

On Neural Networks Architectures

Better viewed using Adobe Reader for the animations.

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ASI 4



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- 1 Convolutional Neural Networks: Computer Vision
- 2 Hands on Lab 4

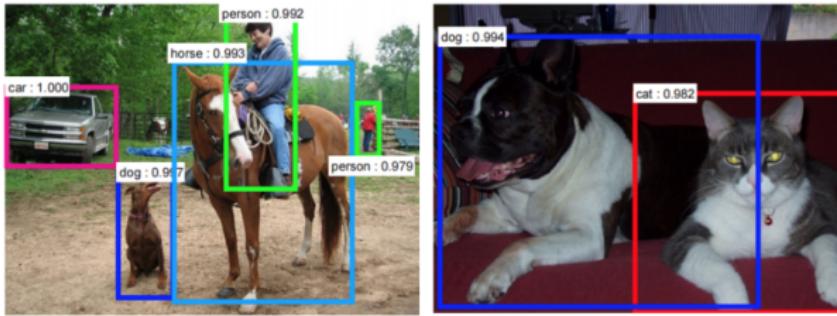
Results

When you finish this course you will:

- ① Know a little about convolutional neural networks.

By doing the **Hands on Lab 3**, you will be able to:

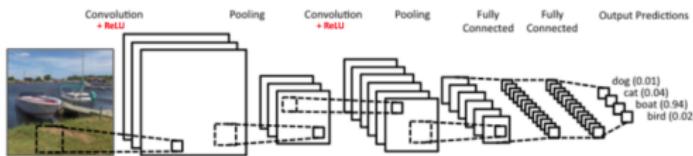
- ① Train some convolutional networks for classification over Mnist using Keras.
- ② Implement/train your first convolutional neural network using Theano.



CNNs are a very important models for computer vision and machine learning in general.

CNNs: Main Operations

- ① Convolution
- ② Non-linearity
- ③ Pooling (sub-sampling)
- ④ Task (classification/regression) layers (fully connected layers)



Input

- Channels, grayscale.

Convolution

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

(a) Image

1	0	1
0	1	0
1	0	1

(b) Filter

Output of the convolution: feature map.

Convolution: Hand-crafted Filters

	Operation	Filter	Convolved Image
Identity		$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	
Edge detection		$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$	
		$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$	
		$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	
Sharpen		$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
Box blur (normalized)		$\frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$	
Gaussian blur (approximation)		$\frac{1}{16} \begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$	



(a) Input image

(b) Filtered image using different filters.

Convolution: Filters

CNN layers are regularization compared to fully connected layers. The parameters are shared (in the opposite of fully connected layers).

The CNN learns on its own the filters (initialized randomly)).

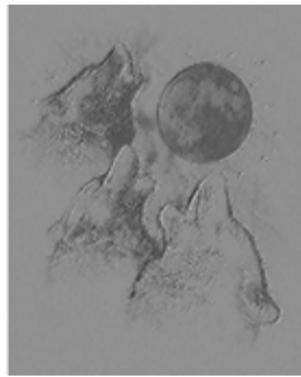
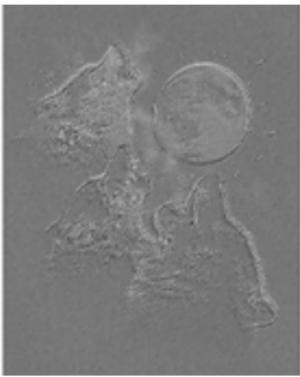
Convolution: Convolution

Convolution: Filters



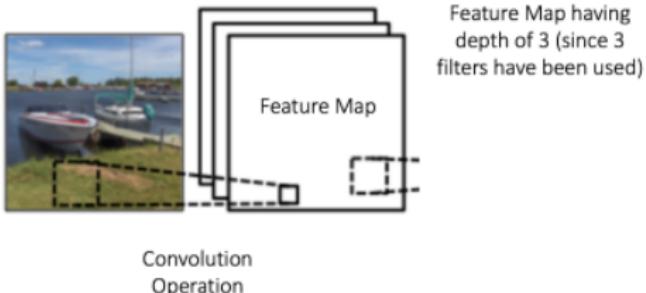
Example of learned filters at the **first** convolution layer.

