Fully convolutional neural networks

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A few words about myself

- Researcher on mathematical morphology and image processing
- Main current application fields:
  - Ophthalmology
  - Dermatology, cosmetology
  - Astronomy (2 years)
- I have been using deep learning methods since 2015

Acronyms

- ANN = artificial neural network
- CNN = convolutional neural network

Image Segmentation with NNs

- Computer vision has been one of the main application domains of NNs
- Image segmentation often is an important step in an image processing work flow
- Image segmentation has been a very active deep learning research field

Image segmentation example

Image definition

Definition: image

An 2-dimensional image I of size $p \times q$ $(p, q \in \mathbb{N}^*)$ is a function from $D = [0, \ldots p-1] \times [0, \ldots q-1]$ into $\mathbb{R}^d$ $(d \in \mathbb{N}^*)$.
The set of these images is $\mathcal{I}^d$.

Examples

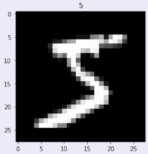


Figure: 28×28 grey level image $(d = 1)$ from the MNIST dataset, and 481×321 colour image $(d = 3)$ from the Berkeley segmentation dataset.

Image-to-image NN

Definition: image-to-image neural network

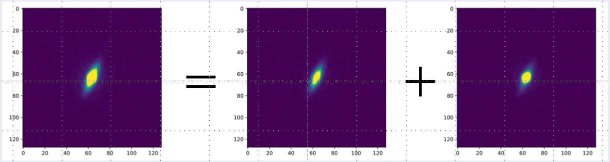
An image-to-image NNs F is a NN that transforms an image into an image of same size:

$$F : \mathcal{I}^{d_1} \longrightarrow \mathcal{I}^{d_2}$$
$$I \longmapsto N(I)$$

Note that the dimensions d_1 and d_2 of the value spaces can be different.

Examples

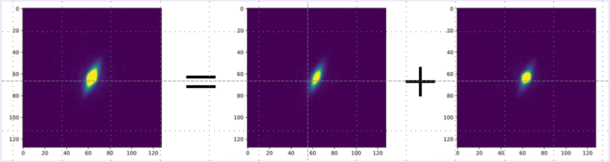
Bulge / disk decomposition



(Credits: Tuccillo, Huertas-Company, Velasco-Forero, Decencière)

Examples

Bulge / disk decomposition



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Deblurring network [Hradiš et al., 2015]

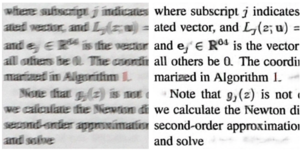

Image-to-image NNs architecture

- Image-to-image NNs are based on convolutional layers
- If downsampling is used, the corresponding upsampling is needed
- The receptive field of the network is an essential property

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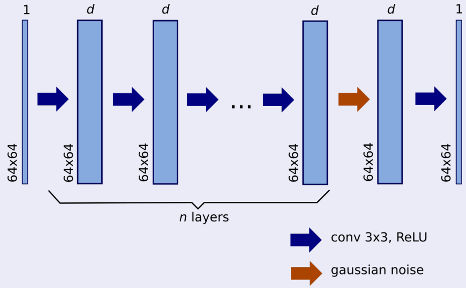
- The receptive field of the network is an essential property

Example: Pang network [Pang et al., 2010]



Receptive field

Definition: links between neurons

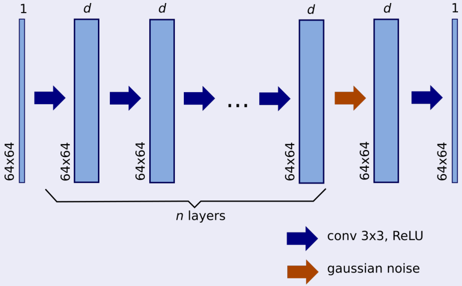
In a NN, we say that neuron a is linked to neuron b if there is an oriented path in the corresponding graph going from a to b.

