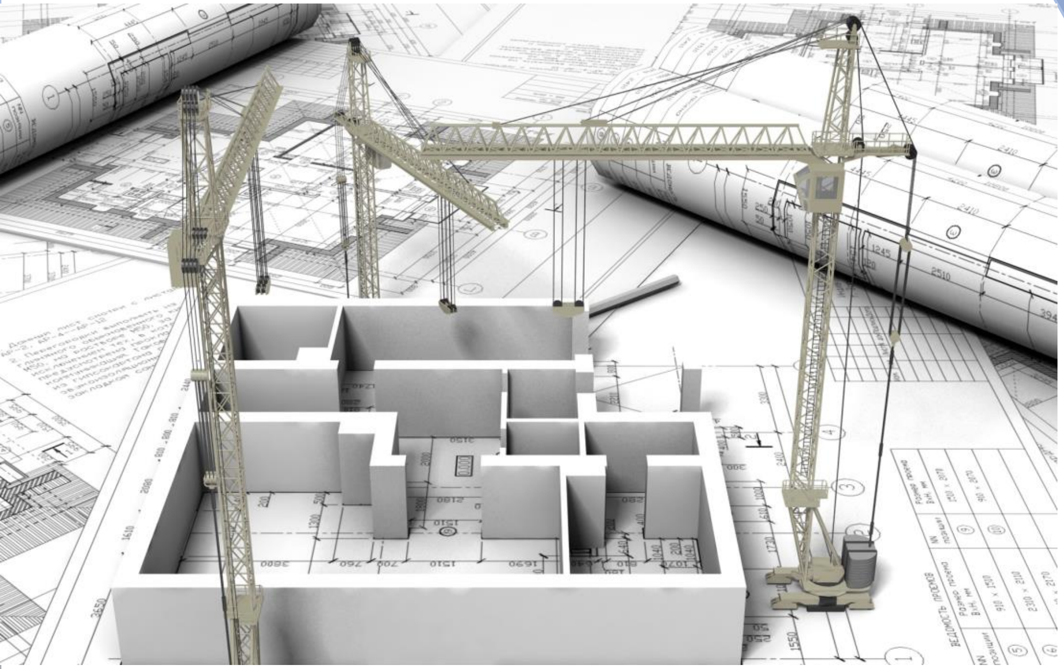


Two-Minute Papers

CNN Famous Architectures



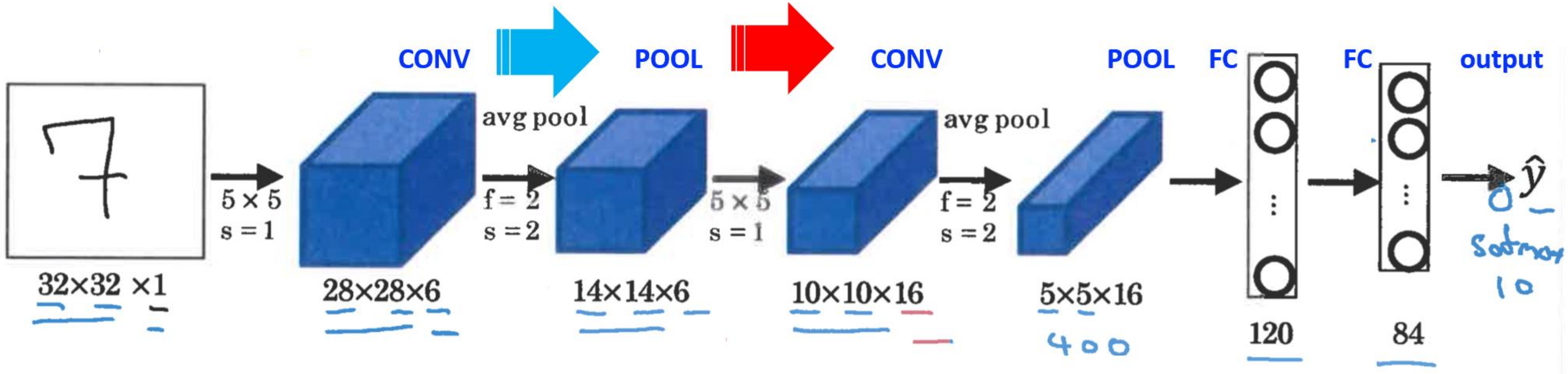
1. LeNet-5
2. AlexNet
3. GoogLeNet
4. ResNet

1. LeNet-5 (1998)

- Used for hand-written digit recognition (MNIST)
  - Images (28x28) zero-padded to 32x32 and normalized
  - The rest of the network does not use padding, which is why the size keeps shrinking

- Activation functions : sigmoid/tanh

- 60K parameters



Exercise

- Fill the table with the parameters corresponding to the figure of the LeNet-5 architecture (previous slide)

Type	Feature Map	Size	Kernel size	Stride	Activation
Input image	1	32x32	-	-	-
Convolution					
Average pooling					
Convolution					
Average pooling					
FC					
FC	-		-	-	
Output	-		-	-	

2. AlexNet (2012)

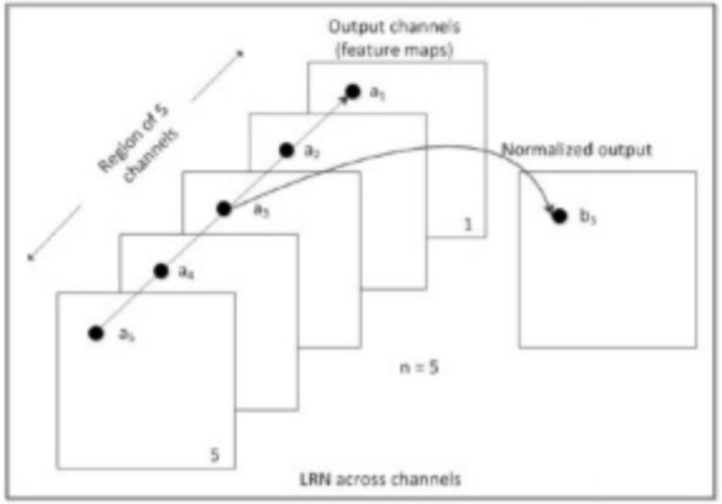
- Quite similar to LeNet_5, only much larger and deeper
- First one to stack CONV layers directly on top of each other instead of stacking a POOL layer on top of each CONV layer
- Activation functions : ReLU
- 60mio parameters
- To reduce overtiftting :
  - 50% dropout in FC layers
  - data augmentation
- Local Response Normalization used a normalization step

Type	Feature Map	Size	Kernel size	Stride	Activation
Input	3 (RGB)	227x227	-	-	-
Convolution	96	55x55	11x11	4	ReLU
Max Pooling	96	27x27	3x3	2	-
Convolution	256	27x27	5x5	1	ReLU
Max Pooling	256	13x13	3x3	2	-
Convolution	384	13x13	3x3	1	ReLU
Convolution	384	13x13	3x3	1	ReLU
Convolution	256	13x13	3x3	1	ReLU
Max Pooling	256	6x6	3x3	2	-
Fully connected	-	4096	-	-	ReLU
Fully connected	-	4096	-	-	ReLU
Fully connected	-	1000	-	-	Softmax