Convolution: Filters



Results of convolution of two random filters (middle and right) over an image (left).

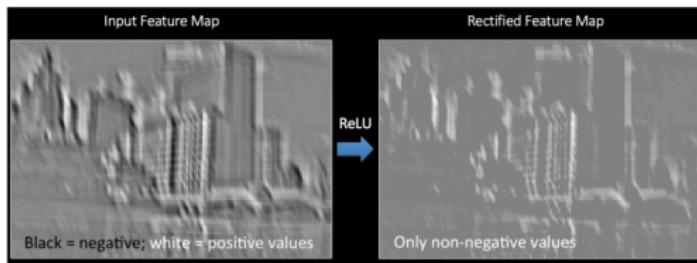
Convolution: Depth



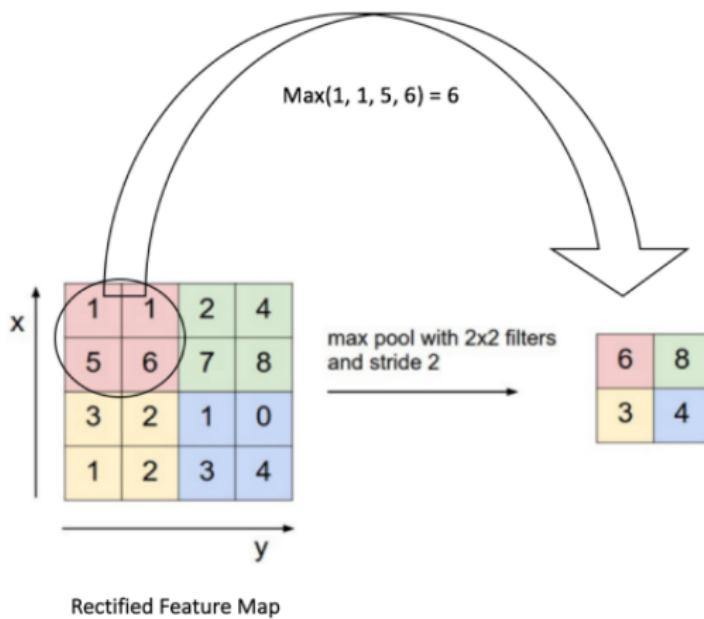
- **Depth:** number of filters in a layer.
- **Stride:** The number of pixels by which we slide out the filter matrix over the image.
- **Zero-padding:** Adding zeros around the image border.
- 2D/3D filters.
- In a convolution layer: it is up to you to fixe: the number of filters and the size of the filter. Usually, we use filters with the same size at each layer.

Convolution: Non-linearity

Output = Max(zero, Input)

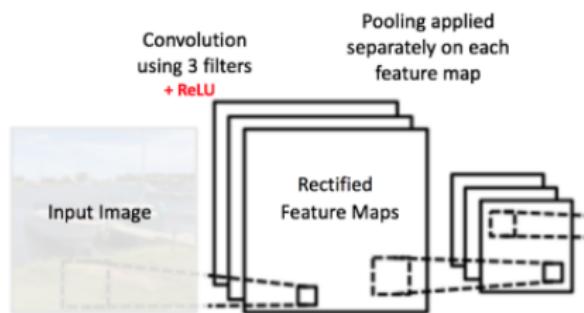


Convolution: Pooling



Invariance: translation, rotation and shifting.