Definition

The receptive field of a neuron in a NN is the set of input neurons that are linked to that neuron.
The size of the receptive field is an essential property when designing a fully-convolutional NN architecture.

Receptive field of the Pang network

What is the size of the receptive field of the neurons in the last layer?



Receptive field of the Pang network

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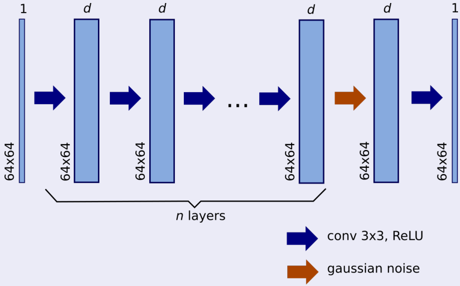

Answer: $1 + 2 \times (n + 1)$

The specific case of image segmentation

Definition: image segmentation

Let I be an image defined on D. A segmentation of I is a partition of D. In practice the regions of the segmentation should correspond to the objects in I, which is application dependant.

- A partition is often represented as a labelled image
- In order to make the segments symmetric, each one is represented by a different channel

Some vocabulary on segmentation

- **Object detection / localization**: bounding box around the object(s).
- **Binary segmentation**: segmentation in 2 classes, background and object.
- **Semantic segmentation**: a label is given to each pixel, according to the object it belongs to.
- **Instance segmentation**: identify each separate object, even if they belong to the same class.

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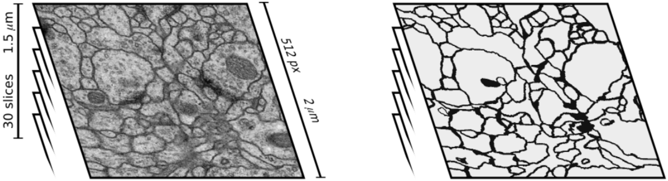
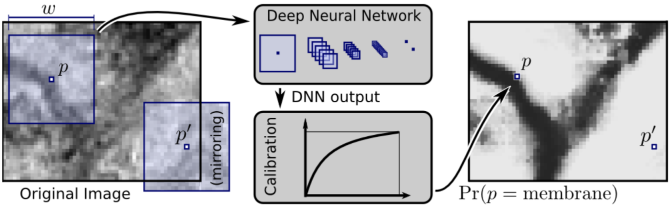
Neuron membrane segmentation challenge (ISBI 2012)

- Train: single stack of size $30 \times 512 \times 512$.
- Test: a second stack of same size.



Neuron membrane segmentation challenge winner [Ciresan et al., 2012]



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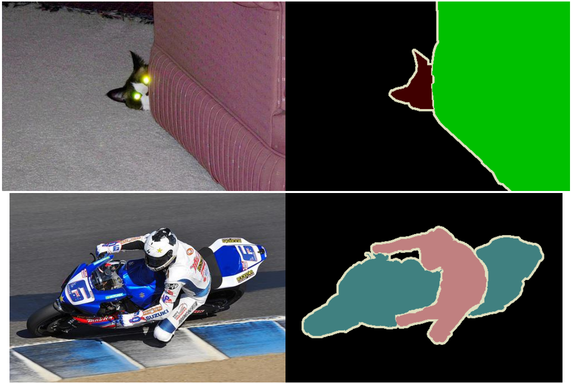
Pascal visual object classes segmentation challenge 2012 [Everingham et al., 2014]

- 1464 training and 1449 validation images
- automatic online test, with unknown images
- 20 image categories (cat, sofa, motorbike, person, etc.)

