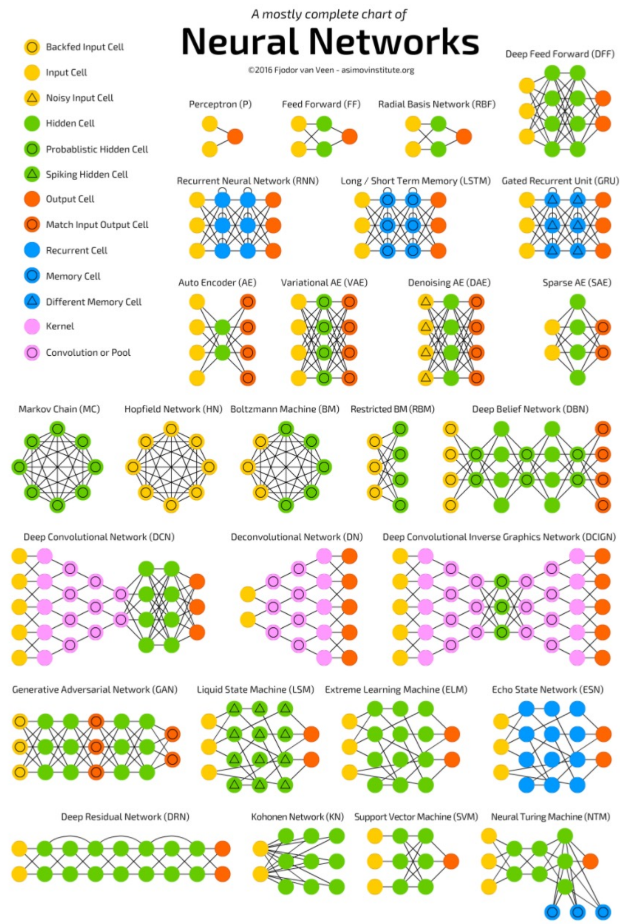
Convolutional Neural Networks

CSCI 4360/6360 Data Science II

The Neural Network Zoo

- http://www.asimovinstitute.org/neural-network-zoo/



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Convolution

- Basically a fancy way of saying "multiplication"
- Originally devised to make non-differentiable signals differentiable
- KDE is related to convolution
- For an input function *f* and convolutional filter *g*:

$$f \circledast g$$

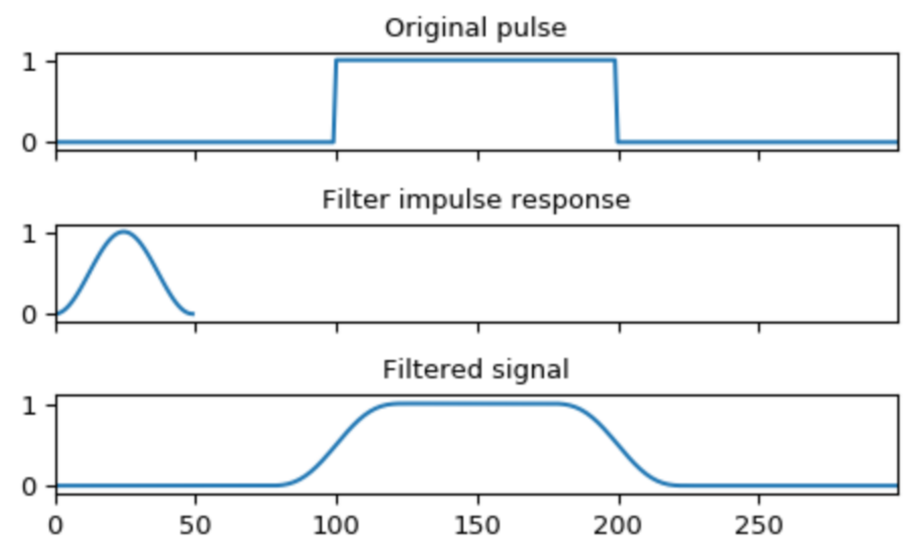
scipy.signal.convolve

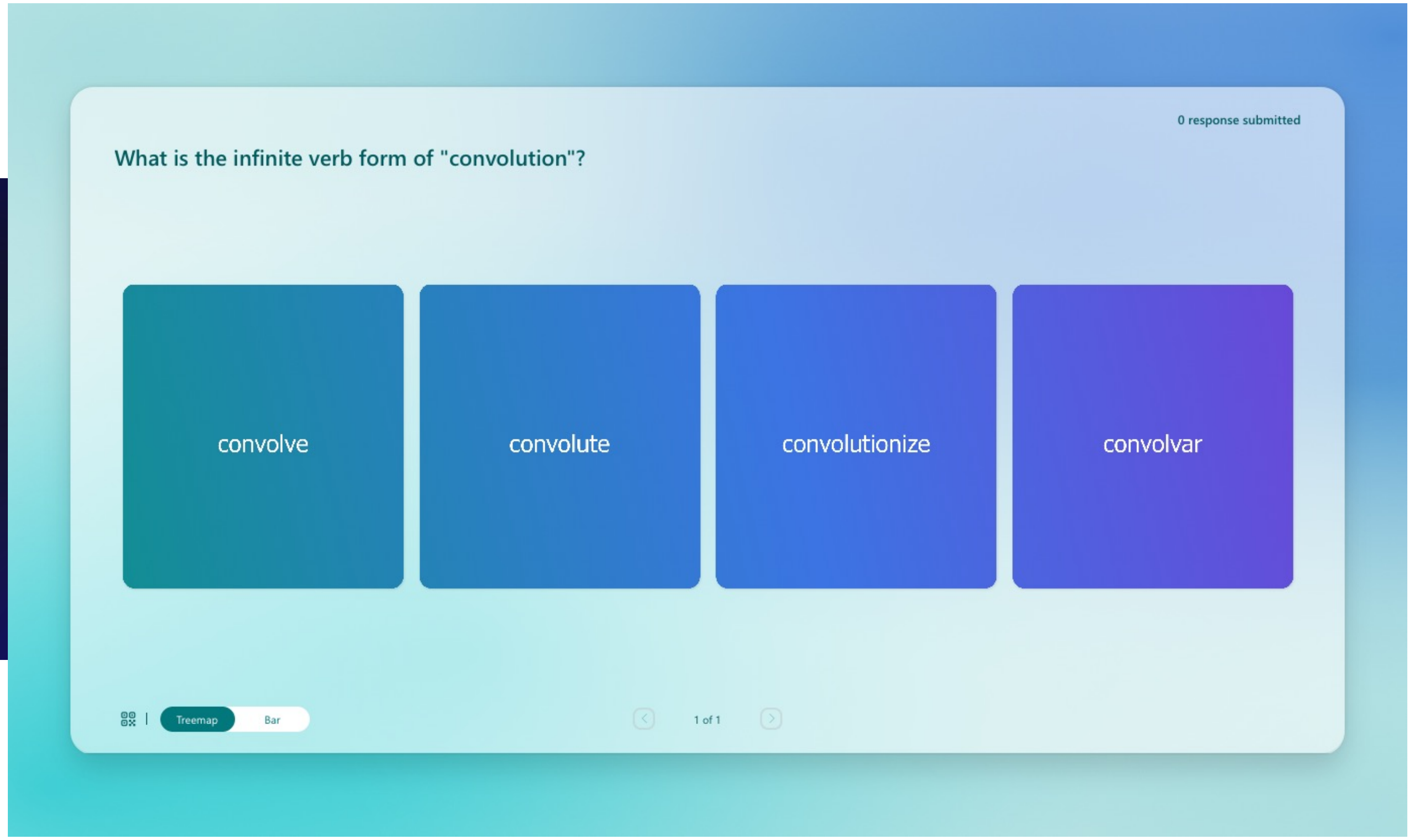
scipy.signal.convolve(*in1*, *in2*, *mode='full'*, *method='auto'*)