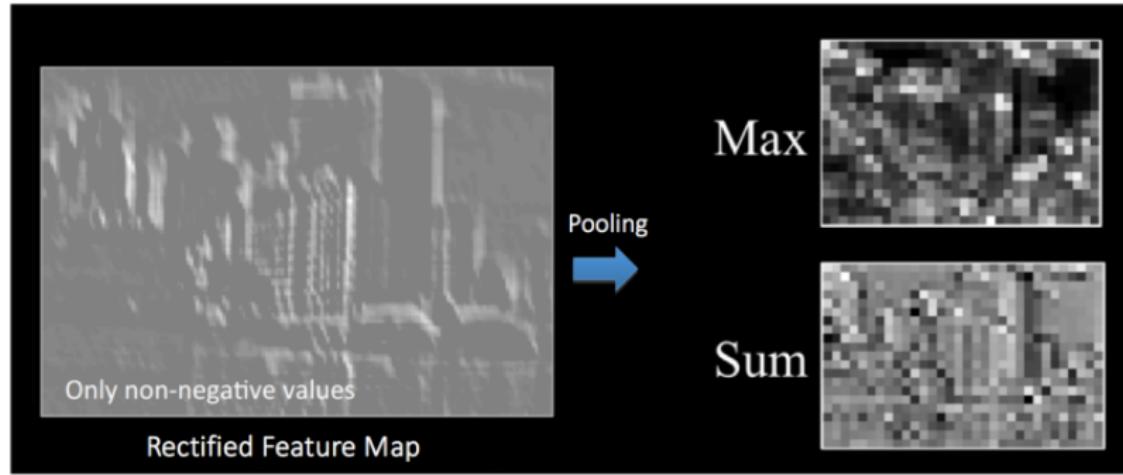
Convolution: Pooling



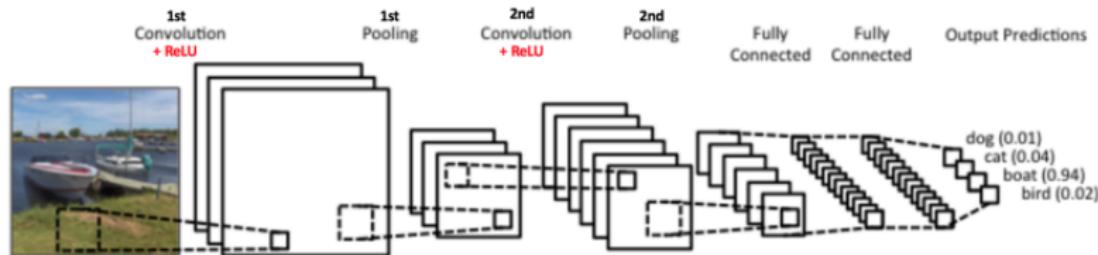
Average pooling, max pooling, sum pooling, ...

The pooling progressively reduces the size of the input representation.