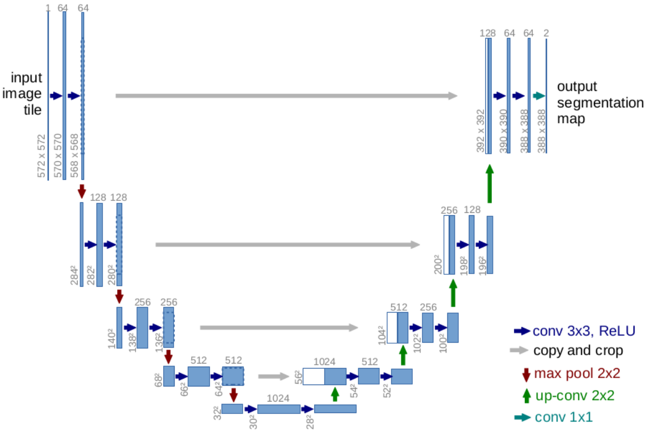


Convolutional nets for semantic image segmentation

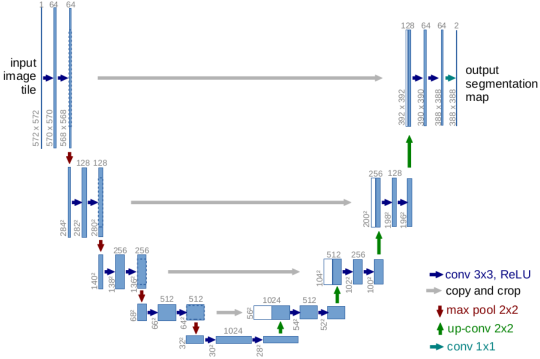
Three papers in 2015:

- Fully convolutional networks for semantic segmentation [Long et al., 2015]
- U-Net: convolutional networks for biomedical image segmentation [Ronneberger et al., 2015]
- SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation [Badrinarayanan et al., 2015]

Example: U-Net architecture [Ronneberger et al., 2015]



What is the size of the receptive field of U-Net



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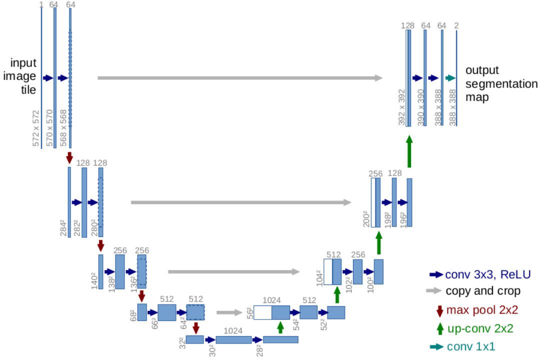
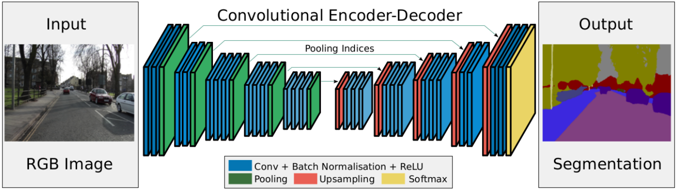


Answer: 185×185

Example: SegNet architecture [Badrinarayanan et al., 2015]



Remarks

- These architectures easily contain a number of parameters of the order of 10^7 (28 million for U-Net)
- Their optimization might be difficult
- For many segmentation applications, they are overkill
  - But you can reduce the number of filters or the number of layers

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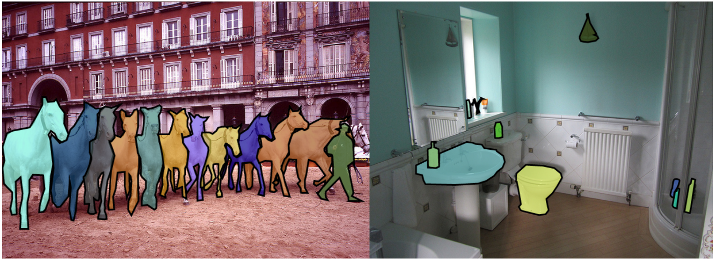
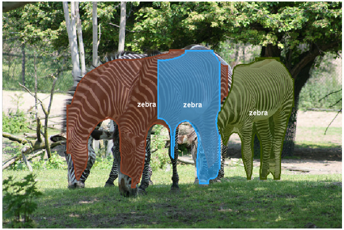
COCO: common objects in context [Lin et al., 2014]

