

Make images come alive with scikit- image

IMAGE PROCESSING IN PYTHON

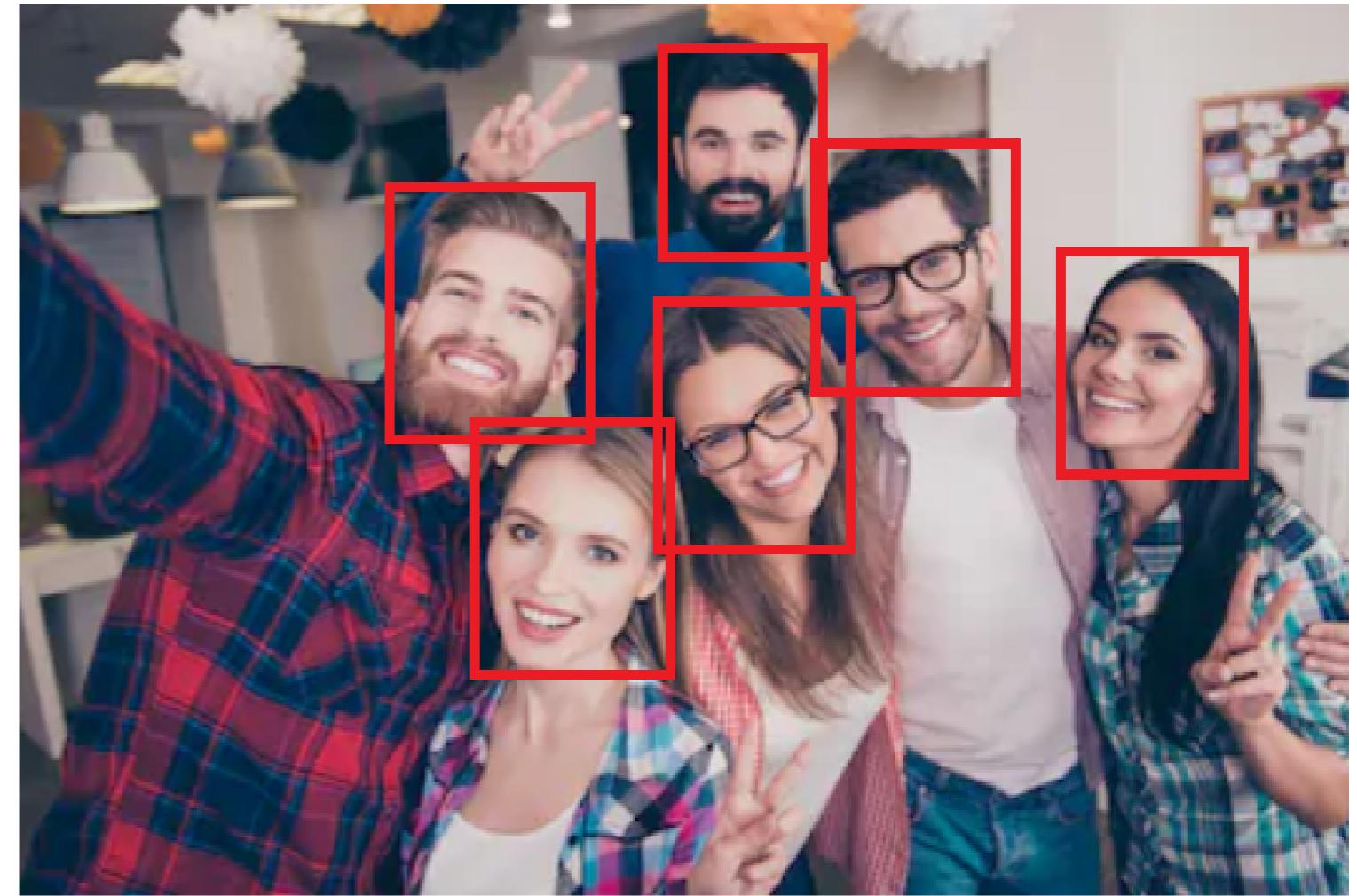


Rebeca Gonzalez
Data Engineer

What is image processing?

Operations on images and videos to:

- Enhance an image
- Extract useful information
- Analyze it and make decisions



What is image processing?

Operations to on images and videos to:

- Enhance an image
- Extract useful information
- Analyze it and make decisions

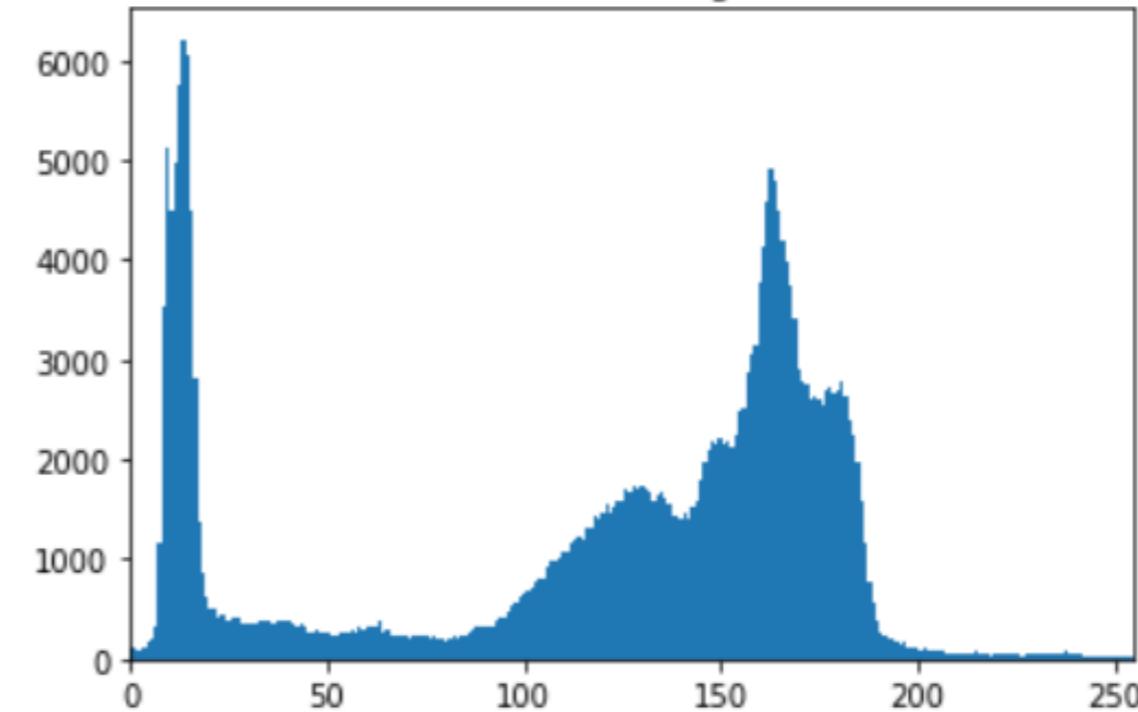
Original Image



Thresholded Image

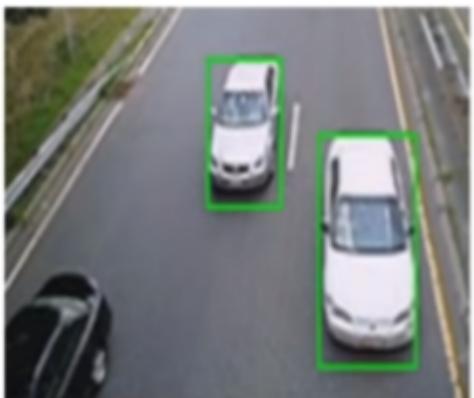
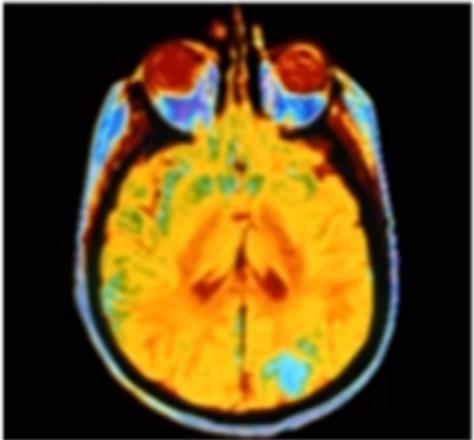


Bimodal histogram



Applications

- Medical image analysis
- Artificial intelligence
- Image restoration and enhancement
- Geospatial computing
- Surveillance
- Robotic vision
- Automotive safety
- And many more...



Purposes

1. Visualization:
 - Objects that are not visible
2. Image sharpening and restoration
 - A better image
3. Image retrieval
 - Seek for the image of interest
4. Measurement of pattern
 - Measures various objects
5. Image Recognition
 - Distinguish objects in an image

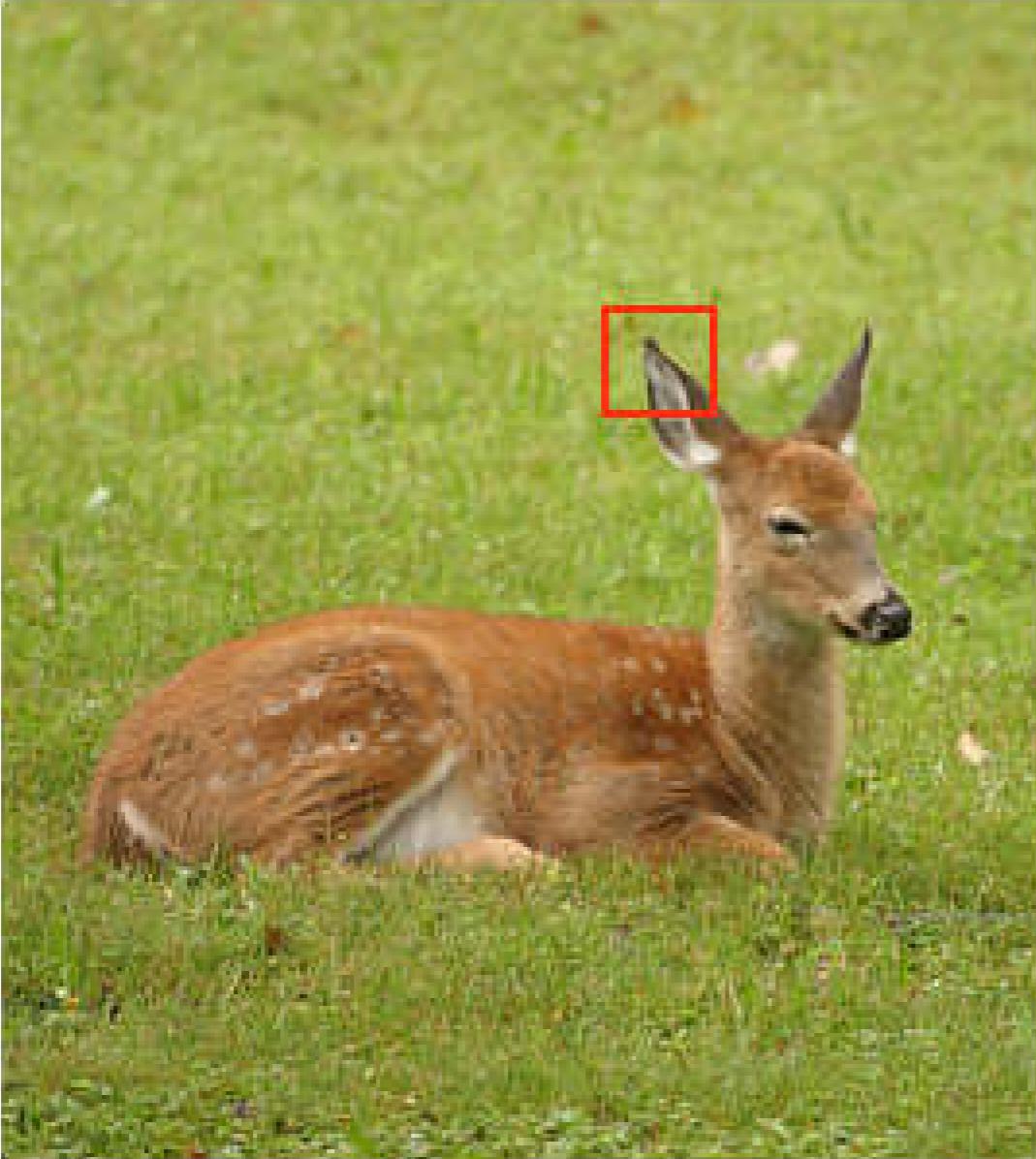
Intro to scikit-image

- Easy to use
- Makes use of Machine Learning
- Out of the box complex algorithms

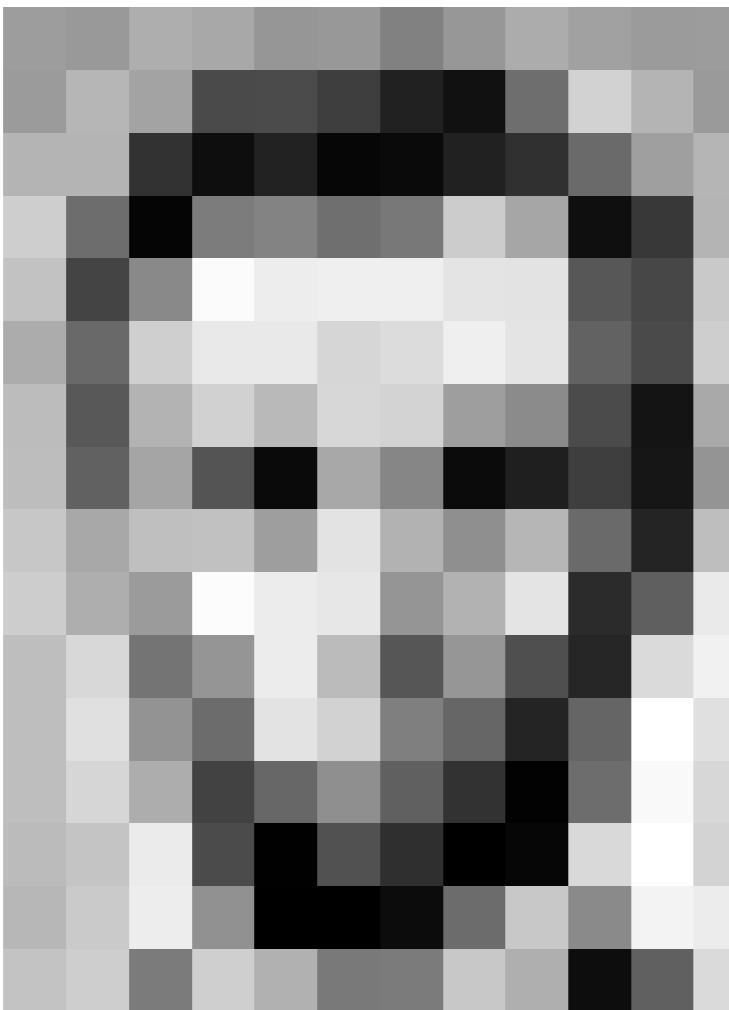


scikit-image
image processing in python

What is an image?



What is an image?



157	153	174	168	150	152	129	151	172	161	155	156
155	182	168	74	75	62	93	17	110	210	180	154
180	180	50	14	34	6	10	33	43	105	159	181
206	169	5	124	191	111	120	204	166	15	56	180
194	68	137	251	237	239	239	228	227	87	71	201
172	106	207	233	233	214	220	239	228	98	74	206
188	88	179	209	185	215	211	158	139	75	20	169
189	97	165	84	10	168	194	11	31	62	22	148
199	168	191	163	158	227	178	143	182	105	36	190
206	174	165	252	236	231	149	178	228	43	95	234
190	216	116	149	236	187	85	150	79	38	218	241
190	224	147	108	227	210	127	102	35	101	255	224
190	214	173	66	103	143	96	59	2	109	249	215
187	196	236	75	1	81	47	0	6	217	254	211
183	202	237	145	0	0	12	108	209	138	243	236
195	206	129	207	177	121	129	209	179	10	96	218

157	153	174	168	150	152	129	151	172	161	155	156
155	182	163	74	75	62	93	17	110	210	180	154
180	180	50	14	34	6	10	33	48	106	159	181
206	169	5	124	191	111	120	204	166	15	56	180
194	68	137	251	237	239	239	228	227	87	71	201
172	106	207	233	233	214	220	239	228	98	74	206
188	88	179	209	185	215	211	158	139	75	20	169
189	97	165	84	10	168	194	11	31	62	22	148
199	168	191	163	158	227	178	143	182	105	36	190
206	174	165	252	236	231	149	178	228	43	95	234
190	216	116	149	236	187	85	150	79	38	218	241
190	224	147	108	227	210	127	102	35	101	255	224
190	214	173	66	103	143	96	59	2	109	249	215
187	196	236	75	1	81	47	0	6	217	256	211
183	202	237	145	0	0	12	108	209	138	243	236
195	206	123	207	177	121	123	209	179	10	96	218

Images in scikit-image

```
from skimage import data  
rocket_image = data.rocket()
```



RGB channels

RGB



Red channel



Green channel



Blue channel



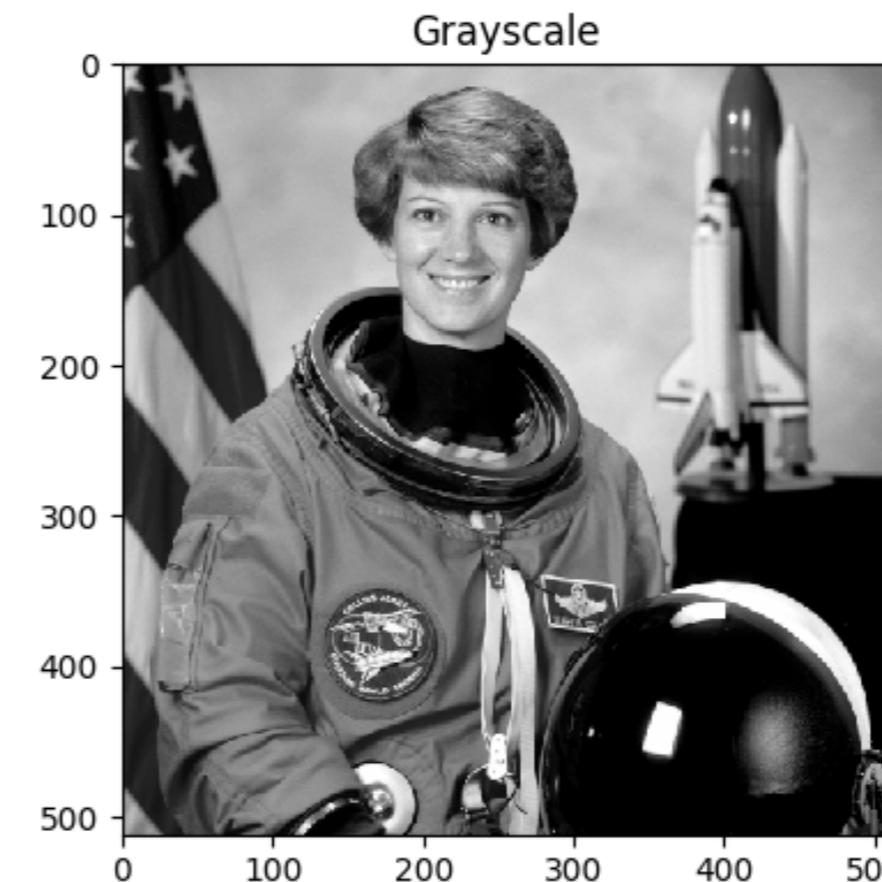
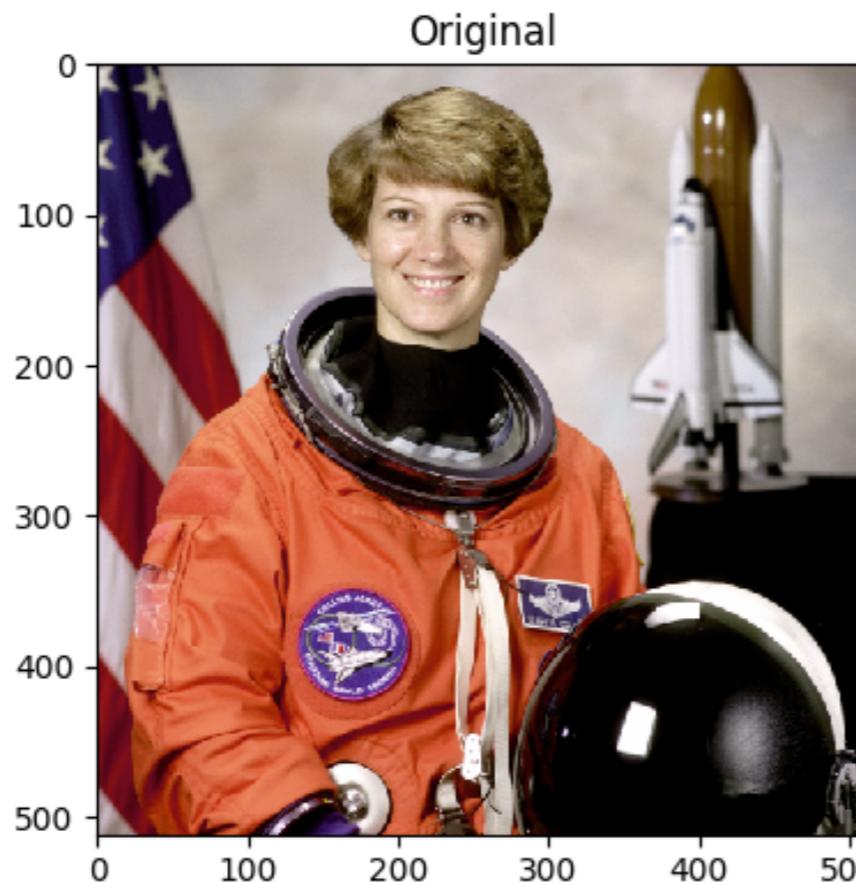
Grayscaled images



230	229	232	234	235	232	148
237	236	236	234	233	234	152
255	255	255	251	230	236	161
99	90	67	37	94	247	130
222	152	255	129	129	246	132
154	199	255	150	189	241	147
216	132	162	163	170	239	122

RGB vs Grayscale

```
from skimage import color  
grayscale = color.rgb2gray(original)  
rgb = color.gray2rgb(grayscale)
```



Visualizing images in the course

Don't worry about Matplotlib!

```
def show_image(image, title='Image', cmap_type='gray'):  
    plt.imshow(image, cmap=cmap_type)  
    plt.title(title)  
    plt.axis('off')  
    plt.show()
```

Visualizing images in the course

```
from skimage import color  
grayscale = color.rgb2gray(original)  
  
show_image(grayscale, "Grayscale")
```

Grayscale

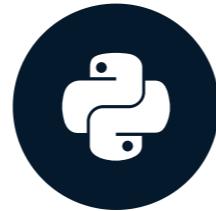


Let's practice!

