2.6. Image manipulation and processing using Numpy and Scipy

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This section addresses basic image manipulation and processing using the core scientific modules NumPy and SciPy. Some of the operations covered by this tutorial may be useful for other kinds of multidimensional array processing than image processing. In particular, the submodule **`scipy.ndimage`** provides functions operating on n-dimensional NumPy arrays.

See also: For more advanced image processing and image-specific routines, see the tutorial Scikit-image: image processing, dedicated to the **`skimage`** module.

Image = 2-D numerical array

(or 3-D: CT, MRI, 2D + time; 4-D, ...)

Here, **image == Numpy array** `np.array`

Tools used in this tutorial:

- `numpy`: basic array manipulation
- `scipy`: `scipy.ndimage` submodule dedicated to image processing (n-dimensional images). See the documentation:

```
>>> from scipy import ndimage
```

Common tasks in image processing:

- Input/Output, displaying images
- Basic manipulations: cropping, flipping, rotating, ...
- Image filtering: denoising, sharpening

- Image segmentation: labeling pixels corresponding to different objects
- Classification
- Feature extraction
- Registration
- ...

Chapters contents

2.6.1. Opening and writing to image files

Writing an array to a file:

```
from scipy import misc
f = misc.face()
misc.imsave('face.png', f) # uses the Image module (PIL)

import matplotlib.pyplot as plt
```

```
plt.imshow(f)
plt.show()
```

Creating a numpy array from an image file:

```
>>> from scipy import misc
>>> face = misc.face()
>>> misc.imsave('face.png', face) # First we need to create
      the PNG file

>>> face = misc.imread('face.png')
>>> type(face)
<... 'numpy.ndarray'>
>>> face.shape, face.dtype
((768, 1024, 3), dtype('uint8'))
```

dtype is uint8 for 8-bit images (0-255)

Opening raw files (camera, 3-D images)

```
>>> face.tofile('face.raw') # Create raw file
>>> face_from_raw = np.fromfile('face.raw', dtype=np.uint8)
>>> face_from_raw.shape
(2359296,)
>>> face_from_raw.shape = (768, 1024, 3)
```

Need to know the shape and dtype of the image (how to separate data bytes).

For large data, use `np.memmap` for memory mapping:

```
>>> face_memmap = np.memmap('face.raw', dtype=np.uint8, shape=(768, 1024, 3))
```

(data are read from the file, and not loaded into memory)

Working on a list of image files

```
>>> for i in range(10):
...     im = np.random.random_integers(0, 255, 10000).reshape((100, 100))
...     misc.imsave('random_%02d.png' % i, im)
>>> from glob import glob
>>> filelist = glob('random*.png')
>>> filelist.sort()
```

2.6.2. Displaying images

Use `matplotlib` and `imshow` to display an image inside a `matplotlib figure`:

```
>>> f = misc.face(gray=True)  # retrieve a grayscale image
>>> import matplotlib.pyplot as plt
>>> plt.imshow(f, cmap=plt.cm.gray)
<matplotlib.image.AxesImage object at 0x...>
```

Increase contrast by setting min and max values:

```
>>> plt.imshow(f, cmap=plt.cm.gray, vmin=30, vmax=200)
<matplotlib.image.AxesImage object at 0x...>
>>> # Remove axes and ticks
>>> plt.axis('off')
(-0.5, 1023.5, 767.5, -0.5)
```

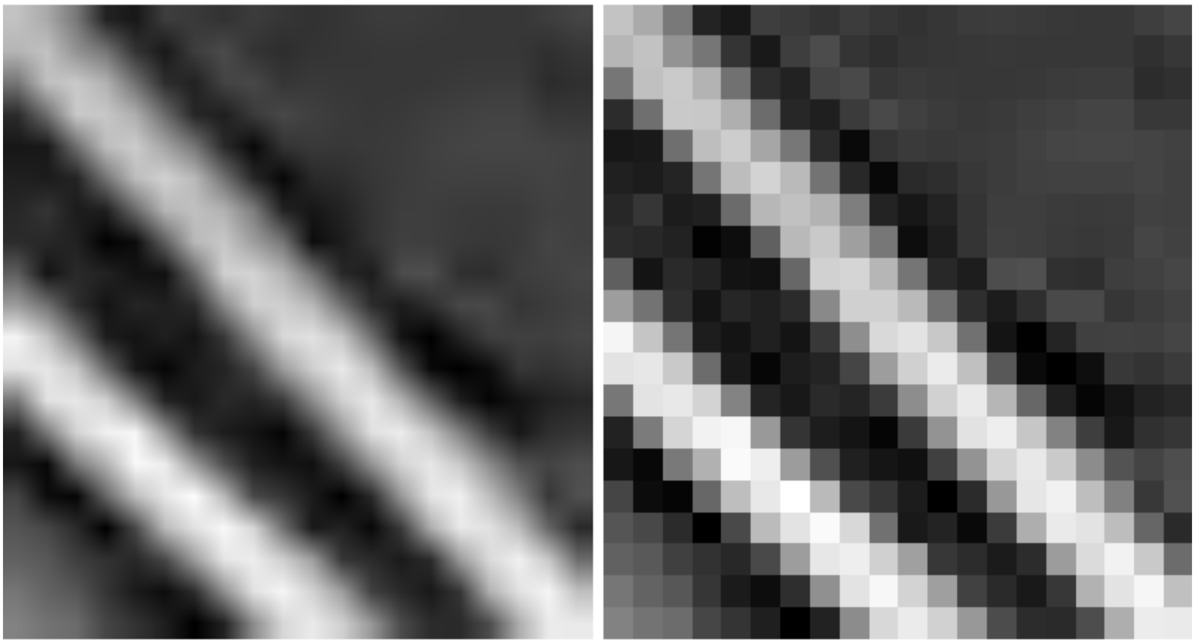
Draw contour lines:

```
>>> plt.contour(f, [50, 200])
<matplotlib.contour.QuadContourSet ...>
```

[Python source code]