Local Response Normalization (LRN)

- Neurobiology : capacity of a neuron to reduce the activity of its neighbors (lateral inhibition)

- In DNNs : inhibition carries out local contrast enhancement so that locally maximum pixel values are used as excitation for the next layers
  - Neuron a3 that most strongly activates will inhibit neurons (a1,a2,a4,a5) at the same location but in neighboring feature maps



- This encourages different feature maps to specialize, pushing them apart and forcing them to explore a wider range of features

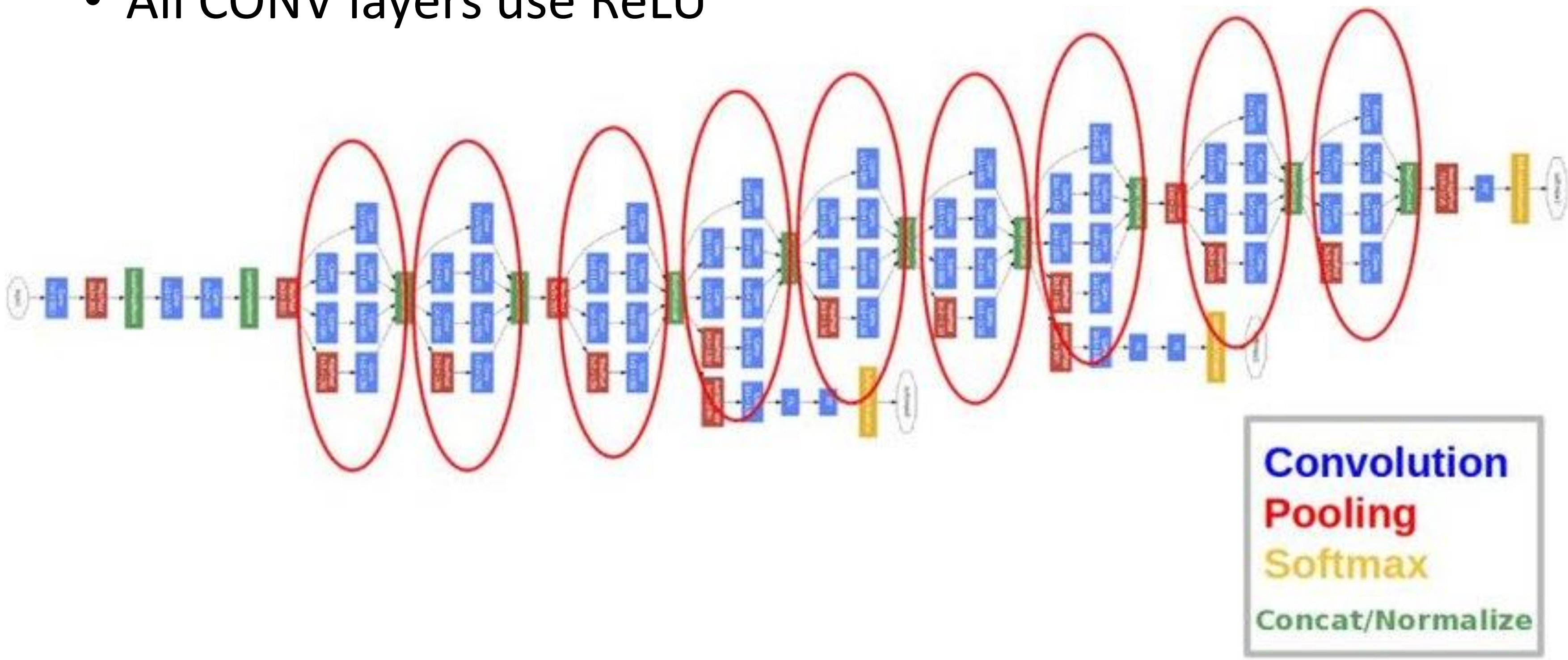
Exercise

- Draw the scheme corresponding to the AlexNet architecture (previous slide)

3. GoogLeNet (2014)

- Much deeper than previous CNNs thanks to sub-networks called inception modules
  - These use parameters much more efficiently : 6 mio of parameters instead of 60mio for AlexNet

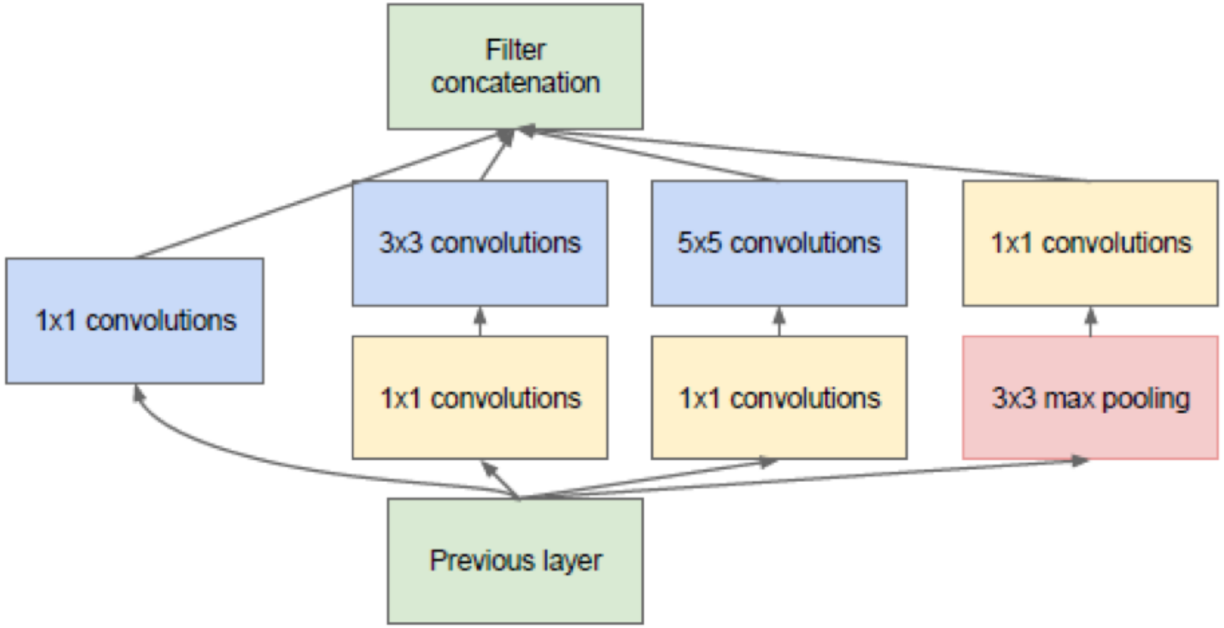
- Architecture :
  - 9 inception modules included
  - All CONV layers use ReLU



Inception Modules

- Input signal copied and fed to 4 layers
  - Second set of CONV layers has different kernel sizes to capture patterns at different scales