IMAGE PROCESSING IN PYTHON

NumPy for images

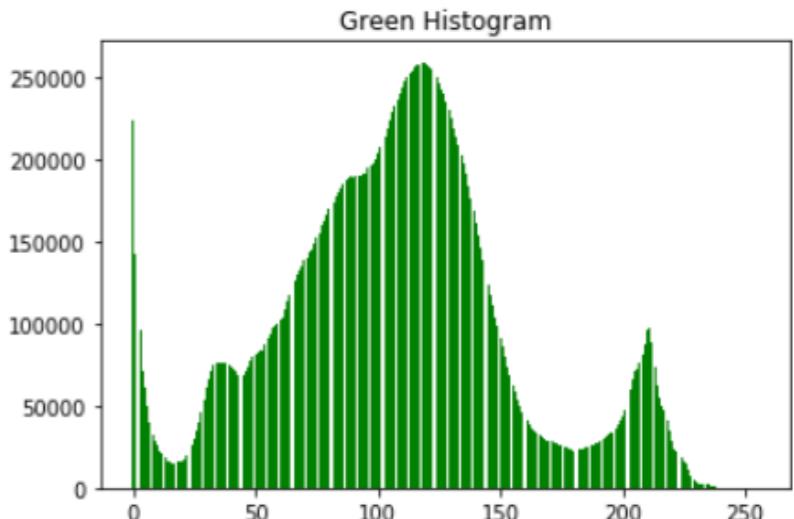
IMAGE PROCESSING IN PYTHON



Rebeca Gonzalez
Data Engineer

NumPy for images

- Fundamentals of image processing techniques
 - Flipping
 - Extract and analyze features



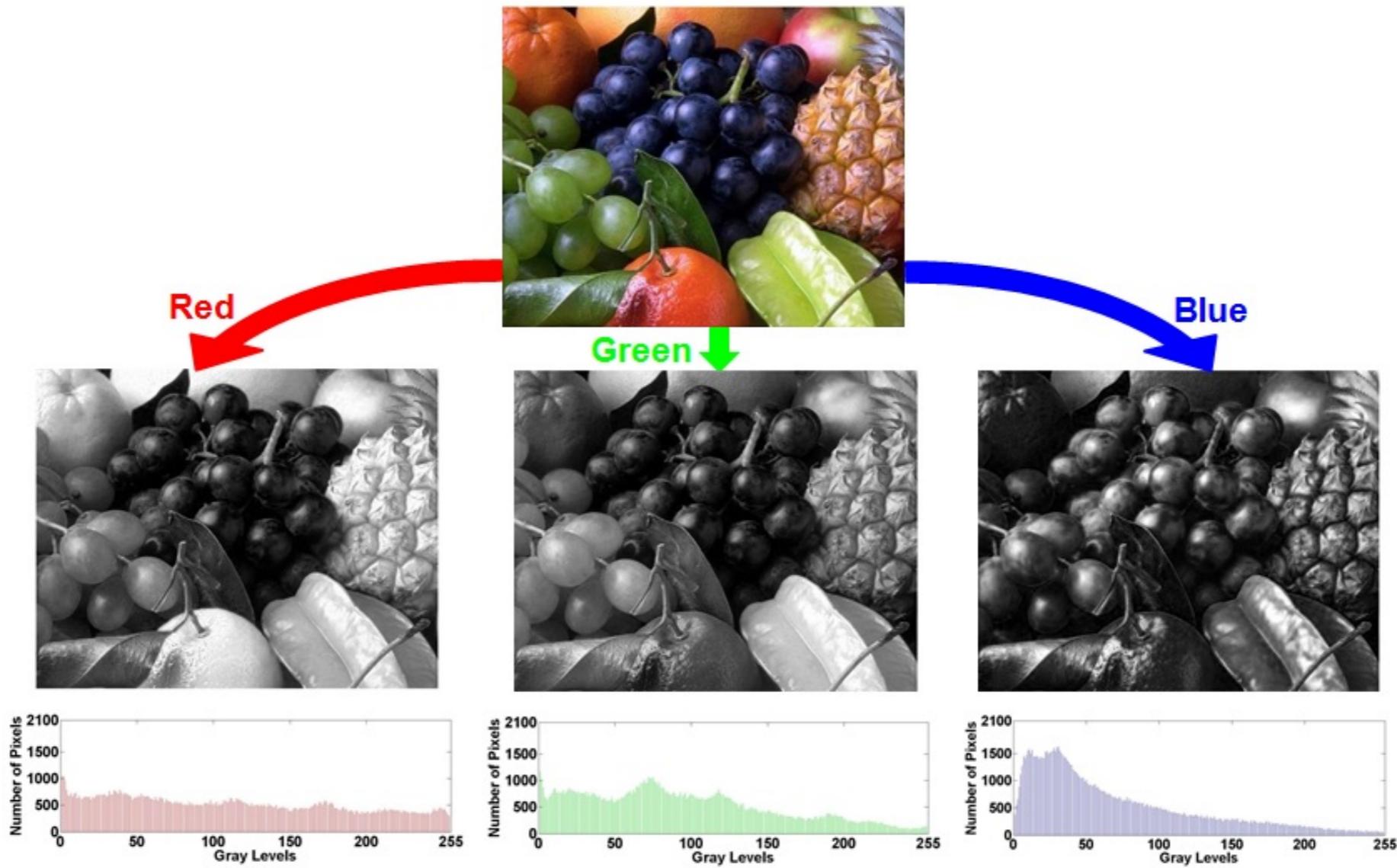
Images as NdArrays



```
# Loading the image using Matplotlib  
madrid_image = plt.imread('/madrid.jpeg')  
  
type(madrid_image)
```

```
<class 'numpy.ndarray'>
```

Colors with NumPy



Colors with NumPy

```
# Obtaining the red values of the image  
red = image[:, :, 0]  
  
# Obtaining the green values of the image  
green = image[:, :, 1]  
  
# Obtaining the blue values of the image  
blue = image[:, :, 2]
```

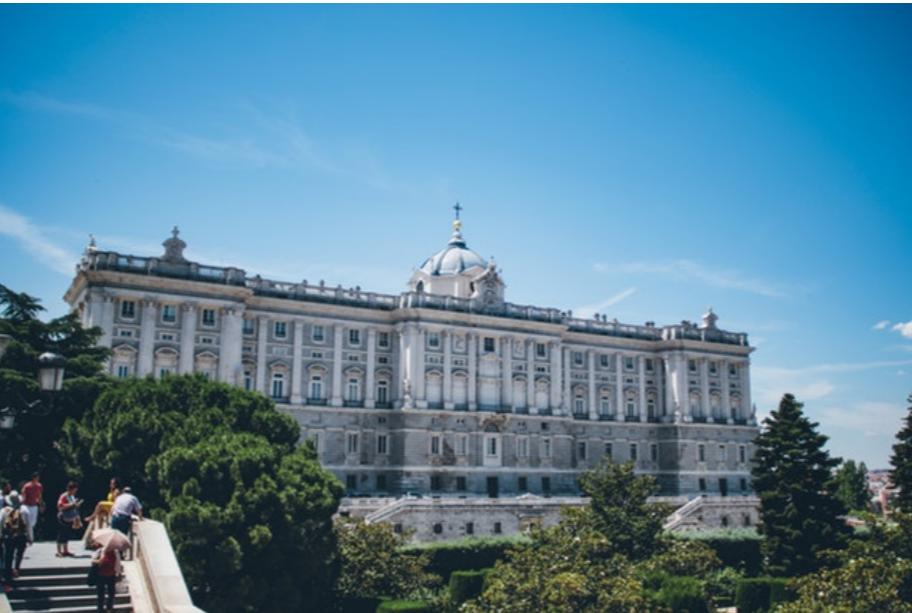


Colors with NumPy



```
plt.imshow(red, cmap="gray")
plt.title('Red')
plt.axis('off')
plt.show()
```

Shapes



```
# Accessing the shape of the image  
madrid_image.shape
```

(426, 640, 3)

Sizes



```
# Accessing the shape of the image  
madrid_image.size
```

817920

Flipping images: vertically

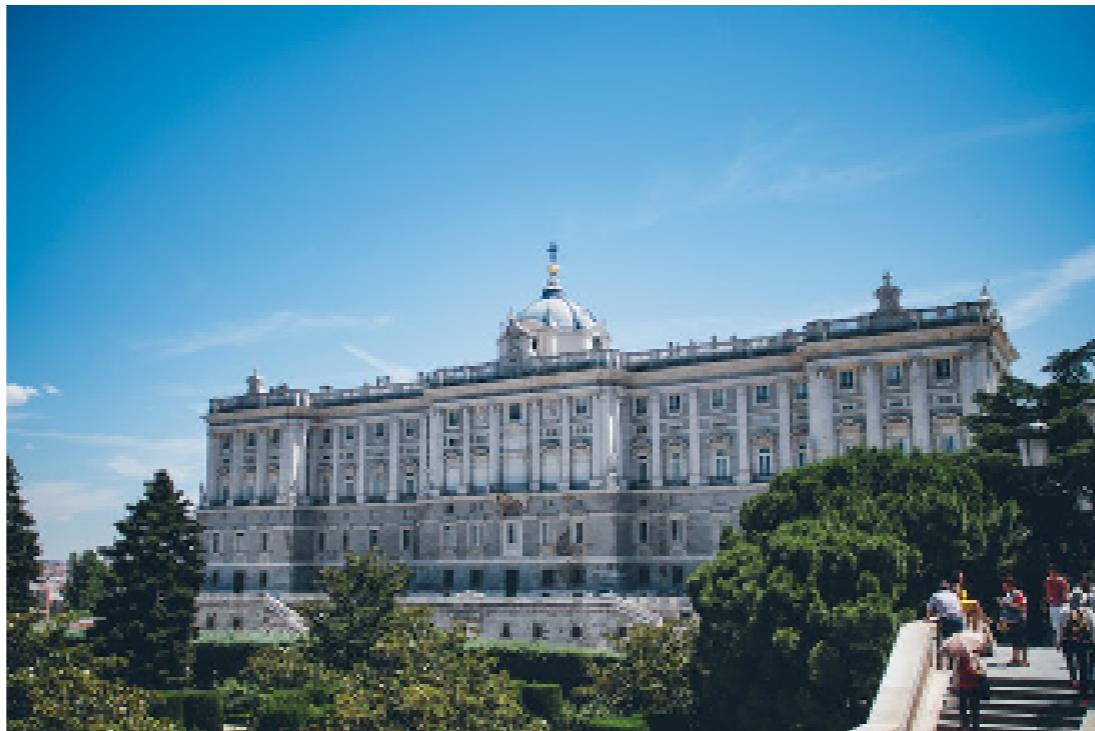
```
# Flip the image in up direction  
vertically_flipped = np.flipud(madrid_image)  
  
show_image(vertically_flipped, 'Vertically flipped image')
```



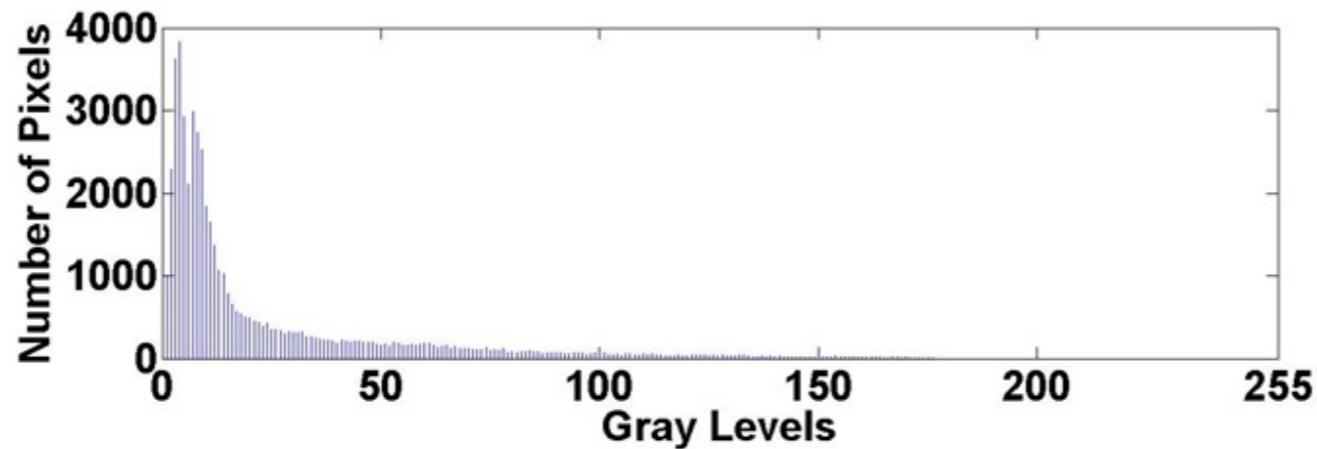
Flipping images: horizontally

```
# Flip the image in left direction  
horizontally_flipped = np.fliplr(madrid_image)  
  
show_image(horizontally_flipped, 'Horizontally flipped image')
```

Horizontally flipped image



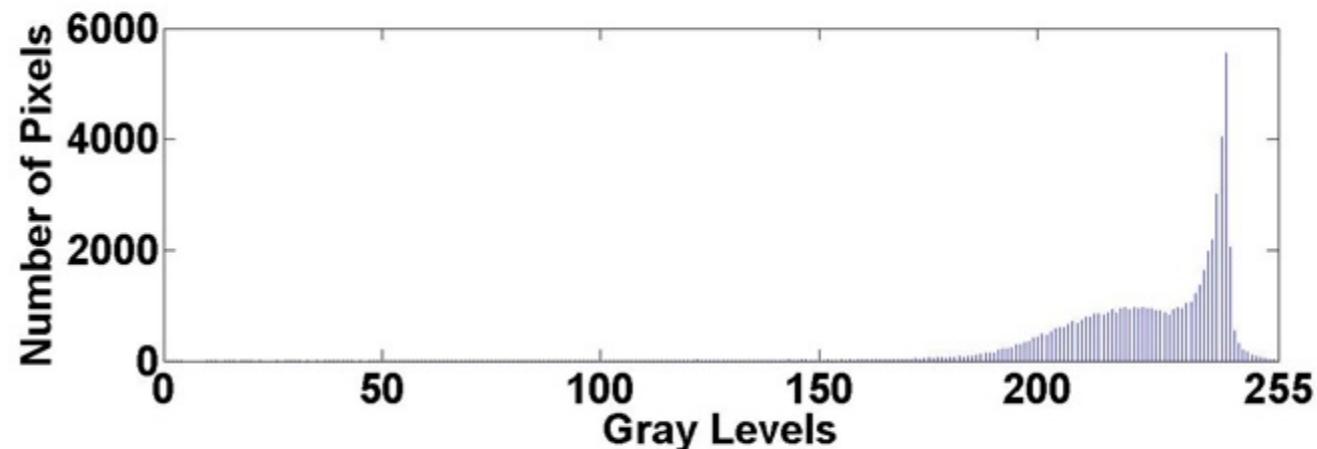
What is a histogram?



(a)



(b)

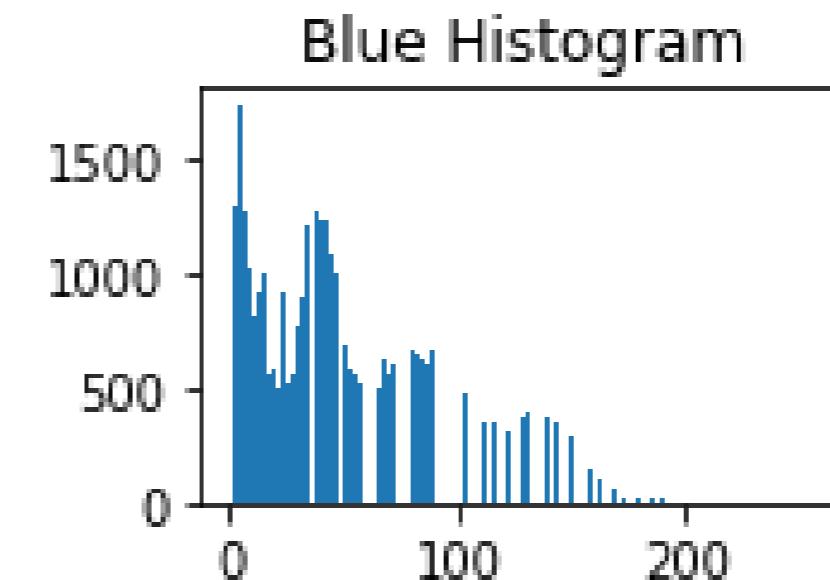
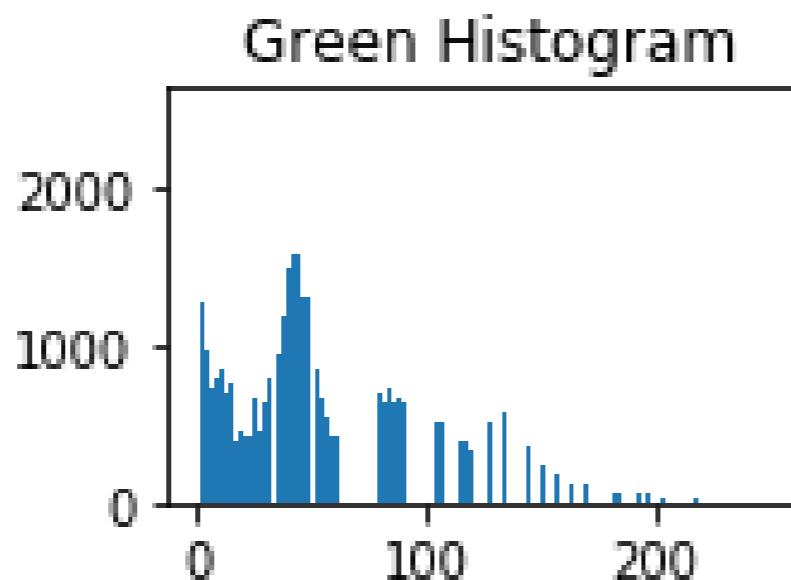
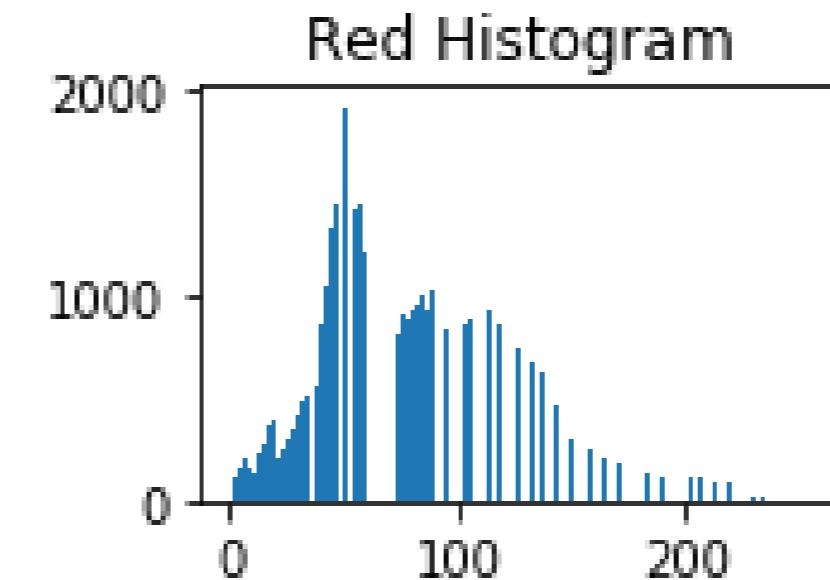
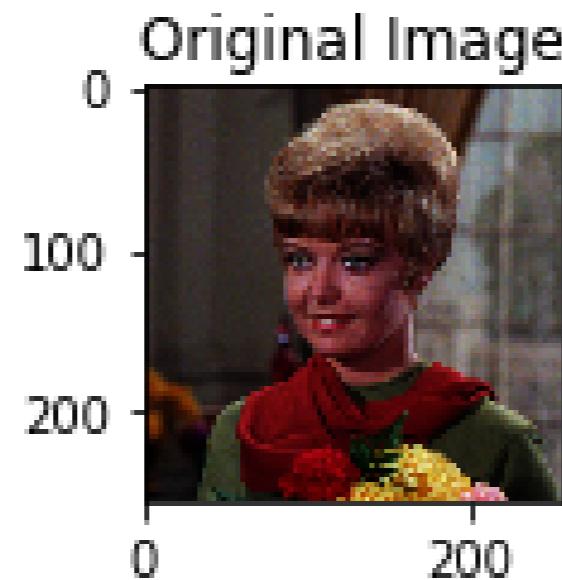