For fine inspection of intensity variations, use `interpolation='nearest'`:

```
>>> plt.imshow(f[320:340, 510:530], cmap=plt.cm.gray)
<matplotlib.image.AxesImage object at 0x...>
>>> plt.imshow(f[320:340, 510:530], cmap=plt.cm.gray, inte
      rpolation='nearest')
<matplotlib.image.AxesImage object at 0x...>
```

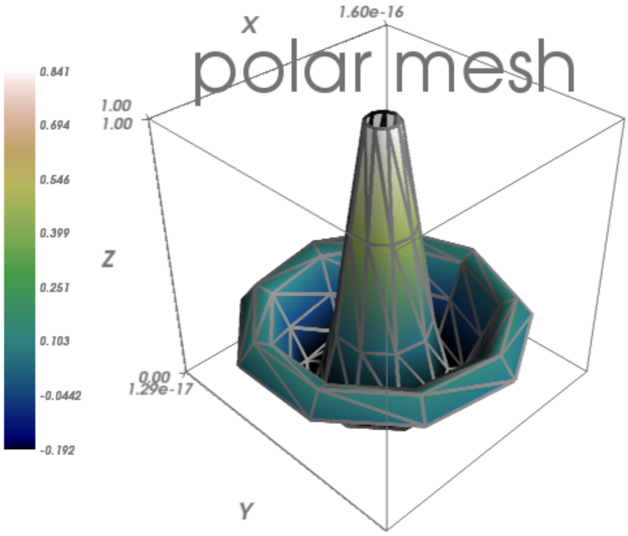


[Python source code]

See also: 3-D visualization: Mayavi

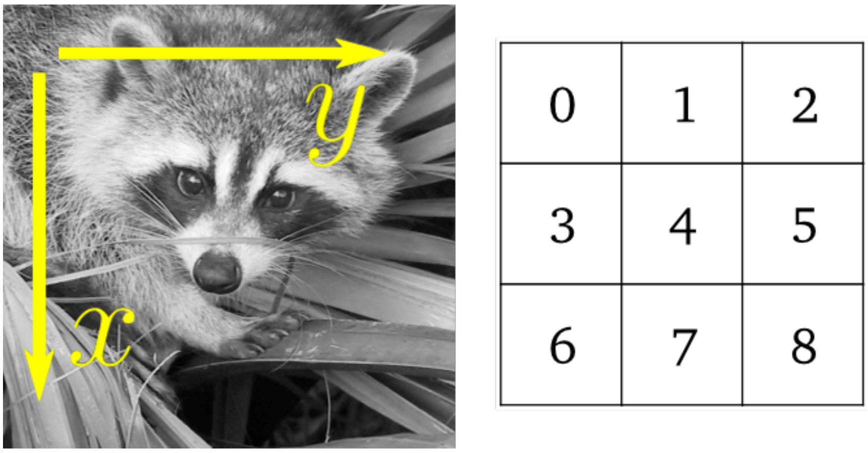
See 3D plotting with Mayavi.

- Image plane widgets
- Isosurfaces
- ...



2.6.3. Basic manipulations

Images are arrays: use the whole numpy machinery.




```
>>> face = misc.face(gray=True)
>>> face[0, 40]
127
>>> # Slicing
```

```
>>> face[10:13, 20:23]
array([[141, 153, 145],
       [133, 134, 125],
       [ 96,  92,  94]], dtype=uint8)
>>> face[100:120] = 255
>>>
>>> lx, ly = face.shape
>>> X, Y = np.ogrid[0:lx, 0:ly]
>>> mask = (X - lx / 2) ** 2 + (Y - ly / 2) ** 2 > lx * ly
    / 4
>>> # Masks
>>> face[mask] = 0
>>> # Fancy indexing
>>> face[range(400), range(400)] = 255
```

[Python source code]

2.6.3.1. Statistical information

```
>>> face = misc.face(gray=True)
>>> face.mean()
113.48026784261067
>>> face.max(), face.min()
(250, 0)
```

`np.histogram`

Exercise

- Open as an array the `scikit-image` logo (http://scikit-image.org/_static/img/logo.png), or an image that you have on your computer.
- Crop a meaningful part of the image, for example the python circle in the logo.
- Display the image array using `matplotlib`. Change the interpolation method and zoom to see the difference.
- Transform your image to greyscale
- Increase the contrast of the image by changing its minimum and maximum values. **Optional**: use `scipy.stats.scoreatpercentile` (read the docstring!) to saturate 5% of the darkest pixels and 5% of the lightest pixels.
- Save the array to two different file formats (png, jpg, tiff)

2.6.3.2. Geometrical transformations

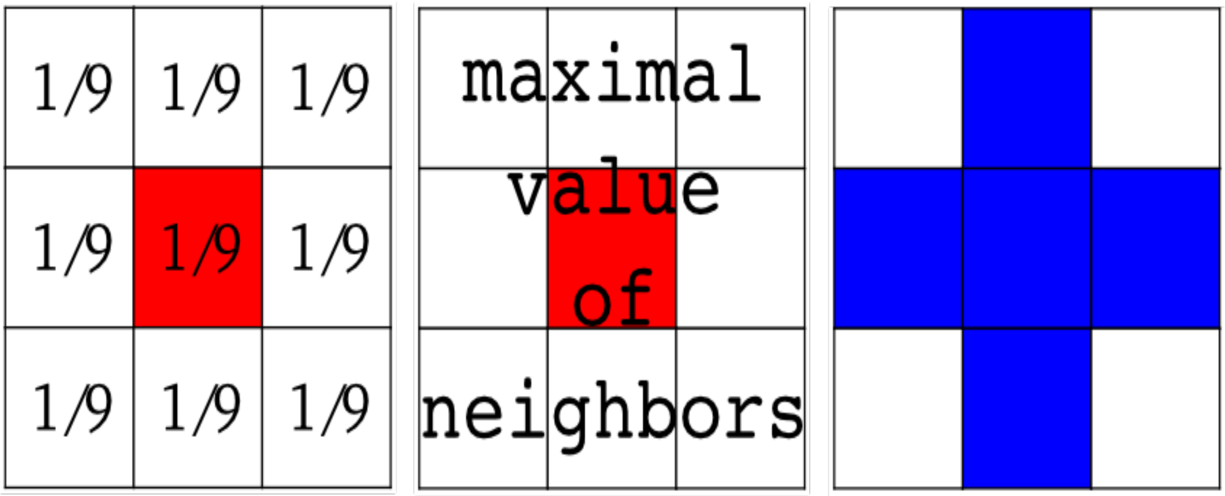
```
>>> face = misc.face(gray=True)
>>> lx, ly = face.shape
>>> # Cropping
>>> crop_face = face[lx / 4: - lx / 4, ly / 4: - ly / 4]
>>> # up <-> down flip
>>> flip_ud_face = np.flipud(face)
>>> # rotation
>>> rotate_face = ndimage.rotate(face, 45)
>>> rotate_face_noreshape = ndimage.rotate(face, 45, reshape=False)
```