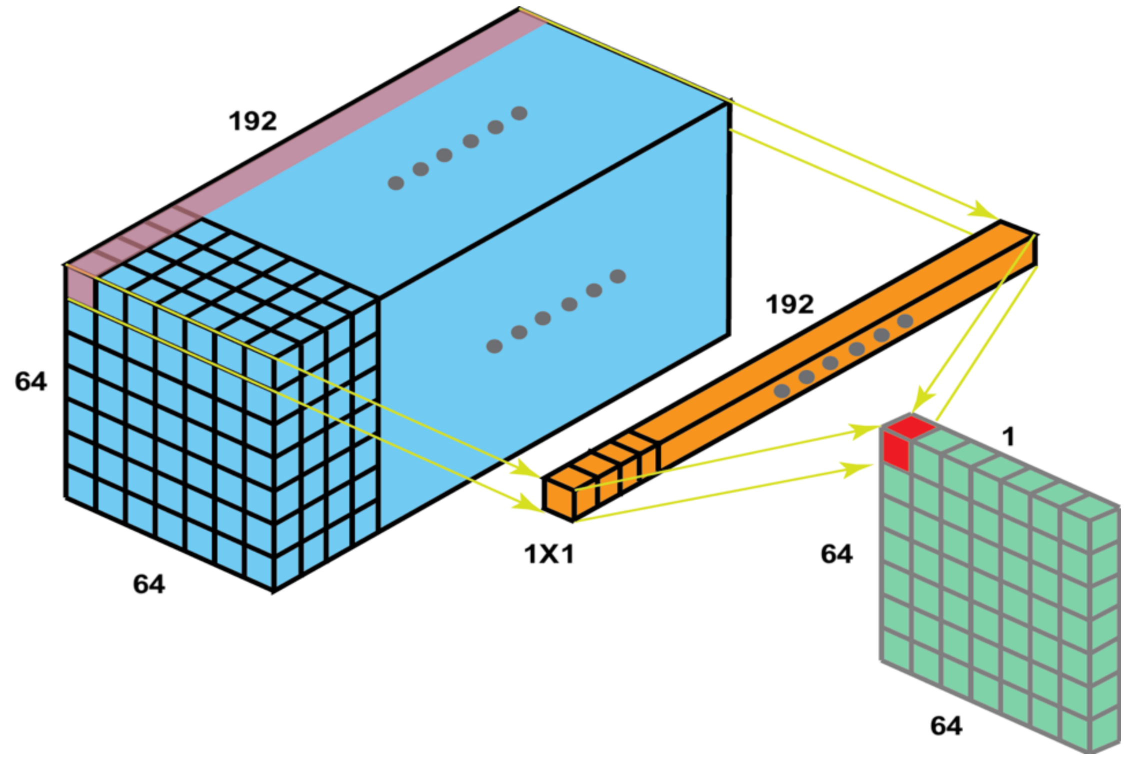
- Output : concatenate the four outputs (i.e. stack the feature maps)



Why use CONV layers with 1x1 kernel ?

1x1 convolutions

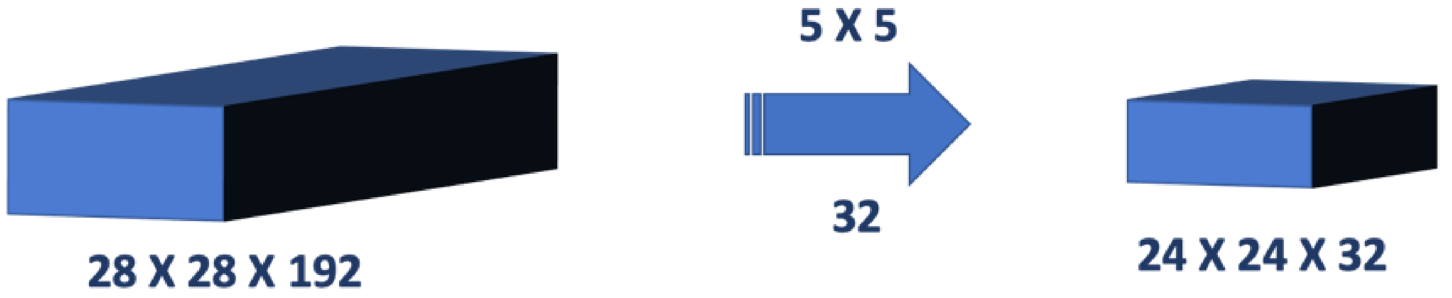
- These layers do not capture any features since they look at only one pixel at a time.
- Reduces the depth, but keep the height and width of the feature map



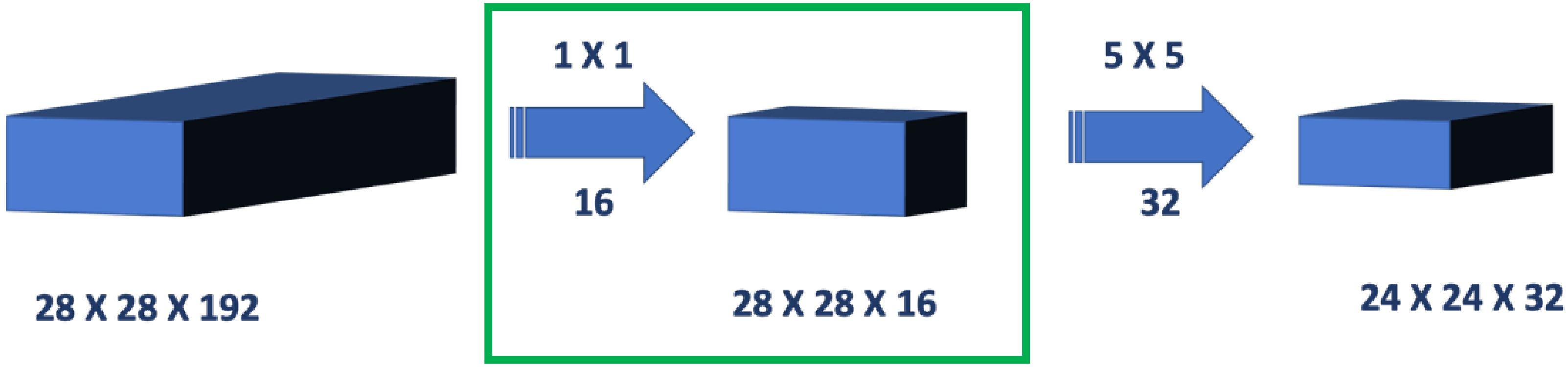
- Use cases :
  - Dimensionality reduction (GoogleNet)
  - Build deeper networks (ResNet)

1x1 convolutions : dimensionality reduction

- These layers do not capture any features since they look at only one pixel at a time.