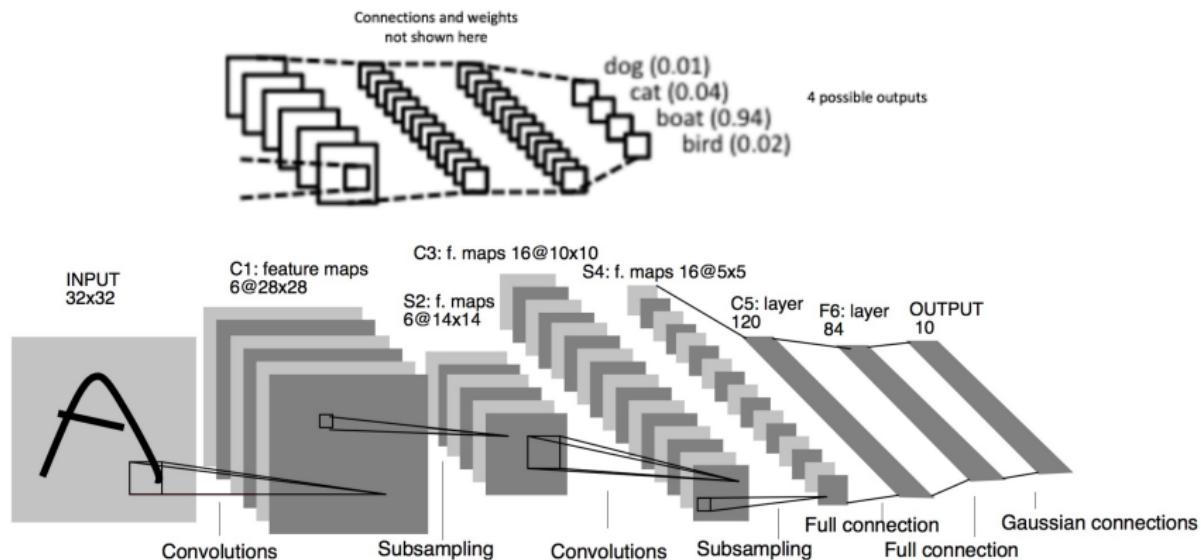
Convolution: Pooling



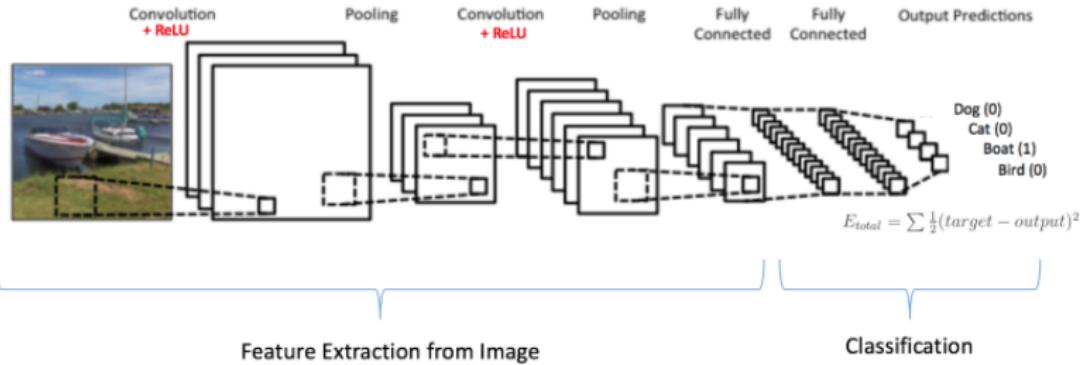
CNNs: Up to Now



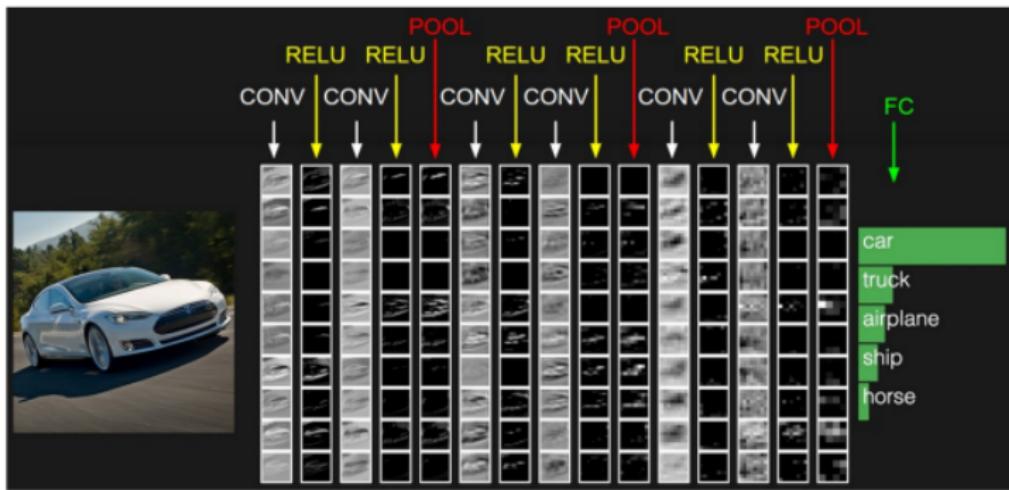
CNNs: Fully Connected Layers



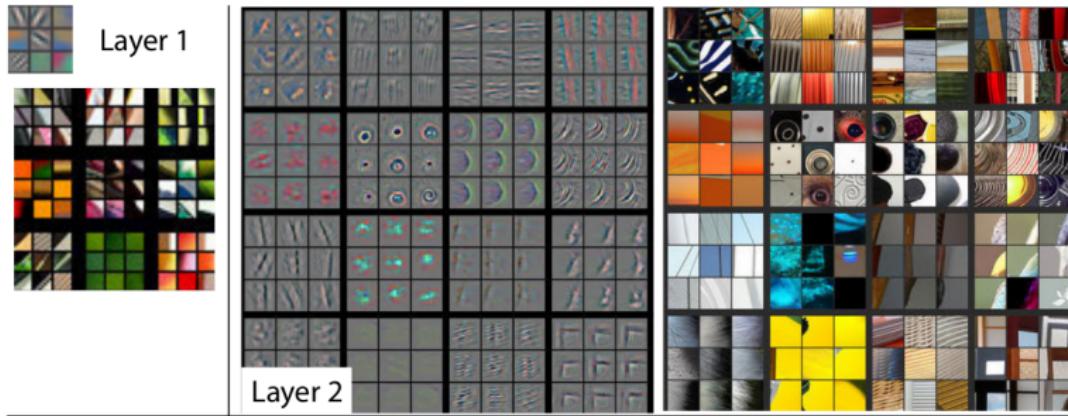
