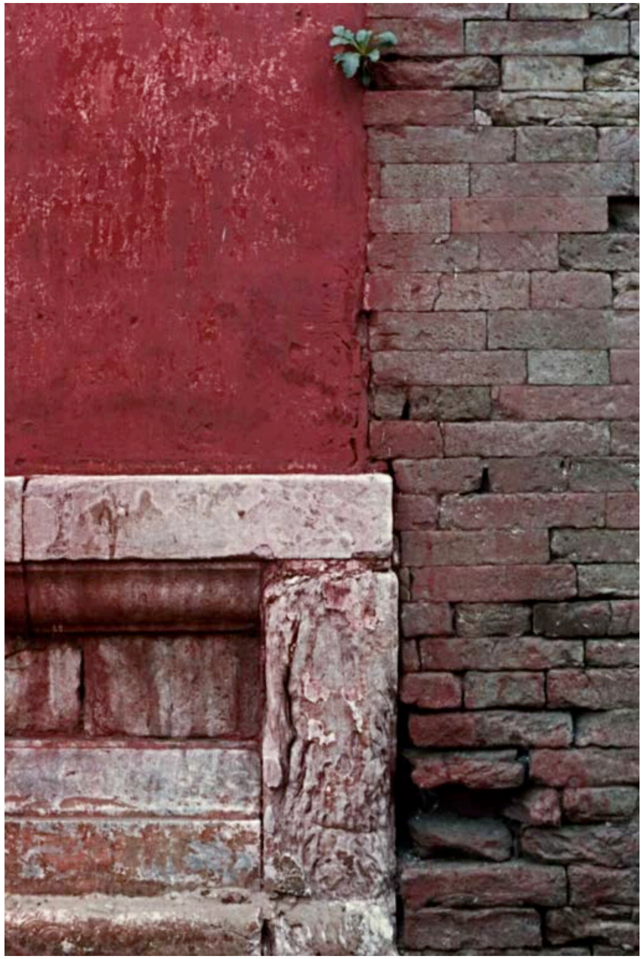
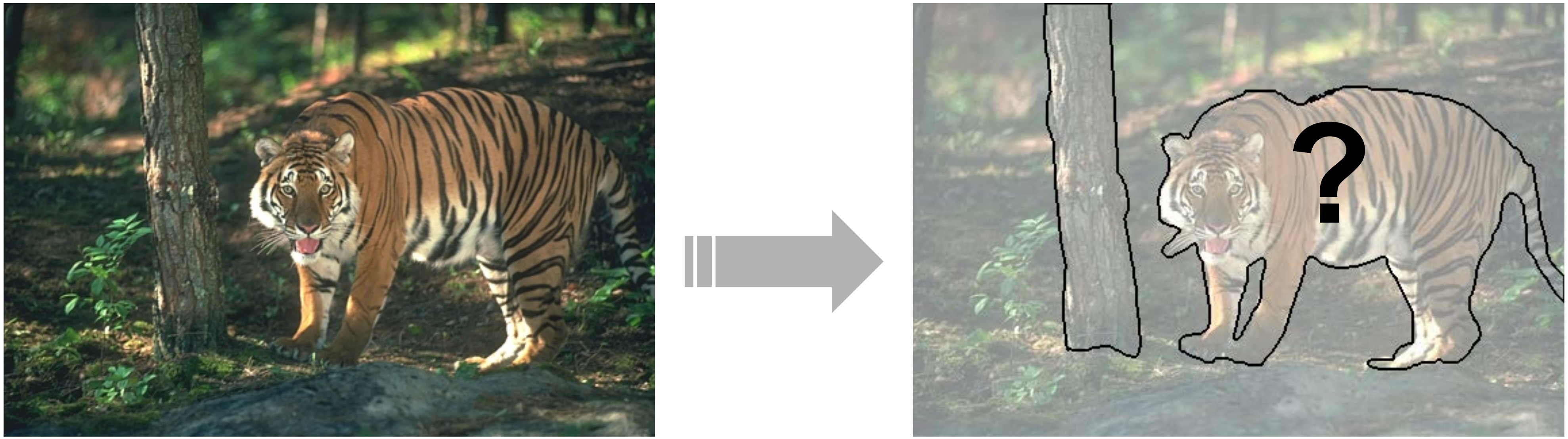
TEXTURE

- What is texture?
- Texture analysis
- Deep Texture



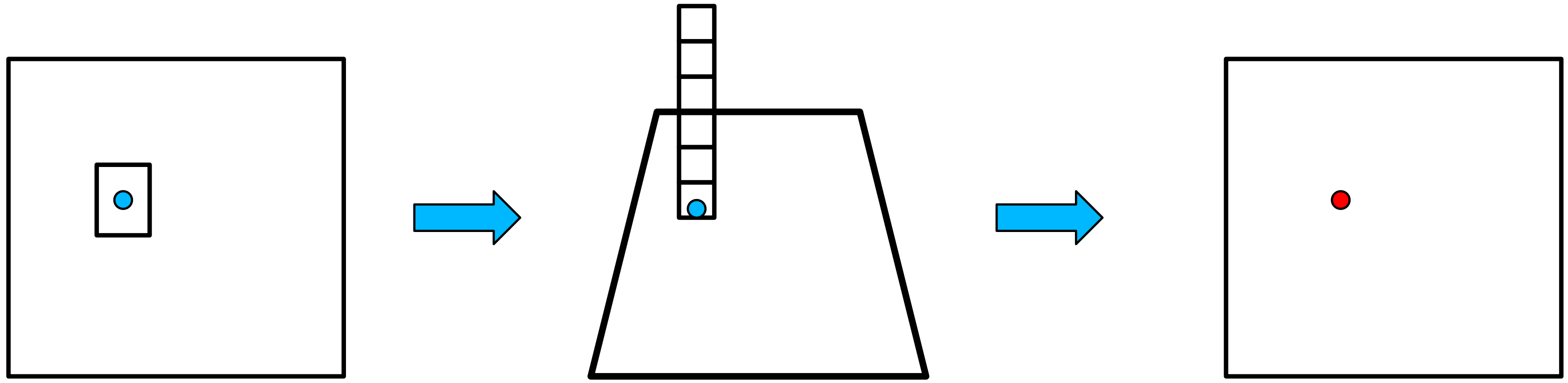
HOMOGENEOUS OR NOT?

TEXTURAL IMAGES



- Assign to individual pixels whose texture is similar the same values to form a textural image.
- Evaluate homogeneity both in the original image and in the textural one.

CREATING TEXTURAL IMAGES



Because texture is non-local, the texture of individual pixels must be estimated using neighborhoods surrounding them:

- For each pixel, compute a feature vector using either an image patch or a set of filters.
- Run a classification algorithm to assign a texture value to each pixel.

DISCRETE FOURIER TRANSFORM

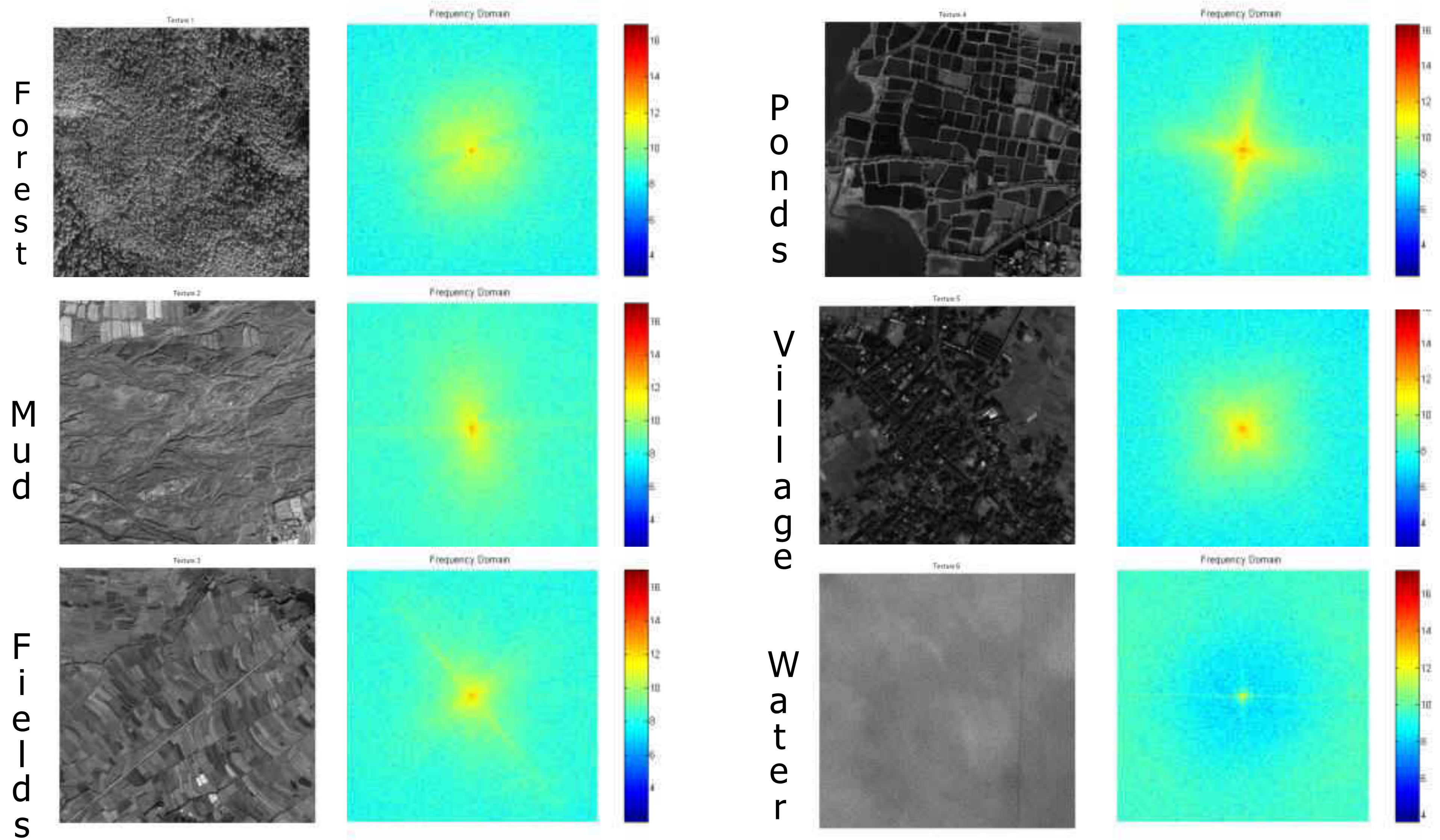
$$F(\mu,\nu) = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) \exp(-2i\pi(\mu x/M + \nu y/N))$$

$$f(x,y) = \frac{1}{MN} \sum_{\mu=0}^{M-1} \sum_{\nu=0}^{N-1} F(\mu,\nu) \exp(+2i\pi(\mu x/M + \nu y/N))$$

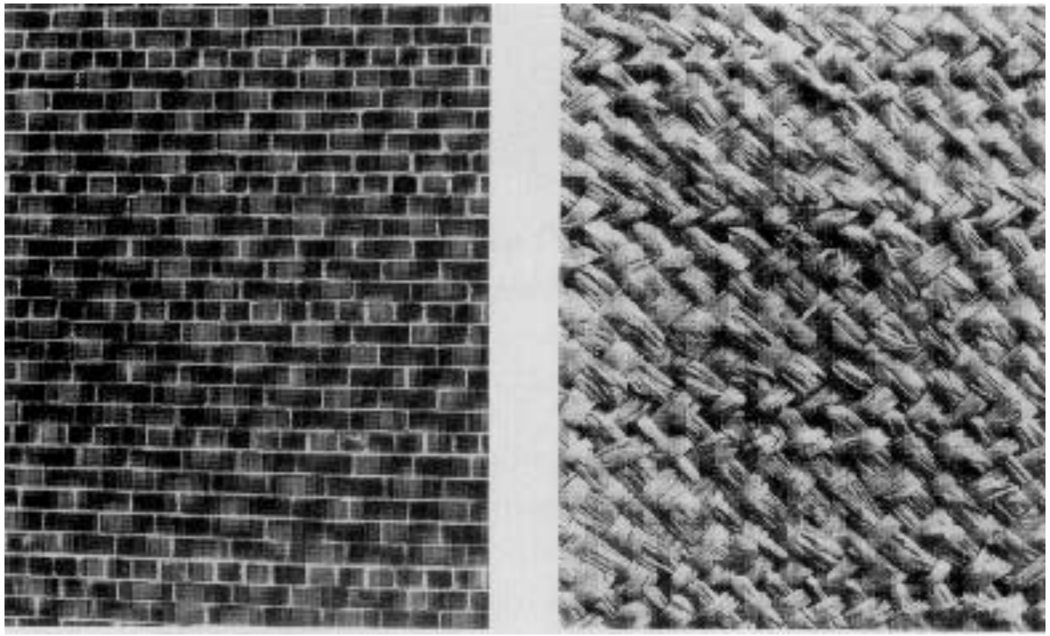
- The DFT of f * g is the product of the DFT of f with the DFT of g.
- The DFT of a symmetric function is real.

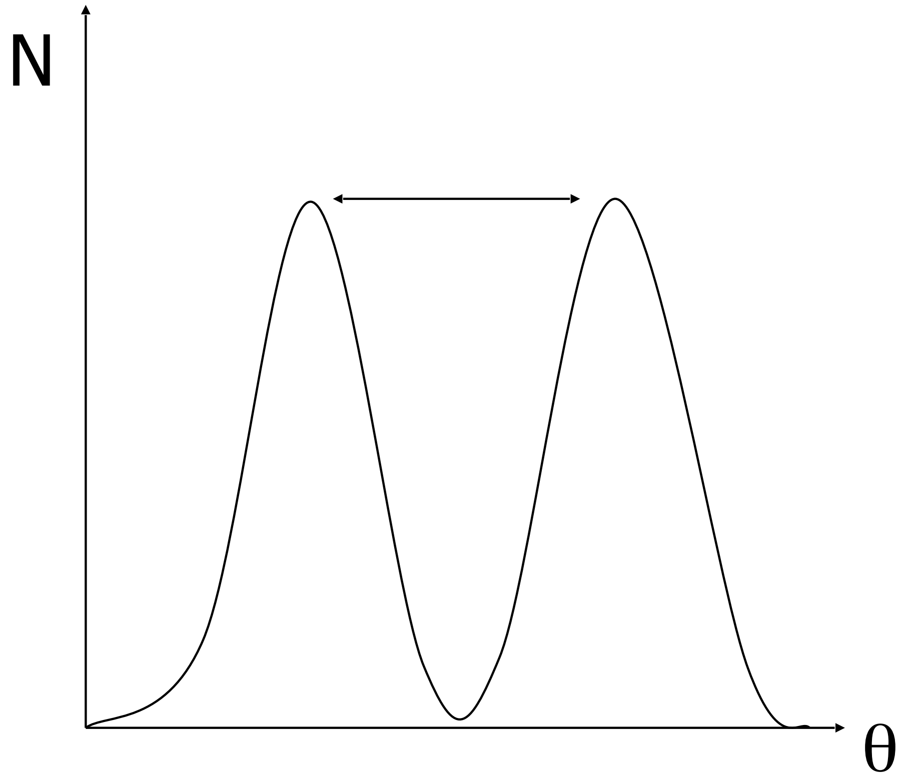
Bracewell, chap. 11

TEXTURE CLASSIFICATION



FIRST ORDER TEXTURE





Orientation histogram gives a clue to the orientation of the underlying plane.