Convolve two N-dimensional arrays.

Convolve *in1* and *in2*, with the output size determined by the *mode* argument.

Parameters:	in1 : *array_like* First input. in2 : *array_like* Second input. Should have the same number of dimensions as *in1*. mode : *str {'full', 'valid', 'same'}, optional* A string indicating the size of the output:

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What is the infinite verb form of "convolution"?
convolve
convolute
convolutionize
convolvar
Treemap
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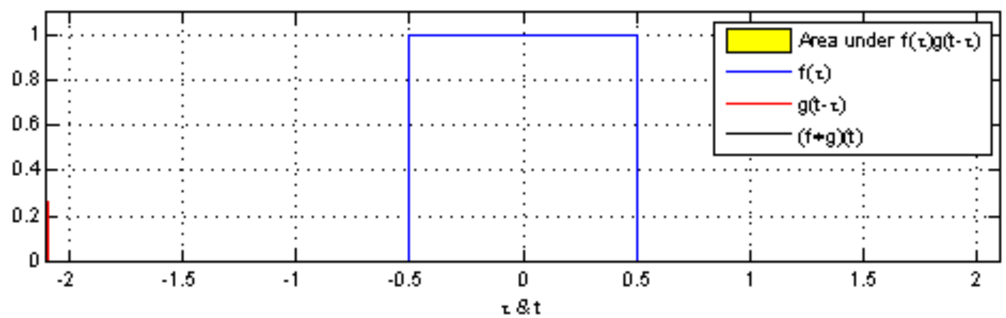
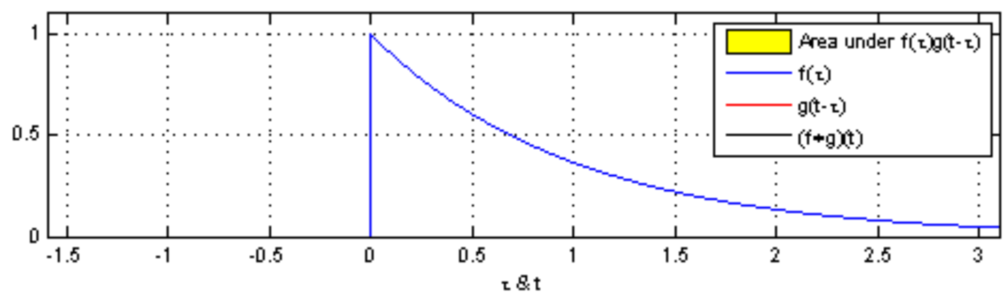
1 of 1

Convolution

- Can be viewed as an *integral transform*
  - One of the signals is shifted

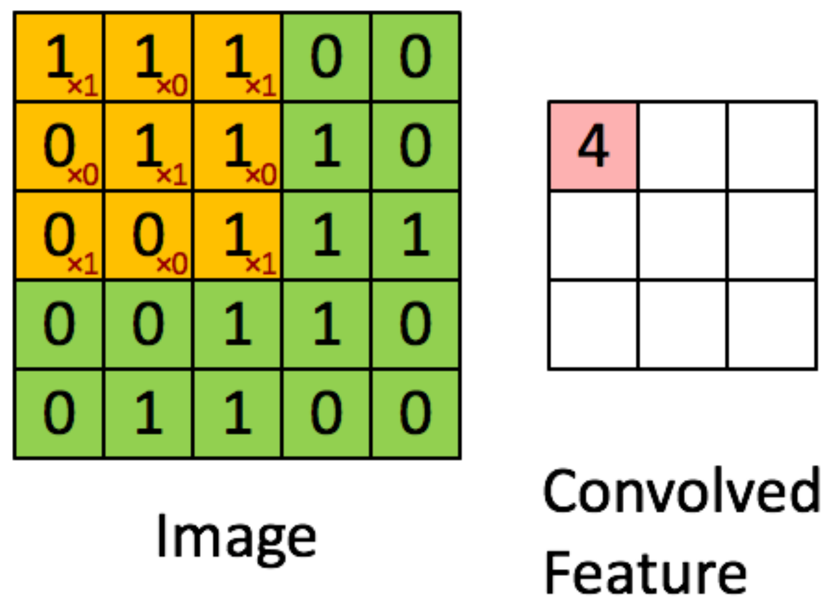


$$(f \circledast g)(t) = \int_{-\infty}^{\infty} f(\tau)g(t-\tau)d\tau$$
$$= \int_{-\infty}^{\infty} f(t-\tau)g(\tau)d\tau$$