(a)



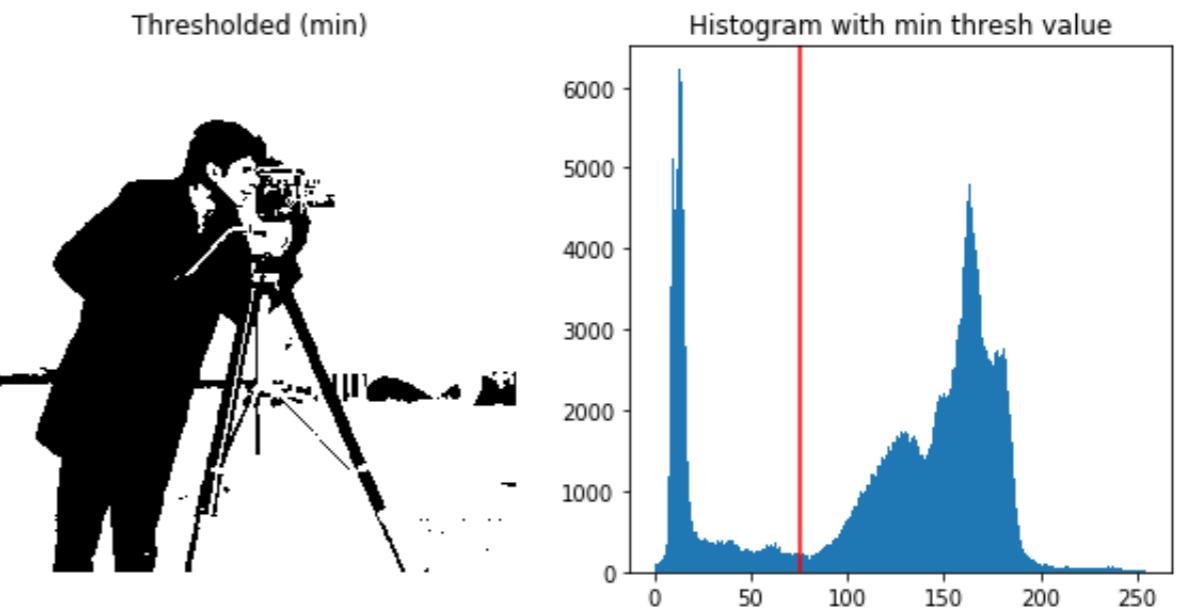
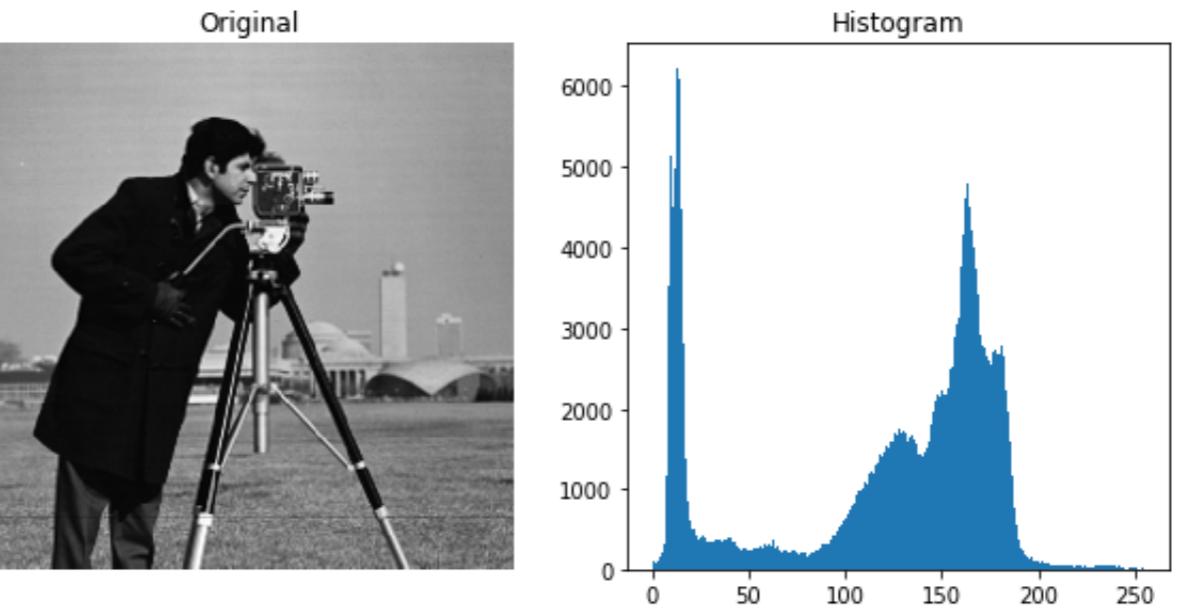
(b)

Color histograms

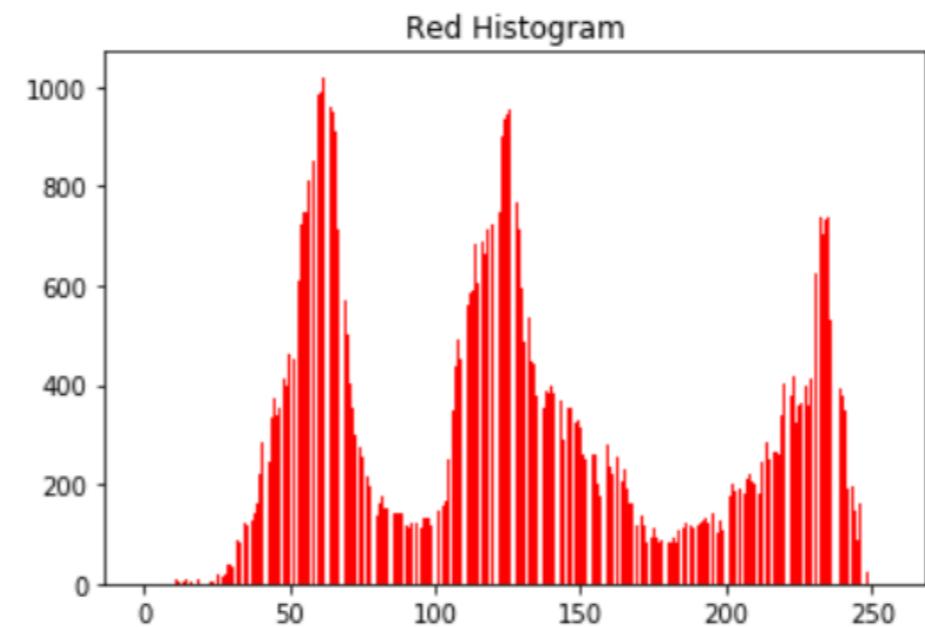


Applications of histograms

- Analysis
- Thresholding
- Brightness and contrast
- Equalize an image



Histograms in Matplotlib

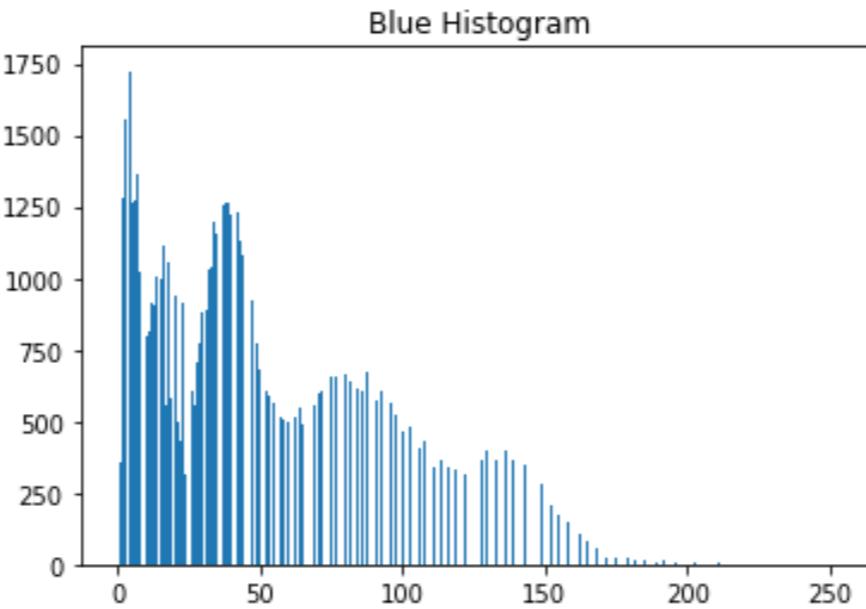


```
# Red color of the image  
red = image[:, :, 0]  
  
# Obtain the red histogram  
plt.hist(red.ravel(), bins=256)
```

Visualizing histograms with Matplotlib

```
blue = image[:, :, 2]

plt.hist(blue.ravel(), bins=256)
plt.title('Blue Histogram')
plt.show()
```



Let's practice!

IMAGE PROCESSING IN PYTHON

Getting started with thresholding

IMAGE PROCESSING IN PYTHON



Rebeca Gonzalez

Data Engineer

Thresholding

Partitioning an image into a foreground and background

By making it **black and white**

We do so by setting each pixel to:

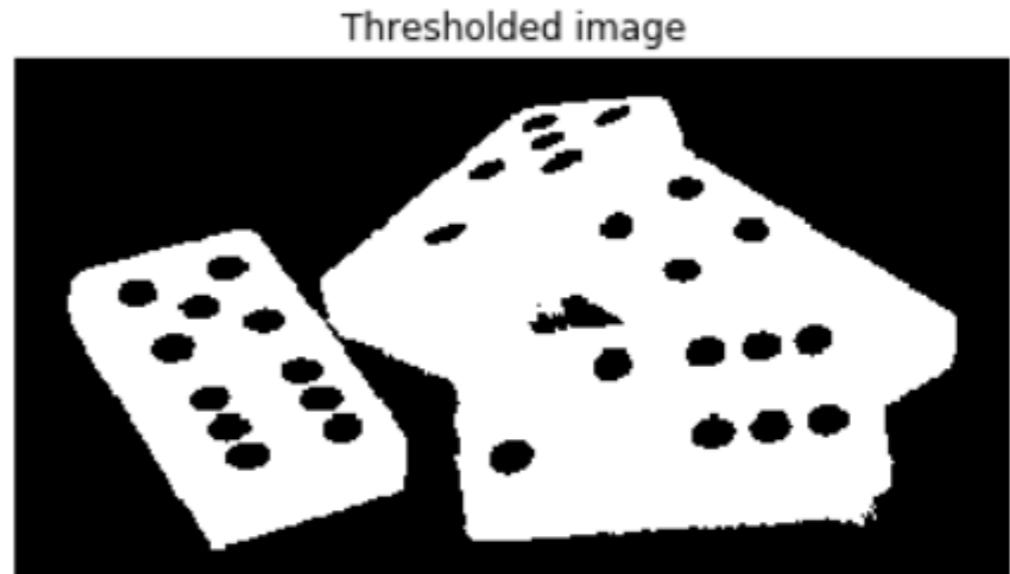
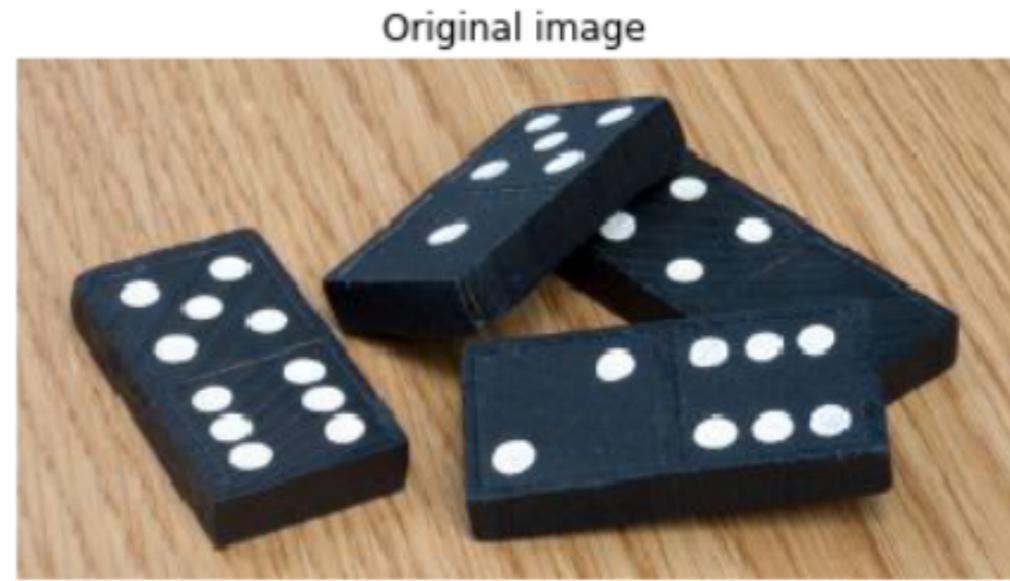
- 255 (white) if $\text{pixel} > \text{thresh value}$
- 0 (black) if $\text{pixel} < \text{thresh value}$



Thresholding

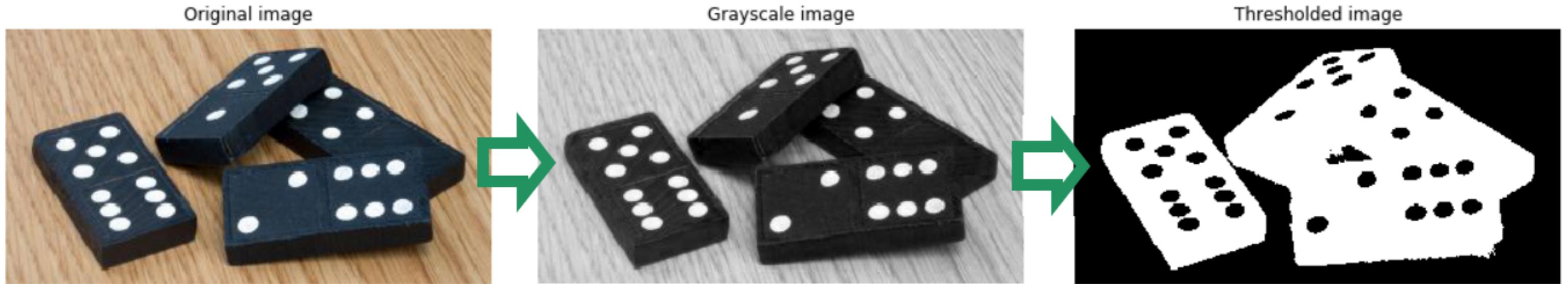
Simplest method of image segmentation

- Isolate objects
 - Object detection
 - Face detection
 - Etc.



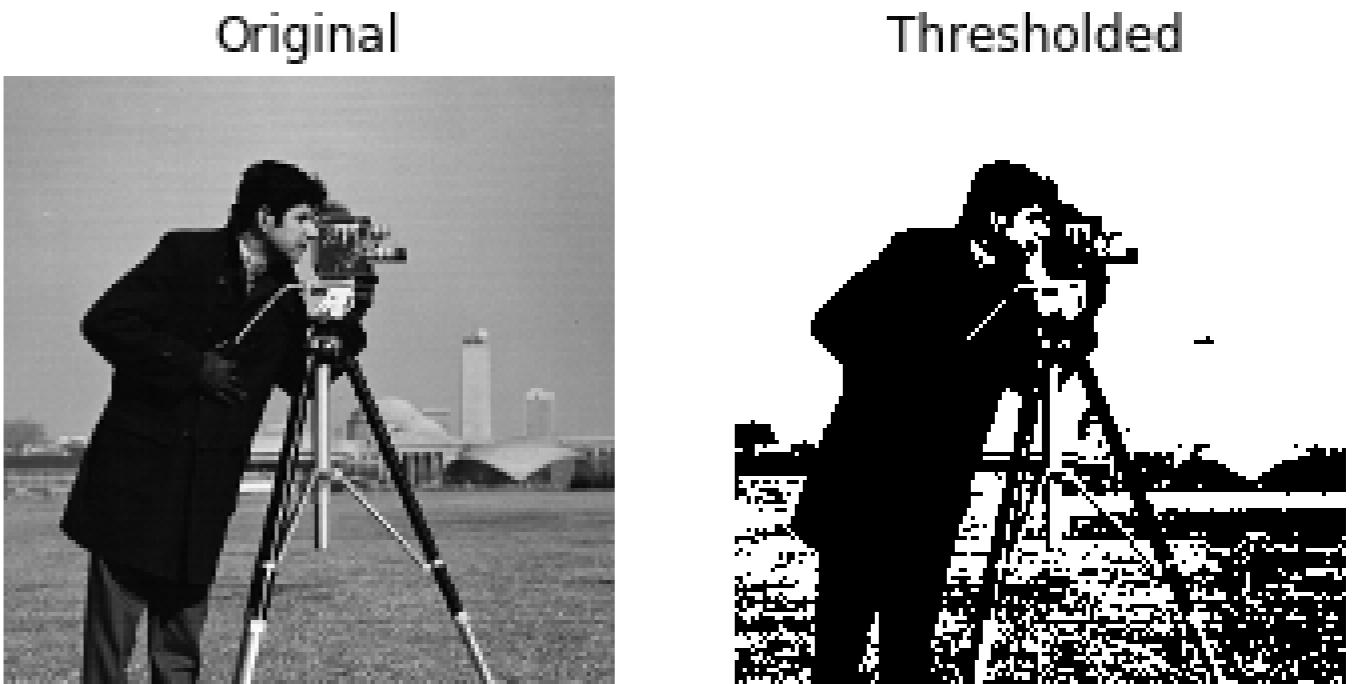
Thresholding

Only from **grayscale** images



Apply it

```
# Obtain the optimal threshold value  
thresh = 127  
  
# Apply thresholding to the image  
binary = image > thresh  
  
# Show the original and thresholded  
show_image(image, 'Original')  
show_image(binary, 'Thresholded')
```



Inverted thresholding

```
# Obtain the optimal threshold value  
thresh = 127  
  
# Apply thresholding to the image  
inverted_binary = image <= thresh  
  
# Show the original and thresholded  
show_image(image, 'Original')  
show_image(inverted_binary,  
           'Inverted thresholded')
```

Original Image



Inverted Thresholded



Categories

- **Global or histogram based:** good for uniform backgrounds
- **Local or adaptive:** for uneven background illumination

Original

Region-based segmentation

Let us first determine markers of the coins and the background. These markers are pixels that we can label unambiguously as either object or background. Here, the markers are found at the two extreme parts of the histogram of grey values:

```
*** markers = np.zeros_like(coins)
```

