Modern Convolutional Neural Networks architectures

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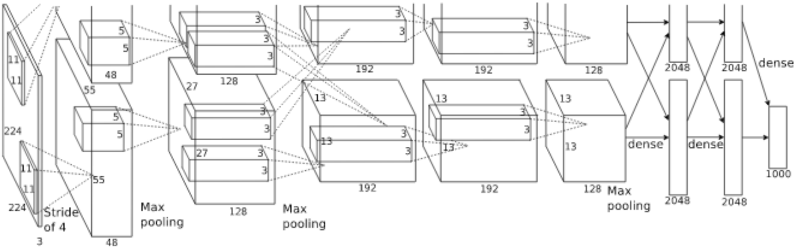
In this talk

1. Present some standard practises for designing modern ConvNets
2. Example application of ConvNets: for semantic segmentation

Recap on ConvNets

- Every neuron has a receptive field
- At every convolutional layer, multiple filters that learn different features are applied
- Three types of layers:
  - convolutional
  - pooling
  - fully connected

E.g. AlexNet



Krizhevsky, Sutskever, et al. 2012

Issues with standard ConvNets

- Lots of different design choices, often task-specific
- Lack of a unified framework for building layers
- What are the most important elements of a ConvNet?
- Deep CNNs contain a lot of parameters and are hard/slow to optimize

In this talk

1. Designing modern ConvNets
   - Very Deep Learning
   - Fully Convolutional Networks
2. Semantic Segmentation

Very Deep ConvNets for Large-Scale Image Recognition [1]

Main ideas:

- Is adding more and more layers good for a model?
- Fix all other parameters in the system and check.
- Use smaller receptive fields (3×3) to reduce computation.
- Structure is deliberately designed to be simple (e.g. only ReLu non-linearity, no Local Response Normalization)

[1] Simonyan and Zisserman 2014

Details of the architecture

- Reception field is 3×3 with stride of 1
  - Compensate by adding more layers
  - Three convolutional layers achieve an effective receptive field of 7×7
  - This includes more non-linearity
  - Also reduces the number of parameters
- Also include layers with 1×1 receptive fields.

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

ConvNet config. (Table 1)	smallest image side		top-1 val. error (%)	top-5 val. error (%)
	train (S)	test (Q)		
A	256	256	29.6	10.4
A-LRN	256	256	29.7	10.5
B	256	256	28.7	9.9
C	256	256	28.1	9.4
	384	384	28.1	9.3
	[256;512]	384	27.3	8.8
D	256	256	27.0	8.8
	384	384	26.8	8.7
	[256;512]	384	25.6	8.1
E	256	256	27.3	9.0
	384	384	26.9	8.7
	[256;512]	384	**25.5**	**8.0**

Results on the ImageNet data from Russakovsky et al. 2015

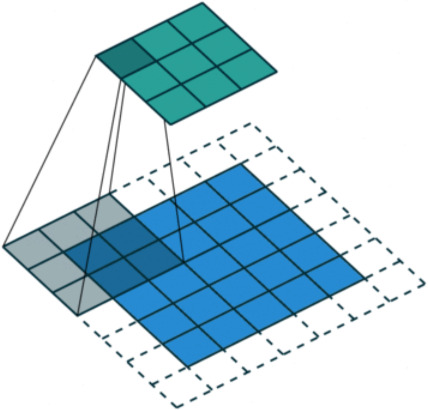
In this talk

Striving for Simplicity: The All Convolutional Net[2]

- Can ConvNets be considered from a more unified perspective?
- A convolutional layer with stride bigger than 1 is similar to pooling
- The network then learns how to perform the dimensionality reduction
- Use global average pooling, instead of fully connected layers

[2] Springenberg et al. 2014

Convolution with stride 2 is like pooling



Source: https://github.com/vdumoulin/conv_arithmetic

Model

A	B	C
Input 32 × 32 RGB image		
5 × 5 conv. 96 ReLU	5 × 5 conv. 96 ReLU 1 × 1 conv. 96 ReLU	3 × 3 conv. 96 ReLU 3 × 3 conv. 96 ReLU
3 × 3 max-pooling stride 2		
5 × 5 conv. 192 ReLU	5 × 5 conv. 192 ReLU 1 × 1 conv. 192 ReLU	3 × 3 conv. 192 ReLU 3 × 3 conv. 192 ReLU
3 × 3 max-pooling stride 2		
3 × 3 conv. 192 ReLU		
1 × 1 conv. 192 ReLU		
1 × 1 conv. 10 ReLU		
global averaging over 6 × 6 spatial dimensions		
10 or 100-way softmax		

Model

Strided-CNN-C	ConvPool-CNN-C	All-CNN-C
Input 32 × 32 RGB image		
3 × 3 conv. 96 ReLU 3 × 3 conv. 96 ReLU with stride $r = 2$	3 × 3 conv. 96 ReLU 3 × 3 conv. 96 ReLU 3 × 3 conv. 96 ReLU	3 × 3 conv. 96 ReLU 3 × 3 conv. 96 ReLU
	3 × 3 max-pooling stride 2	3 × 3 conv. 96 ReLU with stride $r = 2$
3 × 3 conv. 192 ReLU 3 × 3 conv. 192 ReLU with stride $r = 2$	3 × 3 conv. 192 ReLU 3 × 3 conv. 192 ReLU 3 × 3 conv. 192 ReLU	3 × 3 conv. 192 ReLU 3 × 3 conv. 192 ReLU
	3 × 3 max-pooling stride 2	3 × 3 conv. 192 ReLU with stride $r = 2$