Number of Operations : (28X28X32) X (5X5X192) = 120.422 Million Ops



Number of Operations for 1 X 1 Conv Step : (28X28X16) X (1X1X192) = 2.4 Million Ops
Number of Operations for 5 X 5 Conv Step : (28X28X32) X (5X5X16) = 10 Million Ops
Total Number of Operations = 12.4 Million Ops

4. ResNet (2015)

- Extremely deep CNN composed of 152 layers
- Very deep NNs suffer from vanishing gradients : skip connections

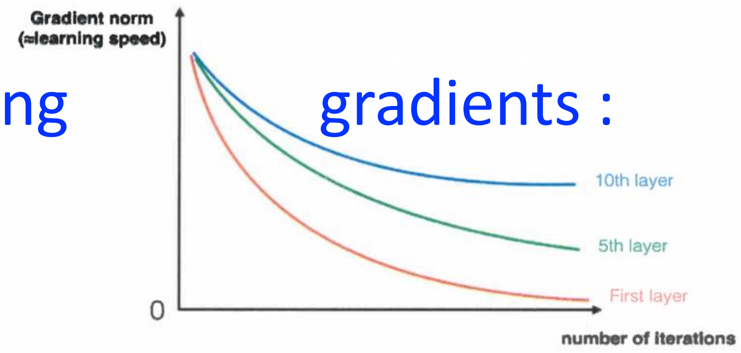
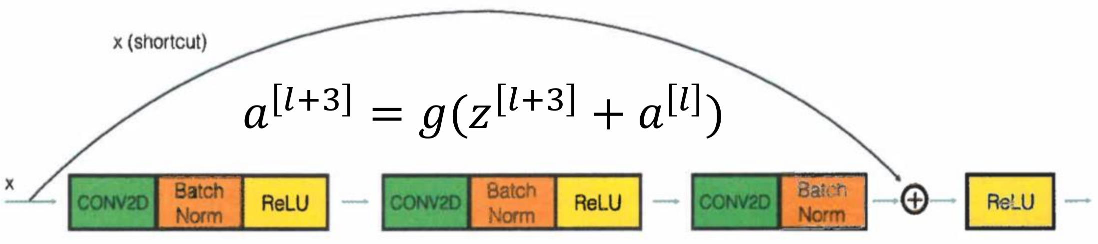


Figure 1 : Vanishing gradient

- Residual training : the signal feeding into a layer is also added to the output of a layer located a bit higher up the stack
  - Network forced to model : f(x) = h(x) – x rather than h(x)
- Architecture : stack of residual units, where each residual unit is a small NN with a skip connection