Global thresholding

Region-based segmentation

determine markers of the coins and the background. These markers are pixels that we can label unambiguously as either object or background - ent. Find at the two extreme parts of the histogram of grey values:

```
*** markers = np.zeros_like(coins)
```

Local thresholding

Region-based segmentation

Let us first determine markers of the coins and the background. These markers are pixels that we can label unambiguously as either object or background. Here, the markers are found at the two extrema parts of the histogram of grey values:

```
*** markers = np.zeros_like(coins)
```

Try more thresholding algorithms

```
from skimage.filters import try_all_threshold

# Obtain all the resulting images
fig, ax = try_all_threshold(image, verbose=False)

# Showing resulting plots
show_plot(fig, ax)
```

Try more thresholding algorithms

Original

Region-based segmentation

Let us first determine markers of the coins and the background. These markers are pixels that we can label unambiguously as either object or background. Here, the markers are found at the two extreme parts of the histogram of grey values:

```
205 markers = np.zeros_like(coins)
```

Li

Region-based segmentation

Let us first determine markers of the coins and the background. These markers are pixels that we can label unambiguously as either object or background. Here, the markers are found at the two extreme parts of the histogram of grey values:

```
205 markers = np.zeros_like(coins);
```

Isodata

Region-based segmentation

Determine markers of the coins and the background. These markers are pixels that we can label unambiguously as either object or background. Here, the markers are found at the two extreme parts of the histogram of grey values:

```
205 markers = np.zeros_like(coins);
```

Minimum

Region-based segmentation

Determine markers of the coins and the background. These markers are pixels that we can label unambiguously as either object or background. Here, the markers are found at the two extreme parts of the histogram of grey values:

```
205 markers = np.zeros_like(coins);
```

Otsu

Region-based segmentation

Determine markers of the coins and the background. These markers are pixels that we can label unambiguously as either object or background. Here, the markers are found at the two extreme parts of the histogram of grey values:

```
205 markers = np.zeros_like(coins);
```

Mean

Region-based segmentation

Determine markers of the coins and the background. These markers are pixels that we can label unambiguously as either object or background. Here, the markers are found at the two extreme parts of the histogram of grey values:

```
205 markers = np.zeros_like(coins);
```

Triangle

Region-based segmentation

Determine markers of the coins and the background. These markers are pixels that we can label unambiguously as either object or background. Here, the markers are found at the two extreme parts of the histogram of grey values:

```
205 markers = np.zeros_like(coins);
```

Yen

Region-based segmentation

Let us first determine markers of the coins and the background. These markers are pixels that we can label unambiguously as either object or background. Here, the markers are found at the two extreme parts of the histogram of grey values:

```
205 markers = np.zeros_like(coins);
```

Optimal thresh value

Global

Uniform background

```
# Import the otsu threshold function
from skimage.filters import threshold_otsu

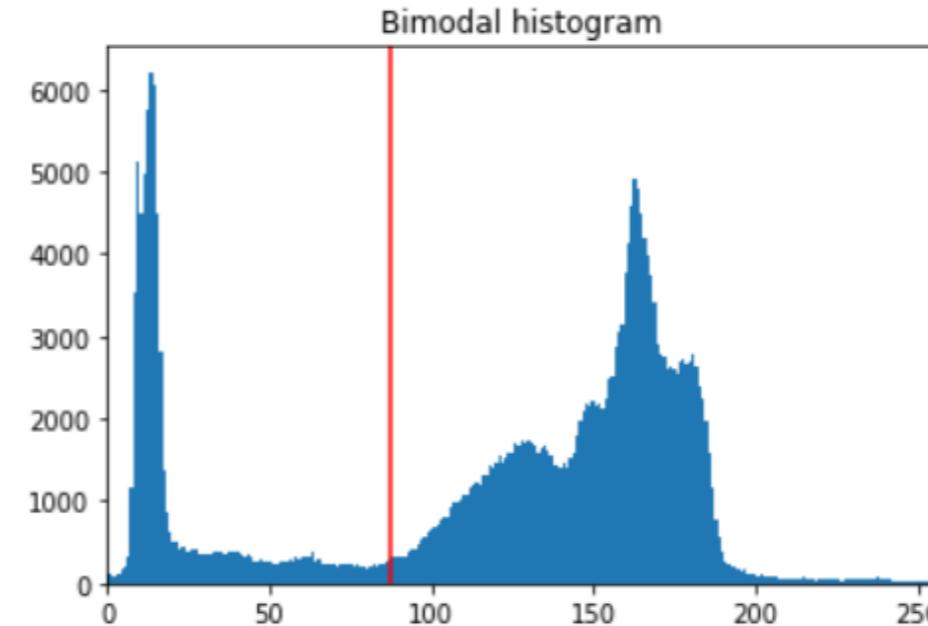
# Obtain the optimal threshold value
thresh = threshold_otsu(image)

# Apply thresholding to the image
binary_global = image > thresh
```

Optimal thresh value

Global

```
# Show the original and binarized image  
show_image(image, 'Original')  
show_image(binary_global, 'Global thresholding')
```



Optimal thresh value

Local

Uneven background

```
# Import the local threshold function
from skimage.filters import threshold_local

# Set the block size to 35
block_size = 35

# Obtain the optimal local thresholding
local_thresh = threshold_local(text_image, block_size, offset=10)

# Apply local thresholding and obtain the binary image
binary_local = text_image > local_thresh
```

Optimal thresh value

Local

```
# Show the original and binarized image  
show_image(image, 'Original')  
show_image(binary_local, 'Local thresholding')
```

Original

Region-based segmentation

Let us first determine markers of the coins and the background. These markers are pixels that we can label unambiguously as either object or background. Here, the markers are found at the two extreme parts of the histogram of grey values:

```
## markers = np.zeros_like(edged)
```

Local thresholding

Region-based segmentation

Let us first determine markers of the coins and the background. These markers are pixels that we can label unambiguously as either object or background. Here, the markers are found at the two extreme parts of the histogram of grey values:

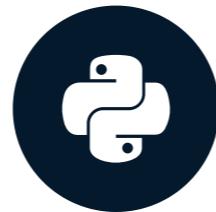
```
## markers = np.zeros_like(edged)
```

Let's practice!

IMAGE PROCESSING IN PYTHON

Jump into filtering

IMAGE PROCESSING IN PYTHON

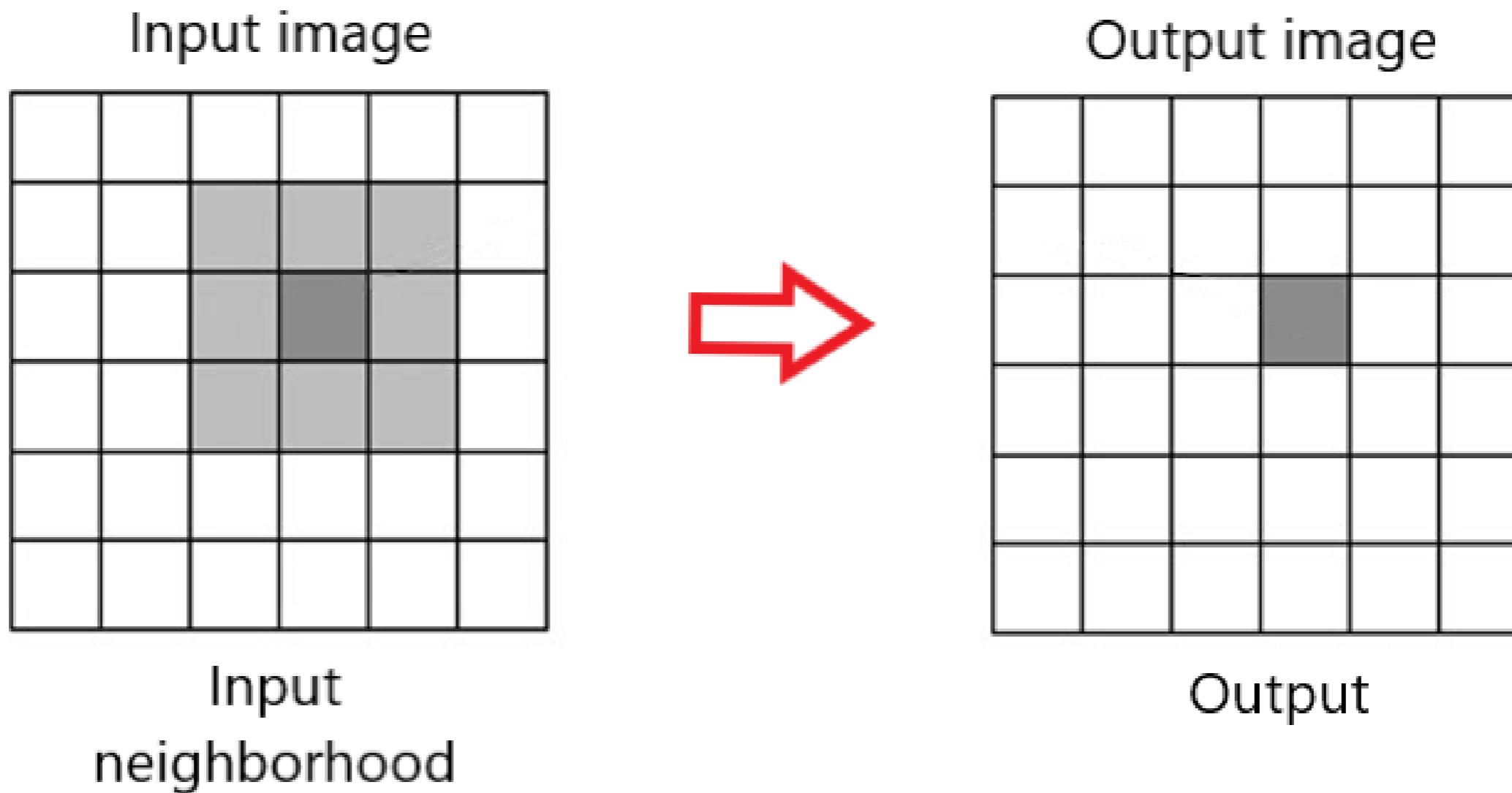


Rebeca Gonzalez
Data Engineer

Filters

- Enhancing an image
- Emphasize or remove features
- Smoothing
- Sharpening
- Edge detection

Neighborhoods

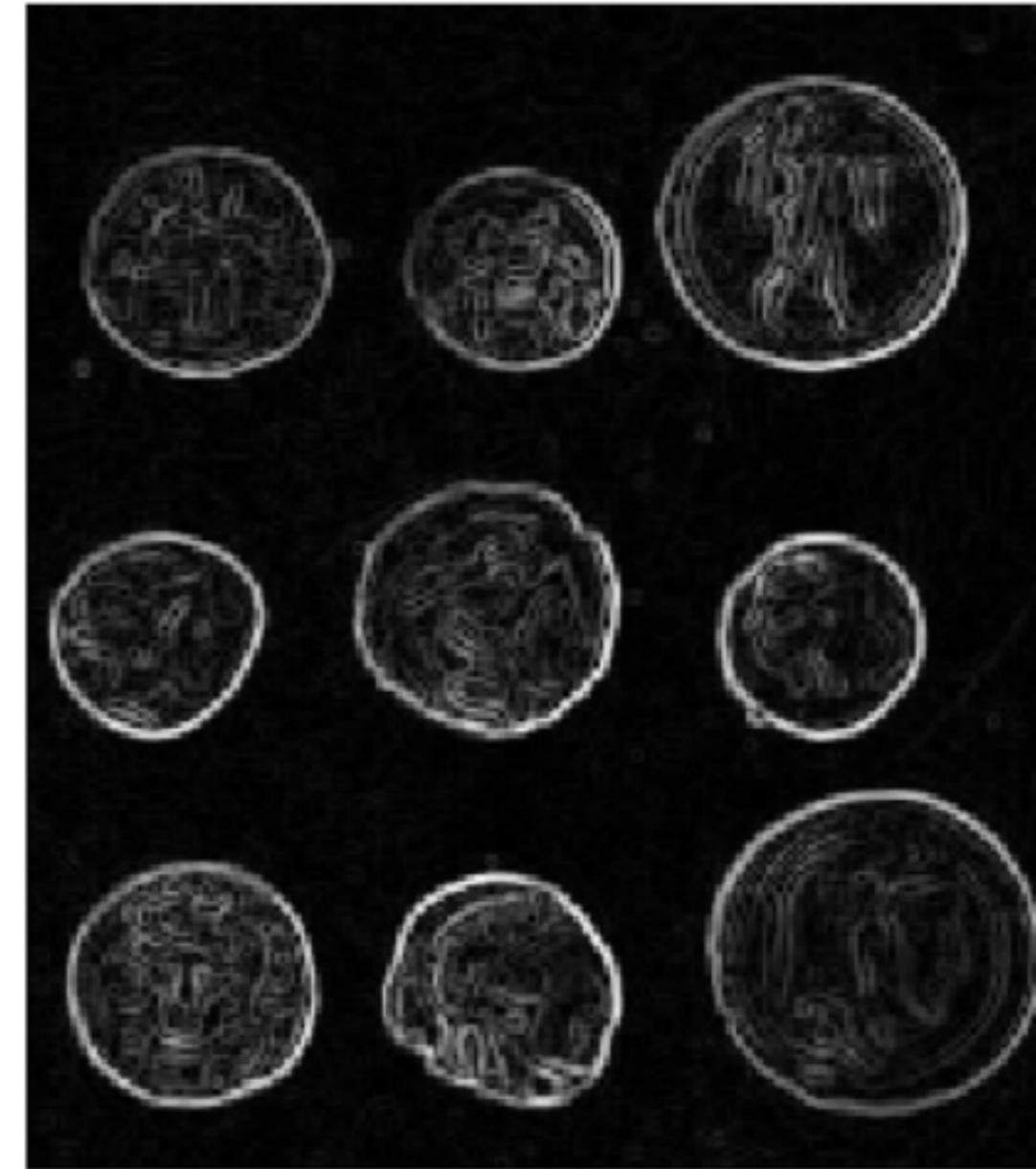


Edge detection

Original



Edges with Sobel

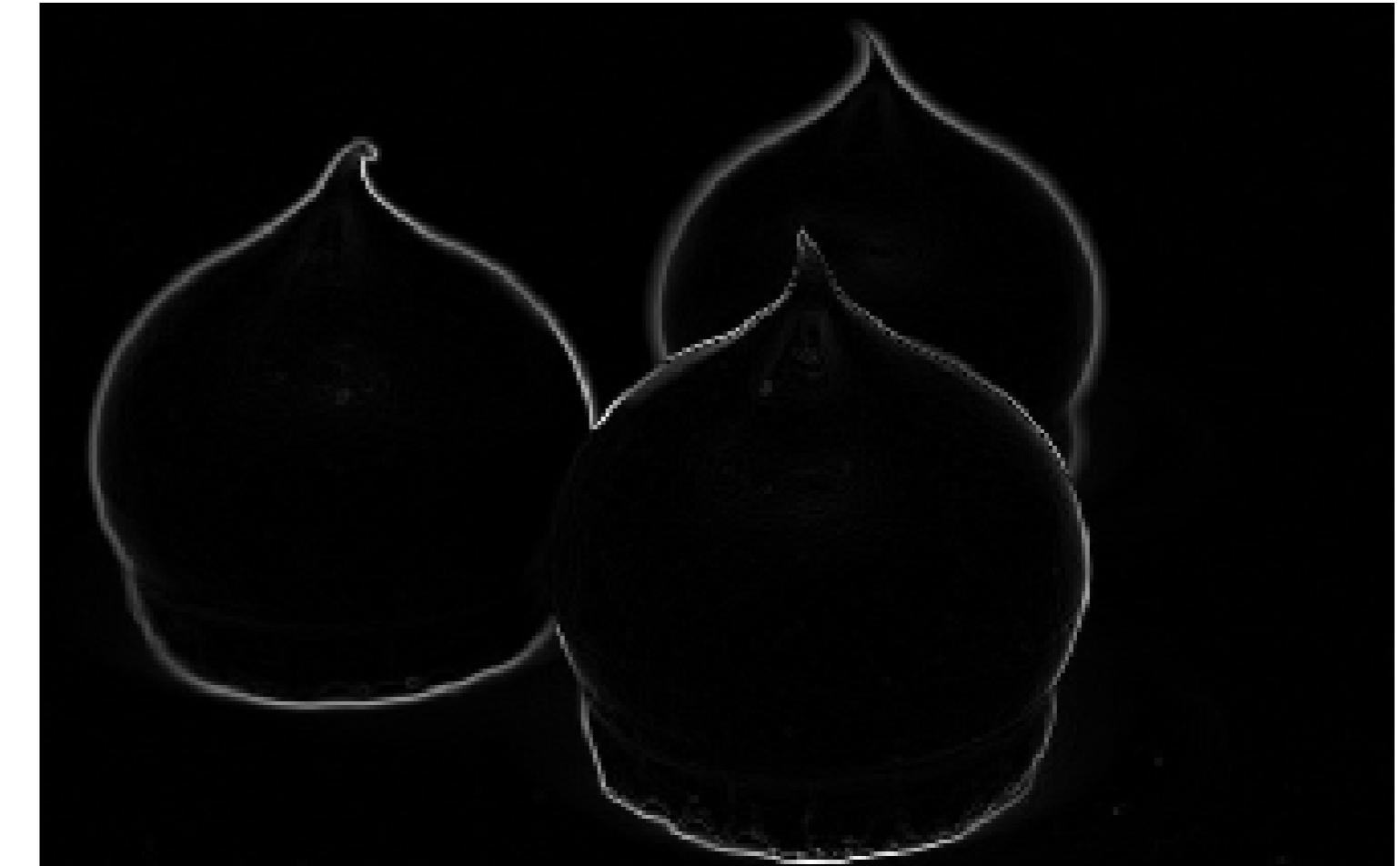


Edge detection

Original chocolate kisses



Edges with Sobel



Edge detection

Sobel

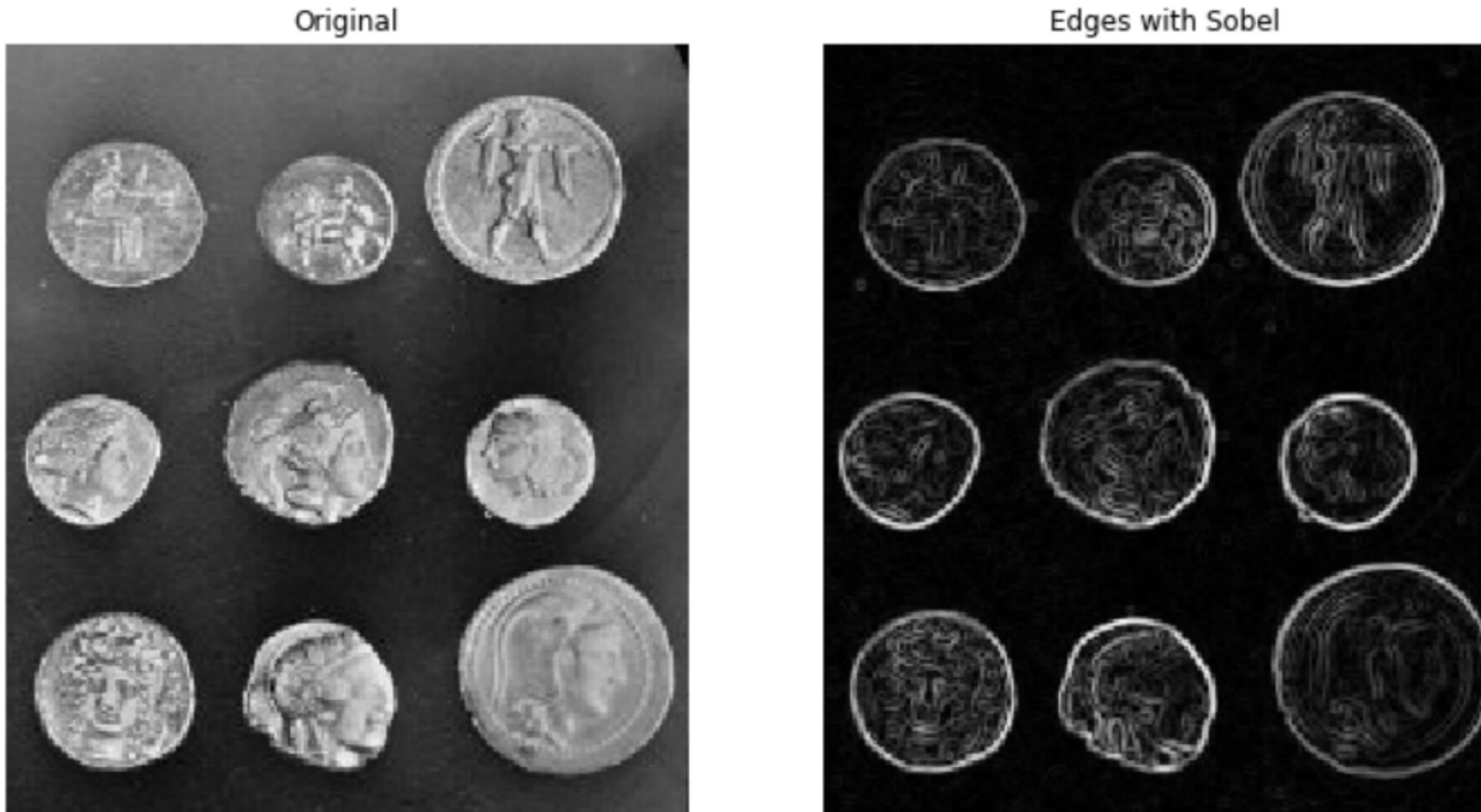
```
# Import module and function
from skimage.filters import sobel

# Apply edge detection filter
edge_sobel = sobel(image_coins)

# Show original and resulting image to compare
plot_comparison(image_coins, edge_sobel, "Edge with Sobel")
```

Edge detection

Sobel



Comparing plots

```
def plot_comparison(original, filtered, title_filtered):  
  
    fig, (ax1, ax2) = plt.subplots(ncols=2, figsize=(8, 6), sharex=True,  
                                  sharey=True)  
    ax1.imshow(original, cmap=plt.cm.gray)  
    ax1.set_title('original')  
    ax1.axis('off')  
    ax2.imshow(filtered, cmap=plt.cm.gray)  
    ax2.set_title(title_filtered)  
    ax2.axis('off')
```

Gaussian smoothing

Original



Blurred with Gaussian filter



Gaussian smoothing



Gaussian smoothing

```
# Import the module and function
from skimage.filters import gaussian

# Apply edge detection filter
gaussian_image = gaussian(amsterdam_pic, multichannel=True)

# Show original and resulting image to compare
plot_comparison(amsterdam_pic, gaussian_image, "Blurred with Gaussian filter")
```

Gaussian smoothing

Original



Blurred with Gaussian filter



Gaussian smoothing

Original



Blurred with Gaussian filter

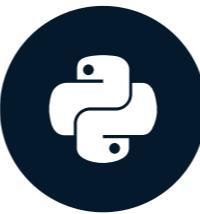


Let's practice!