CNNs: Training using Backpropagation



CNNs: example

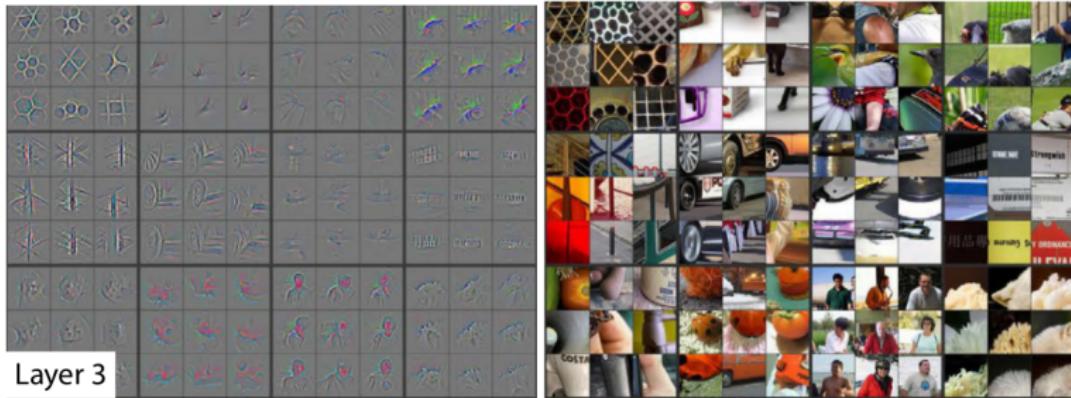


Visualization



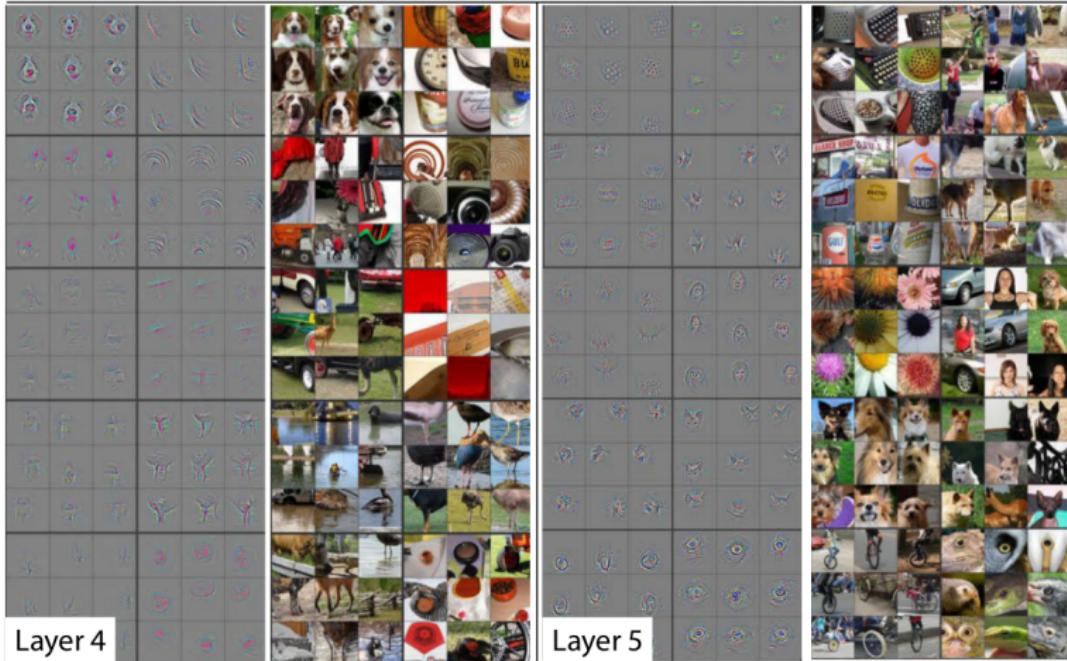
Feature maps over the 1st and the 2nd convolution layers.