SECOND ORDER MEASURES

Histogram of the co-occurrence of particular intensity values in the image.

- Specified in terms of geometric relationships between pixel pairs:
  - Distance
  - Orientation

- $P(i,j,d,\theta)$ Frequency with which a pixel with value j occurs at distance d and orientation θ from a pixel with value i.

2ND ORDER TEXTURE MEASURES

Contrast:

$$\sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2$$

Dissimilarity:

$$\sum_{i,j=0}^{N-1} P_{i,j}|i-j|$$

Homogeneity:

$$\sum_{i,j=0}^{N-1} \frac{P_{i,j}}{1+(i-j)^2}$$

Angular Second Moment (Energy, Uniformity):

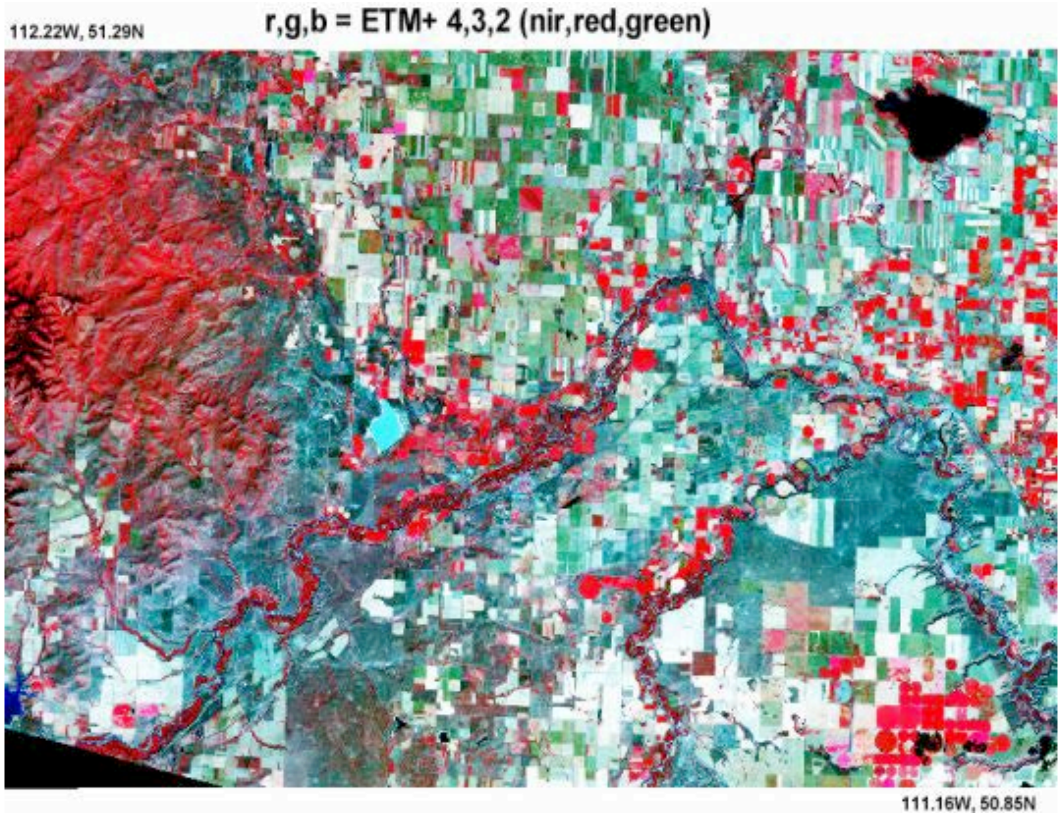
$$\sum_{i,j=0}^{N-1} P_{i,j}^2$$

Entropy:

$$\sum_{i,j=0}^{N-1} P_{i,j}(-\ln P_{i,j})$$

and many more ……

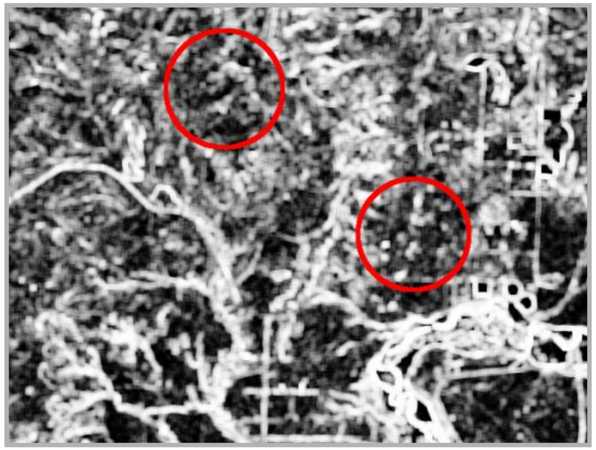
LANDSAT IMAGE



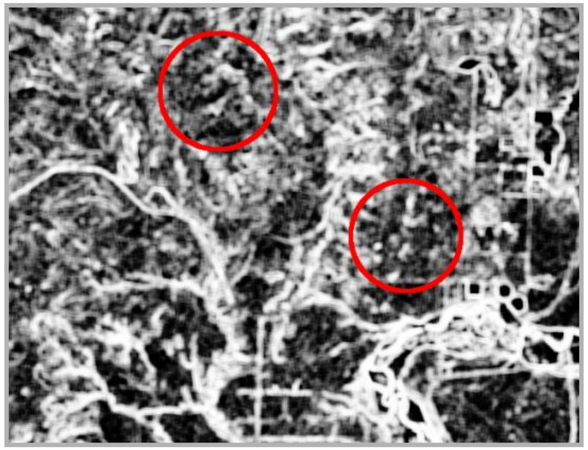
The image is excerpted from Path 41, Row 25 of Landsat 7 ETM+, dated 4 September 1999. This is an area in the Rocky Mountain Foothills near Waterton National Park, Alberta. The western edge of the image contains steep slopes and deep valleys. To the east is both grassland and annual crops, mostly grains. The eastern area is bisected by numerous small streams.

COMPARISON

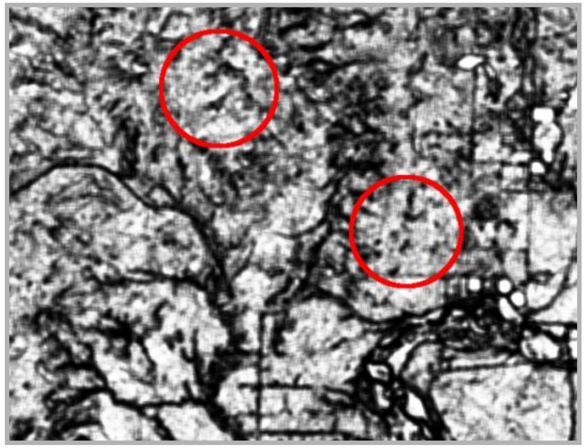
Contrast

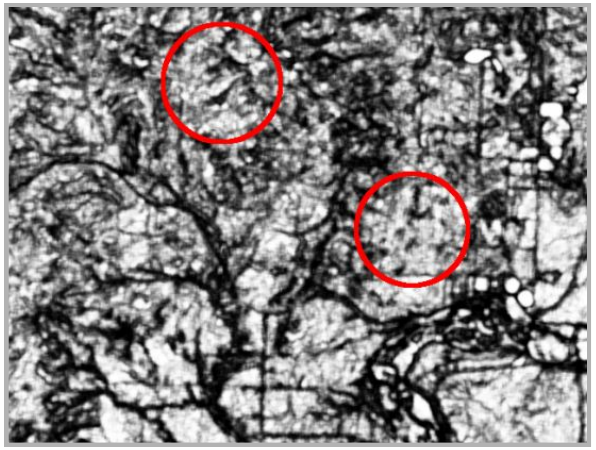


Dissimilarity

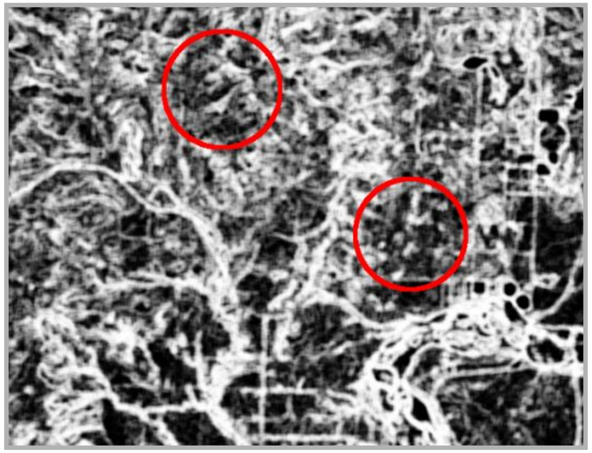


Homogeneity

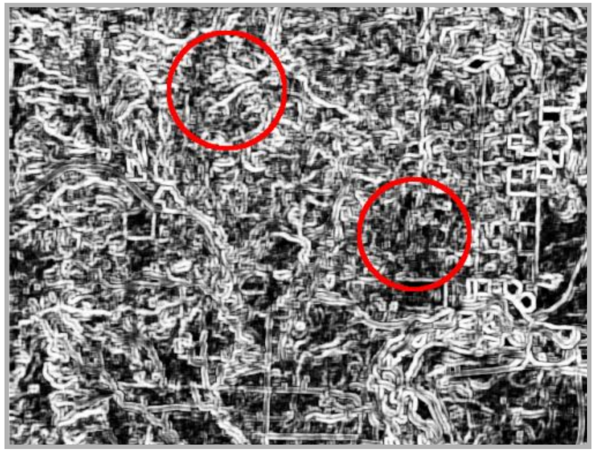




ASM



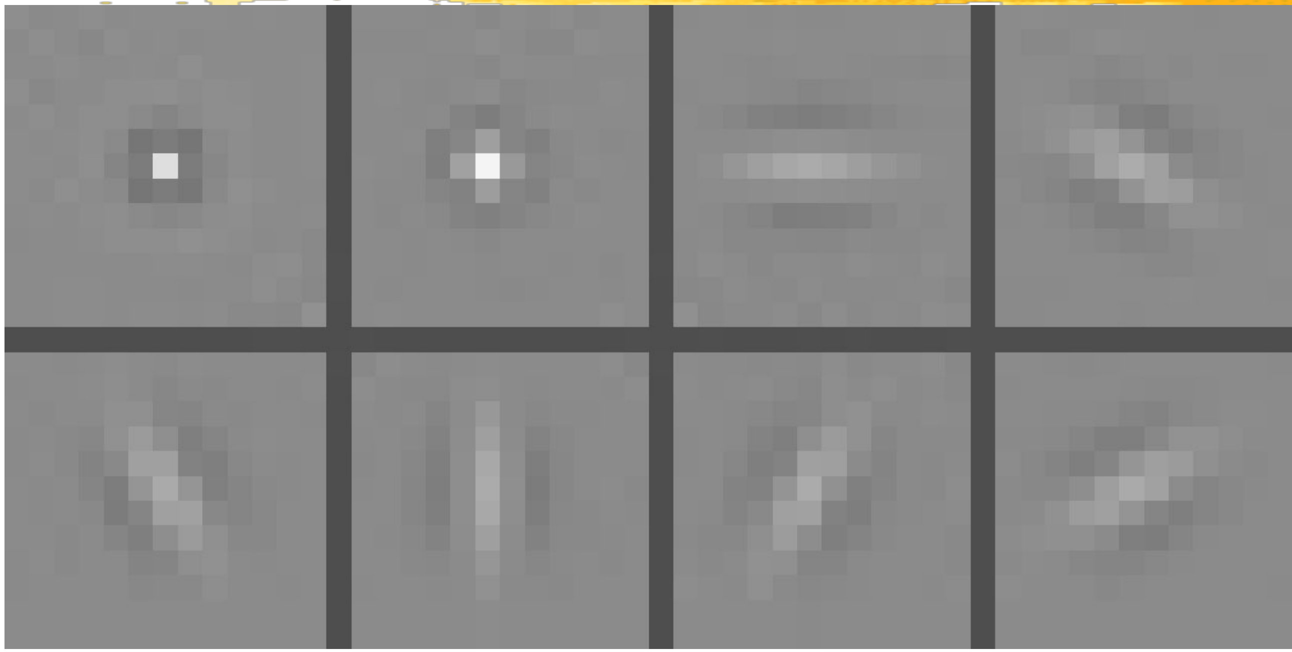
Entropy



Correlation

AERIAL TEXTURES

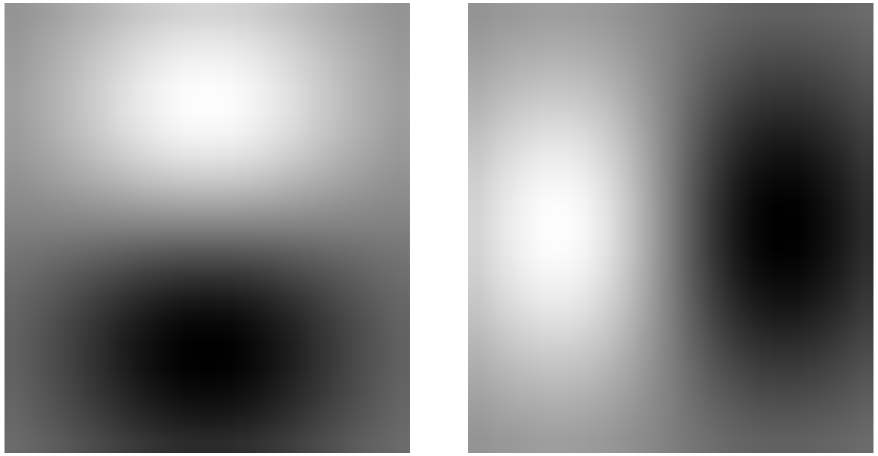
FILTER BASED MEASURES



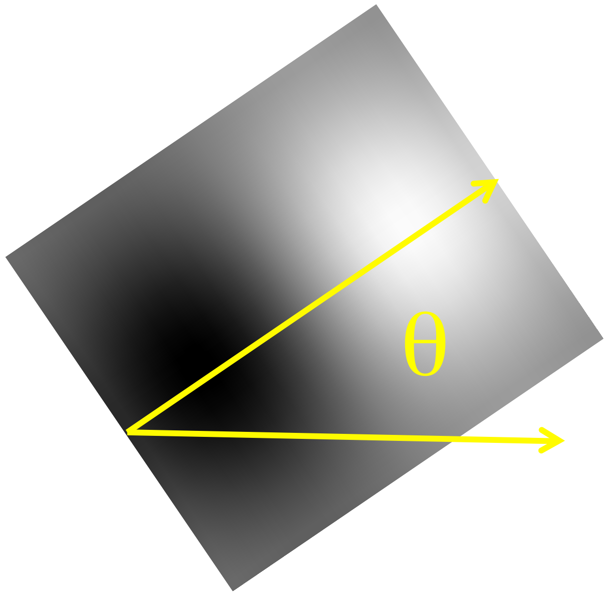
Represent image textures using the responses of a collection of filters.