IMAGE PROCESSING IN PYTHON

Contrast enhancement

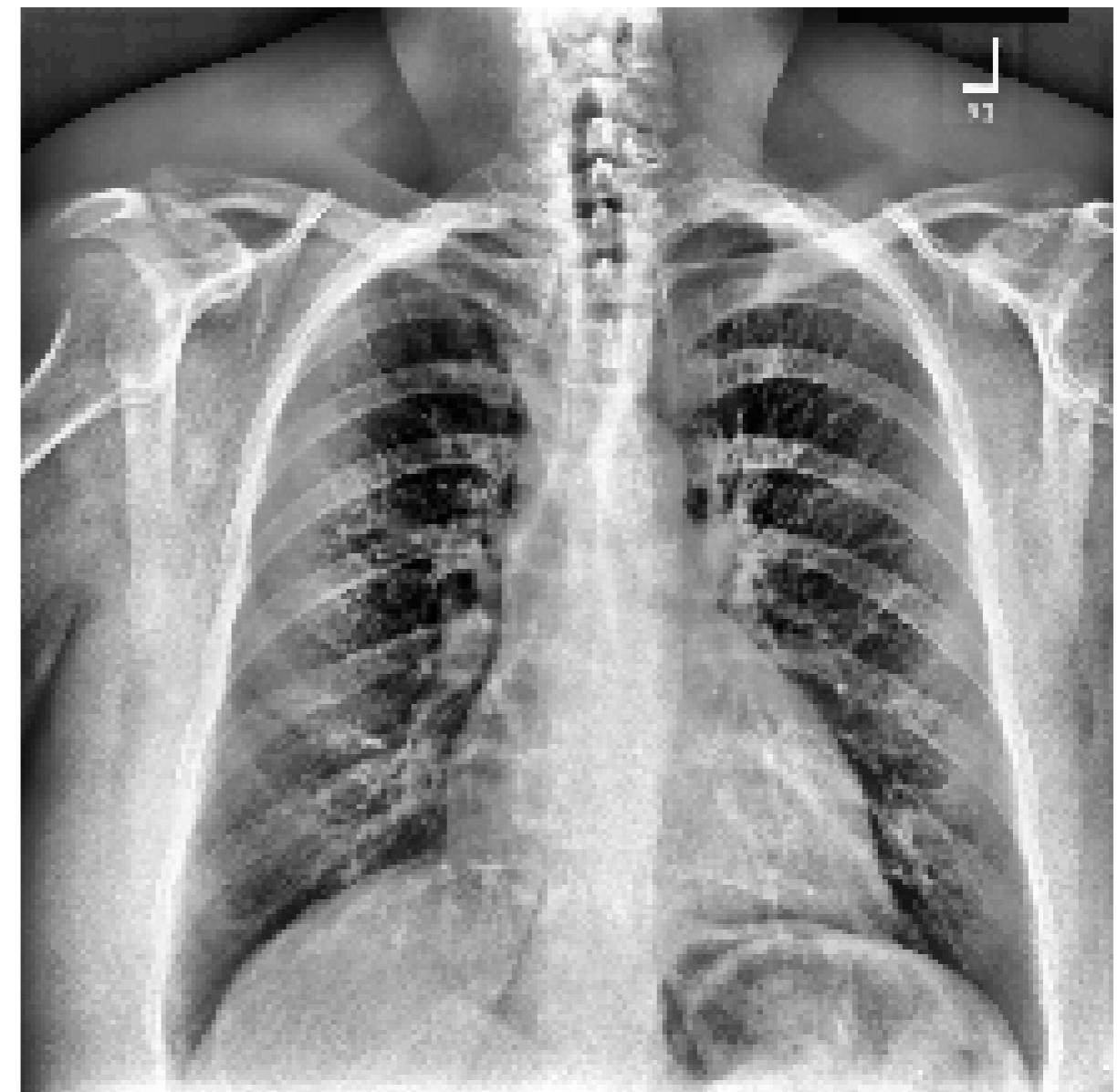
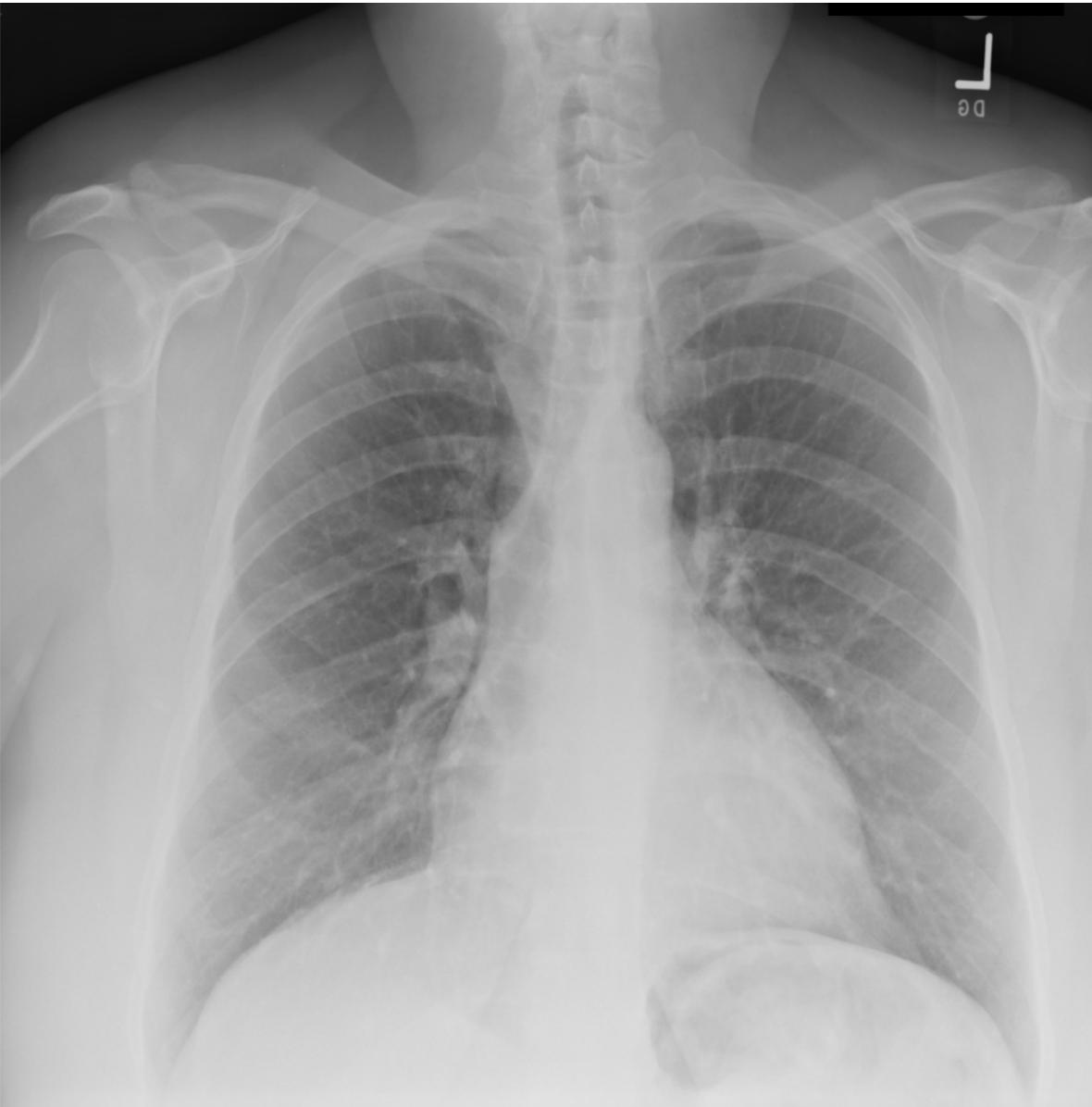
IMAGE PROCESSING IN PYTHON



Rebeca Gonzalez

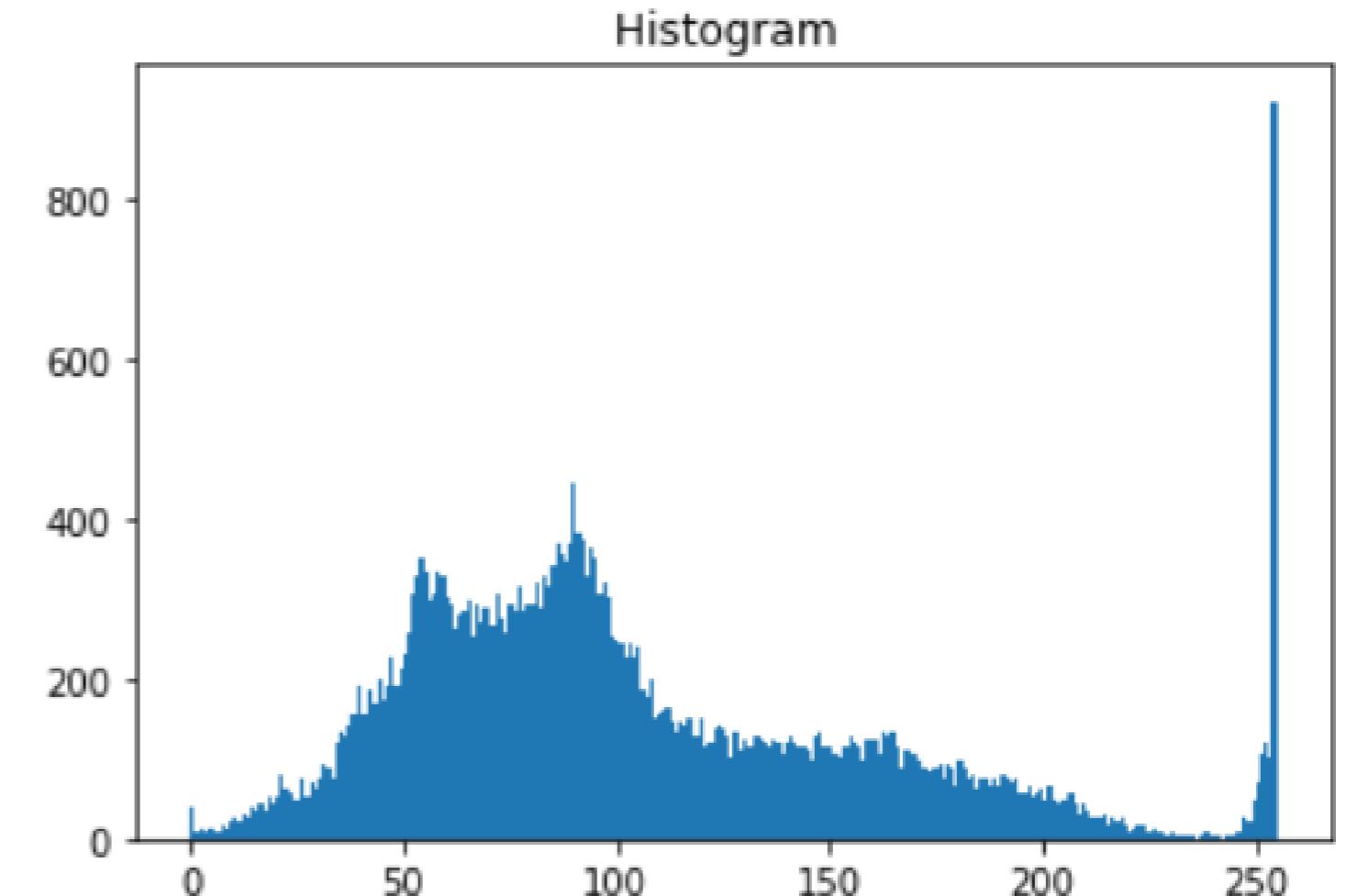
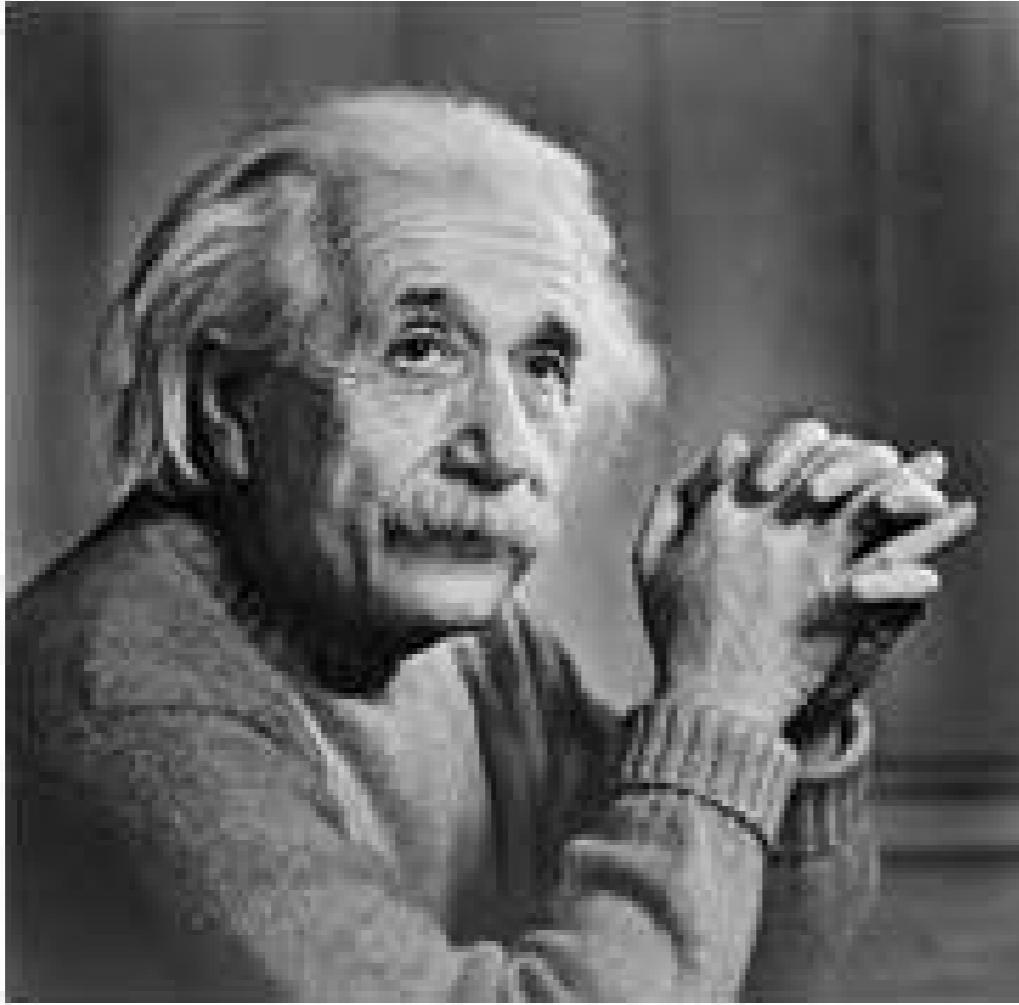
Data engineer

Contrast enhancement



Contrast

Histograms for contrast enhancement

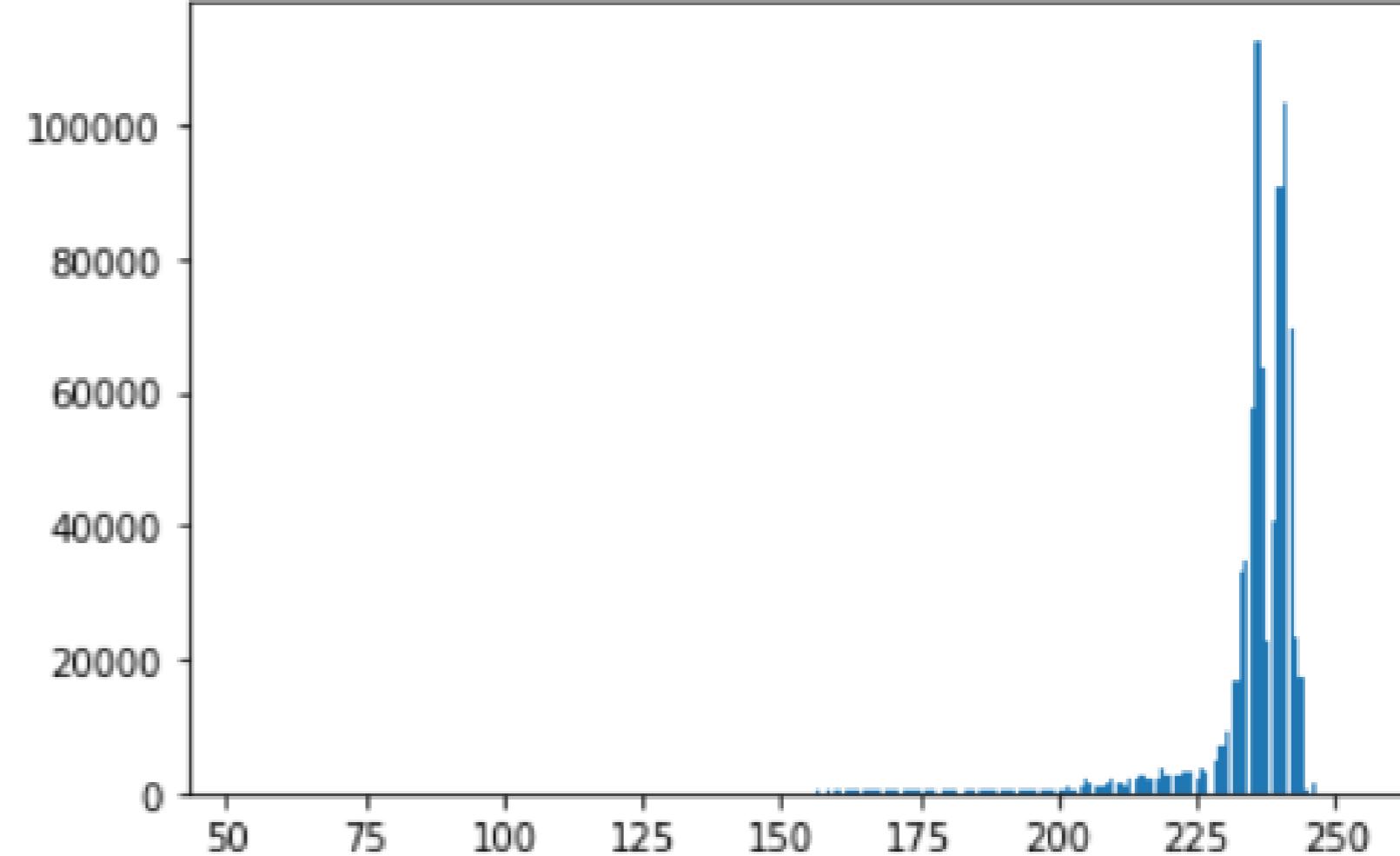


Contrast

Low contrast image - light



Histogram of image



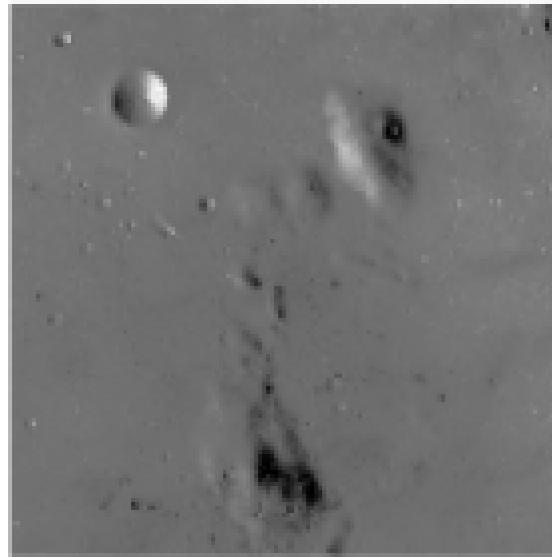
Enhance contrast

- Contrast stretching
- Histogram equalization

Types

- Histogram equalization
- Adaptive histogram equalization
- Contrast Limited Adaptive Histogram Equalization (CLAHE)