Visualization



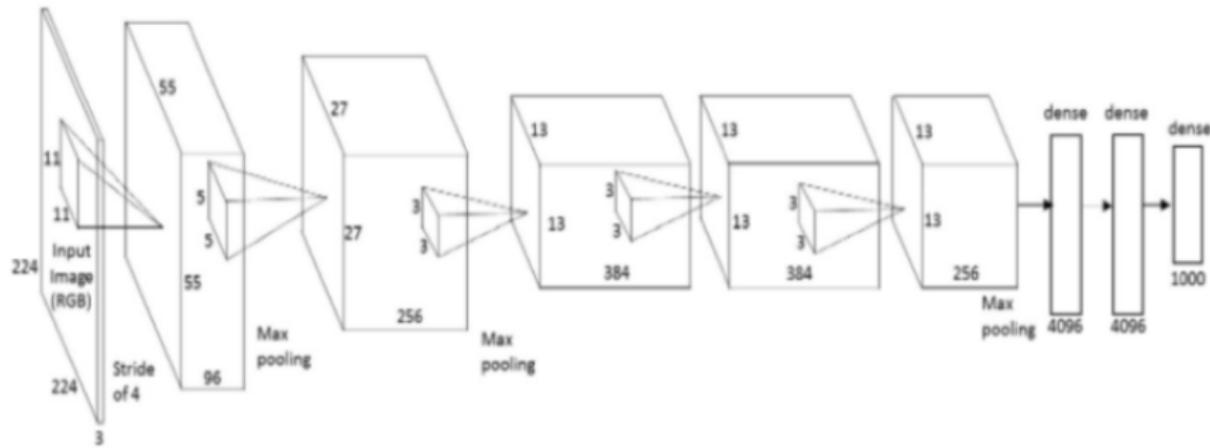
Feature maps over the 3rd convolution layer.

Visualization



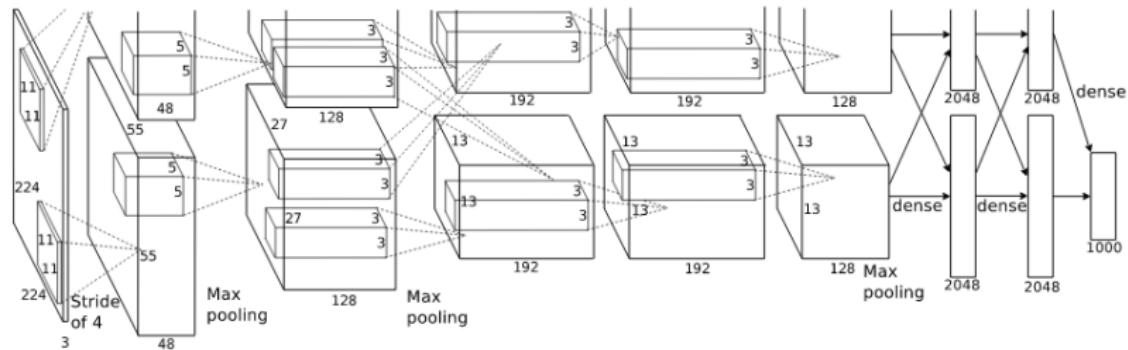
Feature maps over the 4th and the 5th convolution layers.

Some Architectures



Simple architecture.

Some Architectures



Alexnet.

Some Architectures

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 LRN	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 conv1-256	conv3-256 conv3-256 conv3-256	conv3-256 conv3-256 conv3-256 conv3-256
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 conv1-512	conv3-512 conv3-512 conv3-512	conv3-512 conv3-512 conv3-512 conv3-512
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 conv1-512	conv3-512 conv3-512 conv3-512	conv3-512 conv3-512 conv3-512 conv3-512
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

Table 2: Number of parameters (in millions).