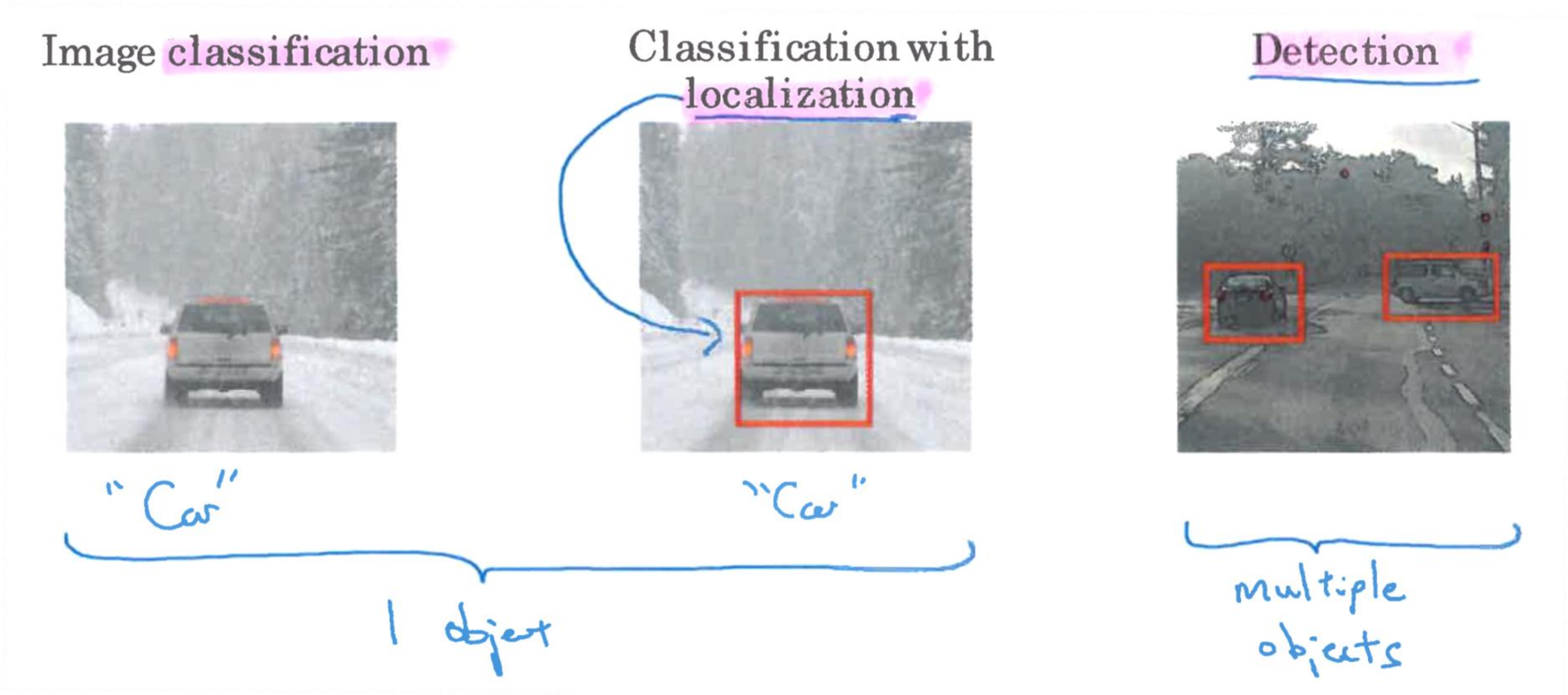


Some reading

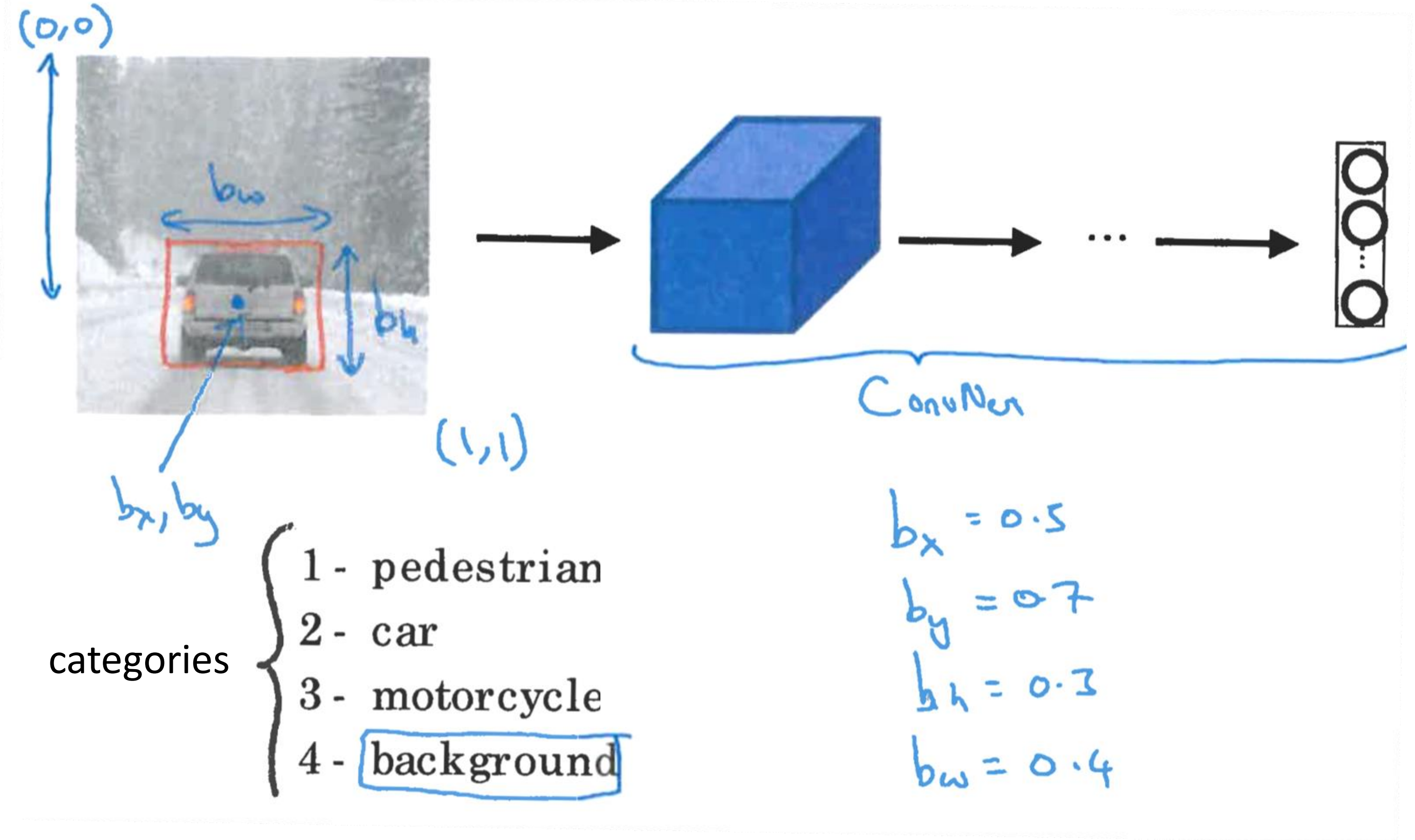
10 Architectures

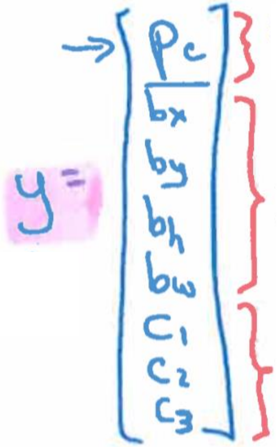
Object Detection

Object Detection



2. Classification with Localization



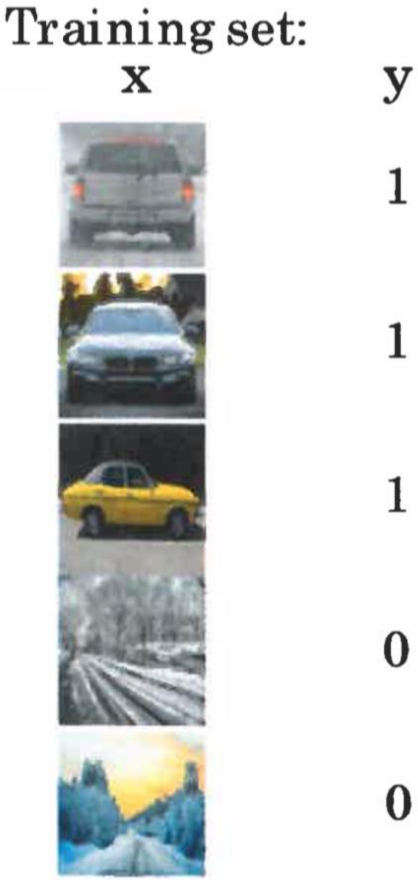


is there any object ?

bounding box shape

categories

3. Detection

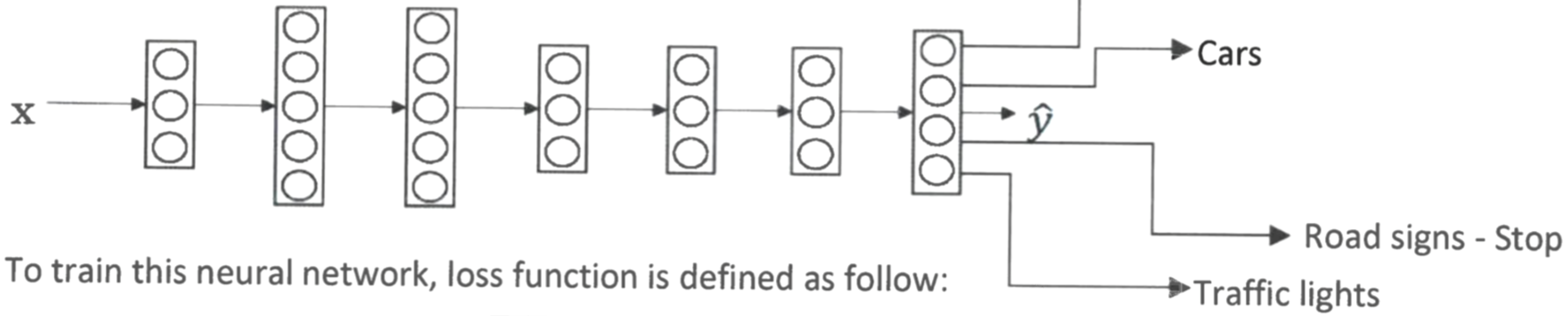


- use closely cropped images for the training set (object of interest centered)
- Define a sliding window
- Convolutional implementation