Low contrast image



Contrast stretching



Histogram equalization



Adaptive equalization



Histogram equalization

Original



Histogram Equalization



Histogram equalization

Original



Histogram equalization

```
from skimage import exposure

# Obtain the equalized image
image_eq = exposure.equalize_hist(image)

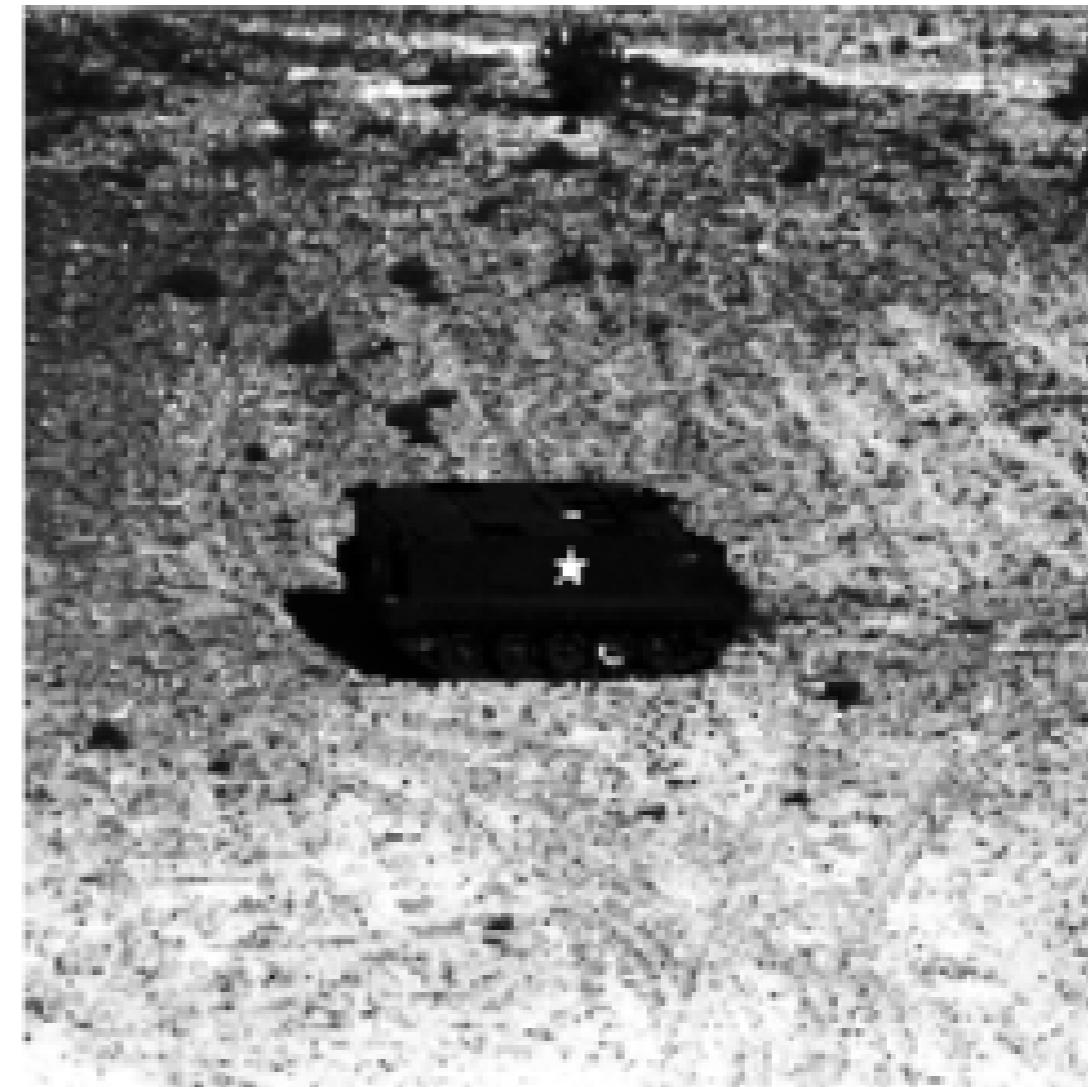
# Show original and result
show_image(image, 'Original')
show_image(image_eq, 'Histogram equalized')
```

Histogram equalization

Original



Histogram Equalization



Adaptive Equalization

- Contrastive Limited Adaptive Histogram Equalization

Original



Adaptive Equalization



Contrastive Limited Adaptive Equalization

Original



Histogram Equalization Adaptive Equalization



CLAHE in scikit-image

```
from skimage import exposure

# Apply adaptive Equalization
image_adapteq = exposure.equalize_adapthist(image, clip_limit=0.03)

# Show original and result
show_image(image, 'Original')
show_image(image_adapteq, 'Adaptive equalized')
```

CLAHE in scikit-image

Original



Adaptive Equalization



Let's practice!

IMAGE PROCESSING IN PYTHON

Transformations

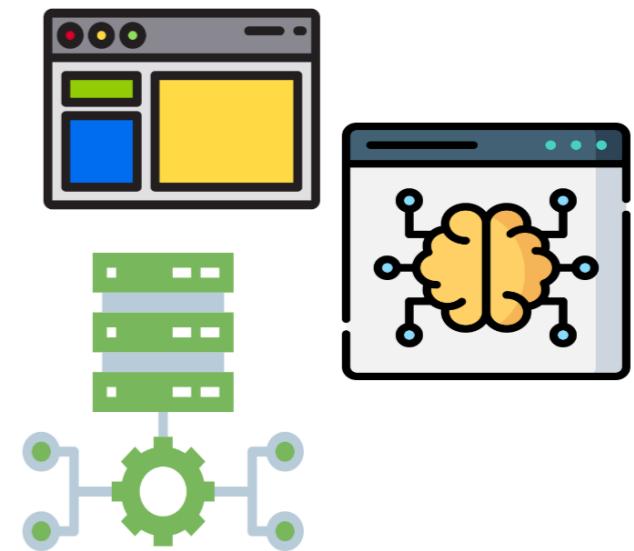
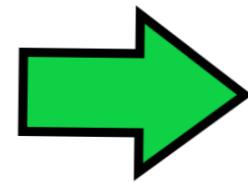
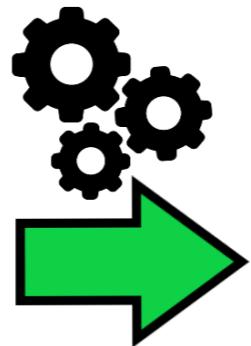
IMAGE PROCESSING IN PYTHON



Rebeca Gonzalez
Data Engineer

Why transform images?

- Preparing images for classification Machine Learning models
- Optimization and compression of images
- Save images with same proportion

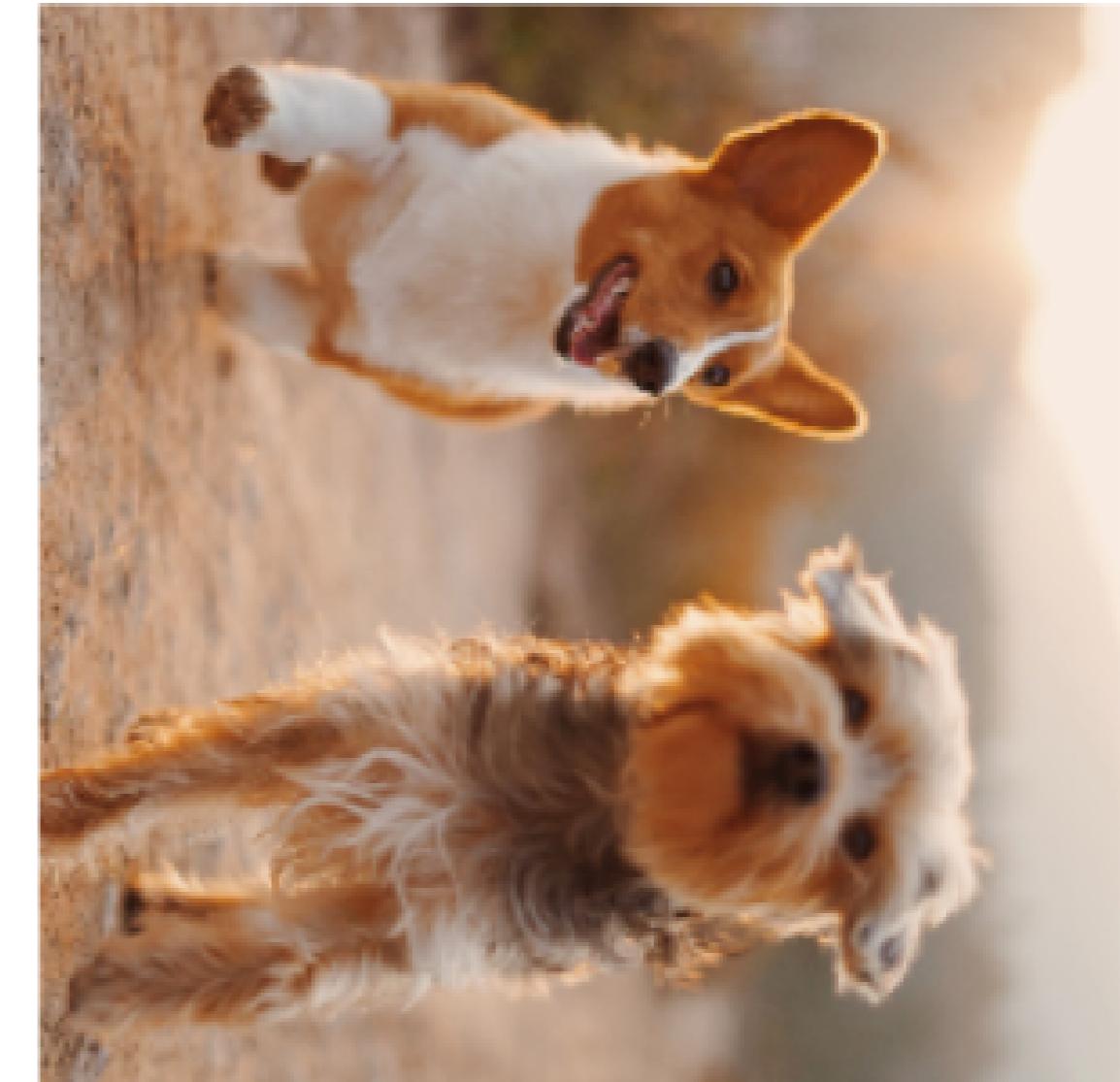


Rotating

Original



Rotated 90 degrees clockwise

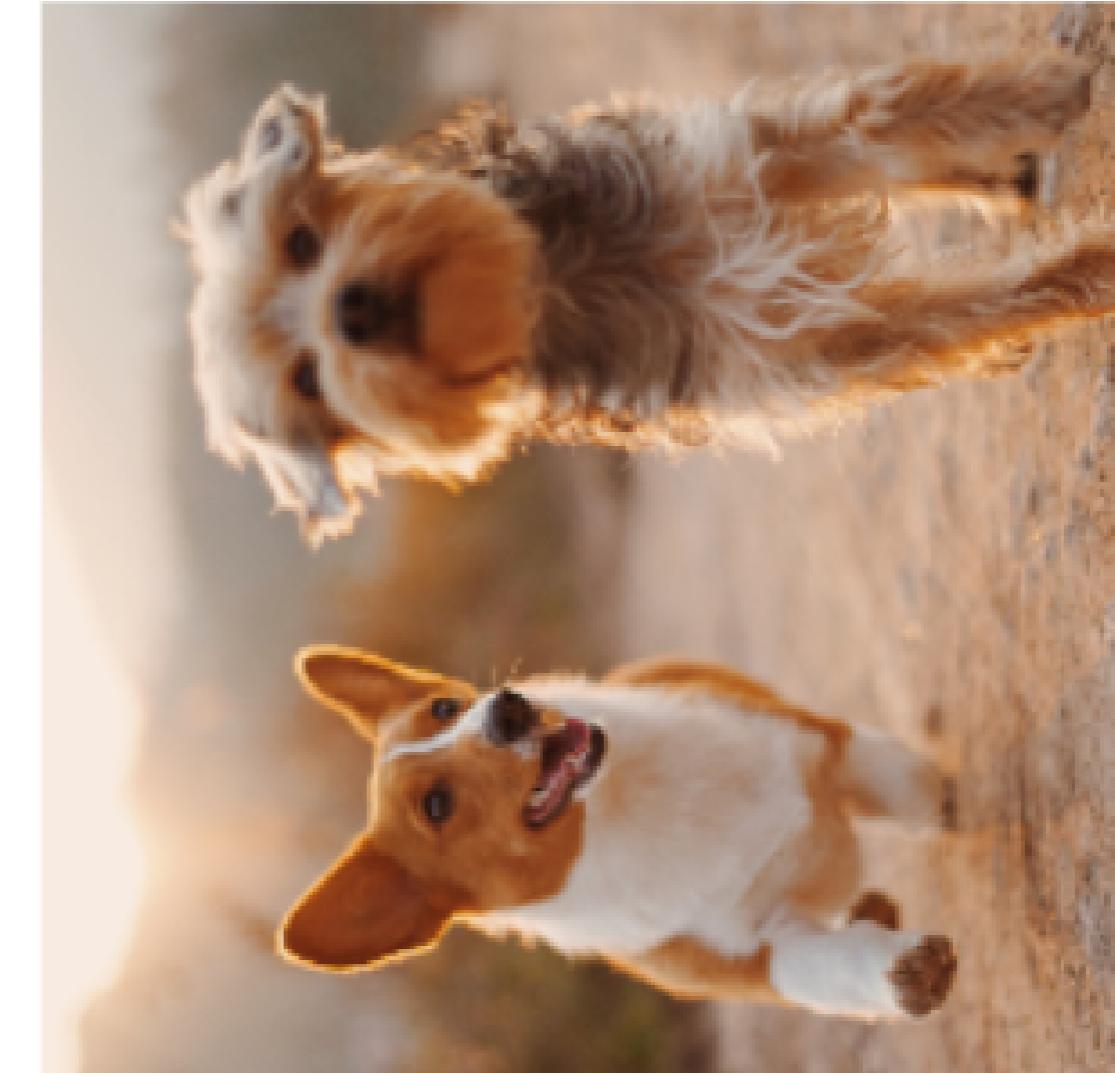


Rotating

Original



Rotated 90 degrees anticlockwise

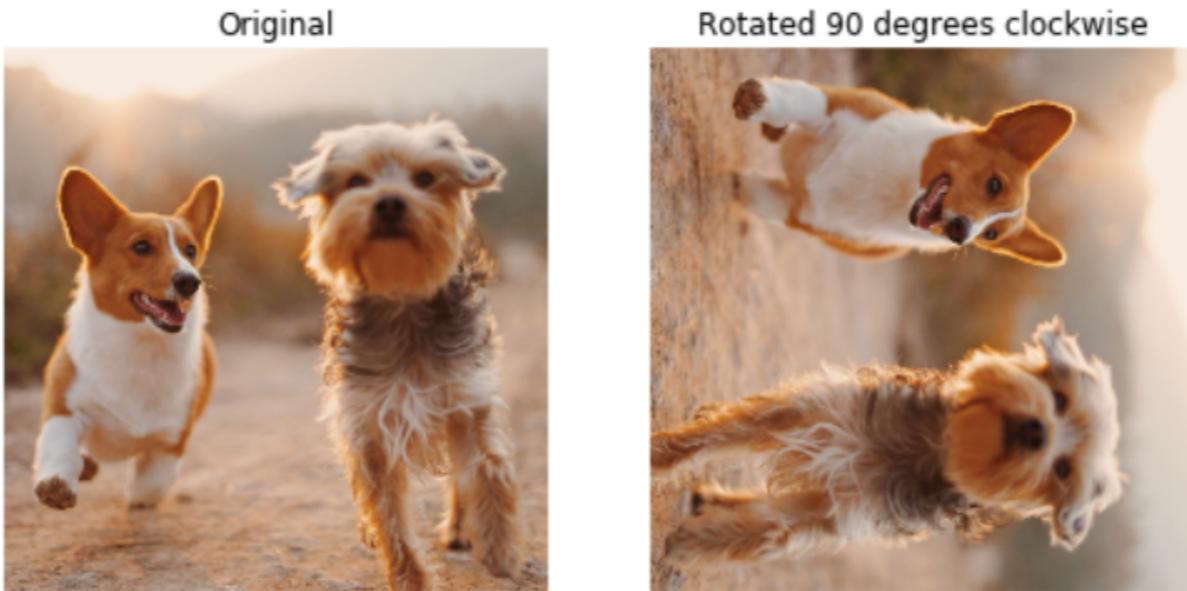


Rotating clockwise

```
from skimage.transform import rotate

# Rotate the image 90 degrees clockwise
image_rotated = rotate(image, -90)

show_image(image_rotated, 'Original')
show_image(image_rotated, 'Rotated 90 degrees clockwise')
```