[Python source code]

2.6.4. Image filtering

Local filters: replace the value of pixels by a function of the values of neighboring pixels.

Neighbourhood: square (choose size), disk, or more complicated *structuring element*.



2.6.4.1. Blurring/smoothing

Gaussian filter from `scipy.ndimage`:

```
>>> from scipy import misc
>>> face = misc.face(gray=True)
>>> blurred_face = ndimage.gaussian_filter(face, sigma=3)
```

```
>>> very_blurred = ndimage.gaussian_filter(face, sigma=5)
```

Uniform filter

```
>>> local_mean = ndimage.uniform_filter(face, size=11)
```

[Python source code]

2.6.4.2. Sharpening

Sharpen a blurred image:

```
>>> from scipy import misc
>>> face = misc.face(gray=True).astype(float)
>>> blurred_f = ndimage.gaussian_filter(face, 3)
```

increase the weight of edges by adding an approximation of the Laplacian:

```
>>> filter_blurred_f = ndimage.gaussian_filter(blurred_f, 1)
>>> alpha = 30
>>> sharpened = blurred_f + alpha * (blurred_f - filter_blurred_f)
```

[Python source code]

2.6.4.3. Denoising

Noisy face:

```
>>> from scipy import misc
>>> f = misc.face(gray=True)
>>> f = f[230:290, 220:320]
>>> noisy = f + 0.4 * f.std() * np.random.random(f.shape)
```

A **Gaussian filter** smoothes the noise out... and the edges as well:

```
>>> gauss_denoised = ndimage.gaussian_filter(noisy, 2)
```

Most local linear isotropic filters blur the image (`ndimage.uniform_filter`)

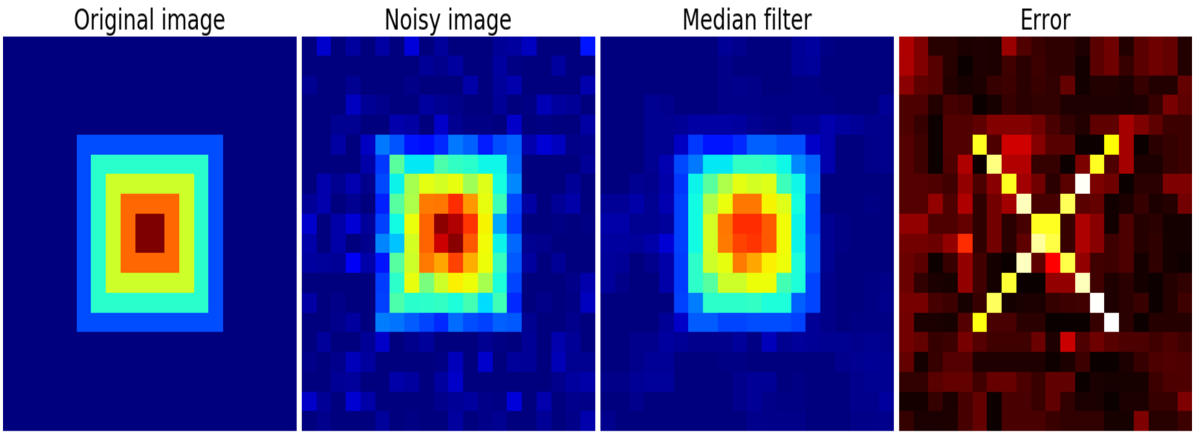
A **median filter** preserves better the edges:

```
>>> med_denoised = ndimage.median_filter(noisy, 3)
```

[Python source code]

Median filter: better result for straight boundaries (**low curvature**):

```
>>> im = np.zeros((20, 20))
>>> im[5:-5, 5:-5] = 1
>>> im = ndimage.distance_transform_bf(im)
>>> im_noise = im + 0.2 * np.random.randn(*im.shape)
>>> im_med = ndimage.median_filter(im_noise, 3)
```



[Python source code]

Other rank filter: `ndimage.maximum_filter`, `ndimage.percentile_filter`

Other local non-linear filters: Wiener (`scipy.signal.wiener`), etc.

Non-local filters

Exercise: denoising

- Create a binary image (of 0s and 1s) with several objects (circles,

ellipses, squares, or random shapes).
- Add some noise (e.g., 20% of noise)
- Try two different denoising methods for denoising the image: gaussian filtering and median filtering.
- Compare the histograms of the two different denoised images. Which one is the closest to the histogram of the original (noise-free) image?

See also: More denoising filters are available in **`skimage.denoising`**, see the Scikit-image: image processing tutorial.

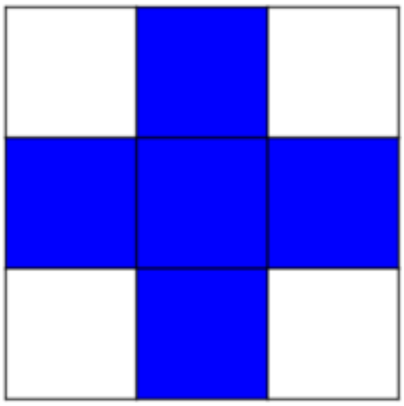
2.6.4.4. Mathematical morphology

See wikipedia for a definition of mathematical morphology.