Multi-Task Learning

- NN does simultaneously several tasks

Neural Network architecture

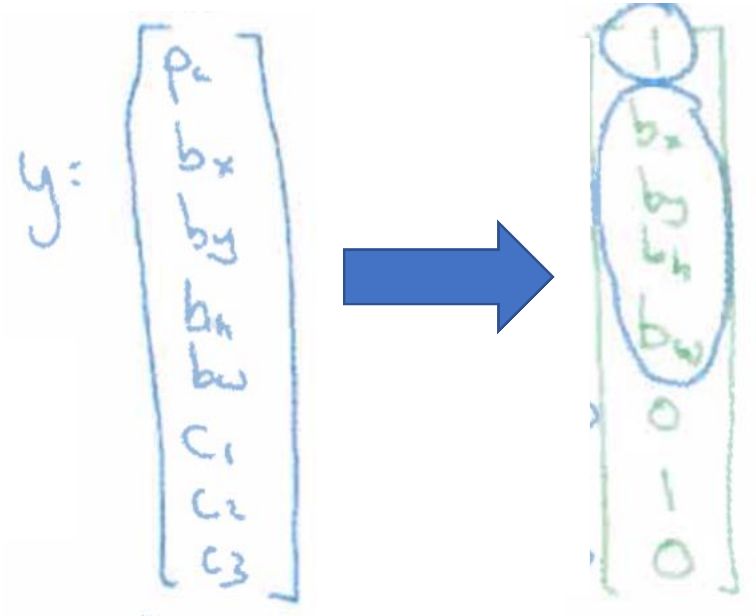


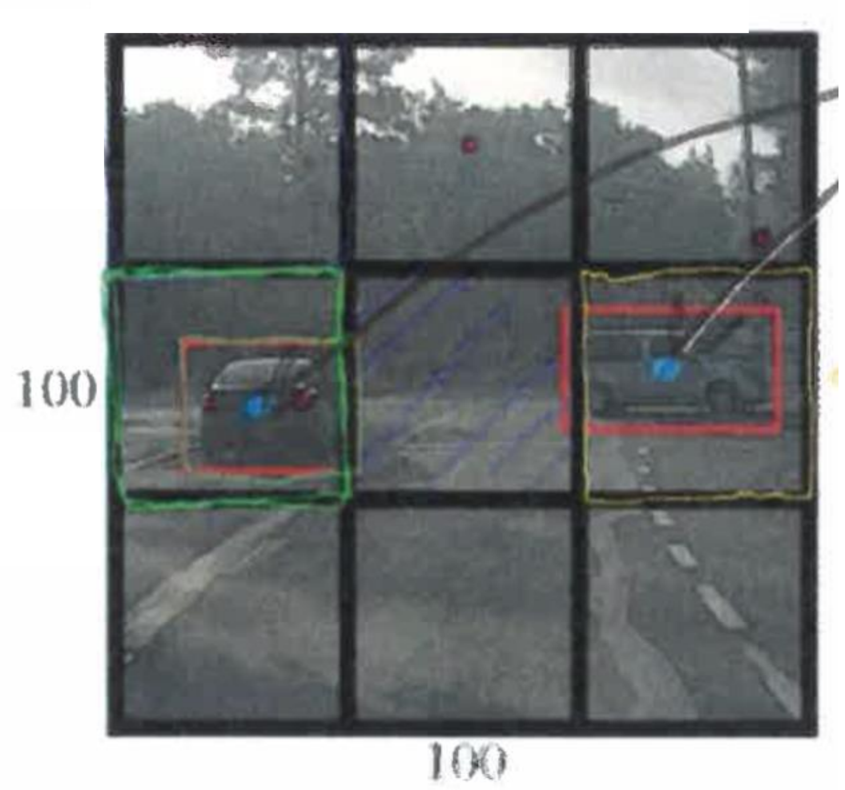
To train this neural network, loss function is defined as follow:

$$-\frac{1}{m}\sum_{i=1}^{m}\boxed{\sum_{j=1}^{4}}\left(y_j^{(i)}\log\left(\hat{y}_j^{(i)}\right)+\left(1-y_j^{(i)}\right)\log\left(1-\hat{y}_j^{(i)}\right)\right)$$

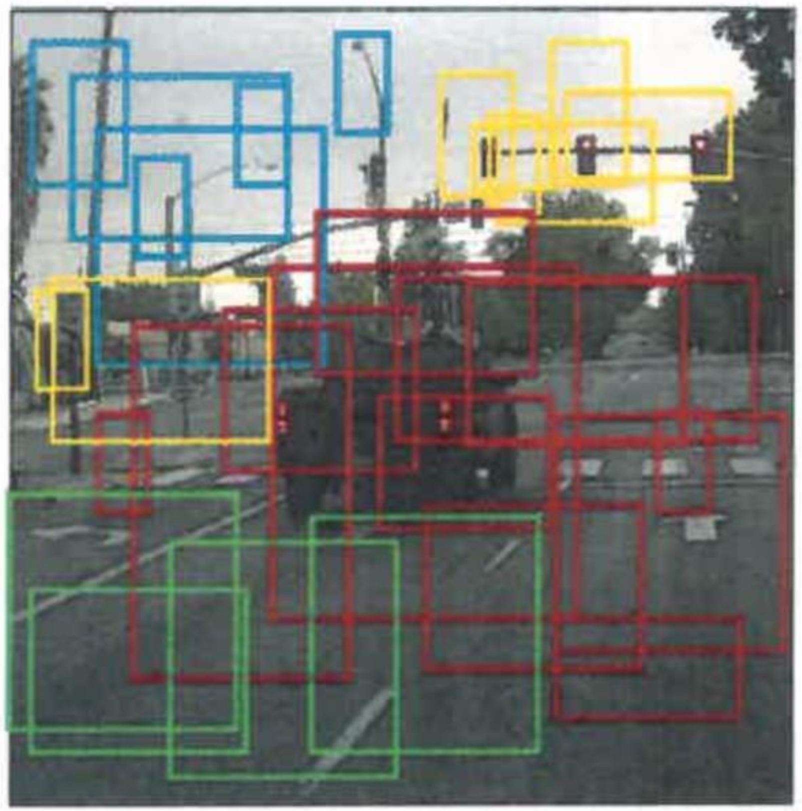
YOLO algorithm

- YOu Look Only once algorithm (YOLO)
- define a grid in the image
- apply the training to each cell