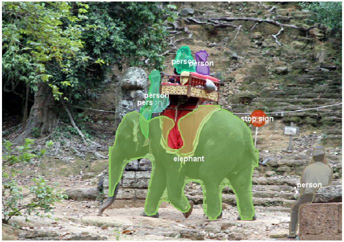
- 2 million objects, from 80 categories, in $300\,000$ images

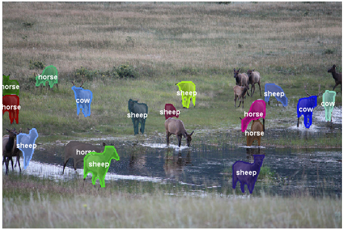


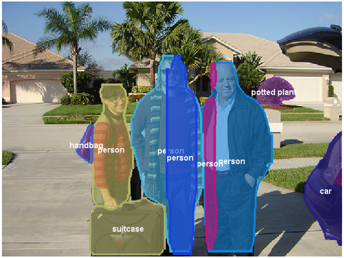
Winner 2016: Fully Convolutional Instance-aware Semantic Segmentation (Microsoft) [Li et al., 2016]

COCO instance segmentation challenge: examples of 2016 winner results

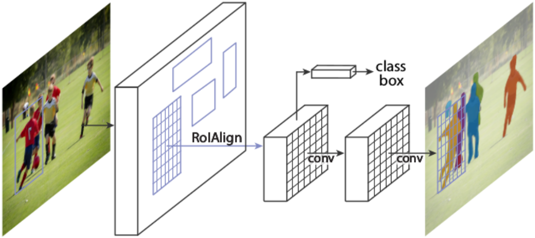




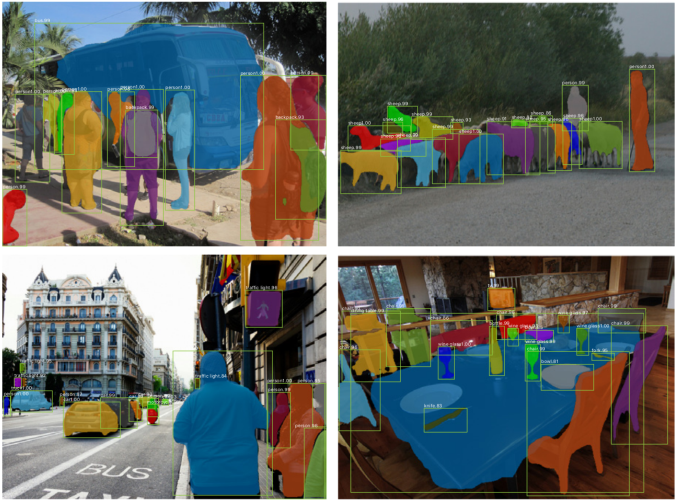




State of the art on the COCO database: Mask R-CNN [He et al., 2017]