Probe an image with a simple shape (a **structuring element**), and modify this image according to how the shape locally fits or misses the image.

Structuring element:

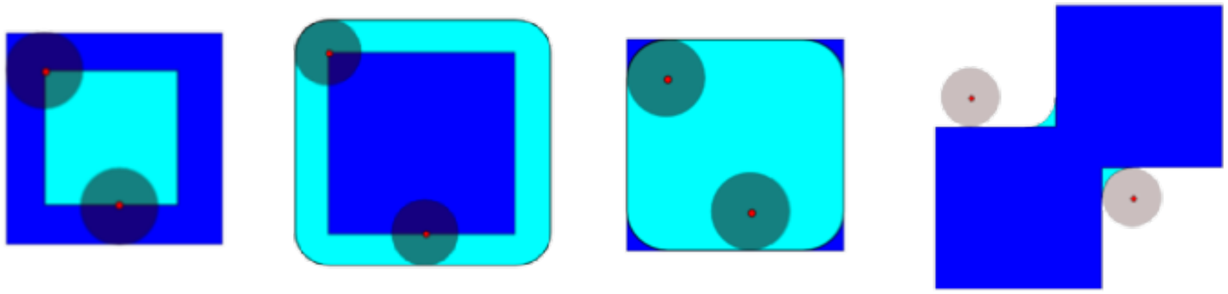
```
>>> el = ndimage.generate_binary_structure(2, 1)
>>> el
array([[False,  True, False],
       [ True,  True,  True],
       [False,  True, False]], dtype=bool)
>>> el.astype(np.int)
array([[0, 1, 0],
       [1, 1, 1],
       [0, 1, 0]])
```



Erosion = minimum filter. Replace the value of a pixel by the minimal value covered by the structuring element.:

```
>>> a = np.zeros((7,7), dtype=np.int)
>>> a[1:6, 2:5] = 1
>>> a
array([[0, 0, 0, 0, 0, 0, 0],
       [0, 0, 1, 1, 1, 0, 0],
       [0, 0, 1, 1, 1, 0, 0],
       [0, 0, 1, 1, 1, 0, 0],
       [0, 0, 1, 1, 1, 0, 0],
       [0, 0, 1, 1, 1, 0, 0],
       [0, 0, 0, 0, 0, 0, 0]])
>>> ndimage.binary_erosion(a).astype(a.dtype)
array([[0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 1, 0, 0, 0],
       [0, 0, 0, 1, 0, 0, 0],
       [0, 0, 0, 1, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0]])
>>> #Erosion removes objects smaller than the structure
>>> ndimage.binary_erosion(a, structure=np.ones((5,5))).ast
      ype(a.dtype)
array([[0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0, 0]])
```

Erosion **Dilation** **Opening** **Closing**

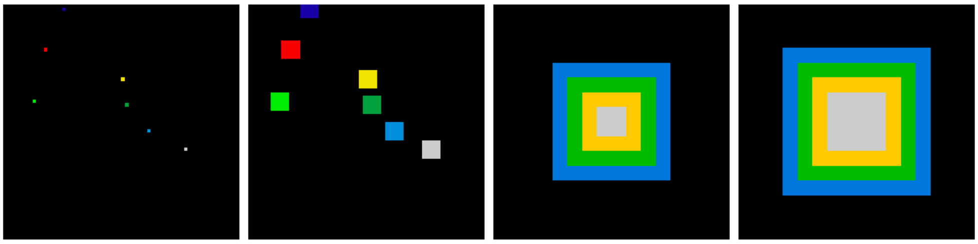


Dilation: maximum filter:

```
>>> a = np.zeros((5, 5))
>>> a[2, 2] = 1
>>> a
array([[ 0.,  0.,  0.,  0.,  0.],
       [ 0.,  0.,  0.,  0.,  0.],
       [ 0.,  0.,  1.,  0.,  0.],
       [ 0.,  0.,  0.,  0.,  0.],
       [ 0.,  0.,  0.,  0.,  0.]])
>>> ndimage.binary_dilation(a).astype(a.dtype)
array([[ 0.,  0.,  0.,  0.,  0.],
       [ 0.,  0.,  1.,  0.,  0.],
       [ 0.,  1.,  1.,  1.,  0.],
       [ 0.,  0.,  1.,  0.,  0.],
       [ 0.,  0.,  0.,  0.,  0.]])
```

Also works for grey-valued images:

```
>>> np.random.seed(2)
>>> im = np.zeros((64, 64))
>>> x, y = (63*np.random.random((2, 8))).astype(np.int)
>>> im[x, y] = np.arange(8)

>>> bigger_points = ndimage.grey_dilation(im, size=(5, 5),
      structure=np.ones((5, 5)))

>>> square = np.zeros((16, 16))
>>> square[4:-4, 4:-4] = 1
>>> dist = ndimage.distance_transform_bf(square)
>>> dilate_dist = ndimage.grey_dilation(dist, size=(3, 3),
      \
...         structure=np.ones((3, 3)))
```



[Python source code]

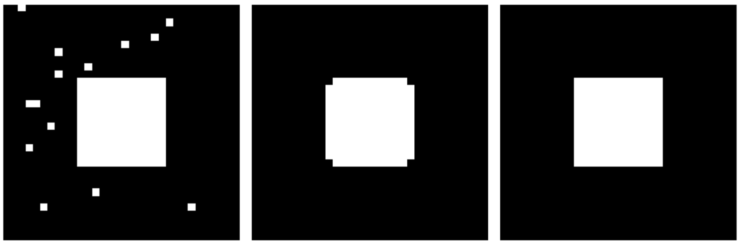
Opening: erosion + dilation:

```
>>> a = np.zeros((5,5), dtype=np.int)
>>> a[1:4, 1:4] = 1; a[4, 4] = 1
>>> a
array([[0, 0, 0, 0, 0],
       [0, 1, 1, 1, 0],
       [0, 1, 1, 1, 0],
       [0, 1, 1, 1, 0],
       [0, 0, 0, 0, 1]])
>>> # Opening removes small objects
>>> ndimage.binary_opening(a, structure=np.ones((3,3))).ast
      ype(np.int)
array([[0, 0, 0, 0, 0],
       [0, 1, 1, 1, 0],
       [0, 1, 1, 1, 0],
       [0, 1, 1, 1, 0],
       [0, 0, 0, 0, 0]])
>>> # Opening can also smooth corners
>>> ndimage.binary_opening(a).astype(np.int)
array([[0, 0, 0, 0, 0],
       [0, 0, 1, 0, 0],
       [0, 1, 1, 1, 0],
       [0, 0, 1, 0, 0],
       [0, 0, 0, 0, 0]])
```