- An appropriate filter bank will extract useful information such as spots and edges
- Traditionally one or two spot filters and several oriented bar filters

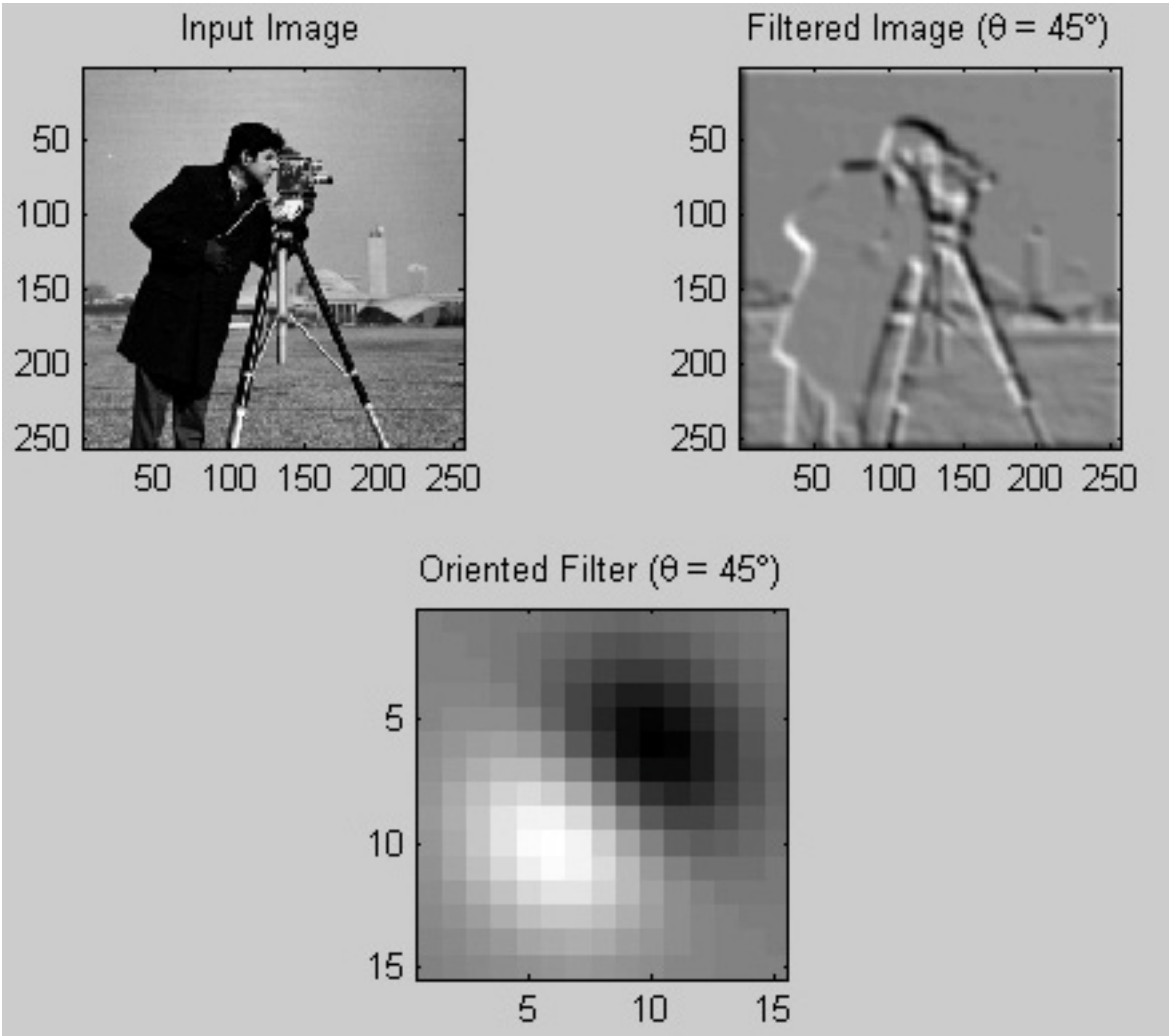
ORIENTED FILTERS



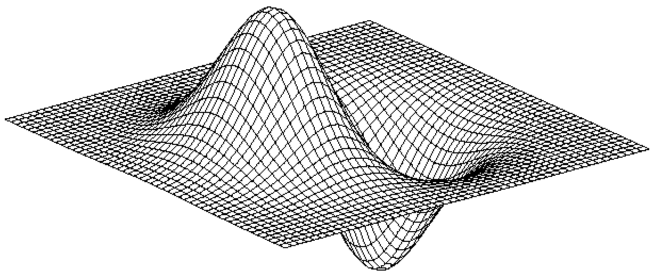
$$\frac{\partial I}{\partial \theta} = cos(\theta)\frac{\partial I}{\partial x} + sin(\theta)\frac{\partial I}{\partial y}$$

