

浙江大学爱丁堡大学联合学院 ZJU-UoE Institute

Basic image manipulation in Python

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Learning objectives

- Perform basic image manipulation (cropping, scaling, rotating, etc)
- Interpret and manipulate image histograms



Outline

A brief recap

Basic image operations

Cropping

Scaling

Rotating

Python tools for image processing

Last time we learnt how to open and display images using Python.





Specific functions for image manipulation



Reading images as Numpy arrays

matpl tlib

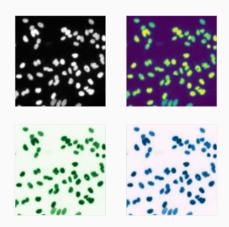
```
import matplotlib.pyplot as plt
img = plt.imread("cells.jpg")
plt.imshow(img)
plt.show()
```



```
from skimage import io
img = io.imread("cells.jpg")
io.imshow(img)
io.show()
```

Colour mapping

```
fig, ax = plt.subplots(ncols=2, nrows=2)
ax[0, 0].imshow(img, "gray")
ax[0, 1].imshow(img, "viridis")
ax[1, 0].imshow(img, "Greens")
ax[1, 1].imshow(img, "PuBu")
```



Check out the Matplotlib website for a list of colourmaps! https://matplotlib.org/stable/tutorials/colors/colormaps.html

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Basic image operations

Often you will need to crop, scale or rotate an image before further manipulation. There are many use cases for this, including

- Analysing only part of an image (cropping)
- Making sure all input images for a pipeline are the same size (scaling, cropping)
- · Aligning multiple images (e.g. in video stabilization) (rotating)

• ...



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Cropping

Cropping is as easy as subsetting the image matrix.

```
# Assume we loaded a 512 x 512 image in the img variable # Take the top-left 100 x 100 pixels img1 = img[0:100, 0:100] # shape (100, 100)
```

Cropping

Cropping is as easy as subsetting the image matrix.

```
# Assume we loaded a 512 x 512 image in the img variable
# Take the top-left 100 x 100 pixels
img1 = img[0:100, 0:100] # shape (100, 100)
# Take a 100 pixel wide strip on the left of the image...
img2 = img[:, 0:100] # shape (512, 100)
# Or on the right!
img3 = img[:, -100:] # shape (512, 100)
```

Cropping in more than two dimensions

Since images are just tensors, we can crop them in any dimensions.

```
# We loaded a 512 x 512 RGB image in img
# img.shape is (3, 512, 512)
# Extract the green channel
img_green = img[1] # Shape (512, 512)
```

Cropping in more than two dimensions

Since images are just tensors, we can crop them in any dimensions.

```
# We loaded a 512 x 512 RGB image in img
# img.shape is (3, 512, 512)
# Extract the green channel
img_green = img[1] # Shape (512, 512)

# We have a 512 x 512 video of 300 frames
# Take the first 50 frames
# video.shape is (300, 512, 512)
video_crop = video[0:50]
```

Question time

We have a 100 frames video of a 512 x 512 z-stack with 60 planes loaded in zstack.

zstack.shape is (100, 60, 512, 512)

What does this code give you?

result = stack[50:70, :, 100:300]



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Scaling

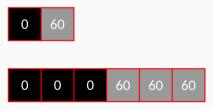


Two problems:

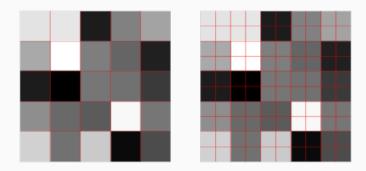
When **upscaling** we need to generate new information. When **downscaling** we need to decide "how to lose" information.

Nearest-neighbor interpolation

The simplest way to resize an image is to use nearest neighbor interpolation. Each pixel of the scaled image will have the colour of the nearest pixel in the original image. In this "1D" example, we resize a 1x2 image to 1x6

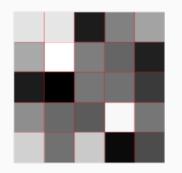


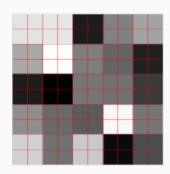
Nearest-neighbour interpolation



Upscaling of a 5x5 image by a factor of 2, to get a 10x10 image, with nearest neighbour interpolation

Nearest-neighbour interpolation





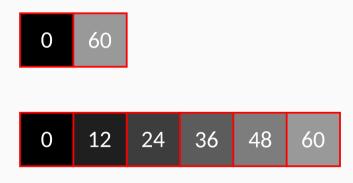
Upscaling of a 5x5 image by a factor of 2, to get a 10x10 image, with nearest neighbour interpolation

from skimage.transform import rescale
img_scaled = rescale(img, 2, order=0)

Scaling with interpolation

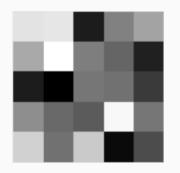
Better ways to scale an image involve changing the pixel values of the rescaled image based on their neighbourhood.

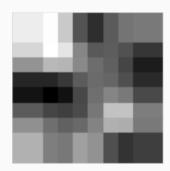
For example we could use linear interpolation



Linear interpolation

The same applies in 2D, although we need to take into accounts the values of both horizontal and vertical neighbours (bilinear interpolation).

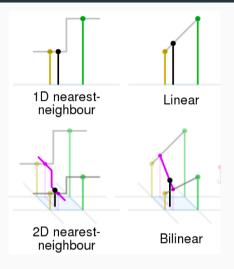




Upscaling of a 5x5 image by a factor of 2, to get a 10x10 image, with bi-linear interpolation

```
from skimage.transform import rescale
img_scaled = rescale(img, 2, order=1)
```

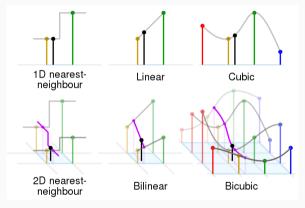
Nearest neighbor vs linear interpolation



Comparison of nearest neighbour and linear interpolation - Source: Wikipedia

Higher orders of interpolation

We can use higher orders of interpolation to produce smoother results.