Application: remove noise:

```
>>> square = np.zeros((32, 32))
>>> square[10:-10, 10:-10] = 1
>>> np.random.seed(2)
>>> x, y = (32*np.random.random((2, 20))).astype(np.int)
>>> square[x, y] = 1

>>> open_square = ndimage.binary_opening(square)
```

```
>>> eroded_square = ndimage.binary_erosion(square)
>>> reconstruction = ndimage.binary_propagation(eroded_squa
      re, mask=square)
```



[Python source code]

Closing: dilation + erosion

Many other mathematical morphology operations: hit and miss transform, tophat, etc.

2.6.5. Feature extraction

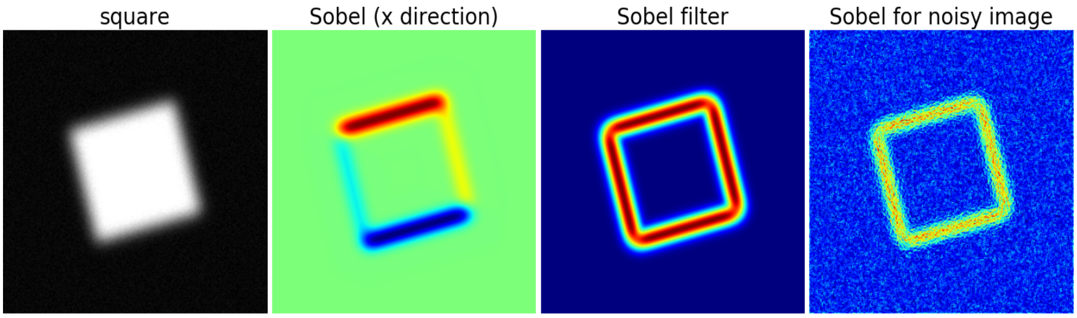
2.6.5.1. Edge detection

Synthetic data:

```
>>> im = np.zeros((256, 256))
>>> im[64:-64, 64:-64] = 1
>>>
>>> im = ndimage.rotate(im, 15, mode='constant')
>>> im = ndimage.gaussian_filter(im, 8)
```

Use a **gradient operator** (**Sobel**) to find high intensity variations:

```
>>> sx = ndimage.sobel(im, axis=0, mode='constant')
>>> sy = ndimage.sobel(im, axis=1, mode='constant')
>>> sob = np.hypot(sx, sy)
```

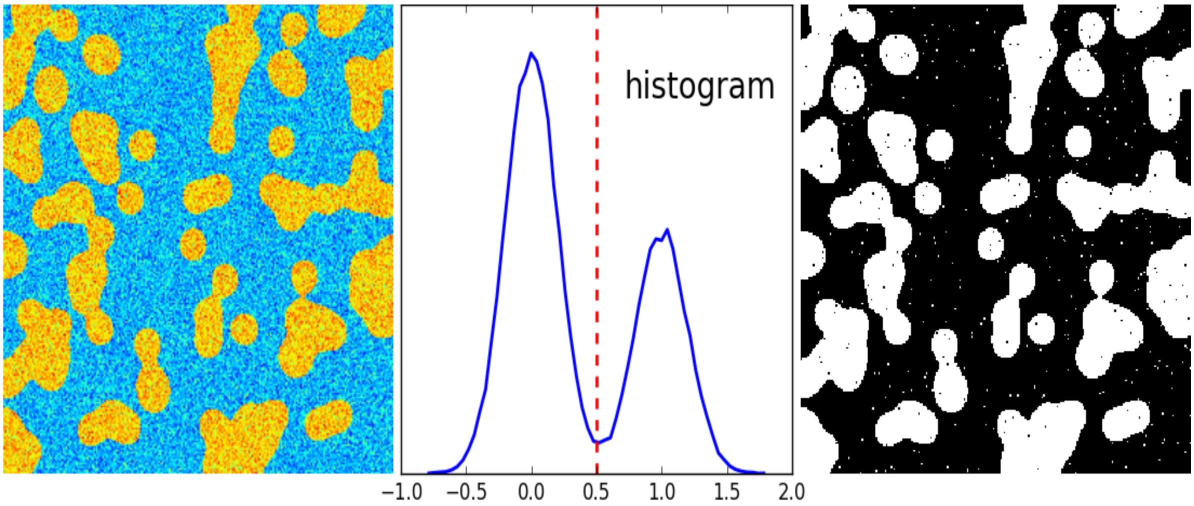


[Python source code]

2.6.5.2. Segmentation

- **Histogram-based** segmentation (no spatial information)