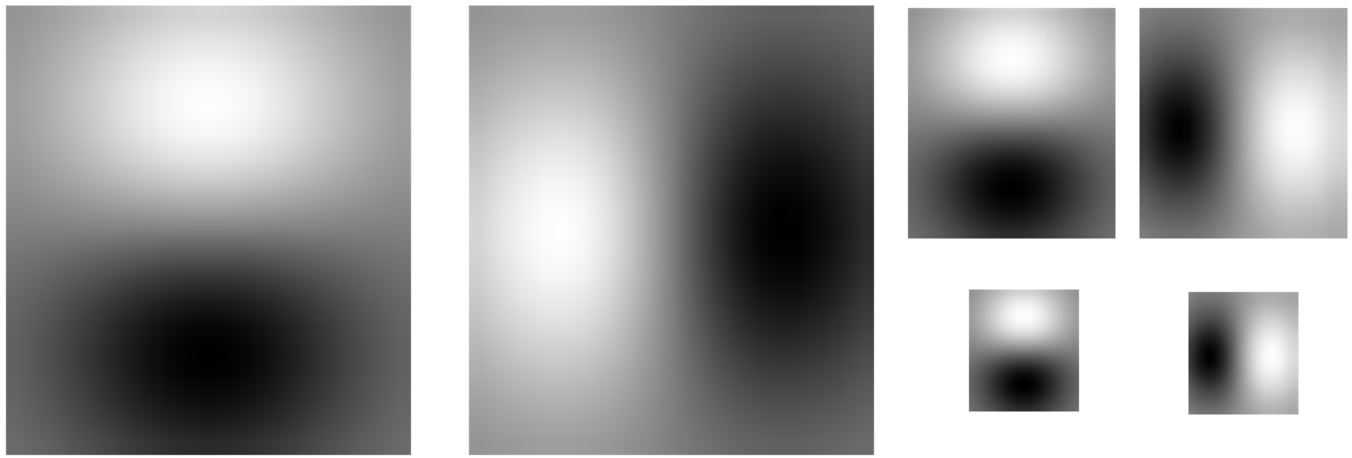


DIRECTIONAL GRADIENTS



GAUSSIAN FILTER DERIVATIVES

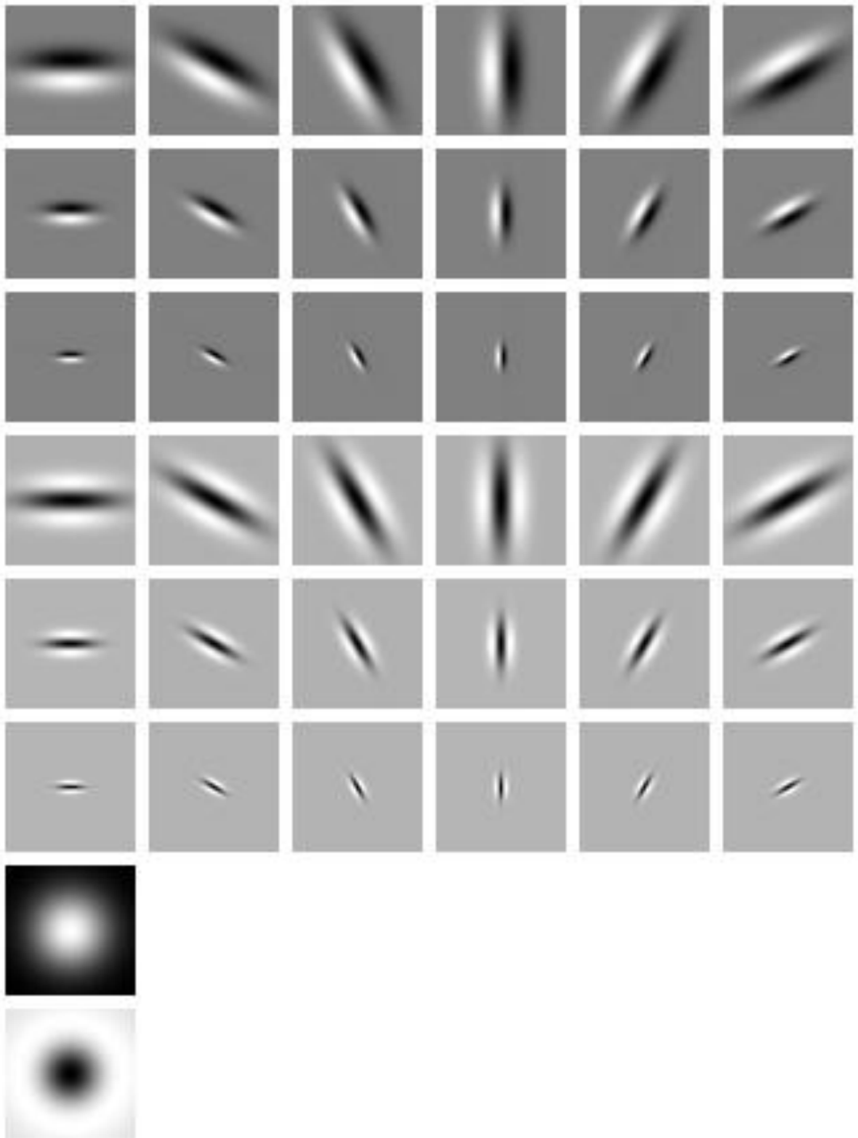




Gaussian Derivative

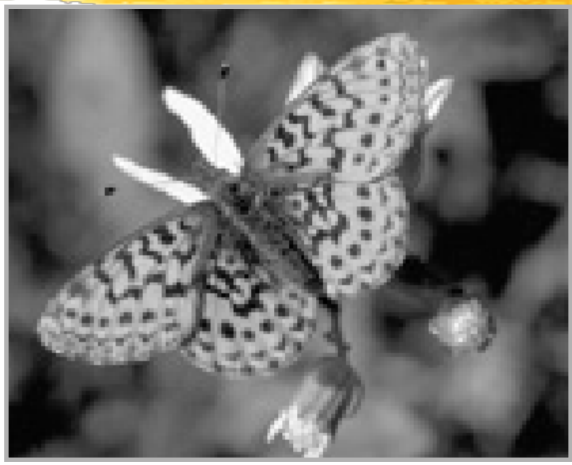
x and y derivatives at different scales

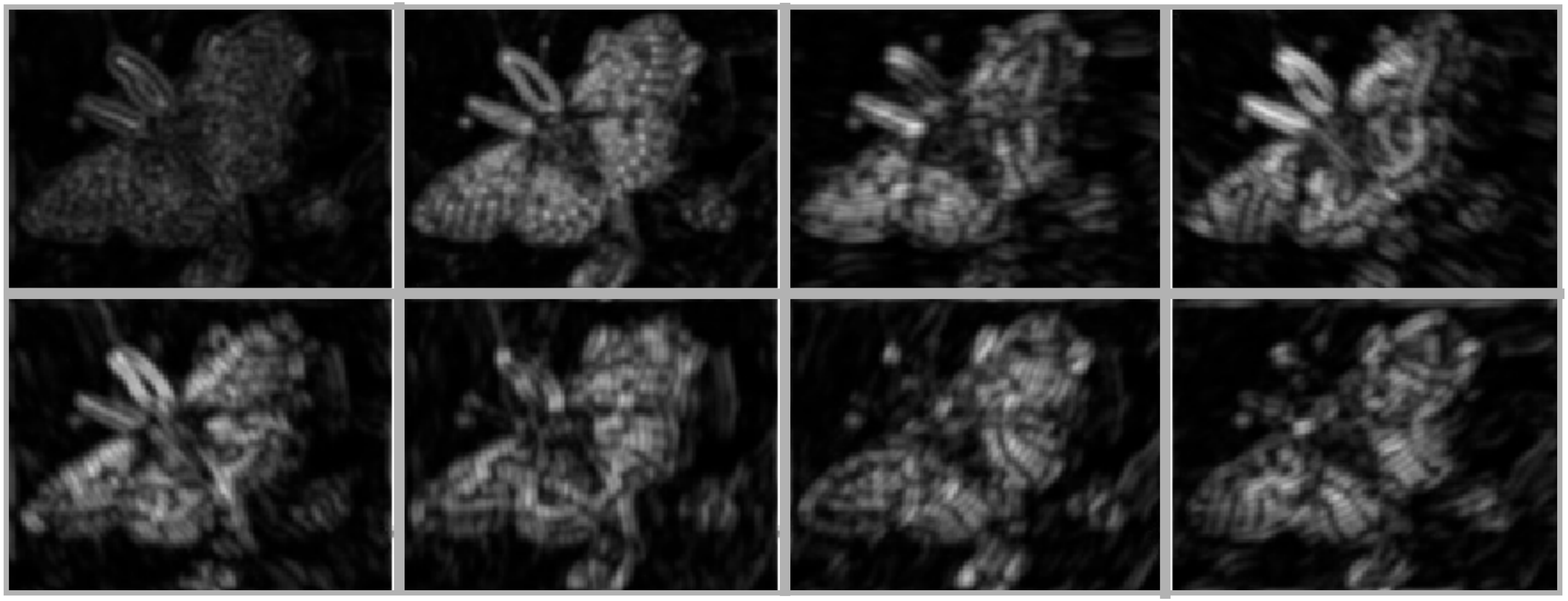
FILTER BANKS



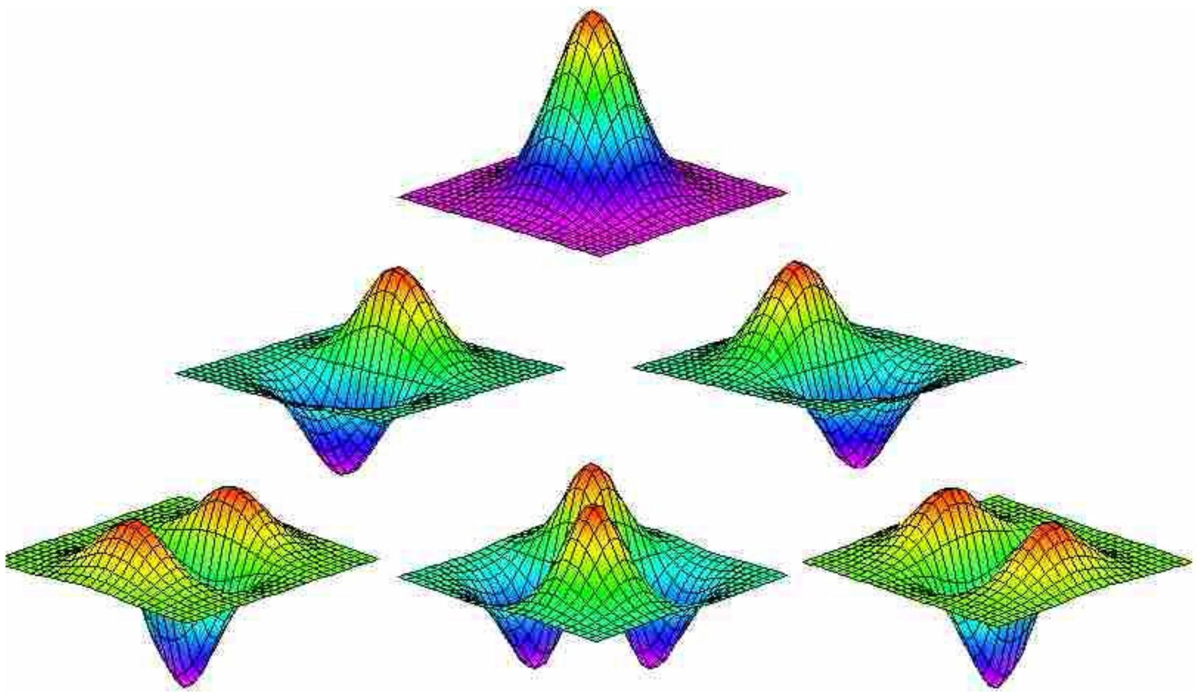
- Different scales.
- Different orientations.
- Derivatives order 0, 1, 2 ..

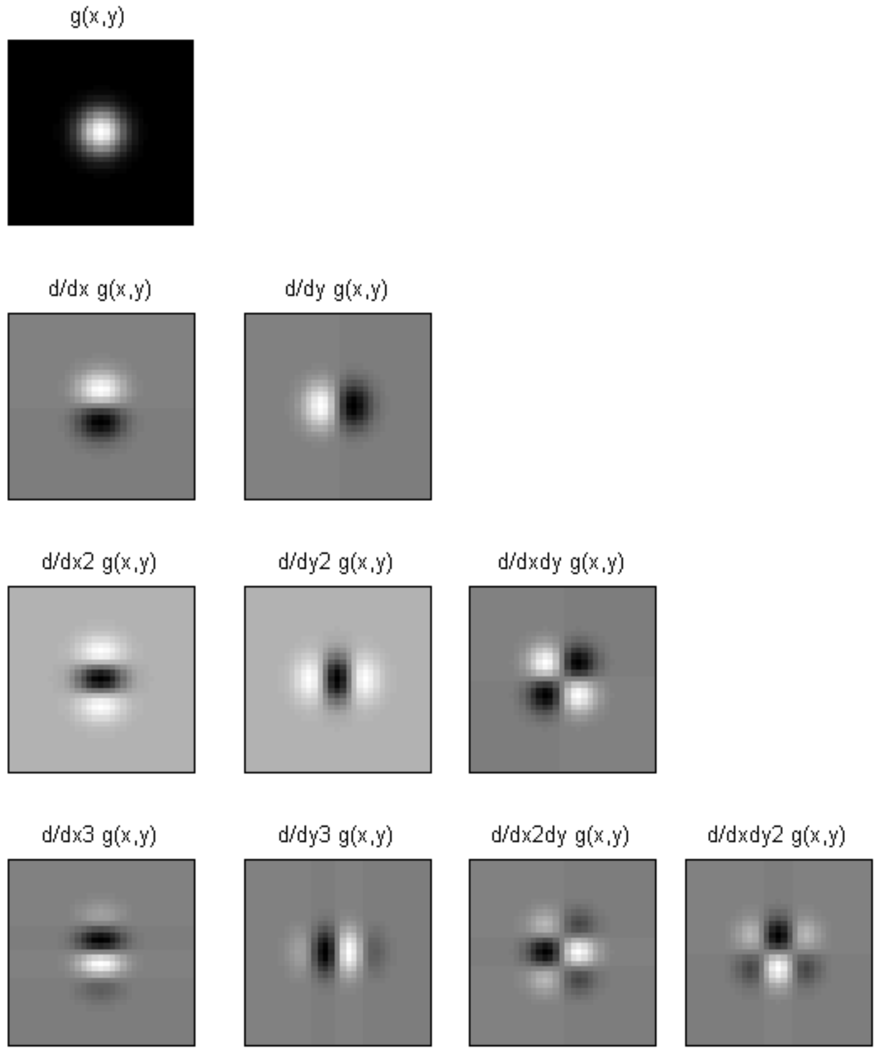
FILTER RESPONSES: HIGH RESOLUTION



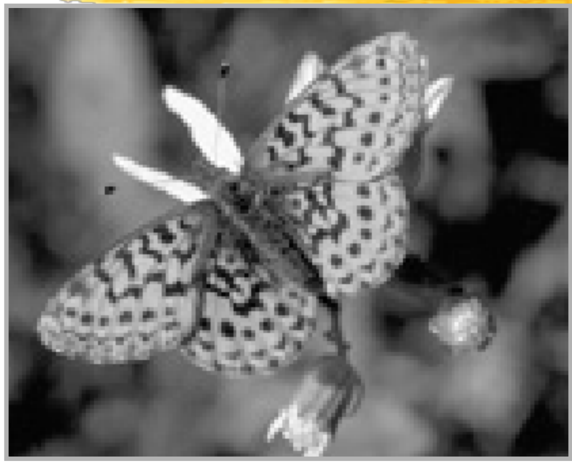


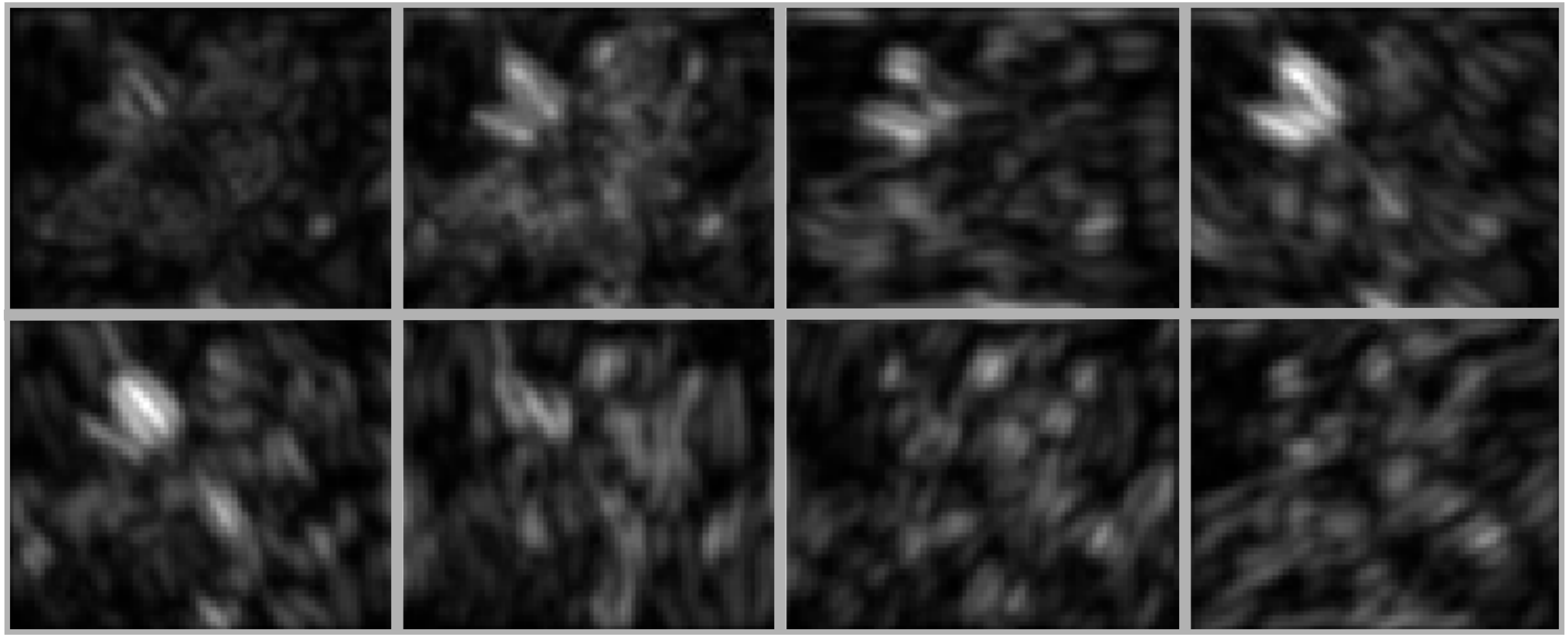
HIGHER ORDER DERIVATIVES





FILTER RESPONSES: LOW RESOLUTION





GABOR FILTERS

Gabor filters are the products of a Gaussian filter with oriented sinusoids. They come in pairs, each consisting of a symmetric filter and an anti-symmetric filter:

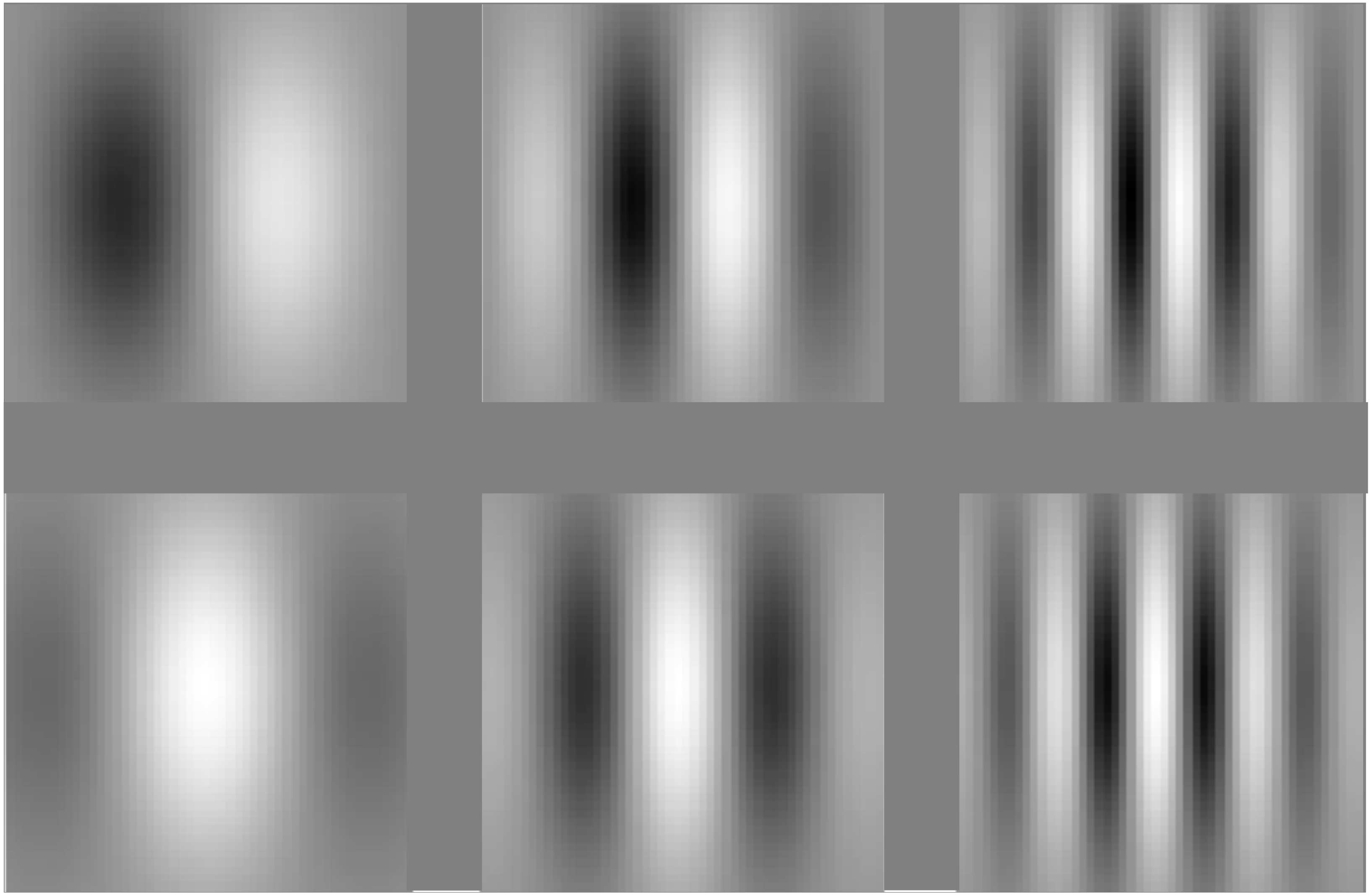
$$G_{\mathrm{sym}}(x,y) = \cos(k_x x + k_y y)\exp(-\frac{x^2+y^2}{2\sigma^2})$$

$$G_{\mathrm{asym}}(x,y) = \sin(k_x x + k_y y)\exp(-\frac{x^2+y^2}{2\sigma^2})$$

where k_x and k_y determine the spatial frequency and the orientation of the filter and σ determines the scale.