⋮

CIFAR-10 classification error

Model	Error (%)	# parameters
without data augmentation		
Model A	12.47%	$\approx$ 0.9 M
Strided-CNN-A	13.46%	$\approx$ 0.9 M
ConvPool-CNN-A	**10.21%**	$\approx$ 1.28 M
ALL-CNN-A	10.30%	$\approx$ 1.28 M
Model B	10.20%	$\approx$ 1 M
Strided-CNN-B	10.98%	$\approx$ 1 M
ConvPool-CNN-B	9.33%	$\approx$ 1.35 M
ALL-CNN-B	**9.10%**	$\approx$ 1.35 M
Model C	9.74%	$\approx$ 1.3 M
Strided-CNN-C	10.19%	$\approx$ 1.3 M
ConvPool-CNN-C	9.31%	$\approx$ 1.4 M
ALL-CNN-C	**9.08%**	$\approx$ 1.4 M

Results on the CIFAR-10 data from Krizhevsky and Hinton 2009

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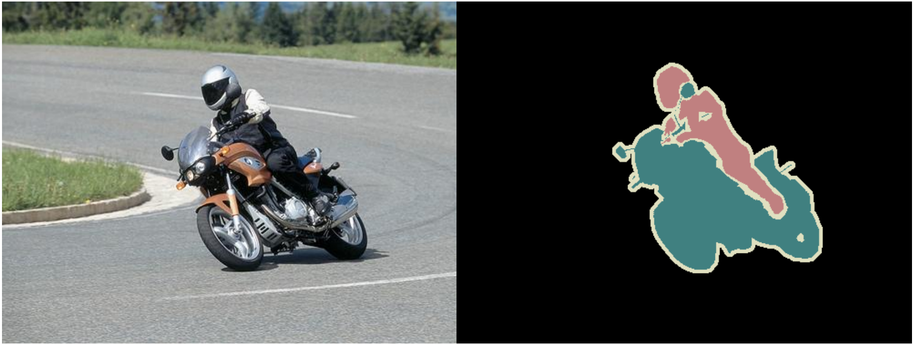
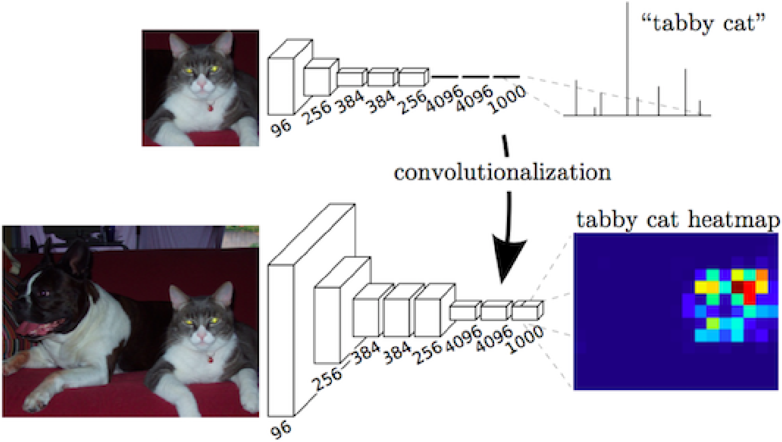
Semantic segmentation



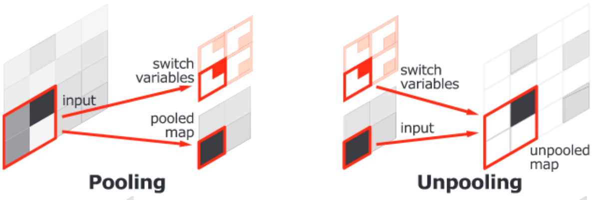
Source: http://host.robots.ox.ac.uk/pascal/VOC...

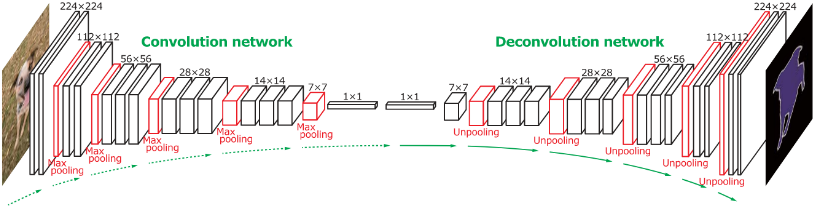
Fully Convolutional Nets can give spatial output