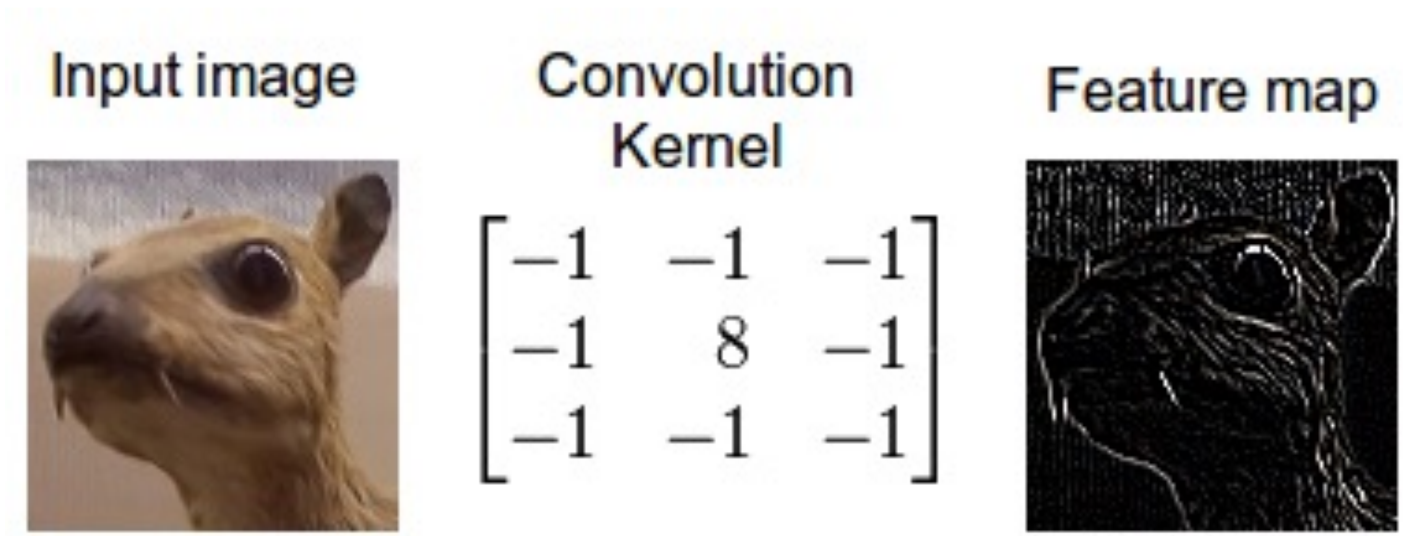
Convolution in 2D

- 2D convolutions are critical in computer vision
- Basic idea is still the same
  - Choose a kernel
  - Run kernel over image
  - Build a representation of the convolved image (likely an intermediate representation)
- Lots of applications



Convolution in 2D

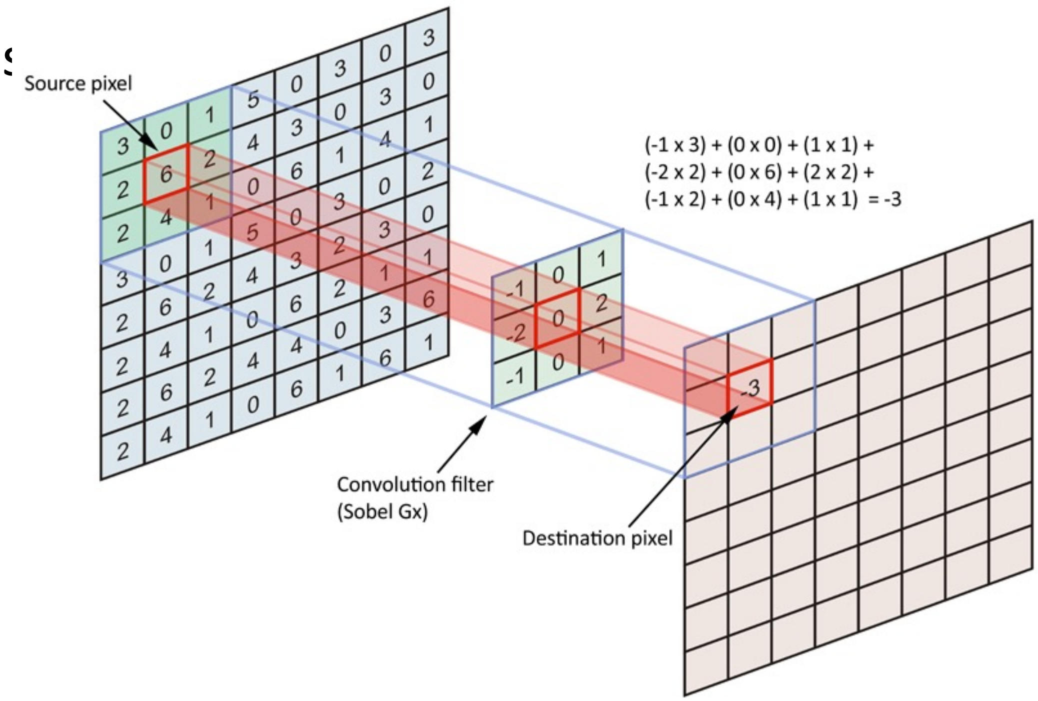
- Specific kernels can highlight different image features



- This kernel is an **edge detector** (others can be smoothers, sharpeners, etc)