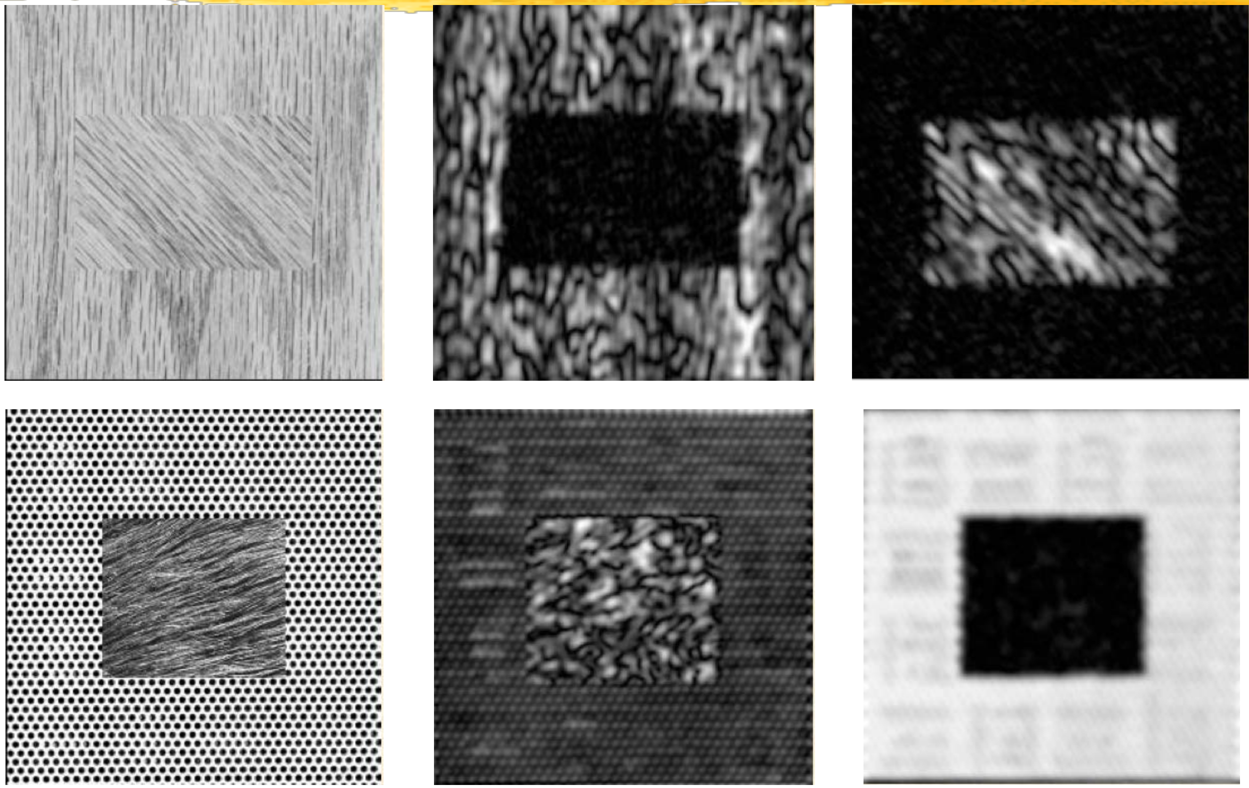
→ A filter bank is formed by varying the frequency, the scale, and the filter orientation

GABOR FILTERS

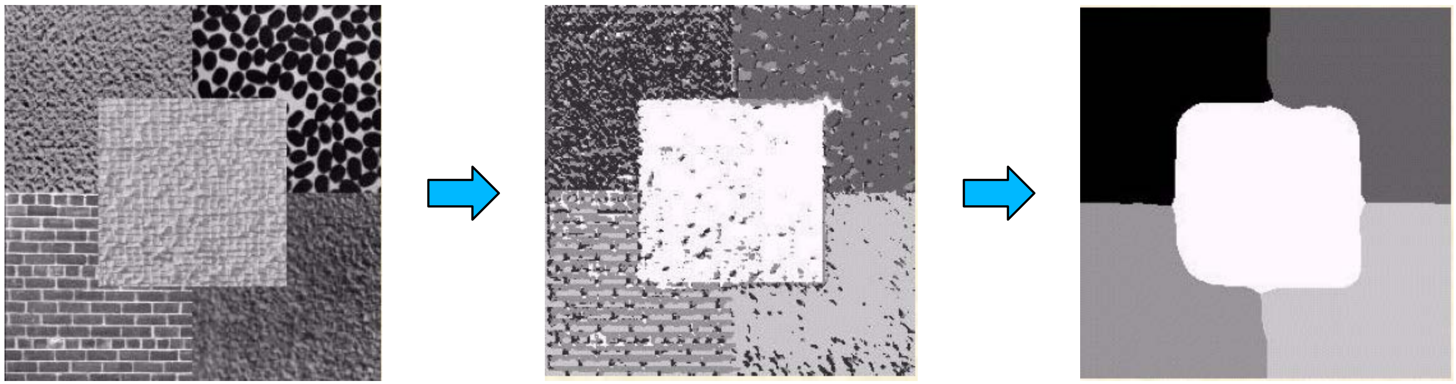


GABOR RESPONSES

Responses:



Segmentation:



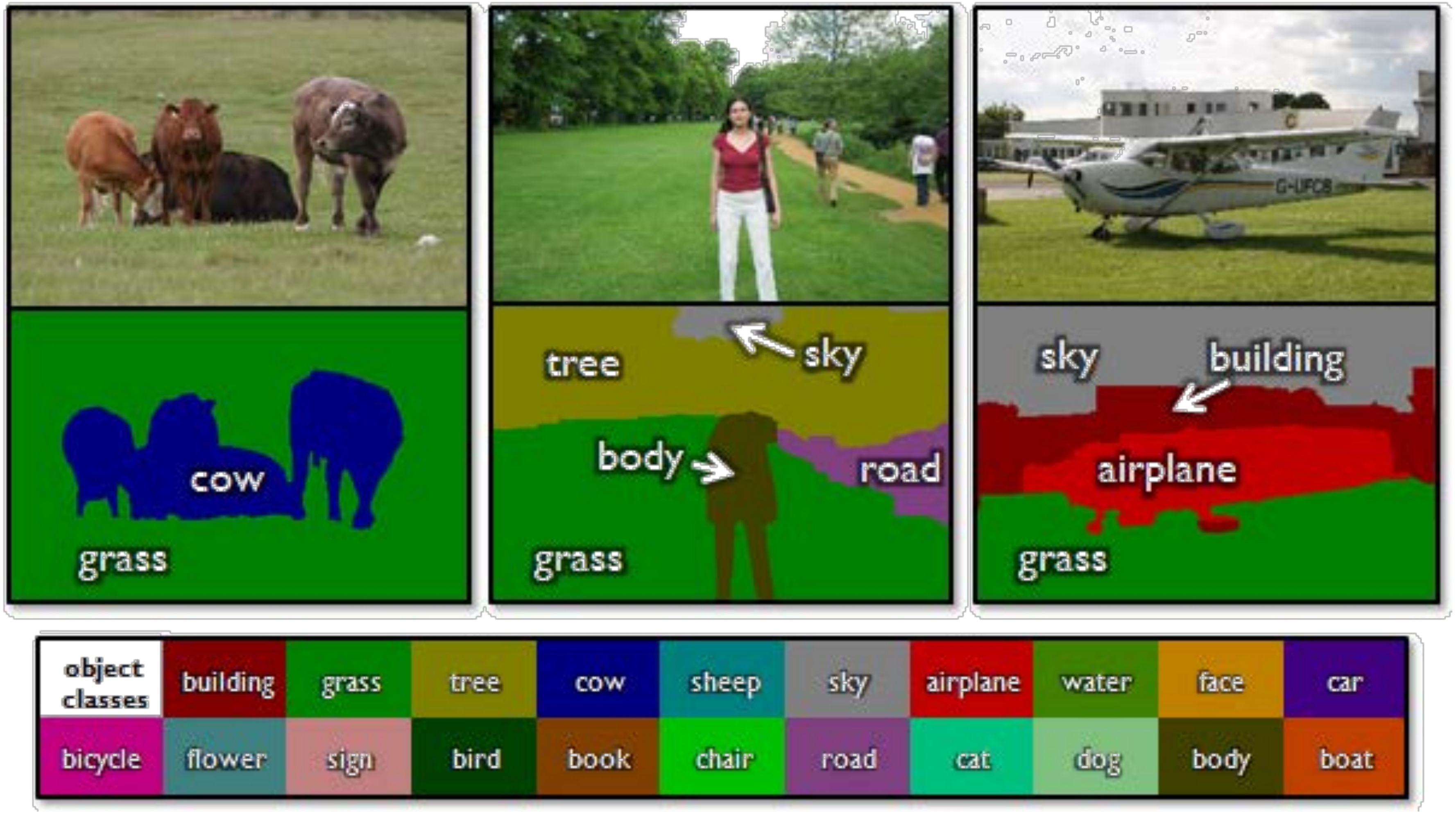
GABOR FILTER CHARACTERISTICS

- Respond strongly at points in an image where there are components that locally have a particular spatial frequency and orientation.

- In theory, by applying a very large number of Gabor filters at different scales, orientations and spatial frequencies, one can analyze an image into a detailed local description.

- In practice, it is not known how many filters, at what scale, frequencies, and orientations, to use. This tends to be application dependent and can be estimated using Machine Learning techniques.

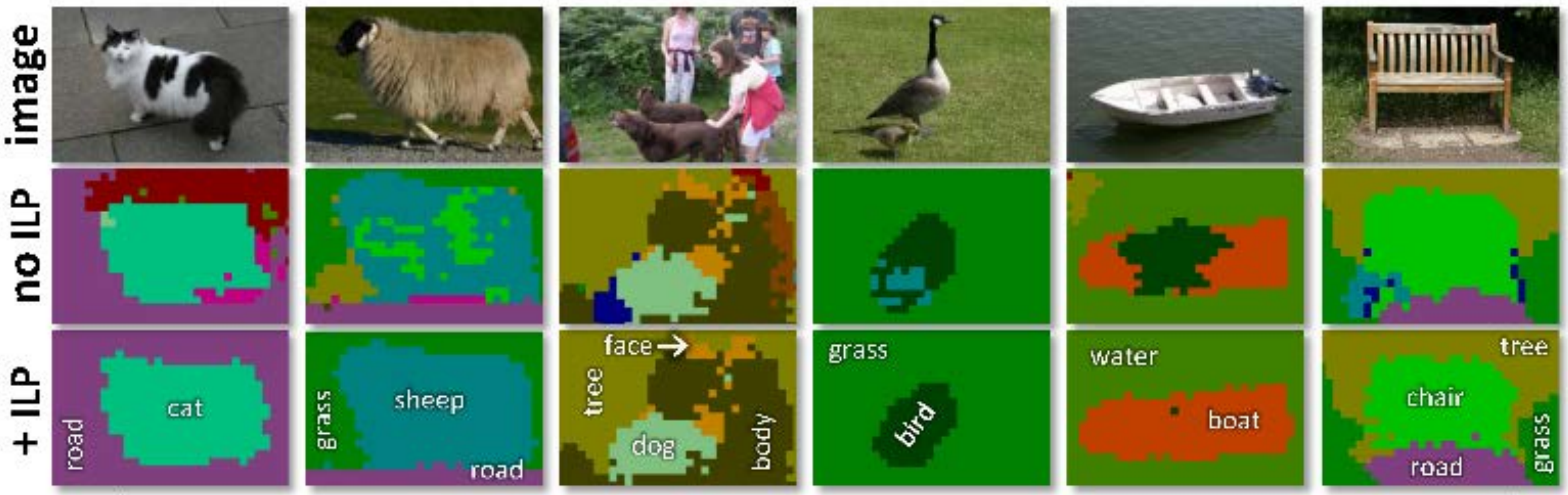
TEXTON BOOST



Performs classification on the output of oriented filters.