Comparison of nearest neighbour and linear interpolation - Source: Wikipedia

Scikit Image supports values from 0 to 5 in the order parameter of the rescale function. O is nearest neighbor, 1 is bi-linear, 2 is bi-quadratic and so on.

Scaling to a target size

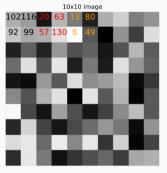
To scale to a target size, rather than by a specific factor, we can use resize instead of rescale.

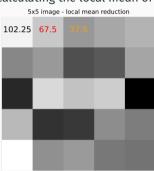
```
import matplotlib.pyplot as plt
from skimage.transform import resize, rescale

img = plt.imread("cells.jpg")
img_scaled1 = rescale(img, 2)
img_scaled2 = resize(img, (150, 150))
```

Local mean downscaling

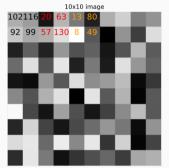
Another simple solution for downscaling is calculating the local mean of each pixel

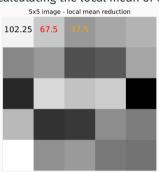




Local mean downscaling

Another simple solution for downscaling is calculating the local mean of each pixel





```
from skimage.transform import downscale_local_mean
img_small = downscale_local_mean(img, (2,2))
```

Image needs to be padded if the size is not a multiple of the downscaling factor. This method is fast but not good at keeping fine details.

Scaling summary

skimage.transform.rescale \rightarrow scales an image by a specific factor (>1 upscaling; <1 downscaling.). Can specify a different scaling factor for each dimension of the image.

 $\mathtt{skimage.transform.resize} \rightarrow \mathbf{scales} \ an \ image \ to \ a \ target \ size.$

 ${\tt skimage.transform.downscale_local_mean} \rightarrow {\tt downscales} \ the \ image \ by \ a \ specific \ factor \ (>1), \\ using \ the \ local \ mean \ of \ each \ pixel.$

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A brief recap

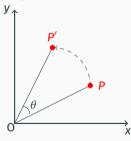
Basic image operations

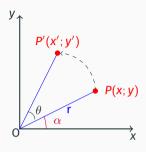
Cropping

Scaling

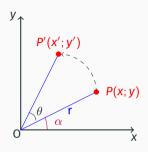
Rotating

We want to rotate a point P(x, y) around the origin by an angle θ to get P'(x', y').





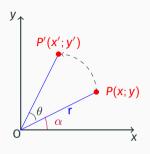
$$P: \begin{cases} x = r\cos(\alpha) \\ y = r\sin(\alpha) \end{cases} \quad P': \begin{cases} x' = r\cos(\alpha + \theta) \\ y' = r\sin(\alpha + \theta) \end{cases}$$



$$P: \begin{cases} x = r\cos(\alpha) \\ y = r\sin(\alpha) \end{cases} \quad P': \begin{cases} x' = r\cos(\alpha + \theta) \\ y' = r\sin(\alpha + \theta) \end{cases}$$

$$P': \begin{cases} x' = r\cos(\alpha)\cos(\theta) - r\sin(\alpha)\sin(\theta) \\ y' = r\sin(\alpha)\cos(\theta) + r\sin(\theta)\cos(\alpha) \end{cases}$$

Why? Wikipedia to the rescue!



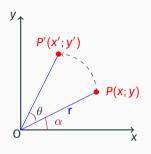
$$P: \begin{cases} x = r\cos(\alpha) \\ y = r\sin(\alpha) \end{cases} \quad P': \begin{cases} x' = r\cos(\alpha + \theta) \\ y' = r\sin(\alpha + \theta) \end{cases}$$

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Why? Wikipedia to the rescue!

Thus:

$$P':\begin{cases} x' = x\cos(\theta) - y\sin(\theta) \\ y' = y\cos(\theta) + x\sin(\theta) \end{cases}$$



Thus:

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Why? Wikipedia to the rescue!

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

Transformation (rotation) matrix

Rotating in Scikit Image

To rotate an image we will:

- Offset our image so that it is centered on the origin
- · Generate a rotation matrix
- Multiply the coordinates of each pixel by the rotation matrix

Rotating in Scikit Image

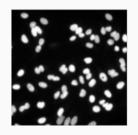
To rotate an image we will:

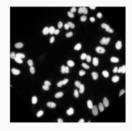
- Offset our image so that it is centered on the origin
- · Generate a rotation matrix
- · Multiply the coordinates of each pixel by the rotation matrix

Luckily, Scikit Image has a ready function for that, skimage.transform.rotate.

```
import matplotlib.pyplot as plt
from skimage.transform import rotate
img = plt.imread("cells.jpg")
img_rotated = rotate(img, 20)

plt.imshow(img_rotated, cmap="gray")
plt.show()
```





Note: we lost part of the image and we "gained" black pixels around it. By default, rotate performs bilinear interpolation.

Optional exercise - want to try by yourself?

It might be interesting to try to code image rotation by yourself.

Hints:

- · You can generate transformation matrices using skimage.transform.SimilarityTransform
- You will need three matrices: one translation matrix to offset your image by (-xcenter, -ycenter); a rotation matrix to rotate your image; and finally another translation matrix to translate your image back to its original position.
- You can combine the matrices as m1+m2+m3
- \bullet You can use ${\tt skimage.transform.warp}$ to apply the transformation matrix to your image.

If you are stuck, try to look at the source code for rotate!