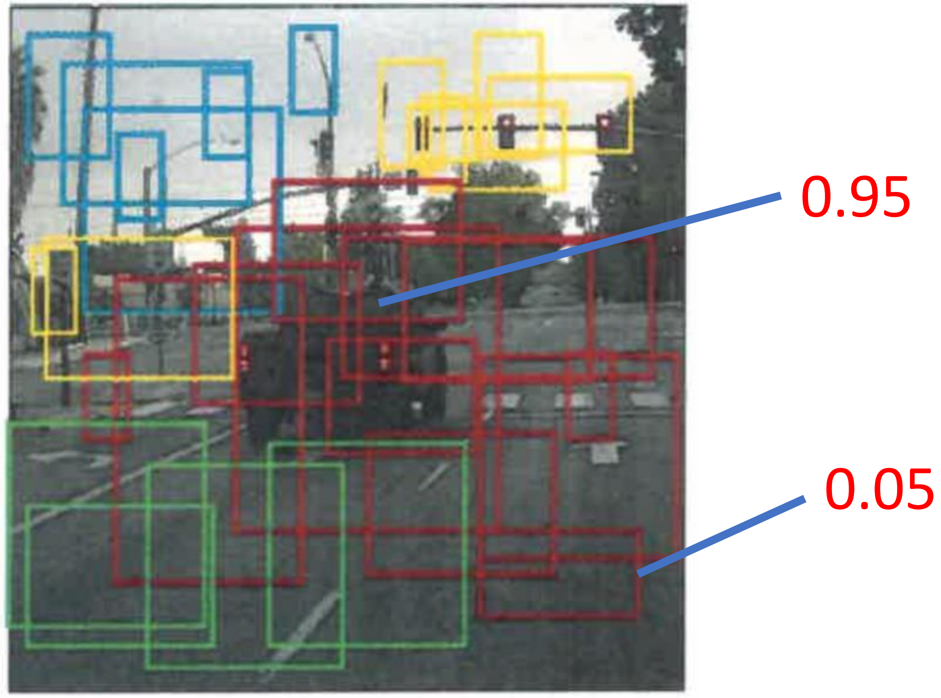
YOLO bounding boxes



- Filter the boxes using :
  1) score thresholding
  2) non-max suppression

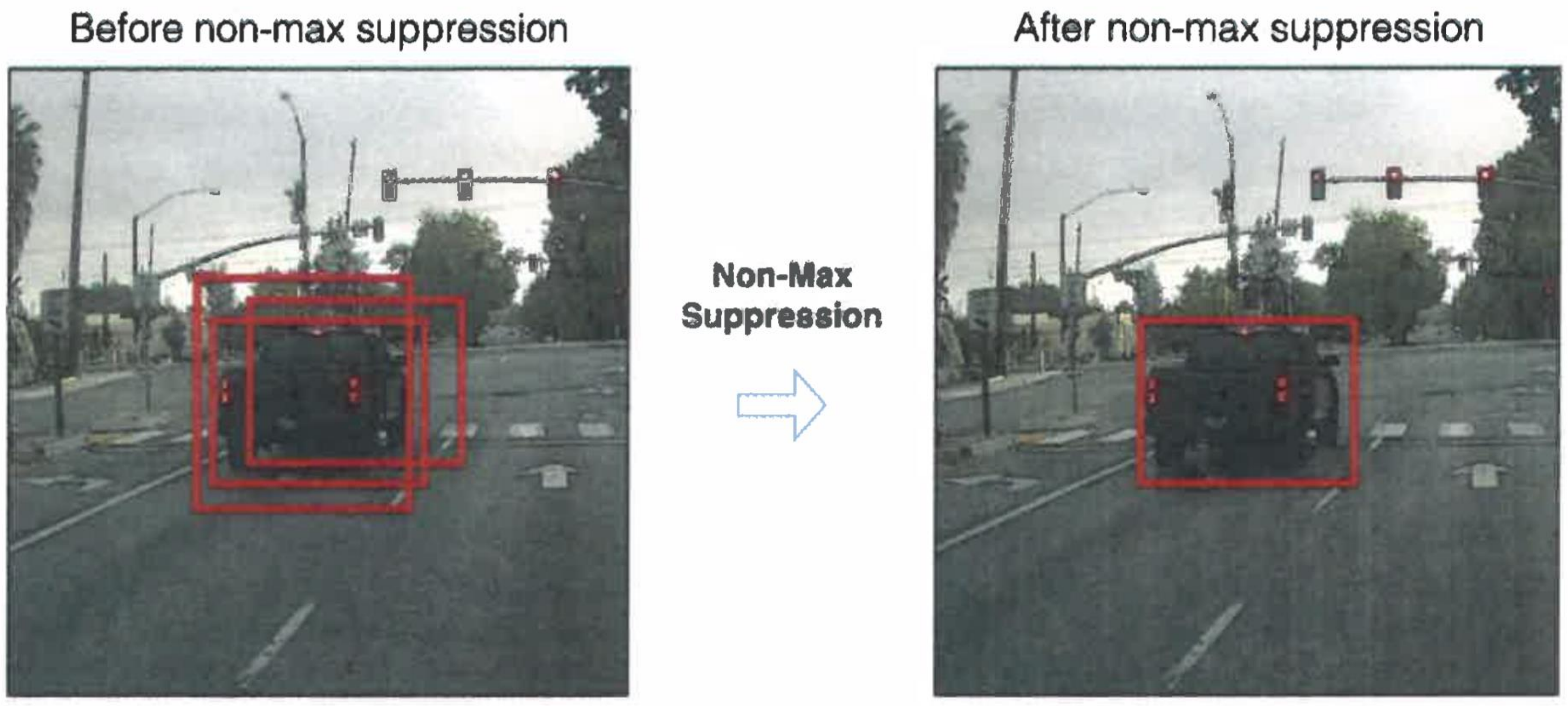
1. Score Thresholding

- Throw away boxes that have detected a class with a score less than the threshold (*0.6 for example*)



2. Non-max suppression

- ensures that an object is detected only once
  - keep the largest p_C output
  - discard any remaining box with intersection over union (IoU)>0.5