Shotton et al., ECCV'06

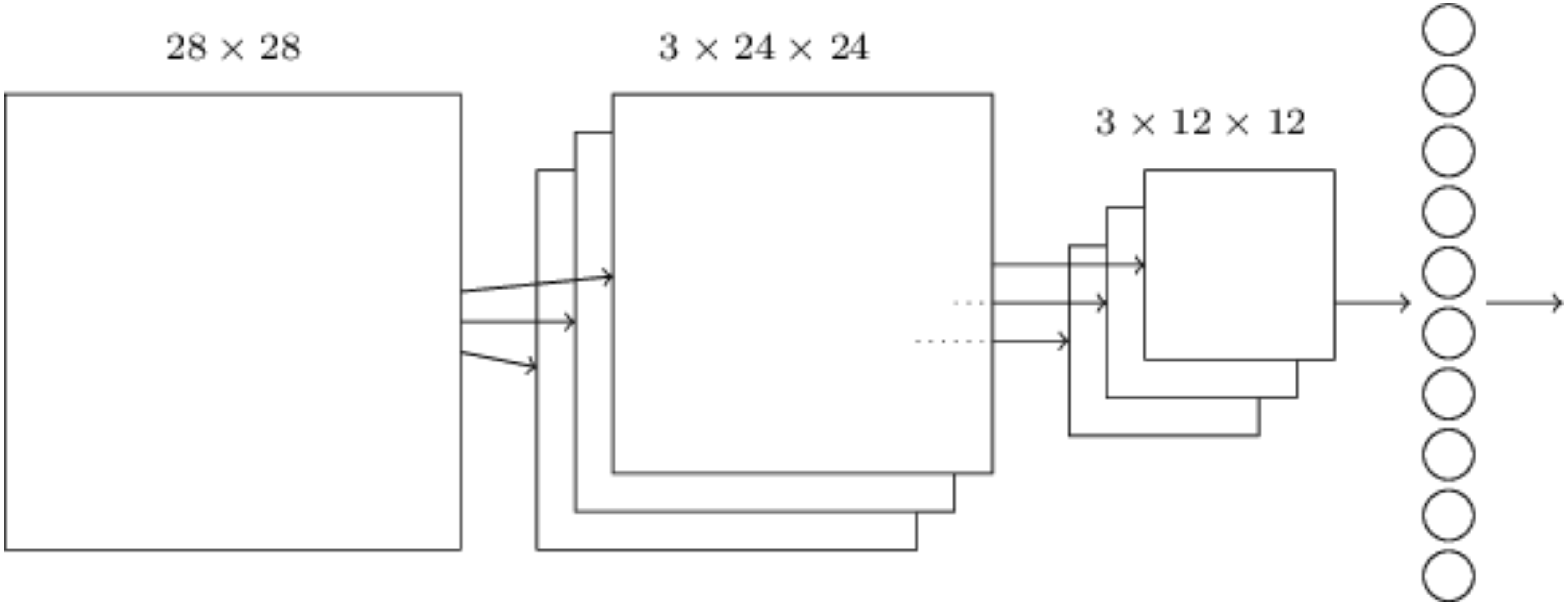
TEXTON FORESTS



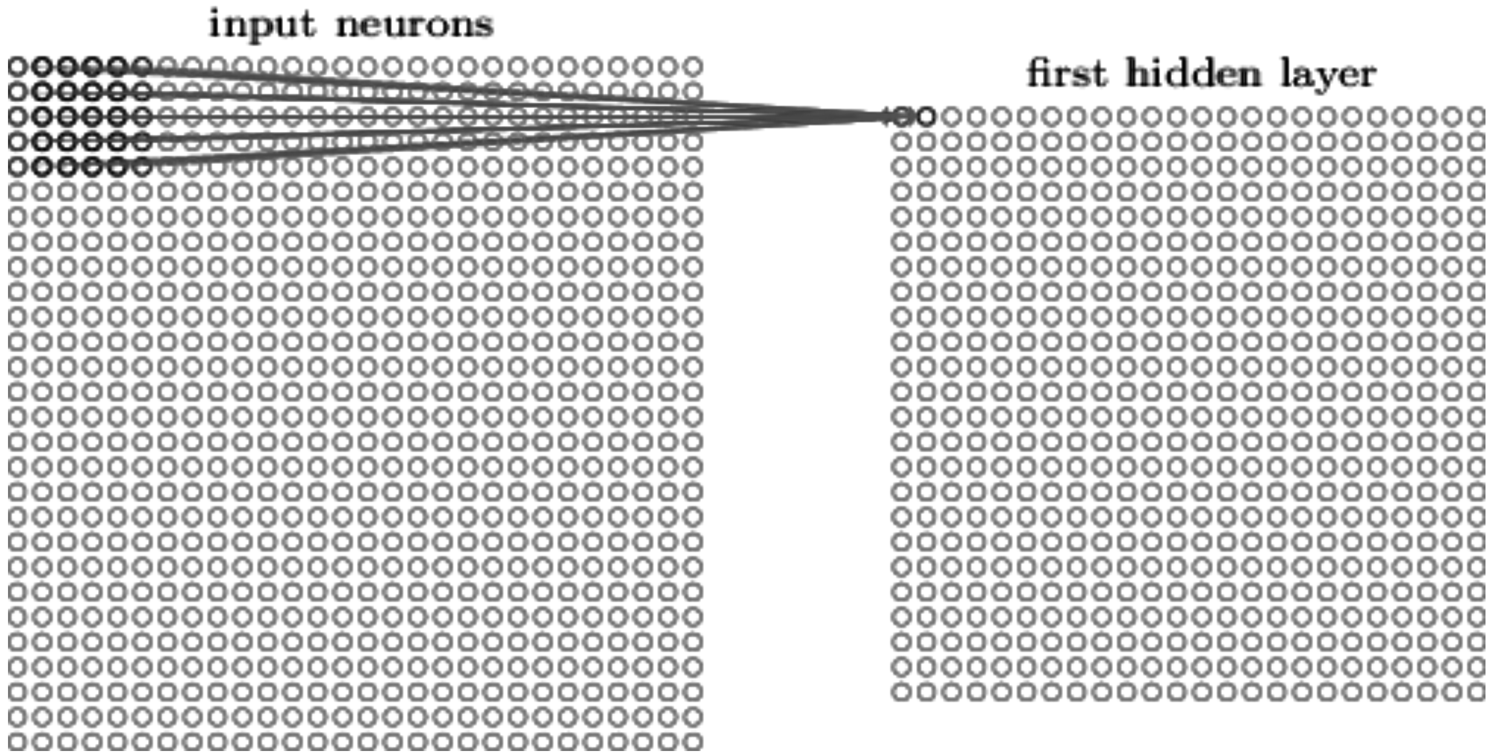
Relies on decision trees and comparisons of colors of pixels belonging to small image patches.

Shotton et al., CVPR'08

BACK TO CONVOLUTIONAL NETS

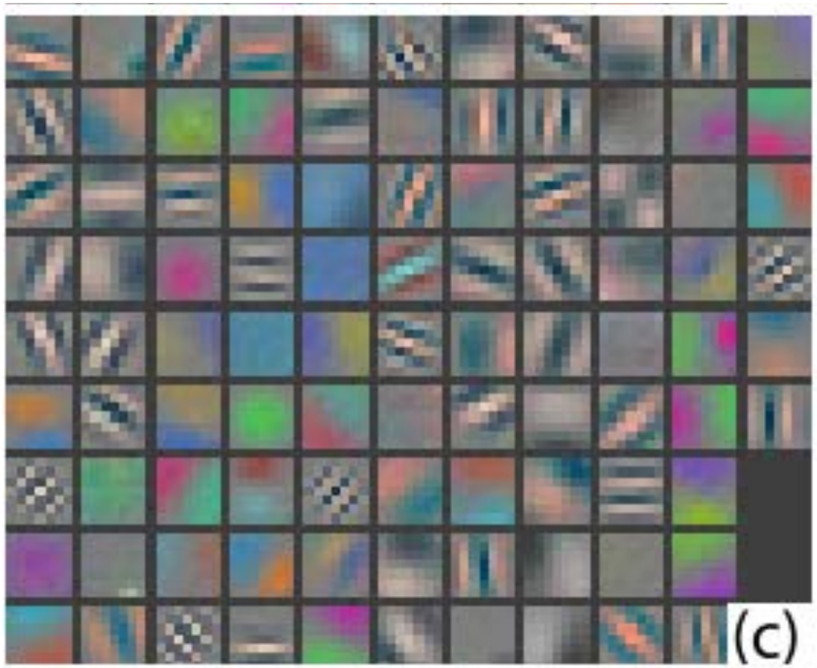


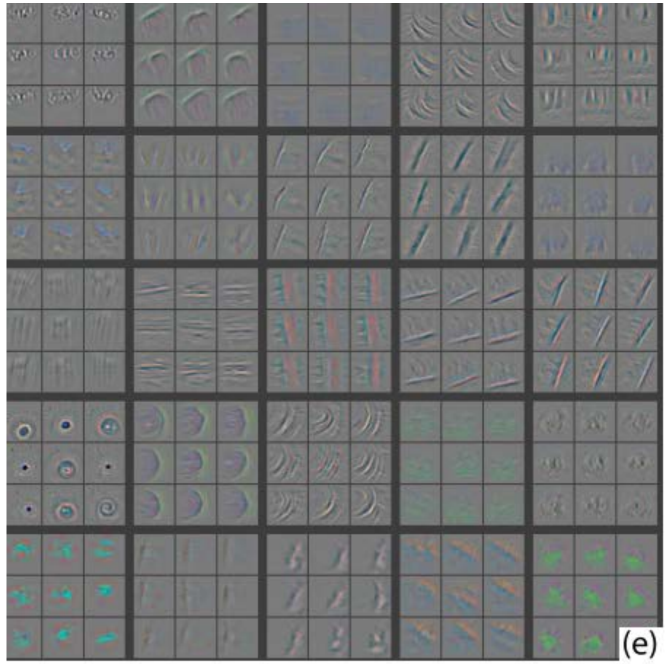
CONVOLUTIONAL LAYER



$$\sigma\left(b + \sum_{x=0}^{n_x} \sum_{y=0}^{n_y} w_{x,y} a_{i+x,j+y}\right)$$

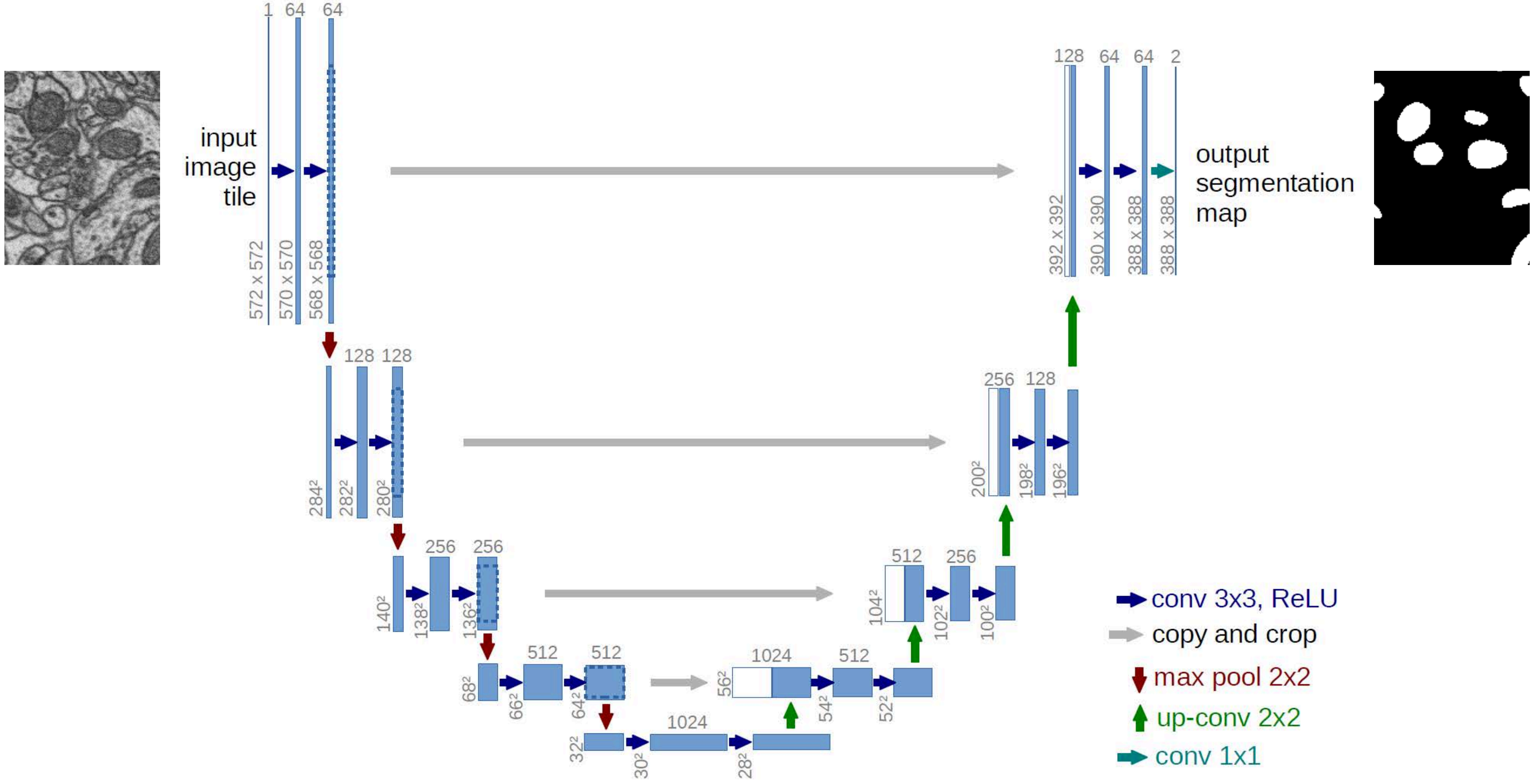
FEATURE MAPS



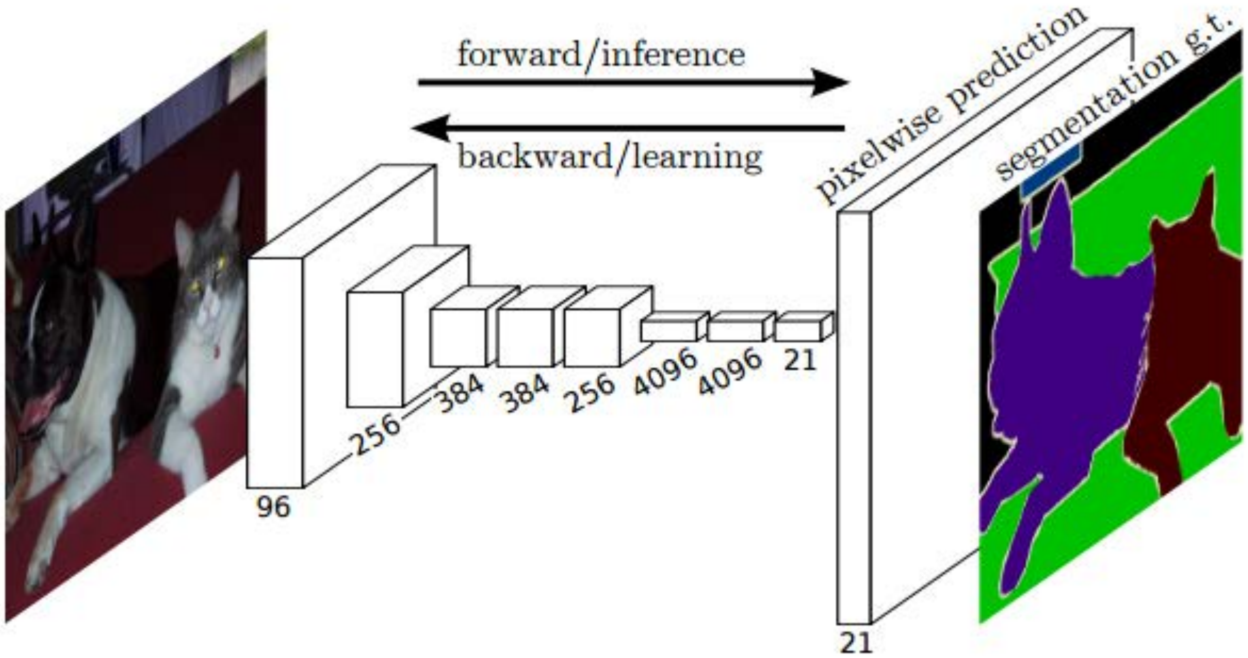


- Some of these convolutional filters look very Gabor like.
- The network learns the right filter bank but still depends on many arbitrary parameters.