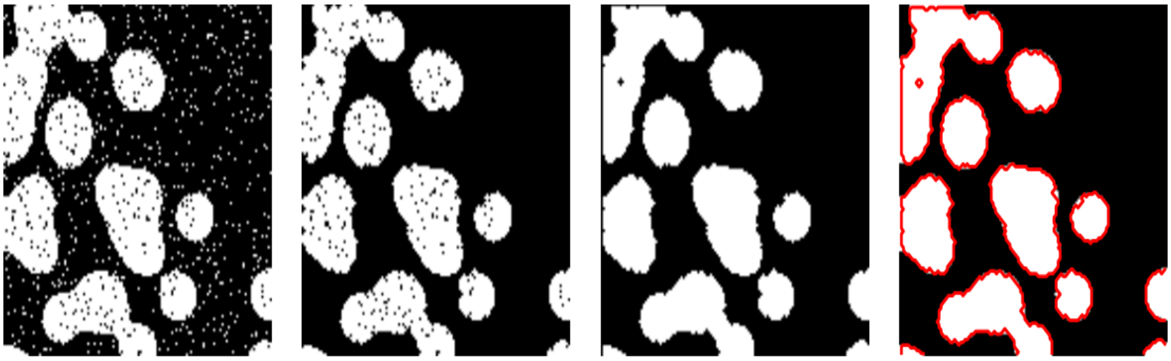
```
>>> n = 10
>>> l = 256
>>> im = np.zeros((l, l))
>>> np.random.seed(1)
>>> points = l*np.random.random((2, n**2))
>>> im[(points[0]).astype(np.int), (points[1]).astype(np.in
    t)] = 1
>>> im = ndimage.gaussian_filter(im, sigma=l/(4.*n))

>>> mask = (im > im.mean()).astype(np.float)
>>> mask += 0.1 * im
>>> img = mask + 0.2*np.random.randn(*mask.shape)

>>> hist, bin_edges = np.histogram(img, bins=60)
>>> bin_centers = 0.5*(bin_edges[:-1] + bin_edges[1:])

>>> binary_img = img > 0.5
```



[Python source code]

Use mathematical morphology to clean up the result:

```
>>> # Remove small white regions
>>> open_img = ndimage.binary_opening(binary_img)
>>> # Remove small black hole
>>> close_img = ndimage.binary_closing(open_img)
```



[Python source code]

Exercise

Check that reconstruction operations (erosion + propagation) produce a better result than opening/closing:

```
>>> eroded_img = ndimage.binary_erosion(binary_img)
>>> reconstruct_img = ndimage.binary_propagation(eroded_im
    g, mask=binary_img)
>>> tmp = np.logical_not(reconstruct_img)
```

```
>>> eroded_tmp = ndimage.binary_erosion(tmp)
>>> reconstruct_final = np.logical_not(ndimage.binary_pro
      pagation(eroded_tmp, mask=tmp))
>>> np.abs(mask - close_img).mean()
0.00727836...
>>> np.abs(mask - reconstruct_final).mean()
0.00059502...
```

Exercise

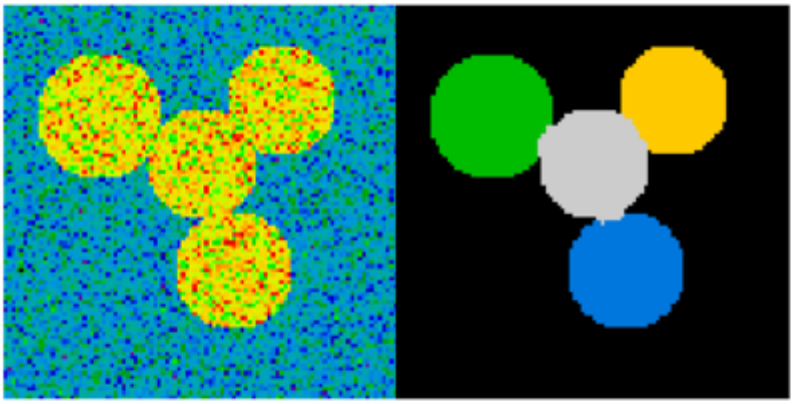
Check how a first denoising step (e.g. with a median filter) modifies the histogram, and check that the resulting histogram-based segmentation is more accurate.

See also: More advanced segmentation algorithms are found in the `scikit-image`: see Scikit-image: image processing.

See also: Other Scientific Packages provide algorithms that can be useful for image processing. In this example, we use the spectral clustering function of the `scikit-learn` in order to segment glued objects.

```
>>> from sklearn.feature_extraction import image
>>> from sklearn.cluster import spectral_clustering

>>> l = 100
>>> x, y = np.indices((l, l))

>>> center1 = (28, 24)
>>> center2 = (40, 50)
>>> center3 = (67, 58)
>>> center4 = (24, 70)
>>> radius1, radius2, radius3, radius4 = 16, 14, 15, 14

>>> circle1 = (x - center1[0])**2 + (y - center1[1])**2 <
      radius1**2
>>> circle2 = (x - center2[0])**2 + (y - center2[1])**2 <
      radius2**2
>>> circle3 = (x - center3[0])**2 + (y - center3[1])**2 <
      radius3**2
>>> circle4 = (x - center4[0])**2 + (y - center4[1])**2 <
```

```
    radius4**2

>>> # 4 circles
>>> img = circle1 + circle2 + circle3 + circle4
>>> mask = img.astype(bool)
>>> img = img.astype(float)

>>> img += 1 + 0.2*np.random.randn(*img.shape)
>>> # Convert the image into a graph with the value of the
    gradient on
>>> # the edges.
>>> graph = image.img_to_graph(img, mask=mask)

>>> # Take a decreasing function of the gradient: we take
    it weakly
>>> # dependant from the gradient the segmentation is clos
    e to a voronoi
>>> graph.data = np.exp(-graph.data/graph.data.std())

>>> labels = spectral_clustering(graph, n_clusters=4, eige
    n_solver='arpack')
>>> label_im = -np.ones(mask.shape)
>>> label_im[mask] = labels
```



2.6.6. Measuring objects properties: `ndimage.measurements`

Synthetic data:

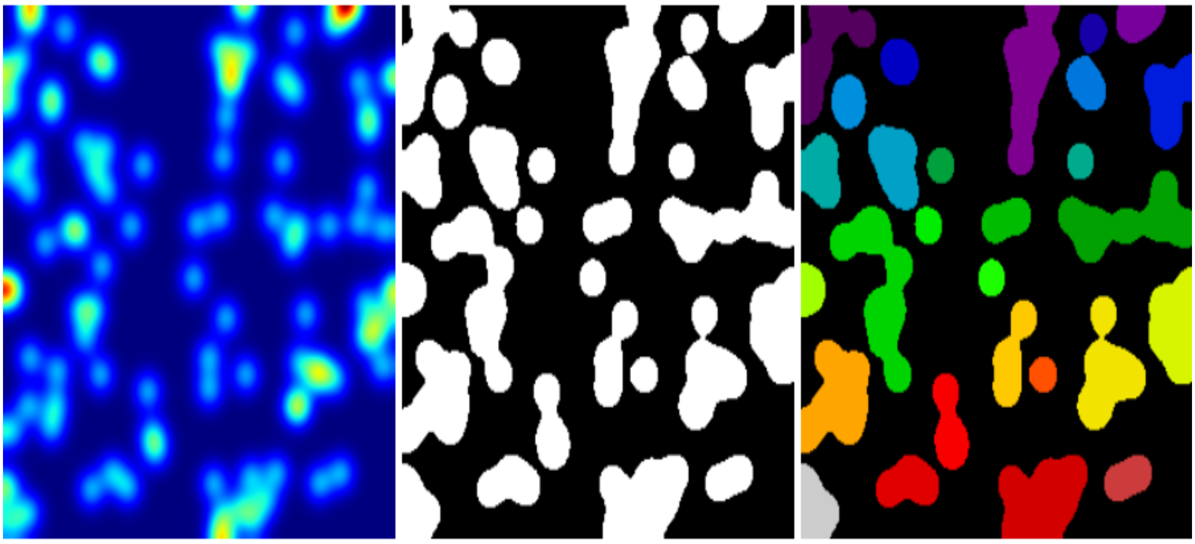
```
>>> n = 10
```

```
>>> l = 256
>>> im = np.zeros((l, l))
>>> points = l*np.random.random((2, n**2))
>>> im[(points[0]).astype(np.int), (points[1]).astype(np.in
      t)] = 1
>>> im = ndimage.gaussian_filter(im, sigma=l/(4.*n))
>>> mask = im > im.mean()
```

- **Analysis of connected components**

Label connected components: `ndimage.label`:

```
>>> label_im, nb_labels = ndimage.label(mask)
>>> nb_labels # how many regions?
16
>>> plt.imshow(label_im)
<matplotlib.image.AxesImage object at 0x...>
```



[Python source code]

Compute size, mean_value, etc. of each region:

```
>>> sizes = ndimage.sum(mask, label_im, range(nb_labels + 1
      ))
>>> mean_vals = ndimage.sum(im, label_im, range(1, nb_label
      s + 1))
```

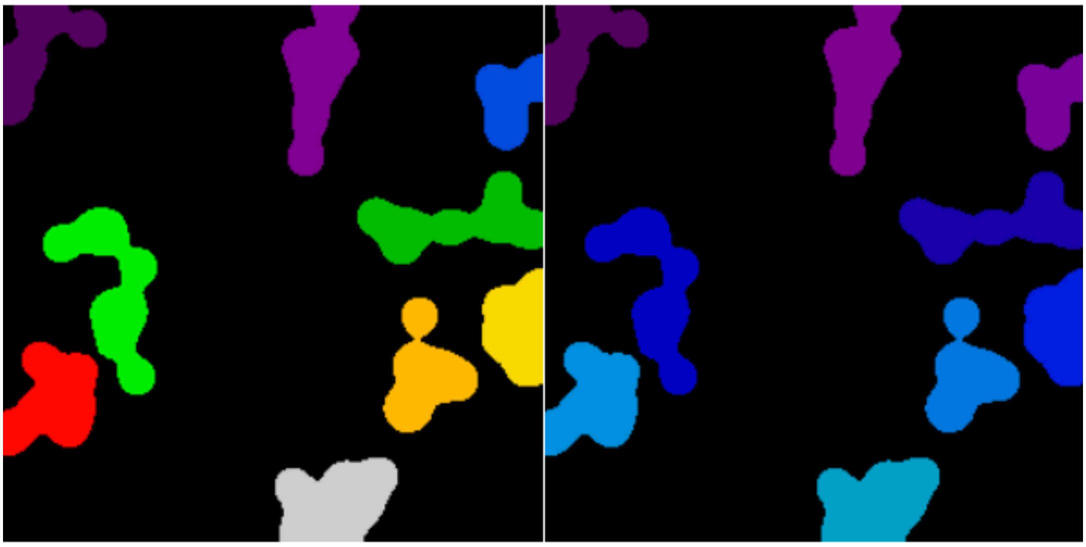
Clean up small connect components:

```
>>> mask_size = sizes < 1000
```

```
>>> remove_pixel = mask_size[label_im]
>>> remove_pixel.shape
(256, 256)
>>> label_im[remove_pixel] = 0
>>> plt.imshow(label_im)
<matplotlib.image.AxesImage object at 0x...>
```

Now reassign labels with `np.searchsorted`:

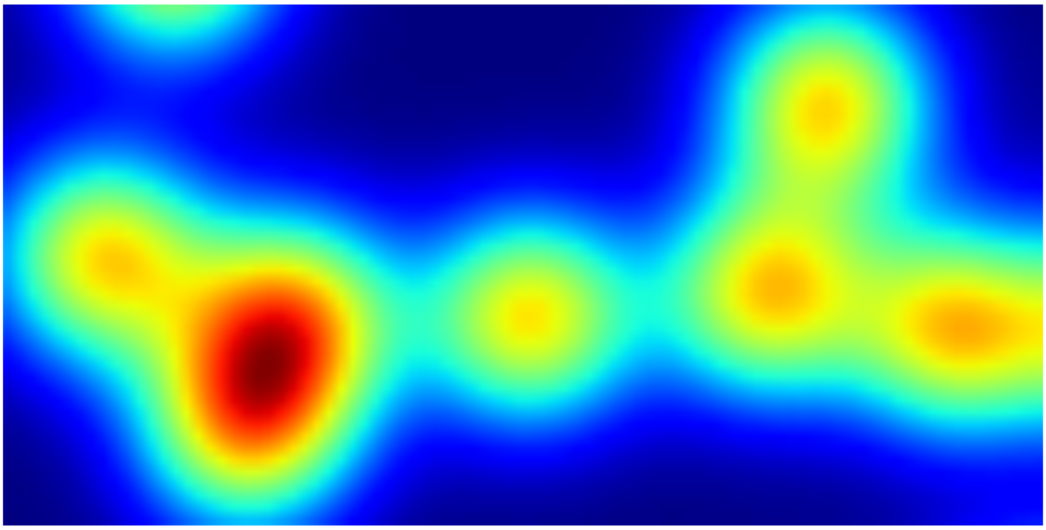
```
>>> labels = np.unique(label_im)
>>> label_im = np.searchsorted(labels, label_im)
```



[Python source code]

Find region of interest enclosing object:

```
>>> slice_x, slice_y = ndimage.find_objects(label_im==4)[0]
>>> roi = im[slice_x, slice_y]
>>> plt.imshow(roi)
<matplotlib.image.AxesImage object at 0x...>
```



[Python source code]

Other spatial measures: `ndimage.center_of_mass`, `ndimage.maximum_position`, etc.