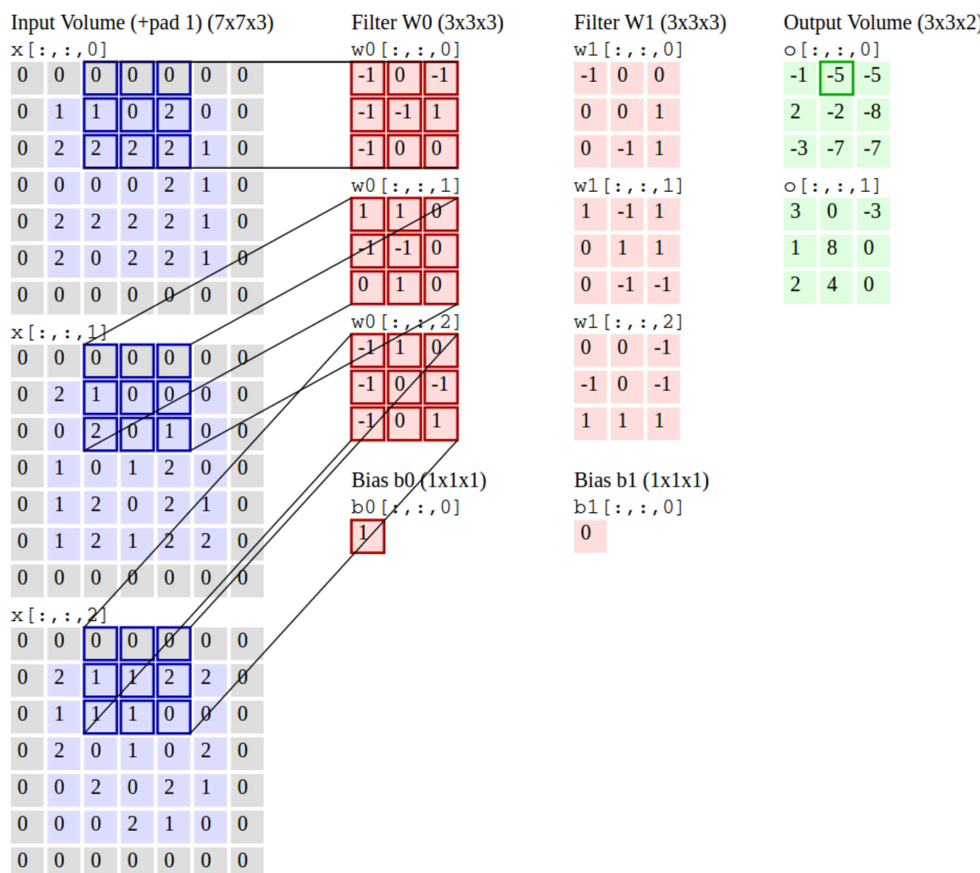
Convolution in 2D

- Works basically the same as 1D
- Filter / kernel computes a dot product with underlying pixels
- Generates an output
- Shift kernel and repeat



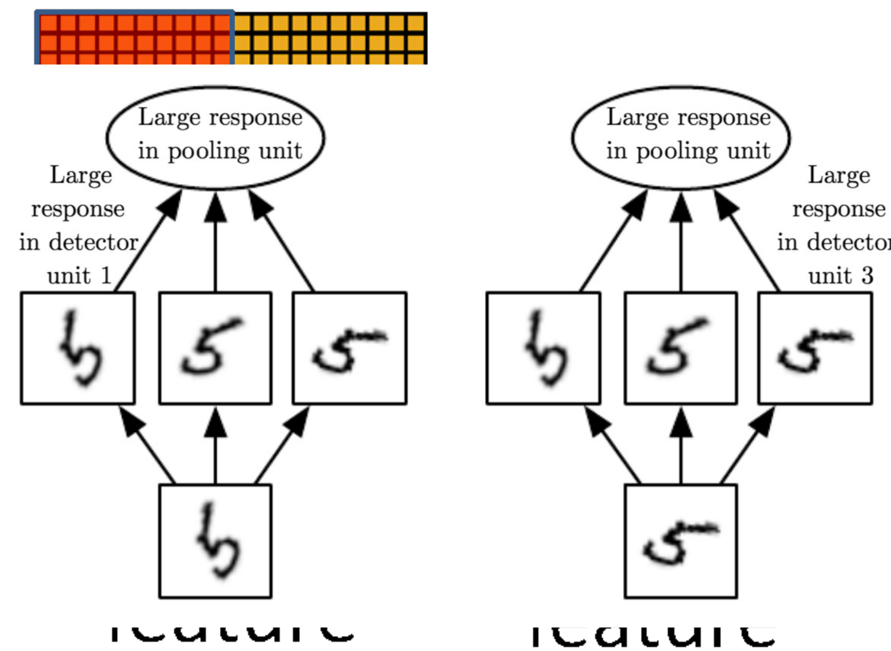
Convolution in 2D

- **Stride** dictates how far the kernel moves after each convolution
- **Padding** is used to help with edge cases
- Pictured: stride of 2, padding of 1



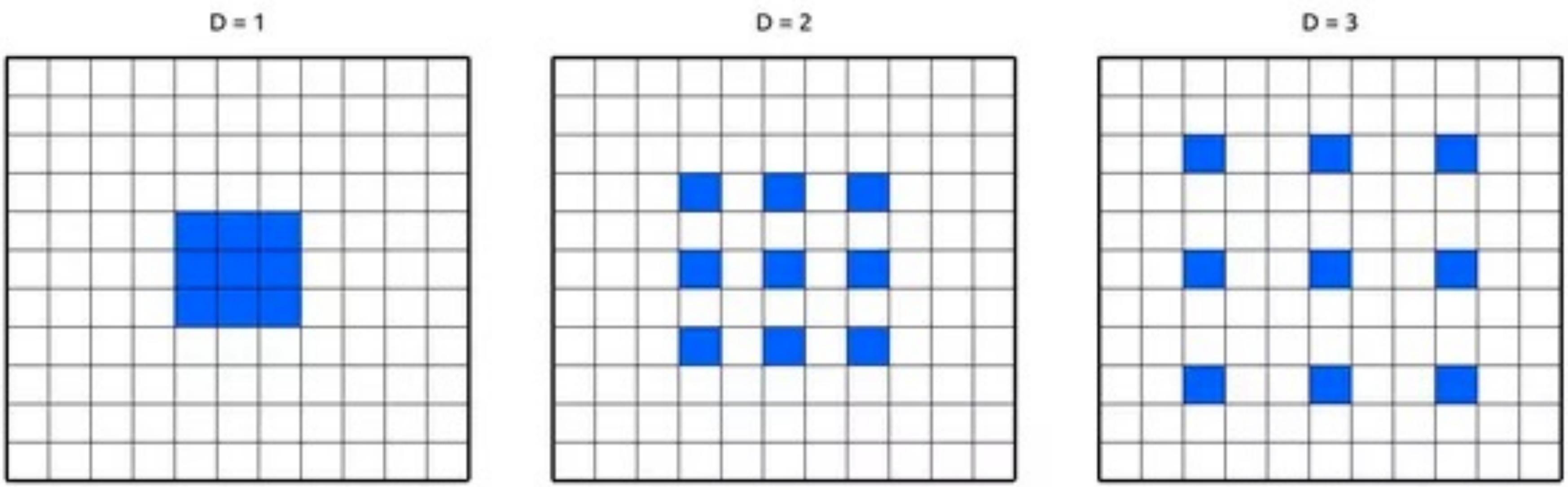
Pooling

- Repeated convolutions can generate large intermediate feature maps
- “Pooling” is used to reduce dimensionality of feature maps while maintaining most informative features
- Mean-pooling, **max-pooling**
- Functions as a regularizer (or an infinitely-strong prior)