U-NET ARCHITECTURE

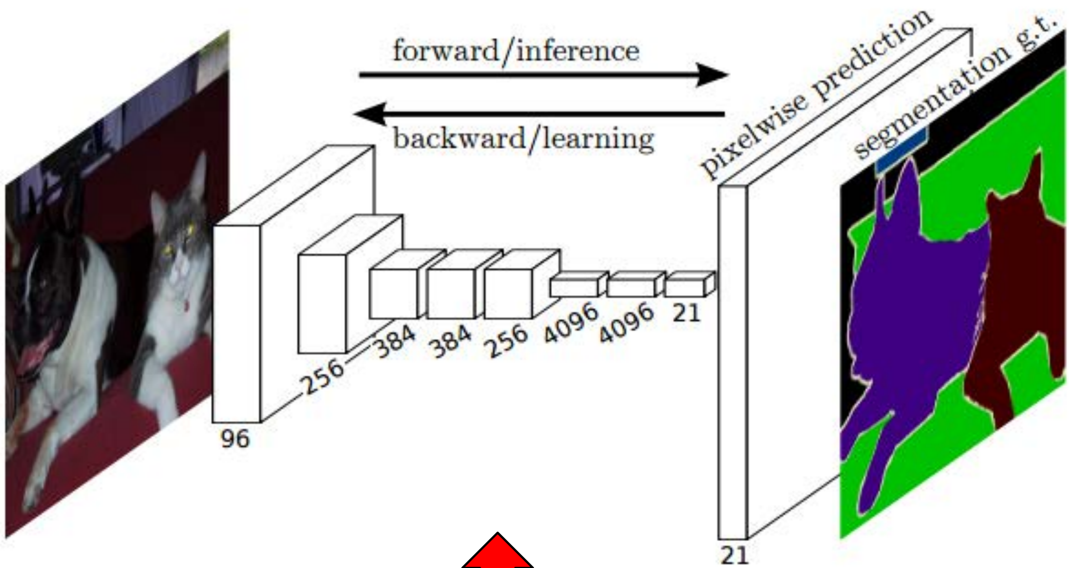


CONVOLUTIONAL NETS

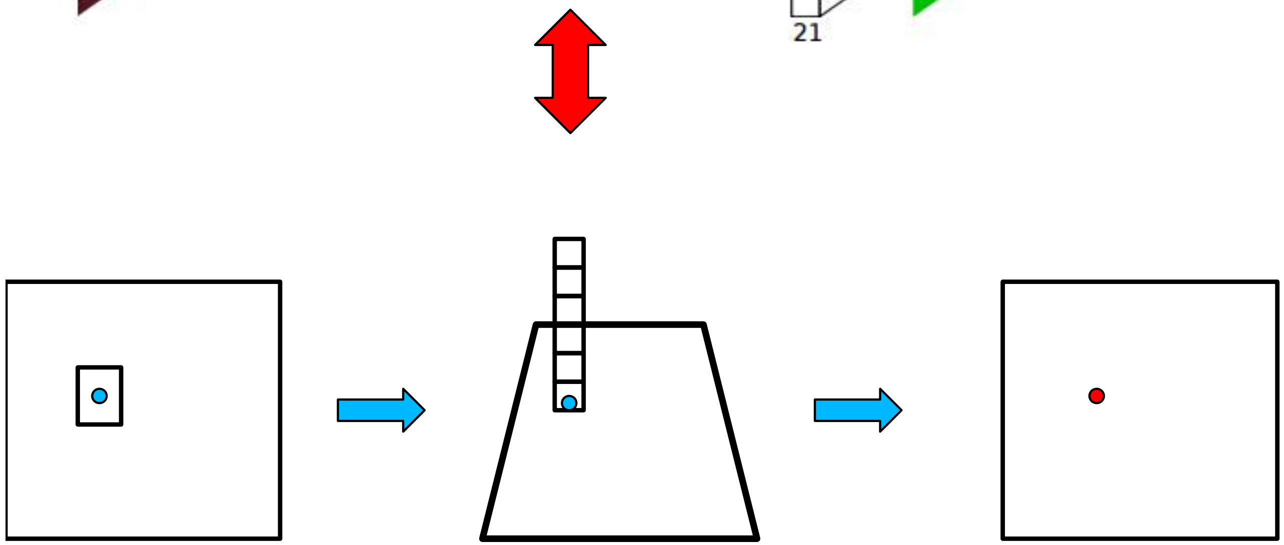


- Connect input layer to output one made of segmentation labels.
- Need layers that both downscale and upscale.
- Connect the lower layers directly to the upper ones.

AN INTERPRETATION



- Can be understood as generating for every output pixel a feature vector containing the output of all the intermediate layers.



IN SHORT

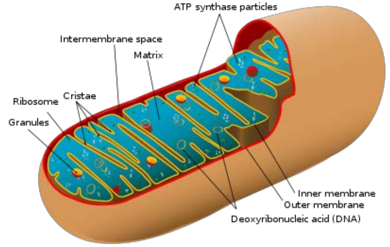
Texture is a key property of objects which is

- Non local
- Non trivial to measure
- Subject to deformations

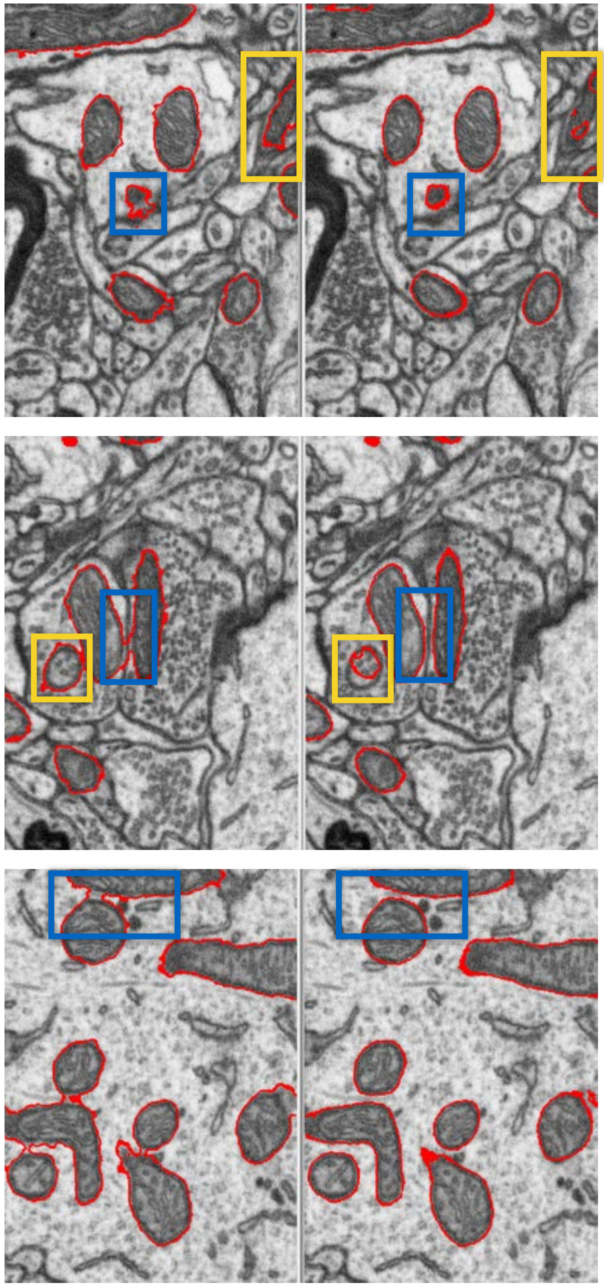
➡ Hard to characterize formally and best used in conjunction with effective Machine Learning techniques.

➡ This seems to be exactly what Convolutional Neural Nets do.

Mitochondria

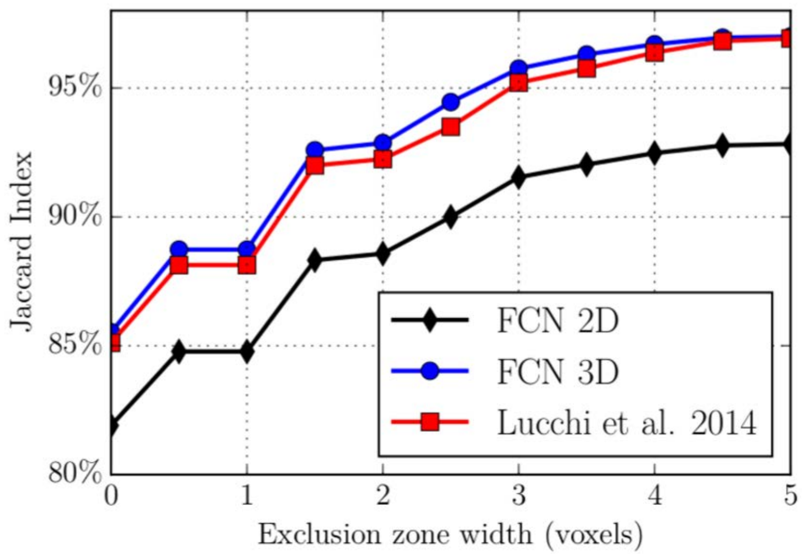


Context Features + CRF | U-Net 3D

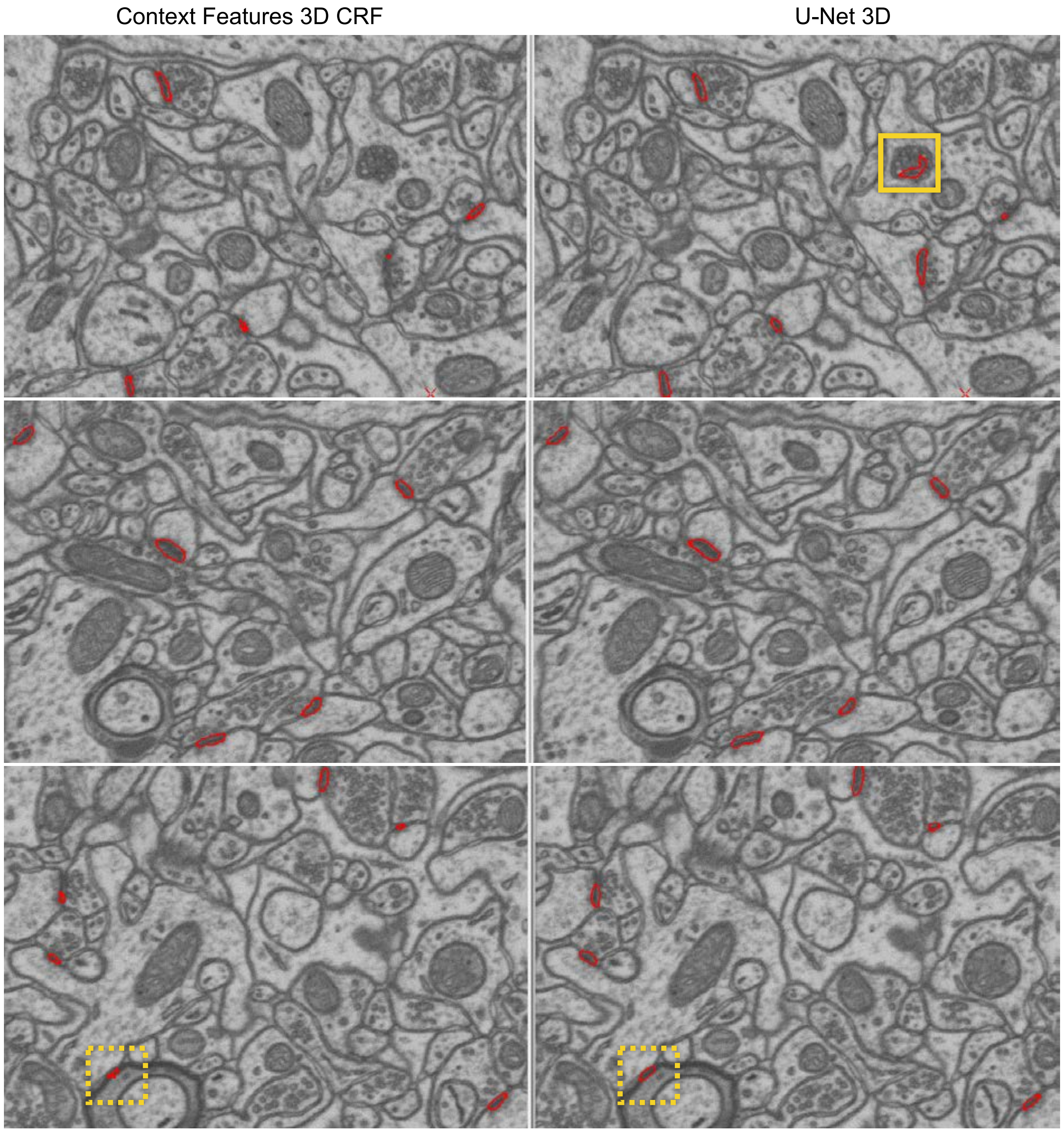


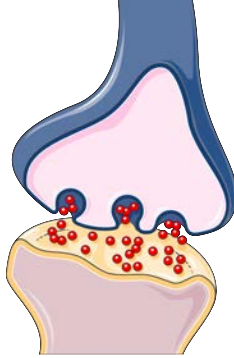
Striatum Mitochondria

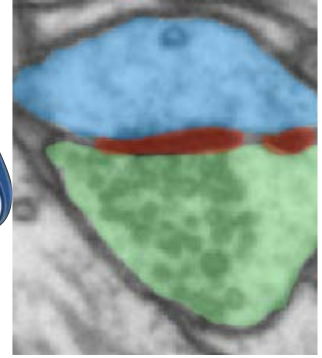
Method	Jaccard Index
Context F. + CRF	84.6%
U-Net 2D	82.4%
U-Net 3D	86.1%



Synapses





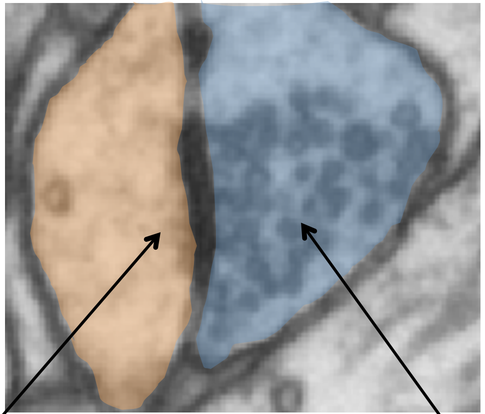


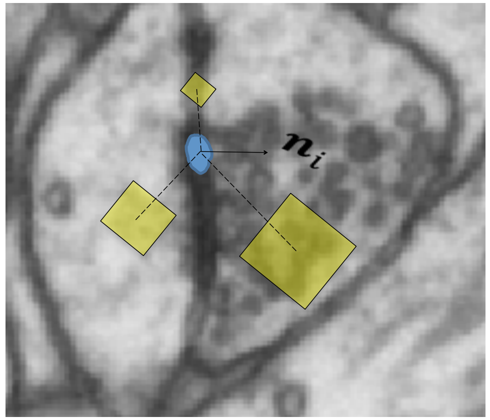
Jaccard Index	Method
66.8%	Context Features 2D
85.2%	Context Features 3D
73.5%	U-Net 2D
77.0%	U-Net 3D

?