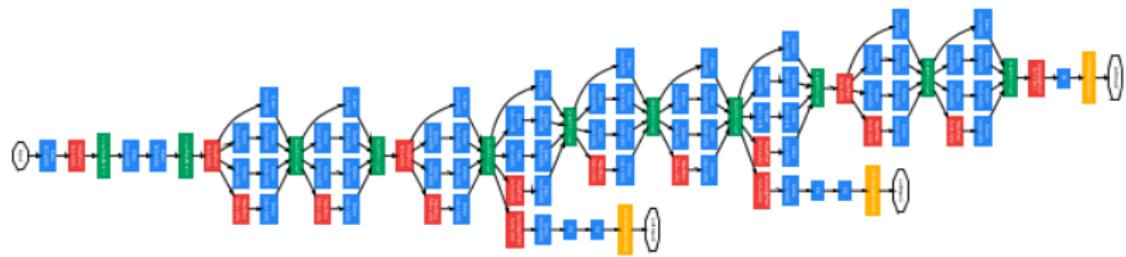
Network	A,A-LRN	B	C	D	E
Number of parameters	133	133	134	138	144

VGG family.

Some Architectures

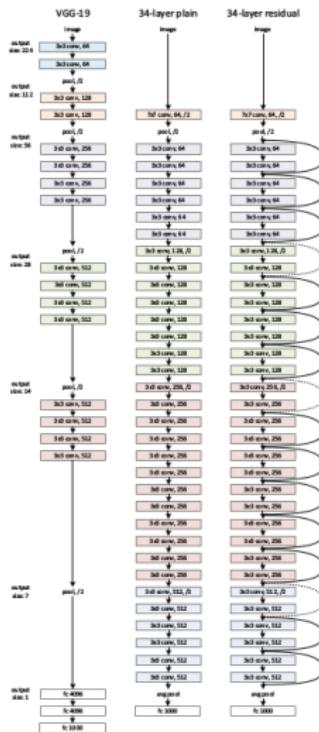
Need to go deeper.

Some Architectures



Googlenet.

Some Architectures



Resnet.

Some Architectures

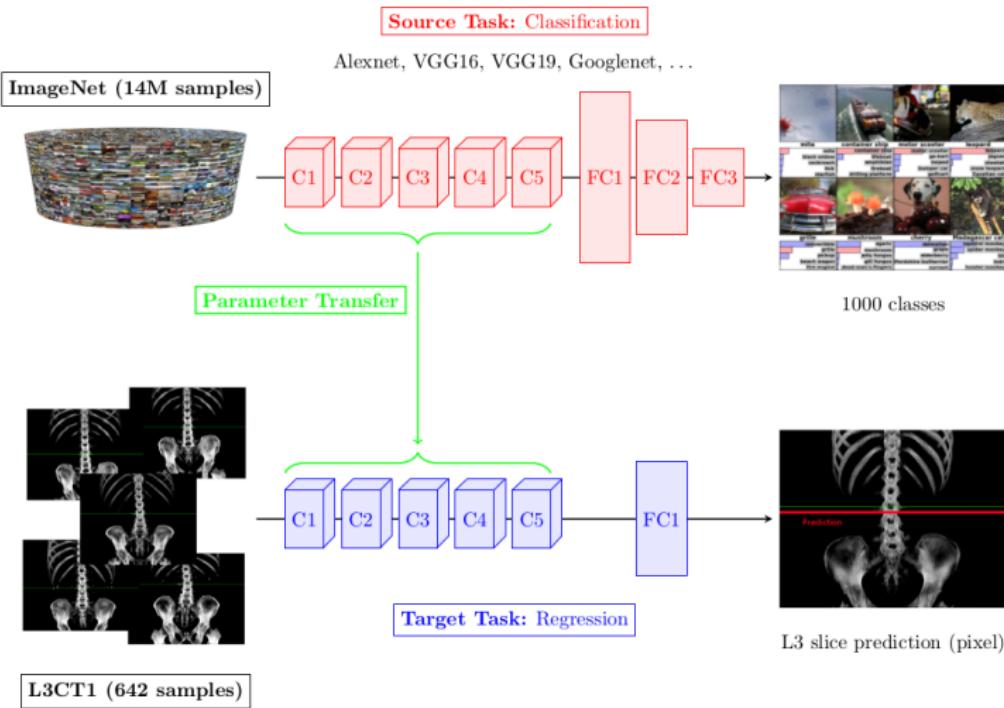
model	top-1 err.	top-5 err.
VGG-16 [41]	28.07	9.33
GoogLeNet [44]	-	9.15
PRelu-net [13]	24.27	7.38
<hr/>		
plain-34	28.54	10.02
ResNet-34 A	25.03	7.76
ResNet-34 B	24.52	7.46
ResNet-34 C	24.19	7.40
<hr/>		
ResNet-50	22.85	6.71
ResNet-101	21.75	6.05
ResNet-152	21.43	5.71