Filters

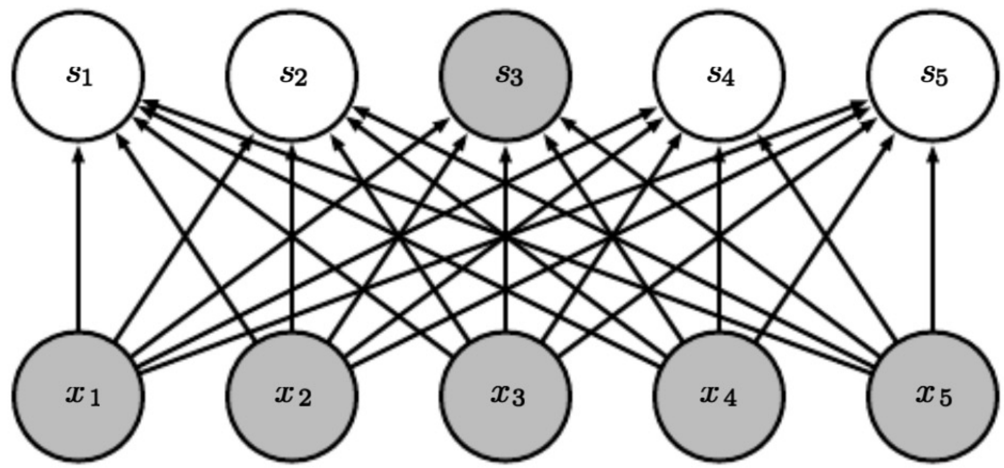
- Different filter topologies



- Captures long-range pixel dependencies
- *Very* computationally expensive to implement