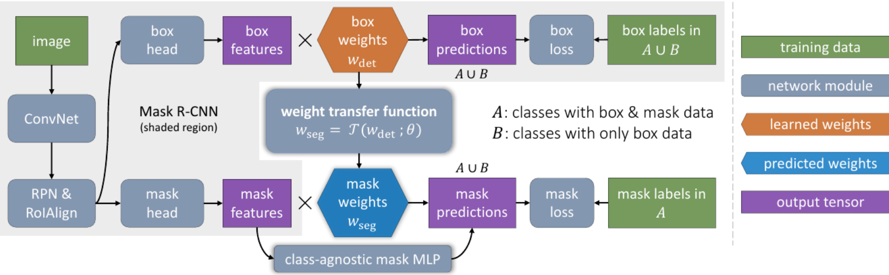


Mask R-CNN on the COCO database

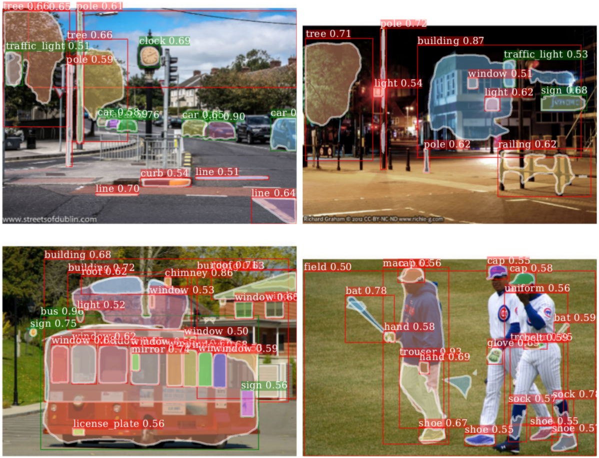


Partially supervised segmentation - [Hu et al., 2017]

- 80 segmented categories from COCO database
- 3000 visual concepts using box annotations from the Visual Genome dataset (100k images)



Partially supervised segmentation - learning to segment every thing



[Hu et al., 2017]

Current (?) trends for instance segmentation

- Region proposal +
- Fully convolutional (very deep) network +
- (Post-processing)

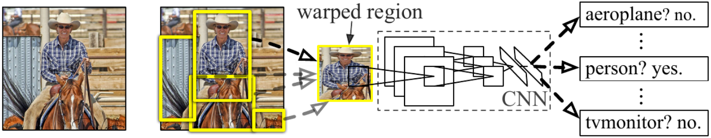


Figure: Regions with CNN features (R-CNN) (from [Girshick et al., 2014])

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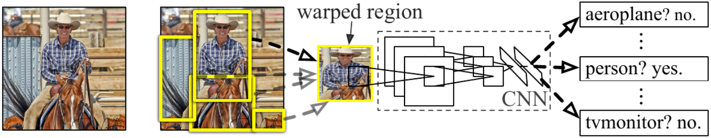

Figure: Regions with CNN features (R-CNN) (from [Girshick et al., 2014])

Meanwhile, on the object detection field...

- YOLO: you look only once [Redmon and Farhadi, 2016]
- SSD: single shot detector [Liu et al., 2016]

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Modeling your problem

Casting your problem into the right representation

- Familiarize yourself with the training data (input and output images)
- Choose the right representation for your images
- Choose an architecture and train it
- Analyze the results on the validation data (look at the images!)
- Do you need preprocessing? Data augmentation? Post-processing?
- Iterate ...
- Only at the end: test!

Preprocessing

- Standard statistical preprocessing: not always useful, and sometimes problematic, when applied to images
- Morphological operators

Data augmentation

- Geometrical transformations: similarities
- Elastic transformations
- Specific methods: articulated objects, ...
- Simulated data

Postprocessing for segmentation

- Superpixels (e.g. [Farabet et al., 2013])
- Conditional random fields (e.g. [**?**])
- Mathematical morphology

What loss to use?

- Classical choice: mean squared error or cross-entropy
- My recommendation: Dice or Jaccard losses

Practical example

(Credits: ESA/Hubble, CC BY 4.0,

https://commons.wikimedia.org/w/index.php?curid=34205833)

How would you:

- segment the background?
- segment the sources?
- separate the sources?

What precision is needed for the ground-truth?

- The ground truth boundaries do not need to be very precise
-

Using a CNN

- A fully convolutional neural network is translation invariant
- Provided that the image size is compatible with network's subsampling process, in theory any image can be processed
- Practical limit: the memory of the system

Contents

A solved problem?

- Progress in image segmentation during the 5 last years has been enourmous
- Several complex problems have now satisfactory solutions
- Training can be a problem (large annotated databases, difficult optimization)
- Some remaining challenges:
  - Making the training database as small as possible
  - Taking *a priori* structural information into account

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