Long et al. 2015

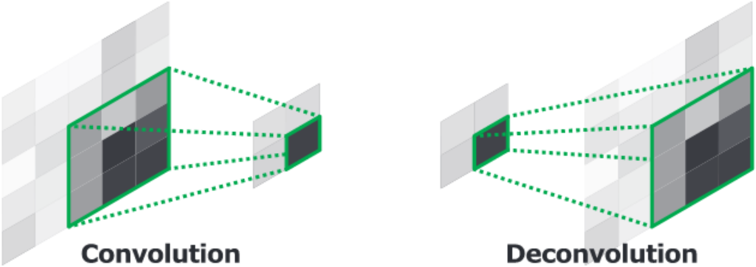
Upsampling





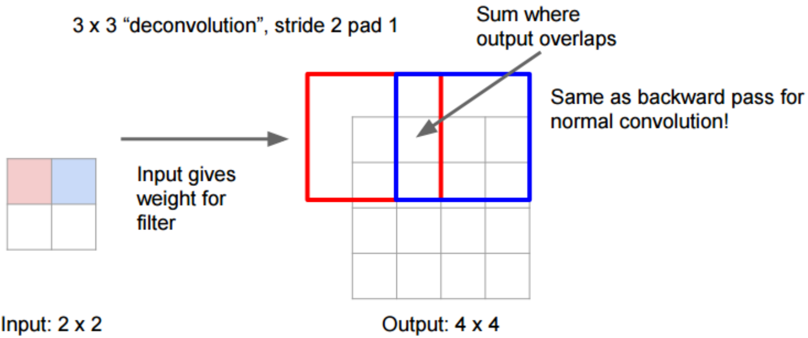
Noh et al. 2015

Transposed convolution (deconvolution)



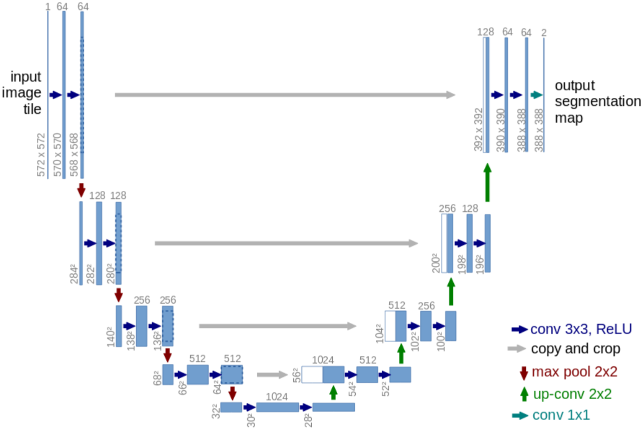
Noh et al. 2015

Deconvolution networks

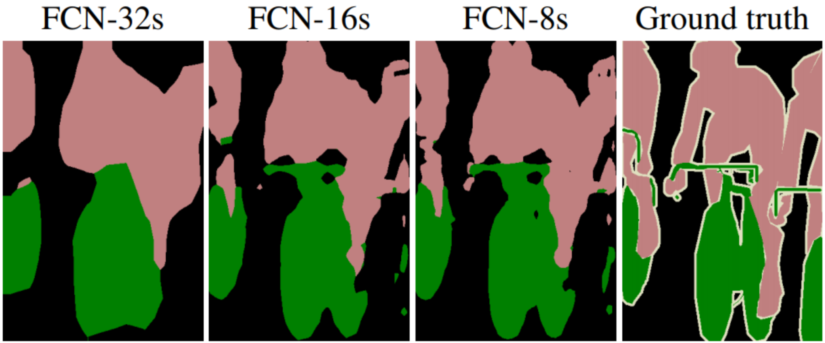


Source: https://leonardoaraujosantos.gitbooks.io/arti...

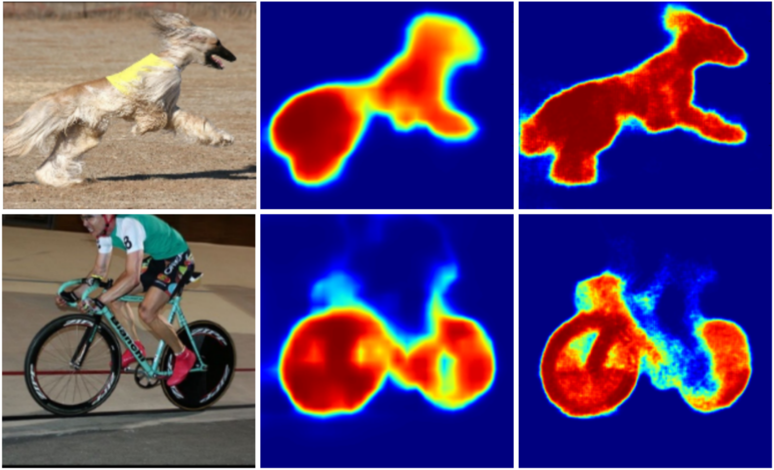
Links to shallow layers help to recover local information



Ronneberger et al. 2015



Long et al. 2015



Noh et al. 2015

Summary

- Using 3×3 convolutions reduces computation and (often) works
- The deeper the network, the better
- Simple designs are often sufficient
- Fully Convolutional Nets are useful for encoding spatial information
- Can use connections from multiple previous layers
- But … deep networks are hard to train

Thank you for your attention!

References I

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