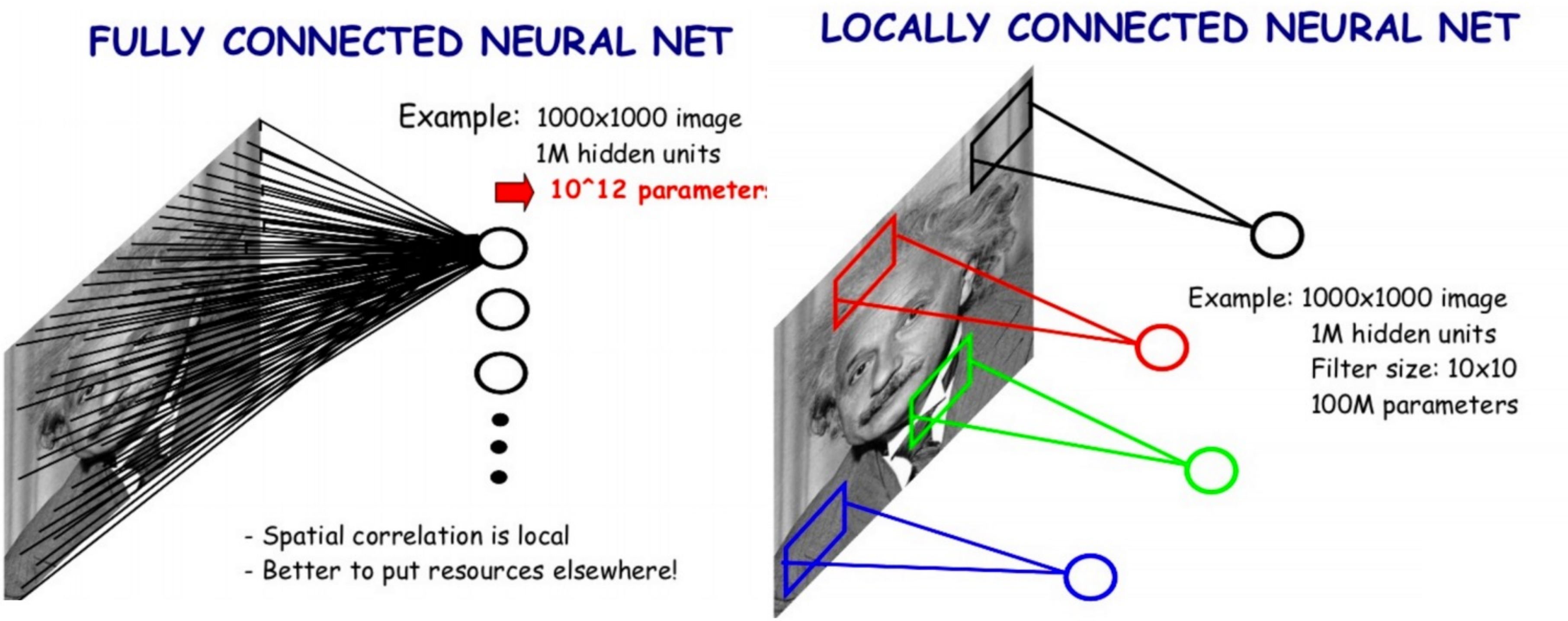
Convolution

- Key point: **parameter sharing**



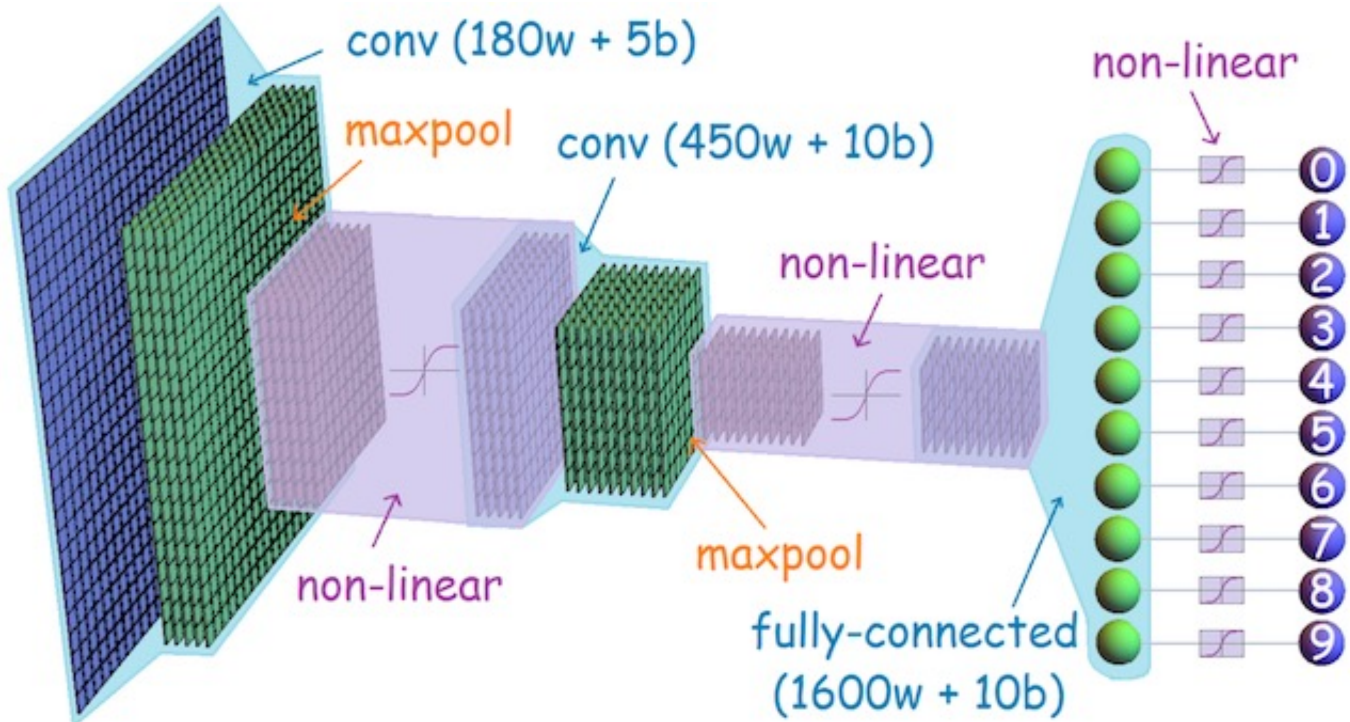
- Images are sparse
  - Pixel dependencies don’t span arbitrarily large distances
  - Important effects are local
- Instead of a fully-connected network…
- …we have one that is more sparsely-connected

Parameter Sharing



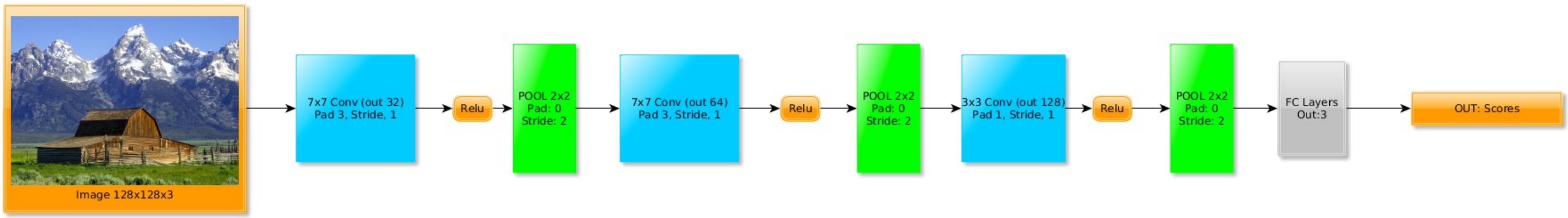
CNNs in Practice

- Stacked
  - Convolutions
  - Pools
  - Activations
- Fully-connected classification layer