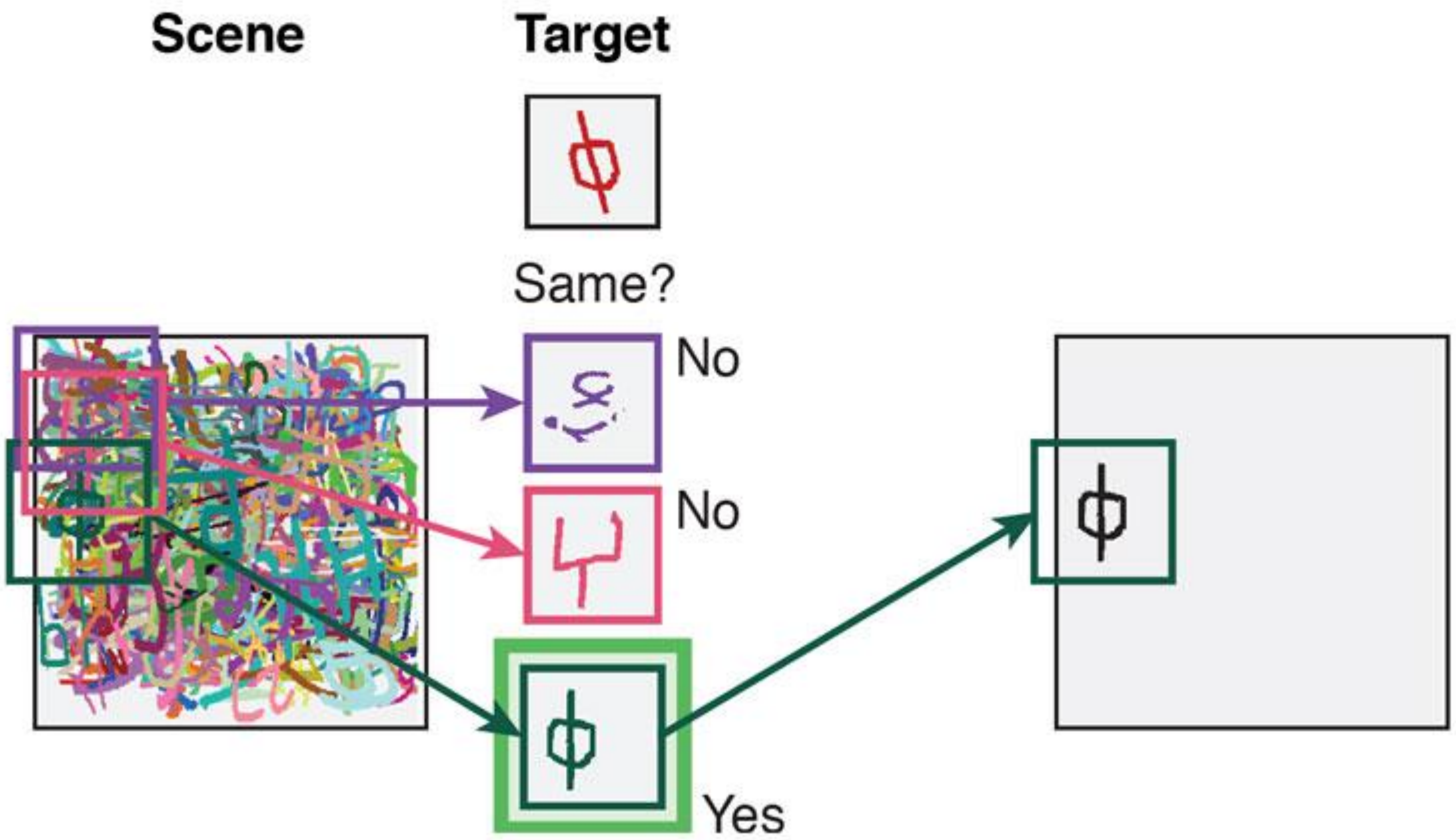


Face Detection

One-shot Learning

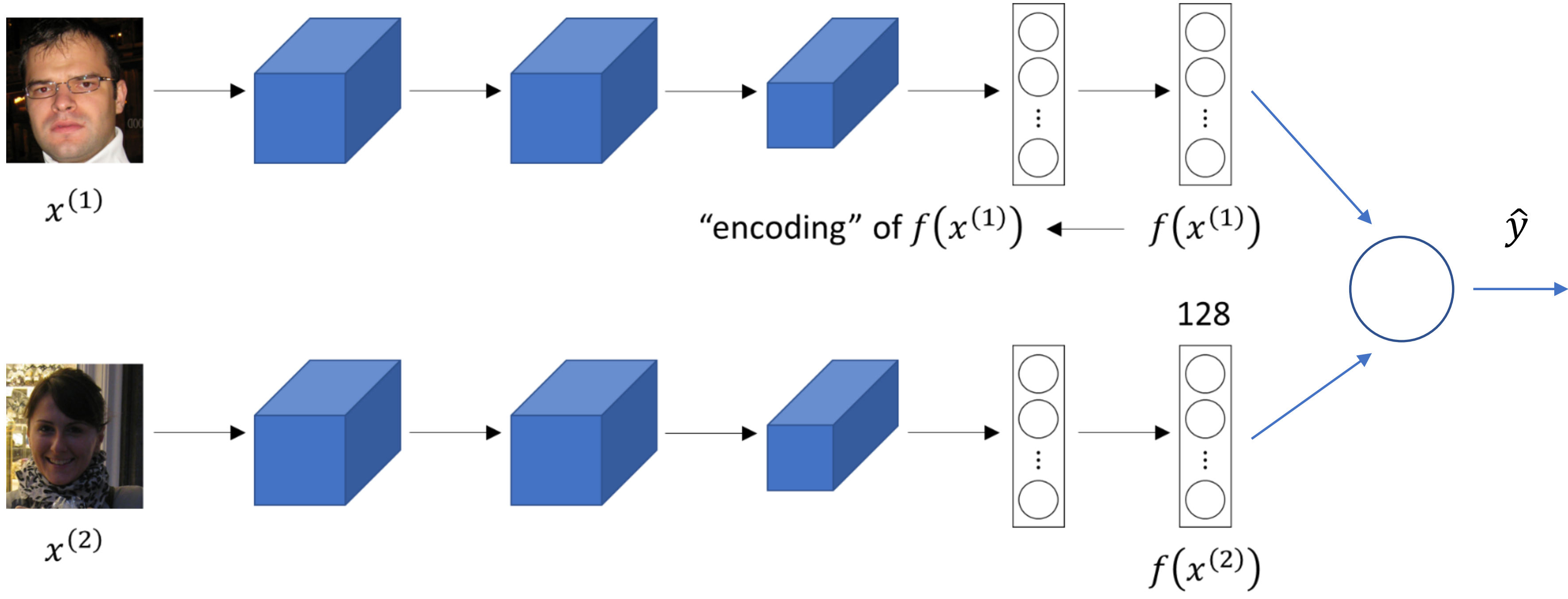
- Learn from one example to recognize the person again (very small training set)

- Learn a similarity function d (degree of difference between images)



Siamese Network

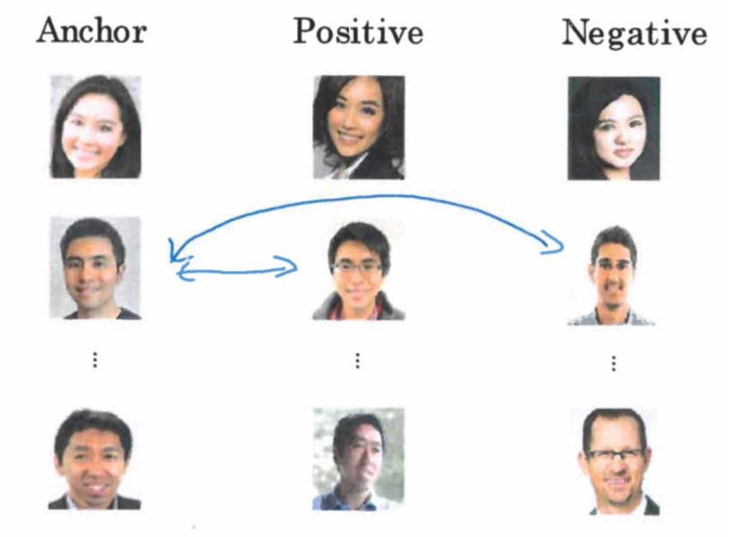
- Network used to learn the function d



$$d\left(x^{(1)}, x^{(2)}\right) = \left\| f\left(x^{(1)}\right) - f\left(x^{(2)}\right) \right\|^2$$

Triplet Loss

- Loss function where a baseline input (anchor) is compared to a positive input and a negative input :



- Often used for learning similarity
- Loss function is described using a Euclidean distance function

$$\mathcal{L}(A, P, N) = \max\Big(\| \mathrm{f}(A) - \mathrm{f}(P) \|^2 - \| \mathrm{f}(A) - \mathrm{f}(N) \|^2 + \alpha, 0 \Big)$$

- Cost function :

$$\mathcal{J} = \sum_{i=1}^{M} \mathcal{L}\left(A^{(i)}, P^{(i)}, N^{(i)} \right)$$

Security

Watch out with your algorithms !

Two-Minute Papers

Quiz

https://b.socrative.com/login/student/

Room : CONTI6128