Context-Based Features

Synapse:





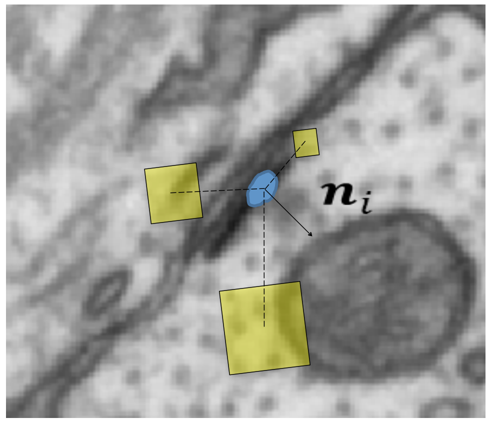
Post-synaptic region

- Dendrite
- No vesicles

Pre-synaptic region

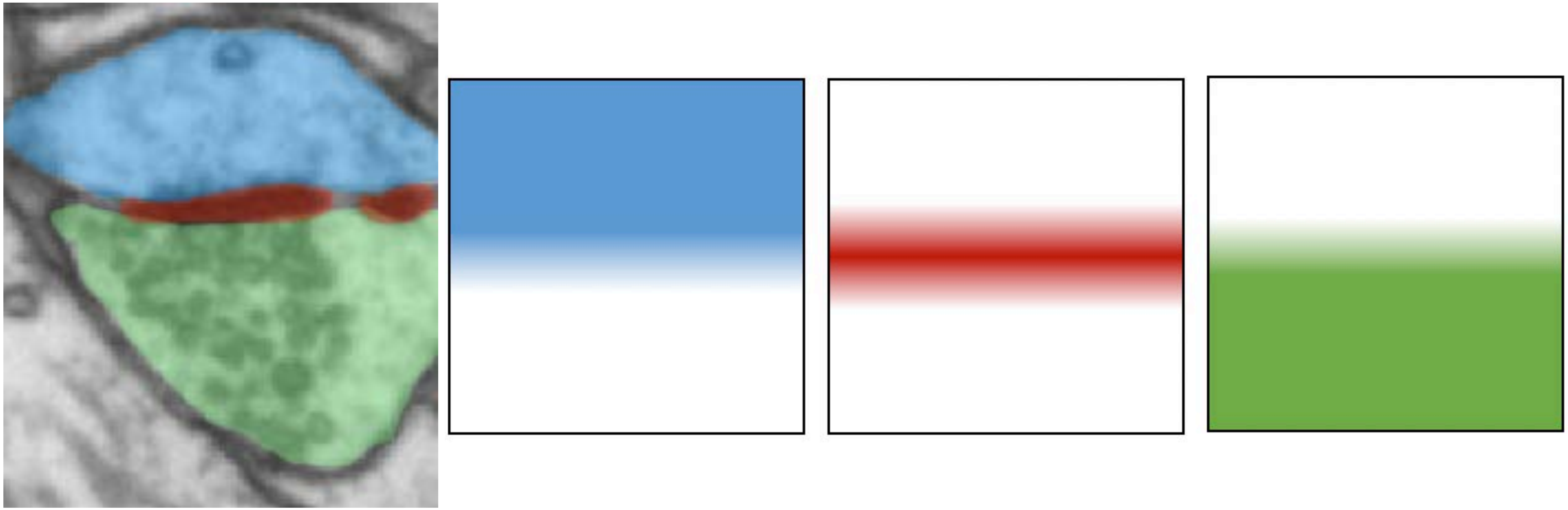
- Axon terminal
- Many vesicles

Non-Synapse:



Becker et al. TMI'13

Probabilistic Atlases



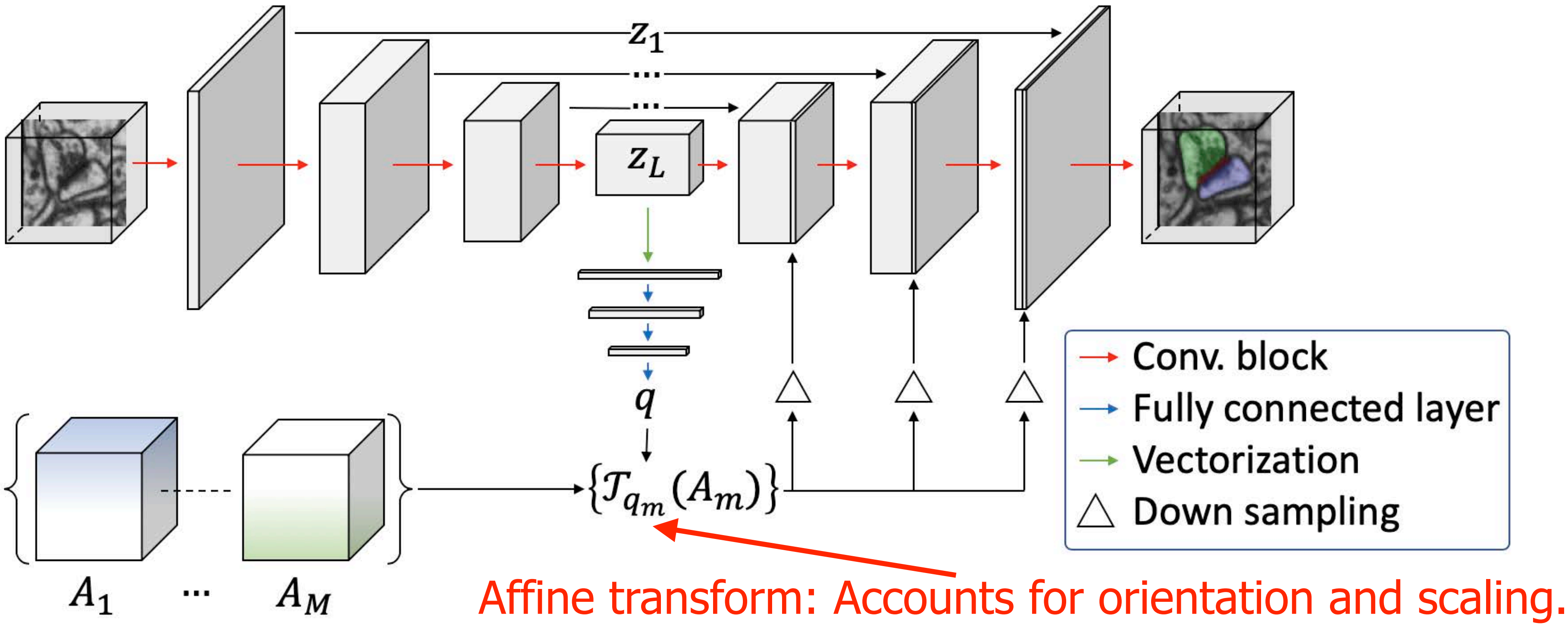
Synapse in canonical orientation

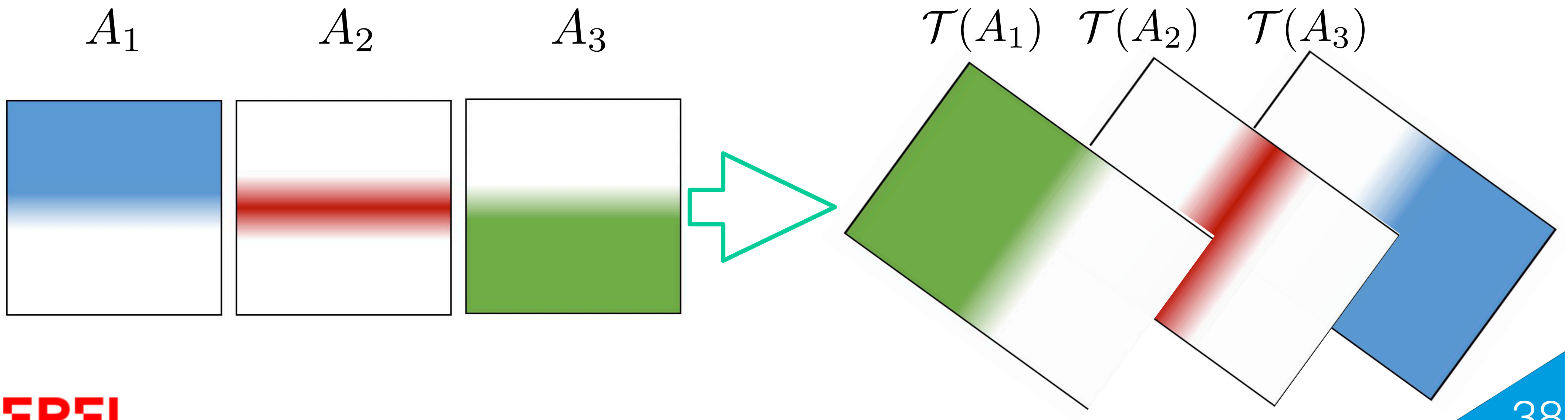
Probability of being a post-synaptic voxel

Probability of being a cleft voxel

Probability of being a pre-synaptic voxel

Using Atlases

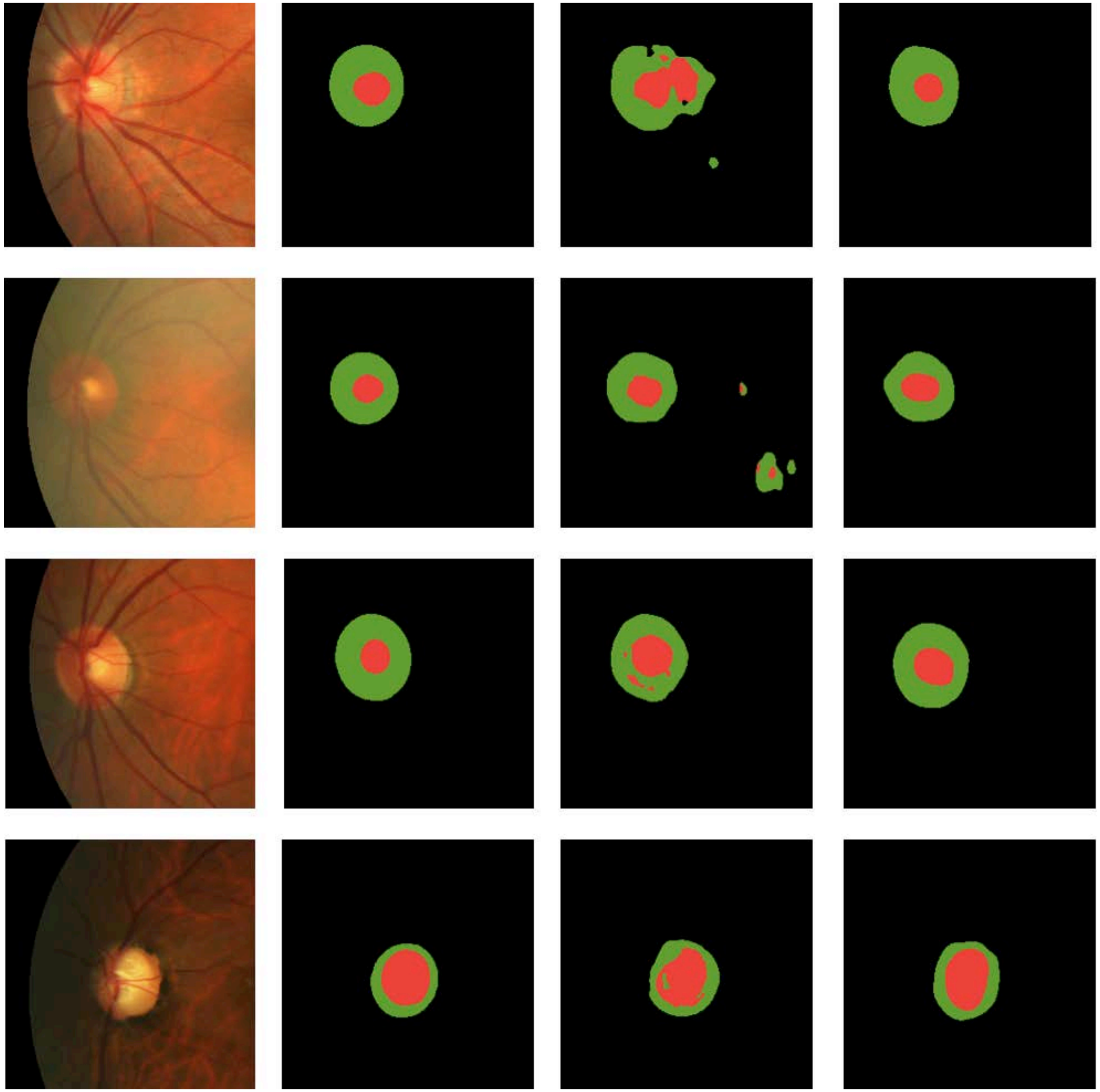




Synaptic Junction Segmentation

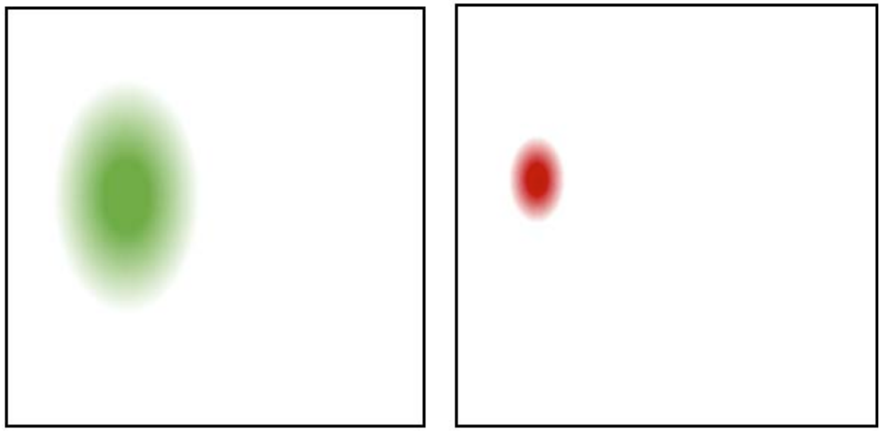
Baseline vs PA-Net

Optic Disk Segmentation



Ground truth U-Net PA-Net

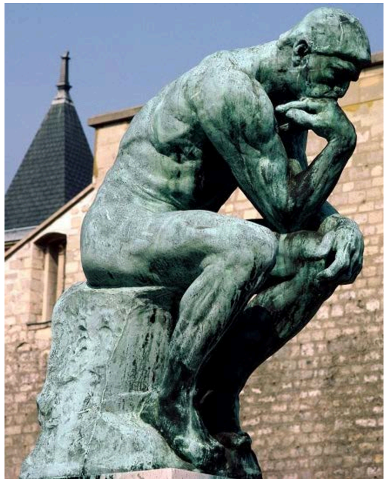
Probabilistic Atlases



Optic disk Optic nerve

Moral of the Story

- Deep Networks are powerful tools, especially when there is enough training data.
- However, modeling your problem properly is still needed to achieve the best possible level of performance.
- The old techniques often inform our design choices.



We still have to think!!