CNNs in Practice

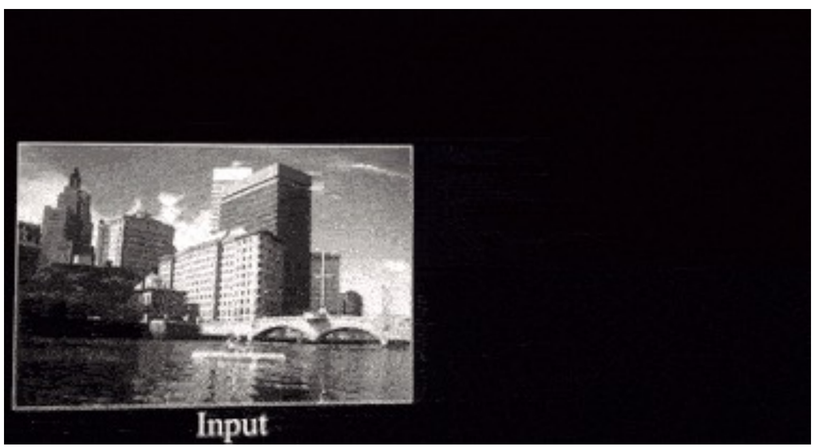
- Pattern can be repeated several times

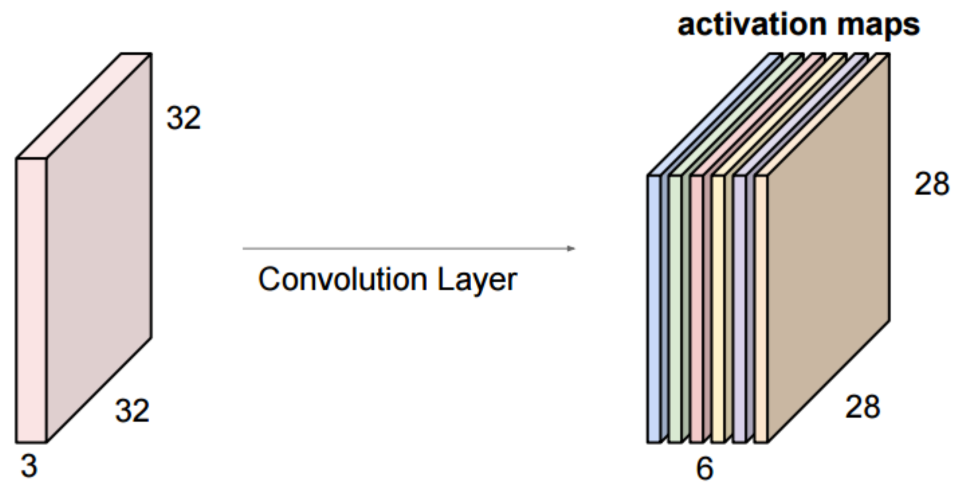


- Still “deep”, but convolutions are **the most important part**

CNNs in Practice

- Filters are the things that "search" for something in particular in an image
- To search for many different things, have many different filters





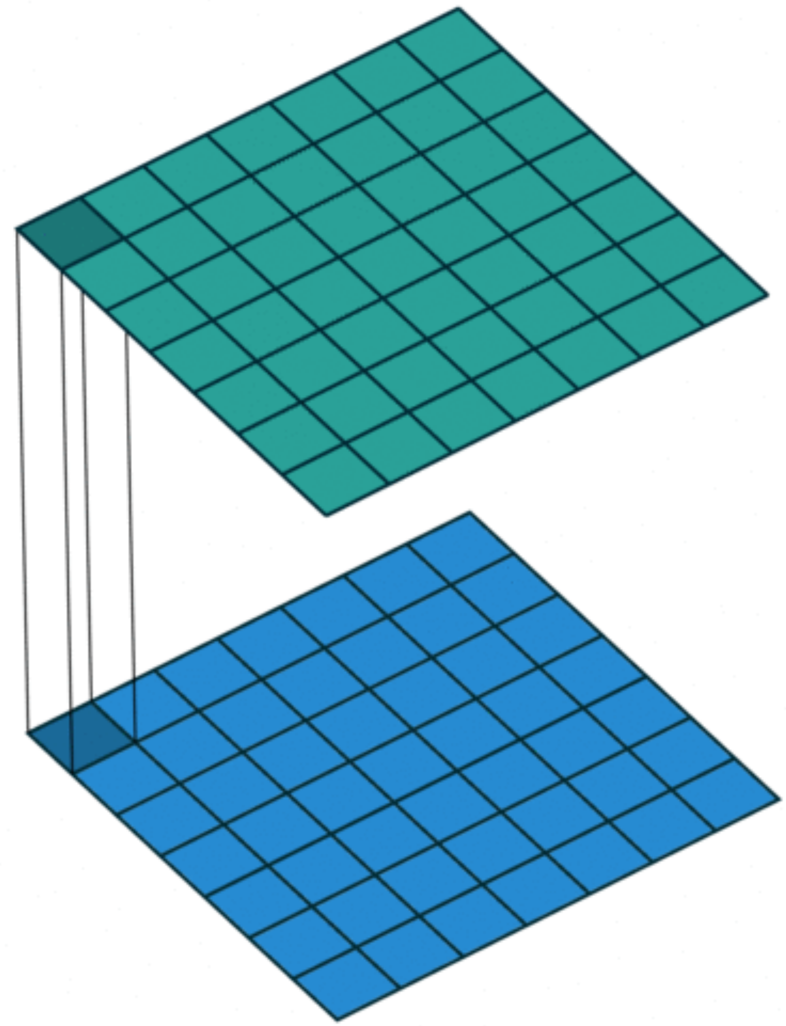
CNNs in Practice

- Hyperparameters relevant to CNNs:

- Kernel size
  - Usually small
- Stride
  - Usually 1 (larger for pooling layers)
- Zero padding depth
  - Enough to permit convolutional output size to be the same as input size
- Number of convolutional filters
  - Number of “patterns” for the network to search for

CNNs in Practice

- 1x1 convolutions are a special case
- Convolve the **feature maps**, rather than the **pixel maps**
- Function as a dimensionality reduction step (like pooling)
  - Can also be used in pooling



CNN Applications: Object Localization

- Two discrete steps:
  - Localizing a bounding box (*regression*)
  - Identifying the object (*classification*)
- Generate “region proposals”
- Classification accuracy

lassification head”

The best result now is Faster RCNN with a resnet 101 layer.

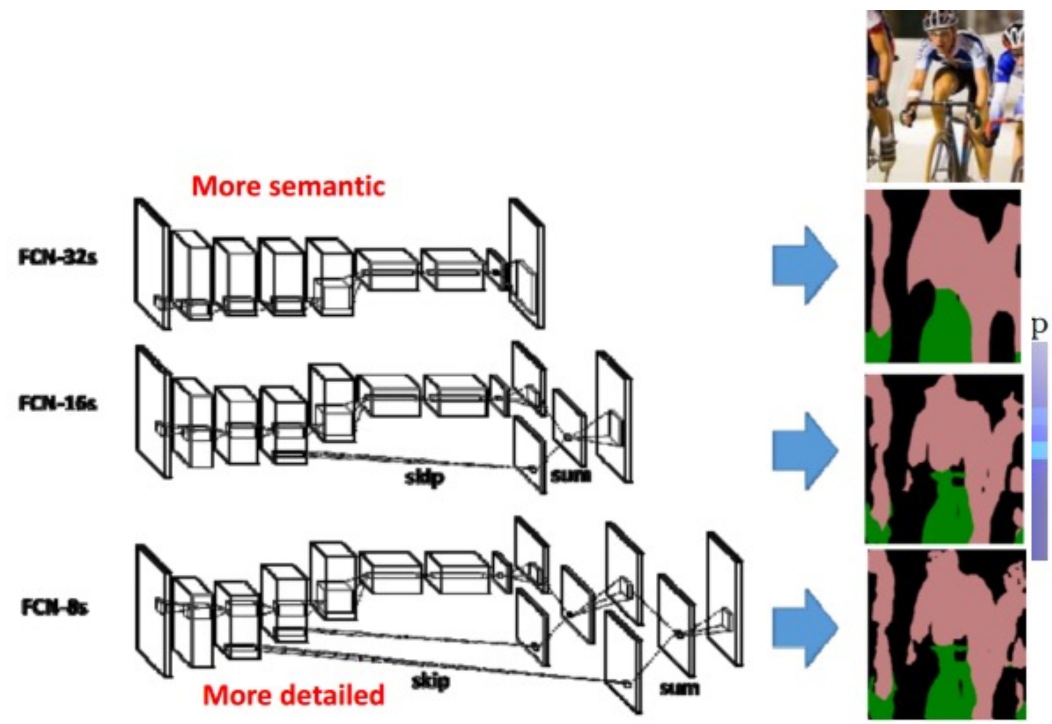
	R-CNN	Fast R-CNN	Faster R-CNN
Test time per image (with proposals)	50 seconds	2 seconds	**0.2 seconds**
(Speedup)	1x	25x	**250x**
mAP (VOC 2007)	66.0	**66.9**	**66.9**