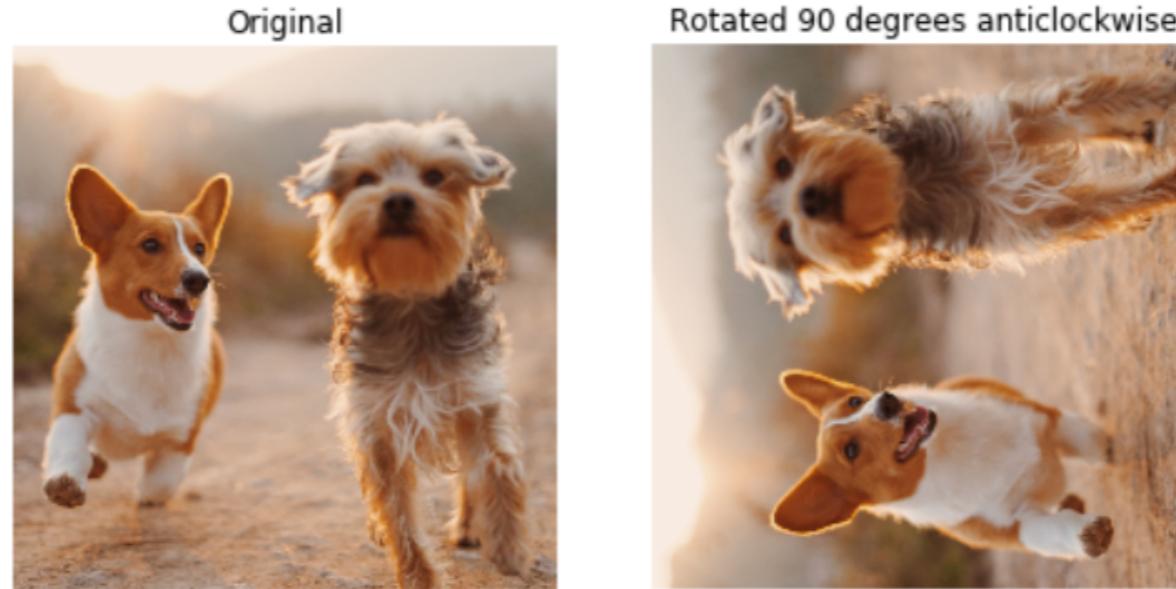


Rotating anticlockwise

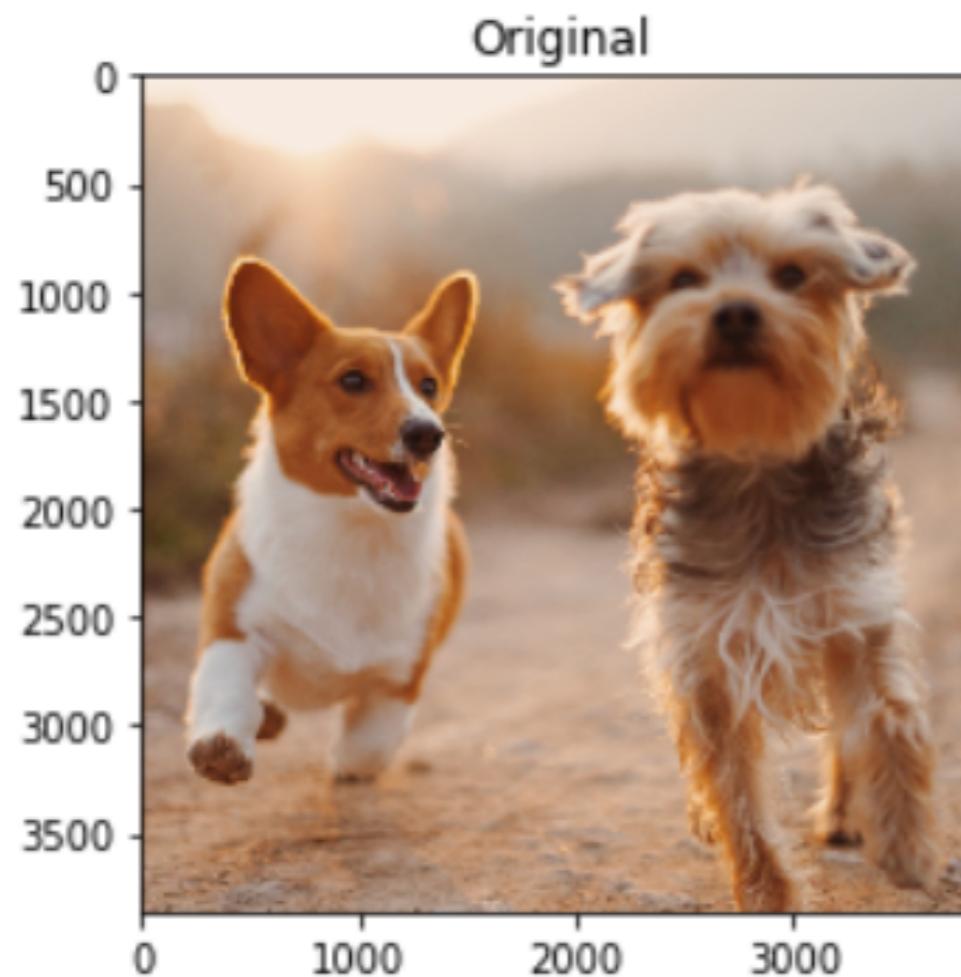
```
from skimage.transform import rotate

# Rotate an image 90 degrees anticlockwise
image_rotated = rotate(image, 90)

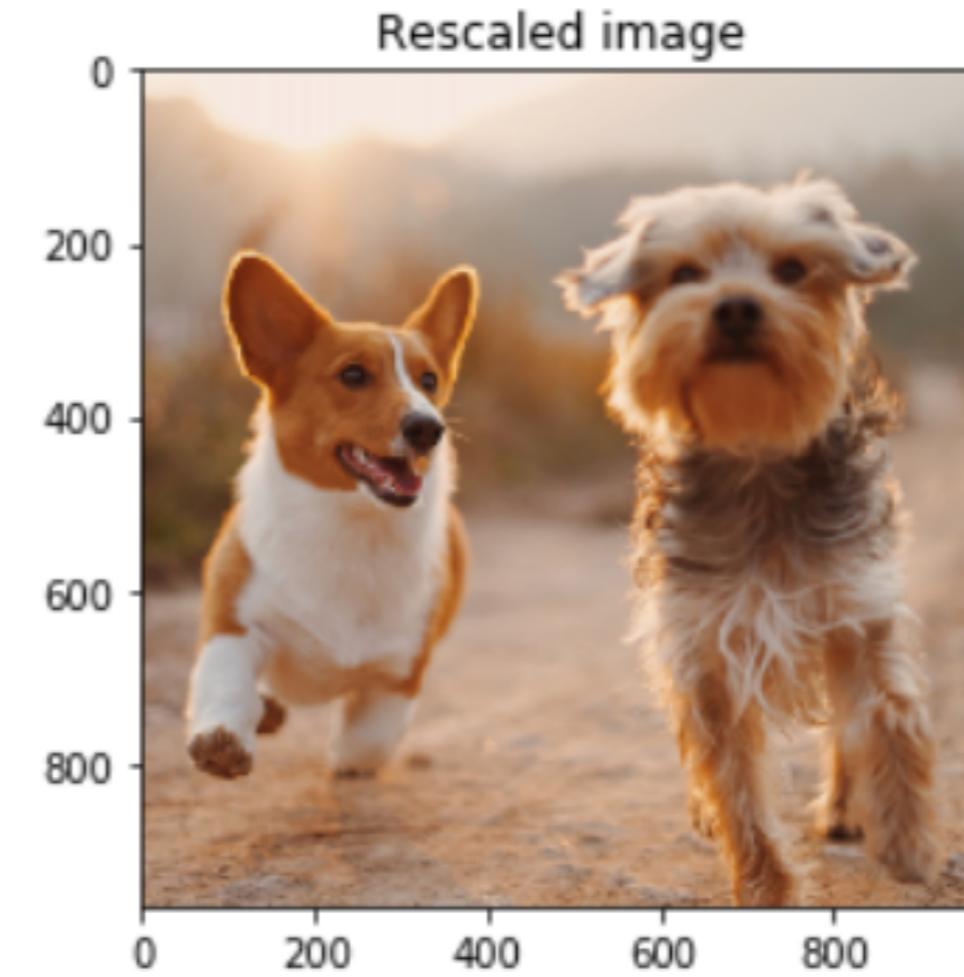
show_image(image, 'Original')
show_image(image_rotated, 'Rotated 90 degrees anticlockwise')
```



Rescaling



Original size



Rescaled size

Rescaling

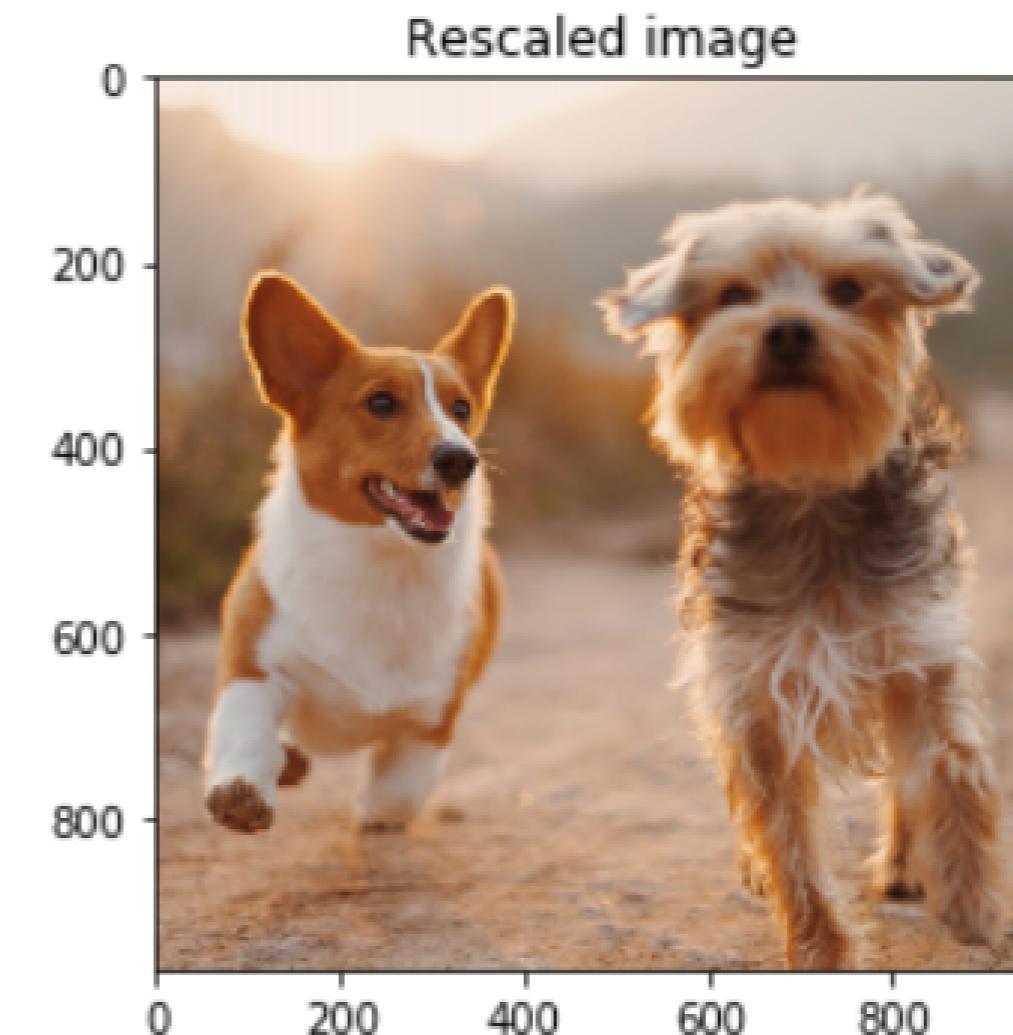
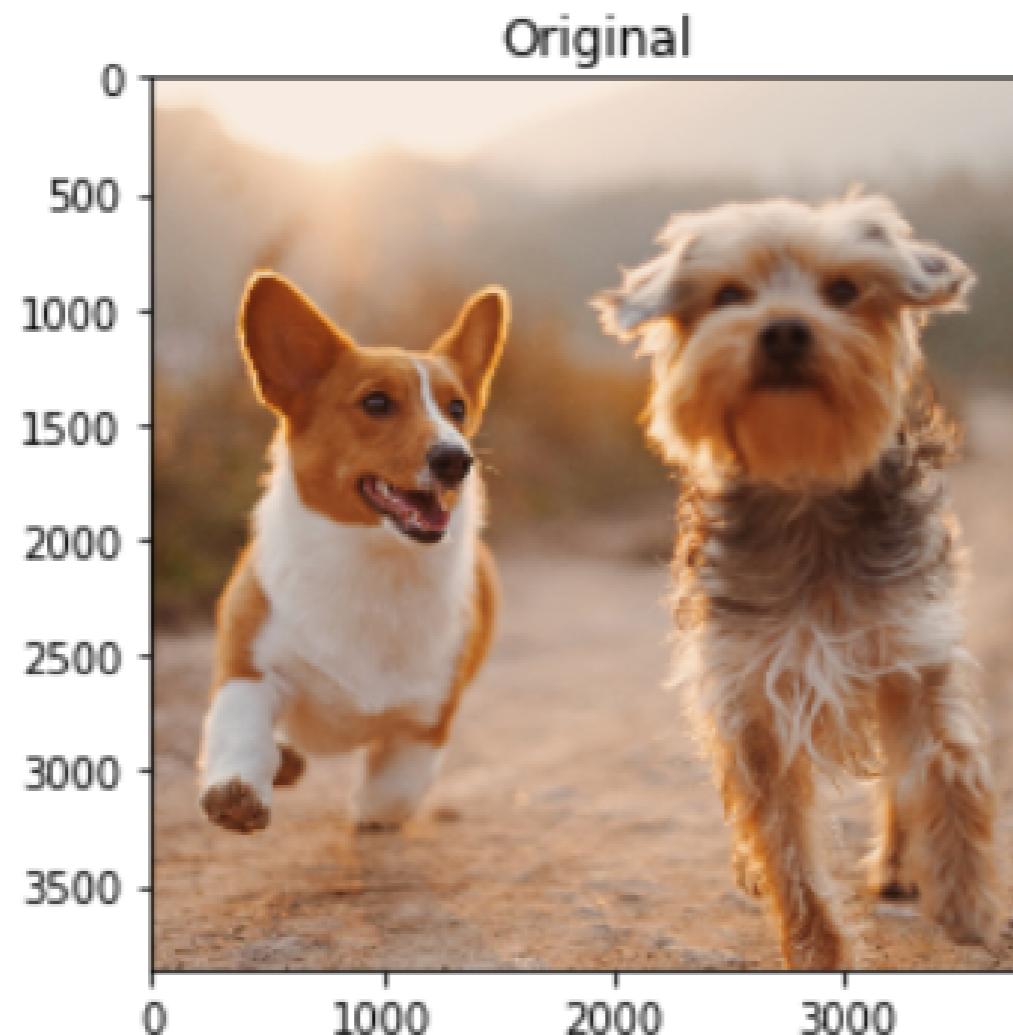
Downgrading

```
from skimage.transform import rescale

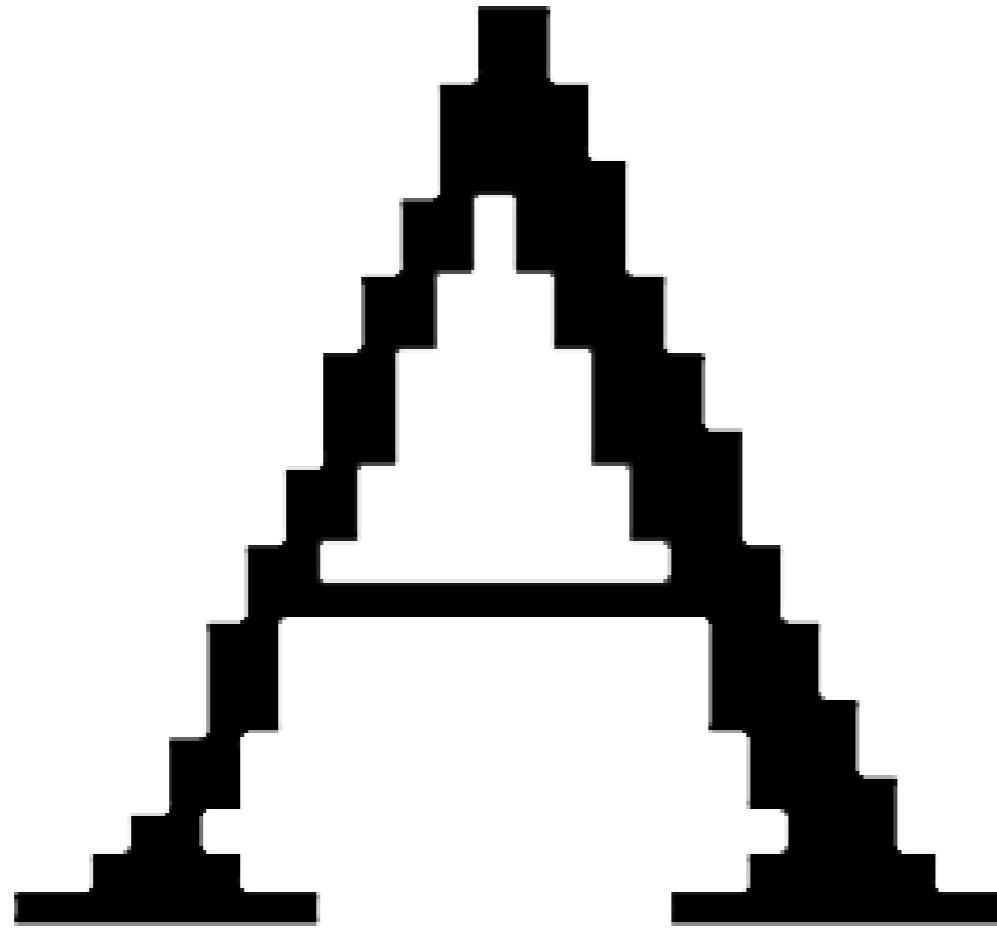
# Rescale the image to be 4 times smaller
image_rescaled = rescale(image, 1/4, anti_aliasing=True, multichannel=True)

show_image(image, 'Original image')
show_image(image_rescaled, 'Rescaled image')
```

Rescaling



Aliasing in digital images

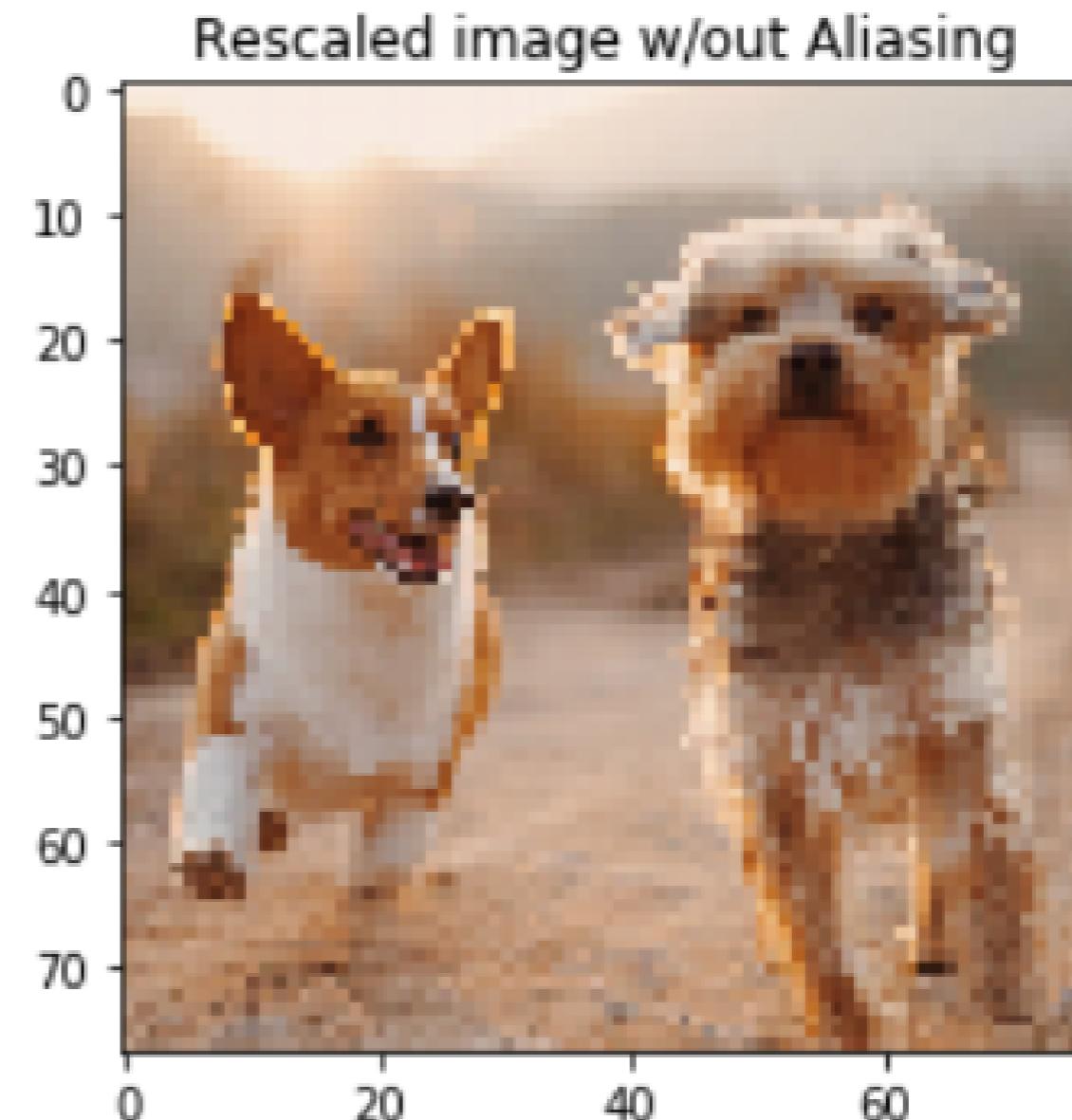
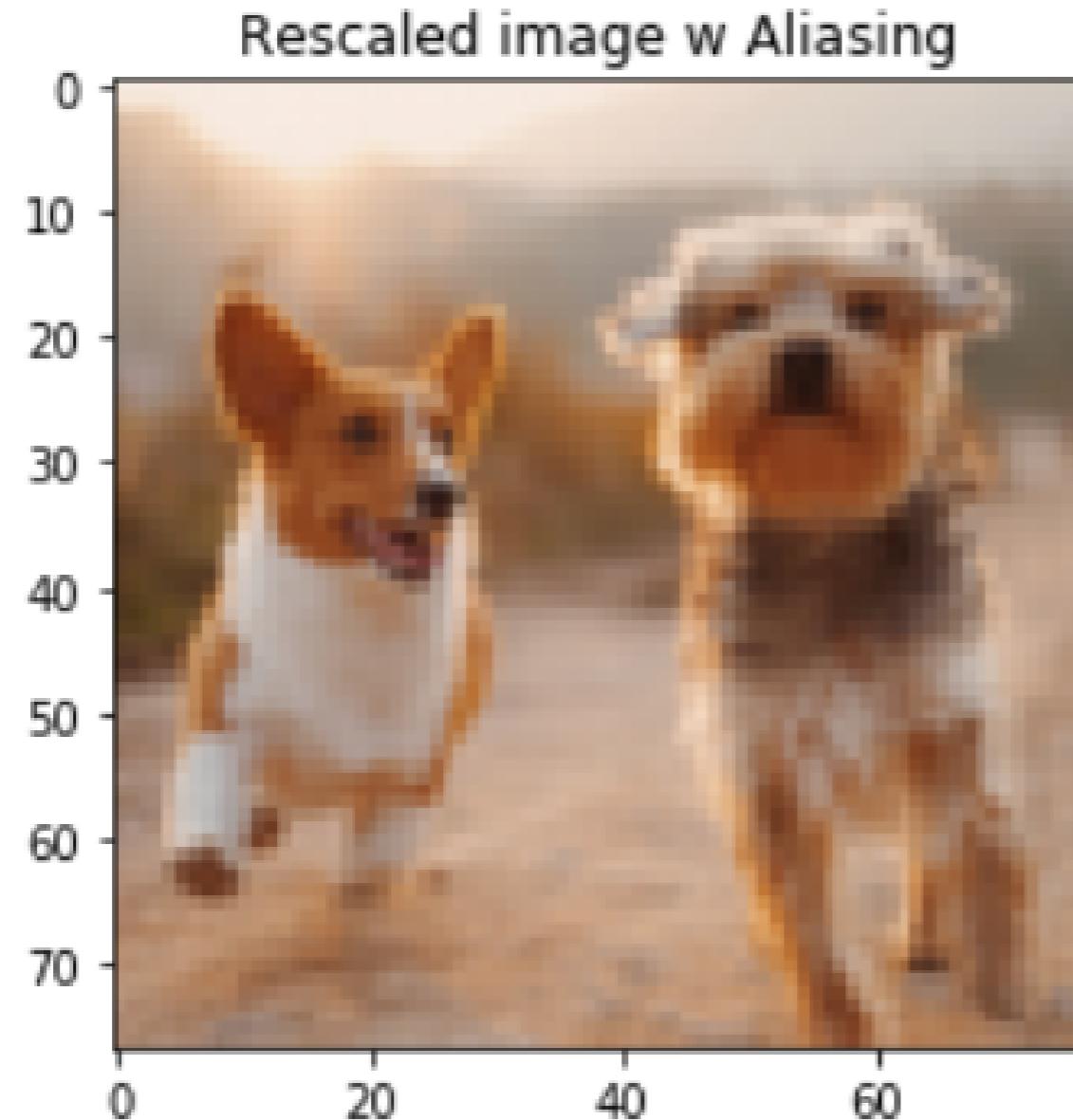