Can be used outside the limited scope of segmentation applications.

Example: block mean:

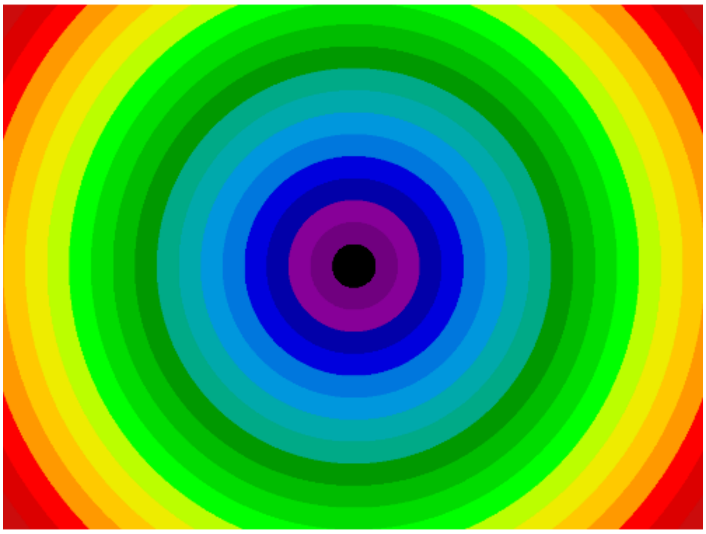
```
>>> from scipy import misc
>>> f = misc.face(gray=True)
>>> sx, sy = f.shape
>>> X, Y = np.ogrid[0:sx, 0:sy]
>>> regions = (sy//6) * (X//4) + (Y//6)  # note that we use broadcasting
>>> block_mean = ndimage.mean(f, labels=regions, index=np.arange(1,
...     regions.max() +1))
>>> block_mean.shape = (sx // 4, sy // 6)
```

[Python source code]

When regions are regular blocks, it is more efficient to use stride tricks (Example: fake dimensions with strides).

Non-regularly-spaced blocks: radial mean:

```
>>> sx, sy = f.shape
>>> X, Y = np.ogrid[0:sx, 0:sy]
>>> r = np.hypot(X - sx/2, Y - sy/2)
>>> rbin = (20* r/r.max()).astype(np.int)
>>> radial_mean = ndimage.mean(f, labels=rbin, index=np.ara
      nge(1, rbin.max() +1))
```



[Python source code]

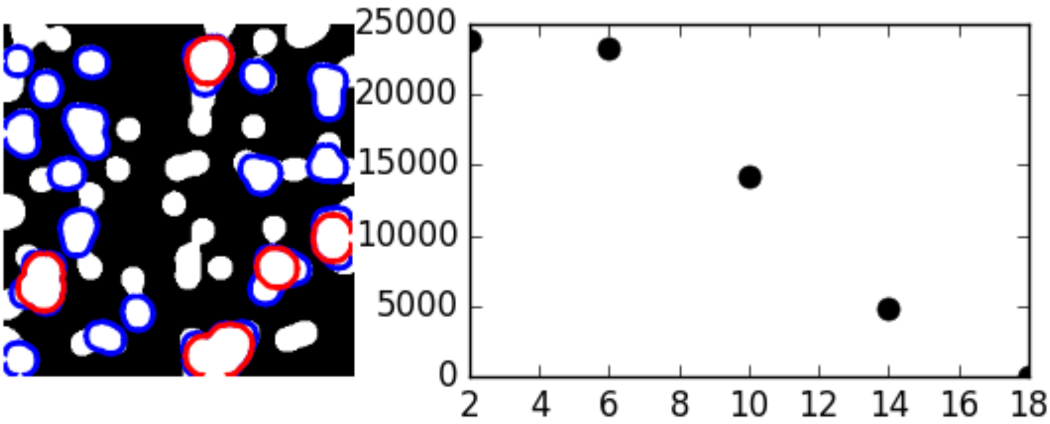
- **Other measures**

Correlation function, Fourier/wavelet spectrum, etc.

One example with mathematical morphology: granulometry

```
>>> def disk_structure(n):
...     struct = np.zeros((2 * n + 1, 2 * n + 1))
...     x, y = np.indices((2 * n + 1, 2 * n + 1))
...     mask = (x - n)**2 + (y - n)**2 <= n**2
...     struct[mask] = 1
...     return struct.astype(np.bool)
...
>>>
>>> def granulometry(data, sizes=None):
...     s = max(data.shape)
...     if sizes == None:
...         sizes = range(1, s/2, 2)
...     granulo = [ndimage.binary_opening(data, \
...         structure=disk_structure(n)).sum() for n in siz
      es]
...     return granulo
...
>>>
>>> np.random.seed(1)
```

```
>>> n = 10
>>> l = 256
>>> im = np.zeros((l, l))
>>> points = l*np.random.random((2, n**2))
>>> im[(points[0]).astype(np.int), (points[1]).astype(np.in
      t)] = 1
>>> im = ndimage.gaussian_filter(im, sigma=l/(4.*n))
>>>
>>> mask = im > im.mean()
>>>
>>> granulo = granulometry(mask, sizes=np.arange(2, 19, 4))
```



[Python source code]

See also: More on image-processing:

- The chapter on Scikit-image
- Other, more powerful and complete modules: OpenCV (Python bindings), CellProfiler, ITK with Python bindings