CNN Applications: Single-shot Detection

- Combines region-proposal (regression) and object detection (classification) into a single step
- Use deep-level feature maps to predict class scores and bounding boxes
- Families of Single-shot detectors:
  - YOLO (single activation map for both class and region)
  - SSD (different activations)
  - R-FCN (like Faster R-CNN)

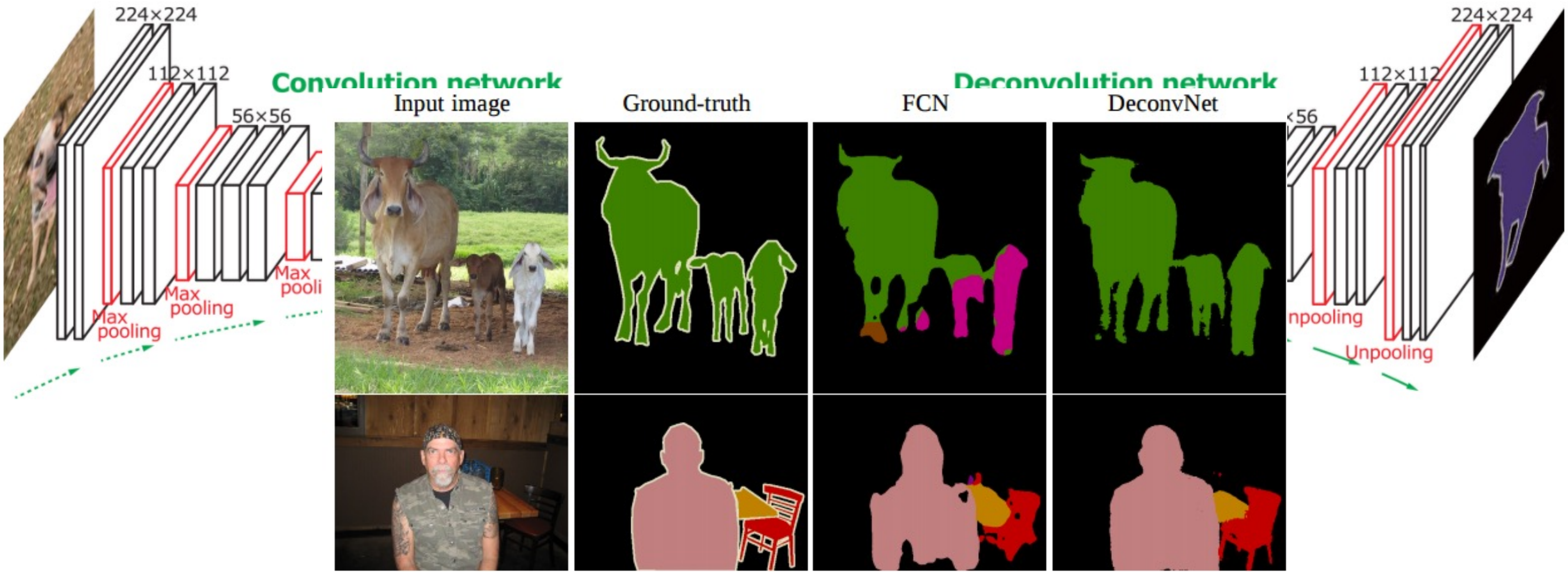
CNN Applications: Object Segmentation

- Create a map of the detected object areas
- “Fully-convolutional” networks
  - Substitute fully-connected layer at end for another convolutional layer
  - Activations show object
- Resolution is lost in upsampling step
  - Skip-connections to bring in some of the “lost” resolution
- *EXTREME* Segmentation
  - Replace upsampling with a complete deconvolution stack



CNN Applications: Object Segmentation

- *"DeconvNet"*: *Super*-expensive to train
- But results are excellent



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The parameter sharing / receptive field architecture unique to CNNs enables dramatically reduced parameter counts in neural architectures, exploiting the inherent sparsity of images. What is a disadvantage of this approach?

- CNNs tend to blur object boundaries, much like optical flow.
- CNNs cannot build up an internal representation of object hierarchy.
- CNNs struggle to identify objects in high-resolution images.
- CNNs have no notion of absolute object locality, or of relative positioning of multiple objects.

Treemap Bar

1 of 1

Conclusions

- CNNs are mostly “convolutions inside a deep network”
  - Main operator (i.e. **most important**) is the convolution
  - Exploits image sparsity: important features are **local**
- A couple new[ish] tricks include
  - Automatically learning the filters as part of the training process
  - Using pooling
  - 1x1 convolutions
- Applications include
  - Object detection (is there an object)
  - Object localization and segmentation (where is the object)
  - Object classification (what is the object)
  - Zero- and single-shot detectors

References

- The Neural Network Zoo
  - http://www.asimovinstitute.org/neural-network-zoo/
- Deep Learning Book, Chapter 9: "Convolutional Networks"
  - http://www.deeplearningbook.org/contents/convnets.html
- Convolution Arithmetic code (for generating awesome gifs)
  - https://github.com/vdumoulin/conv_arithmetic
- 1x1 Convolutions
  - https://iamaaditya.github.io/2016/03/one-by-one-convolution/
- AI Gitbook
  - https://leonardoaraujosantos.gitbooks.io/artificial-inteligence/