Resnet.

Conclusion

- State of the art in computer vision.
- Large number of parameters (in order of millions)
- Requires a very large training set (ImageNet: 14 millions images).
- From hand-crafted features to hand-crafted architectures (too sad).

Today's Bonus: 1- Transfer Learning



Today's Bonus: 2- Image Segmentation (Deconvolution)

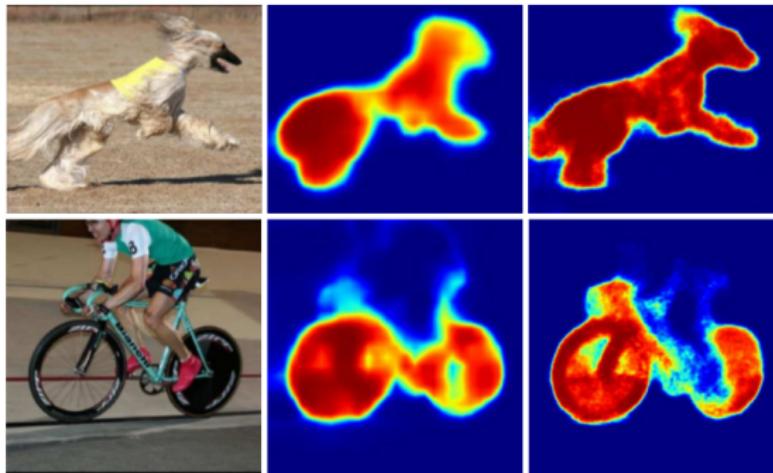
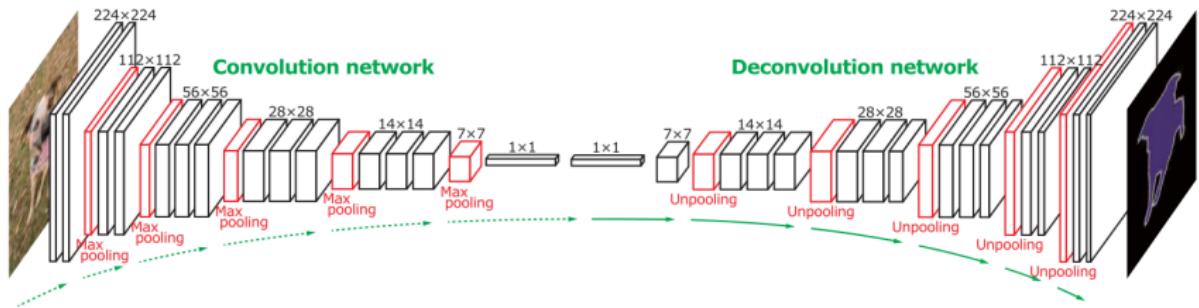


Image segmentation task: predict the label of each pixel in the image.

Today's Bonus: 2- Image Segmentation (Deconvolution)



Learning deconvolution operation (reverse operation of convolution).

Questions

Thank you for your attention,

Questions?

Is that all?

Yes.

What now?

Hands on Lab 4.

Hands on Lab 4

Break for 15 minutes.

....

- ➊ Train some convolutional networks for classification over Mnist using Keras.
- ➋ Implement/train your first convolutional neural network using Theano.