Original letter A

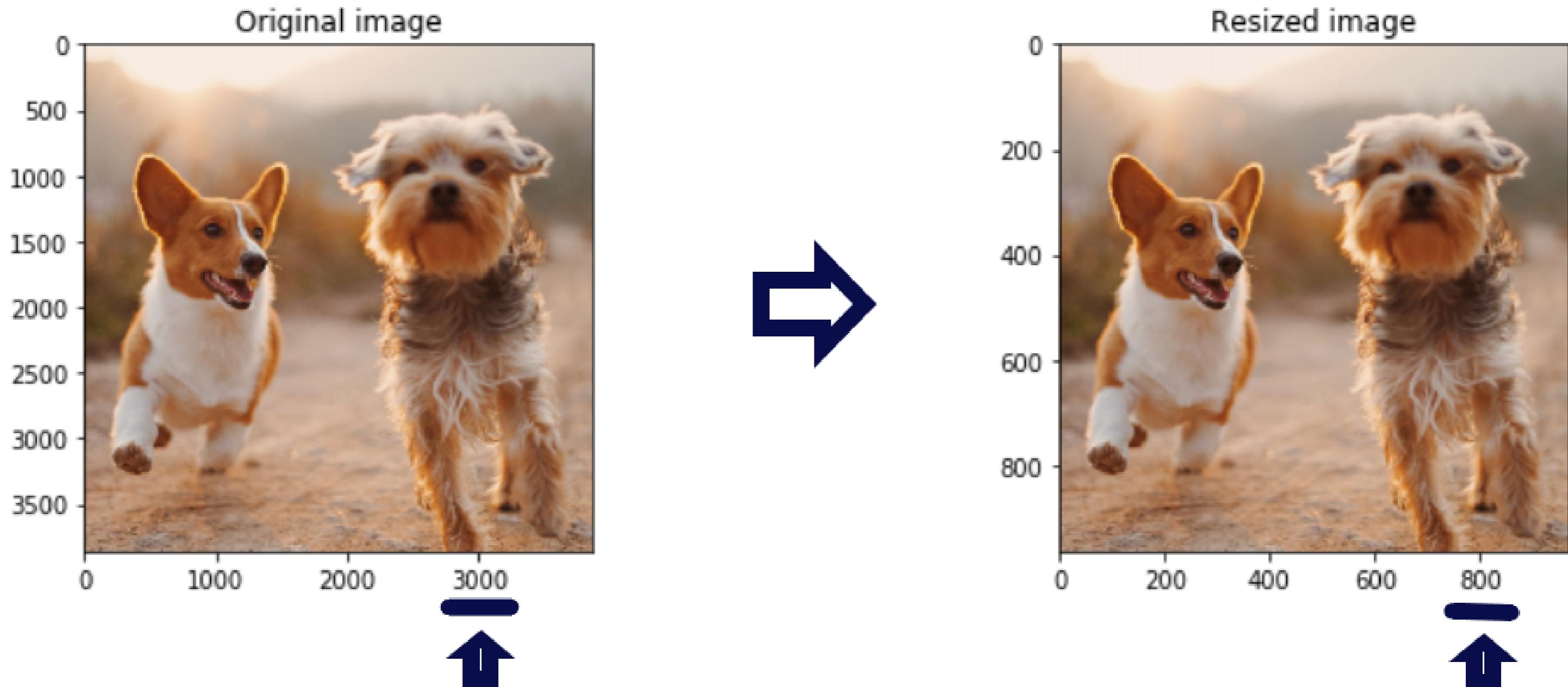


Aliased letter A

Aliasing in digital images



Resizing



Resizing

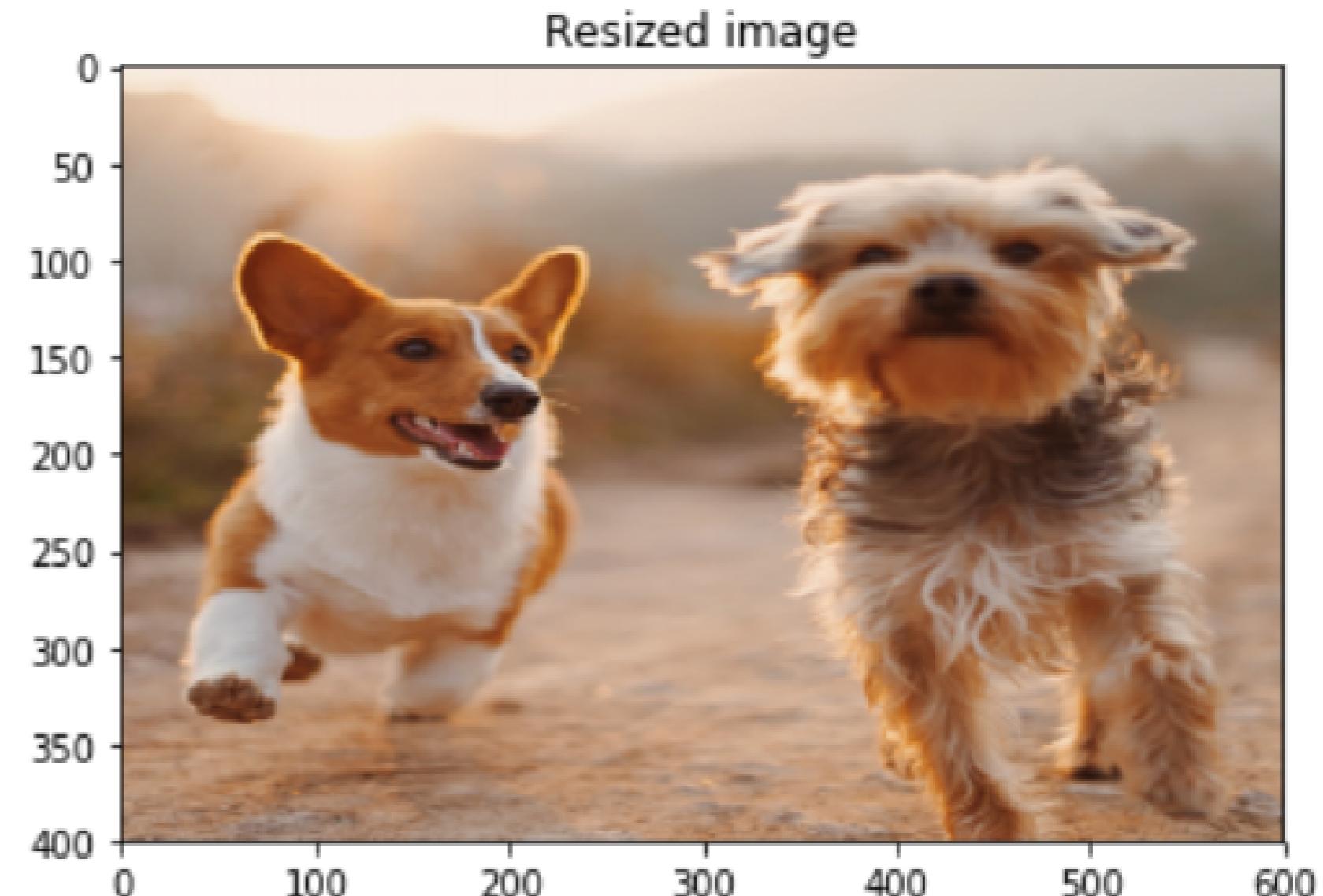
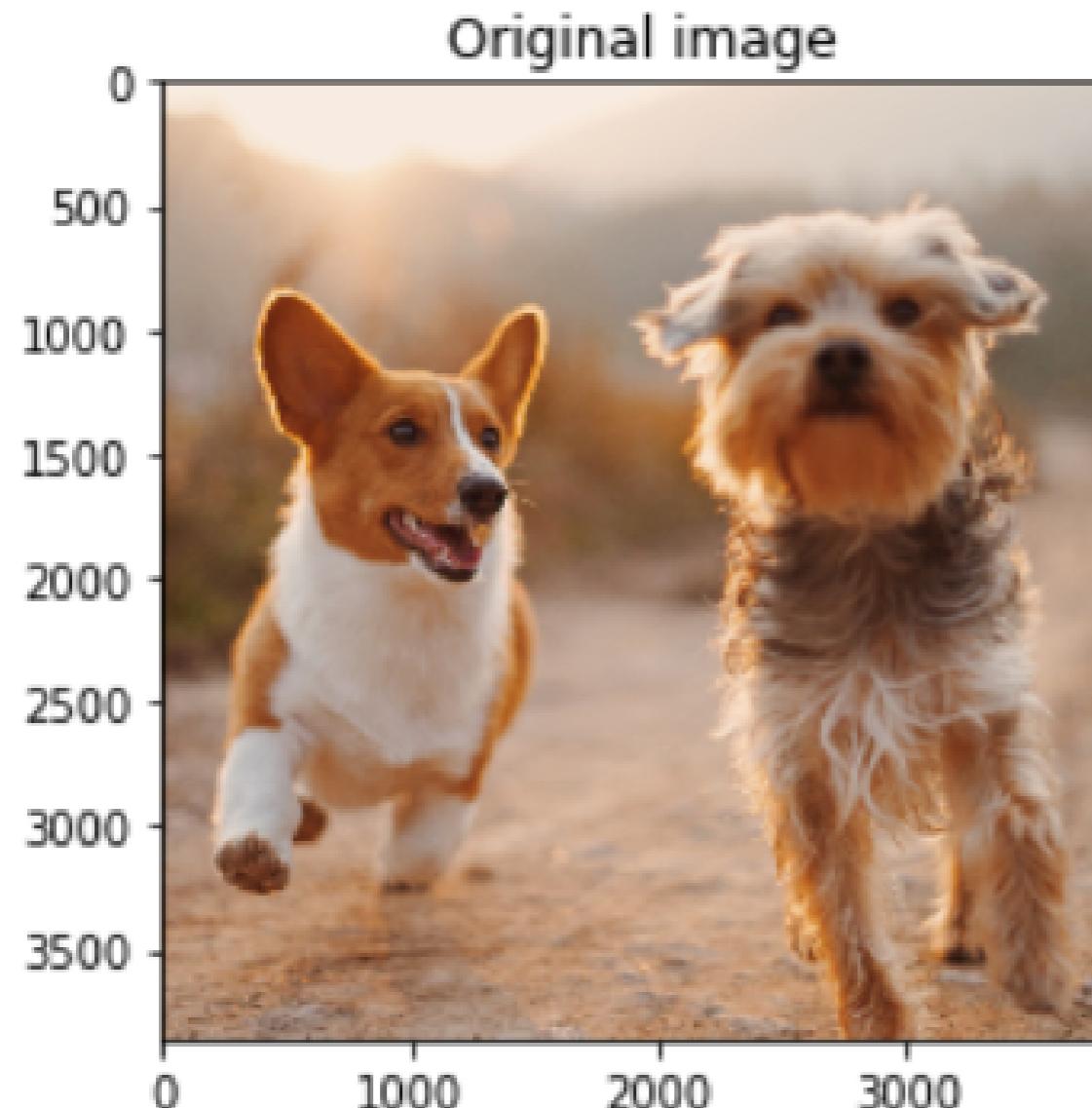
```
from skimage.transform import resize

# Height and width to resize
height = 400
width = 500

# Resize image
image_resized = resize(image, (height, width), anti_aliasing=True)

# Show the original and resulting images
show_image(image, 'Original image')
show_image(image_resized, 'Resized image')
```

Resizing



Resizing proportionally

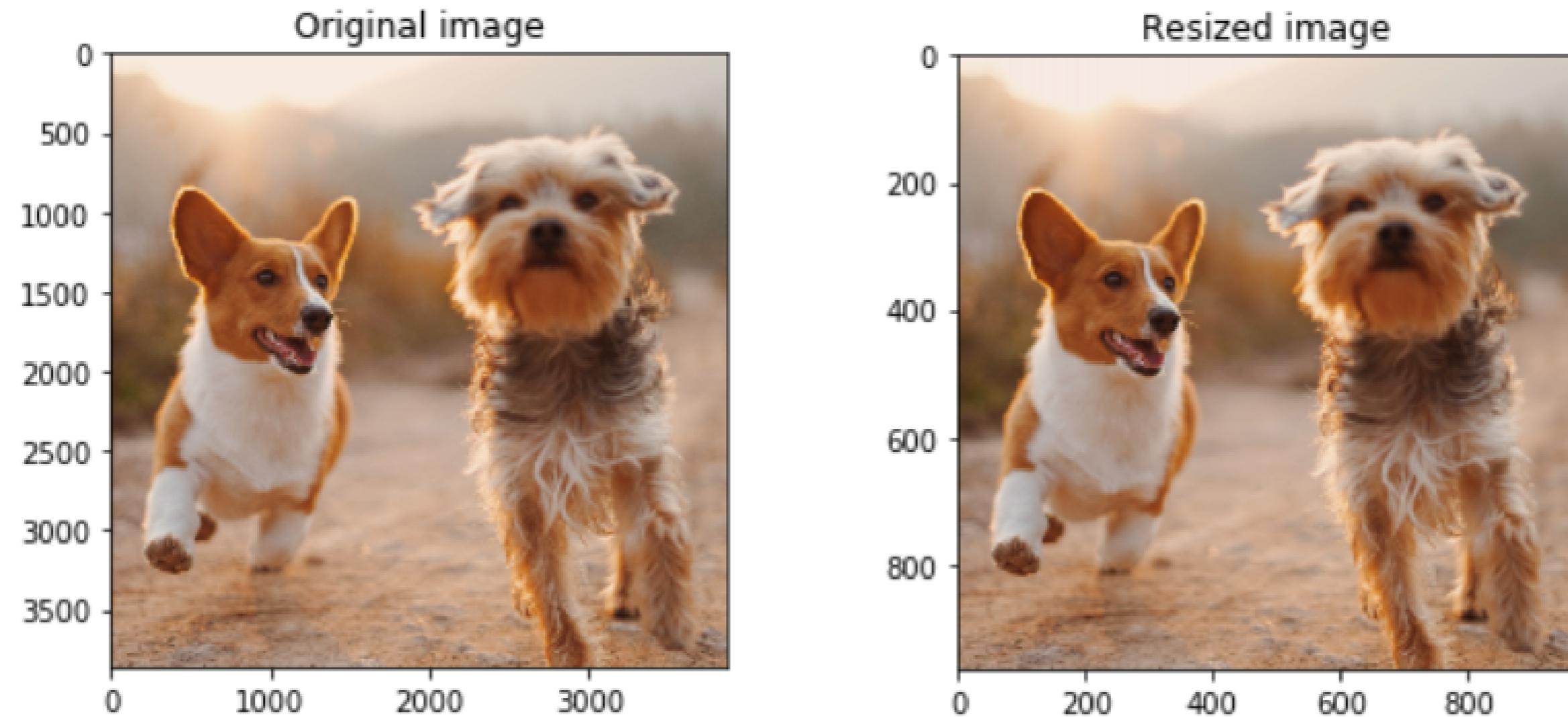
```
from skimage.transform import resize

# Set proportional height so its 4 times its size
height = image.shape[0] / 4
width = image.shape[1] / 4

# Resize image
image_resized = resize(image, (height, width), anti_aliasing=True)

show_image(image_resized, 'Resized image')
```

Resizing proportionally

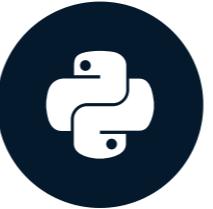


Let's practice!

IMAGE PROCESSING IN PYTHON

Morphology

IMAGE PROCESSING IN PYTHON



Rebeca Gonzalez
Data Engineer

Binary images

original



Thresholded image



Morphological filtering

- Better for binary images
- Can extend for grayscale

Binary image



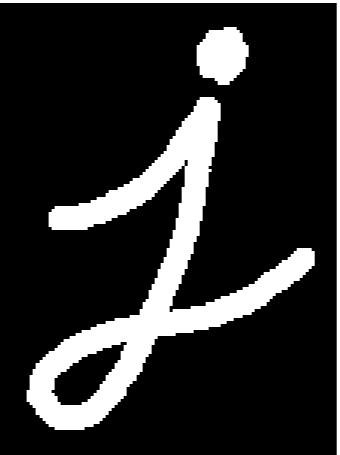
Grayscale



Morphological operations

- Dilation
- Erosion

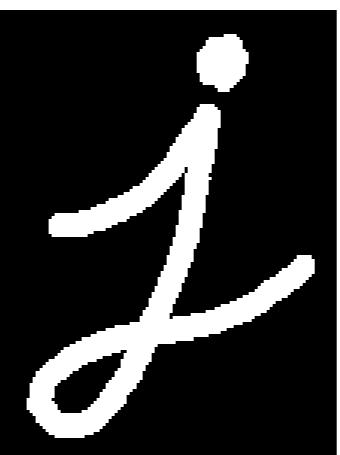
Original



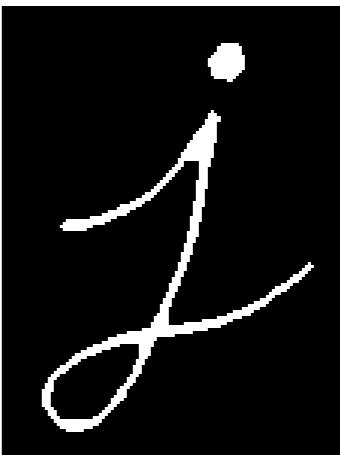
Dilated



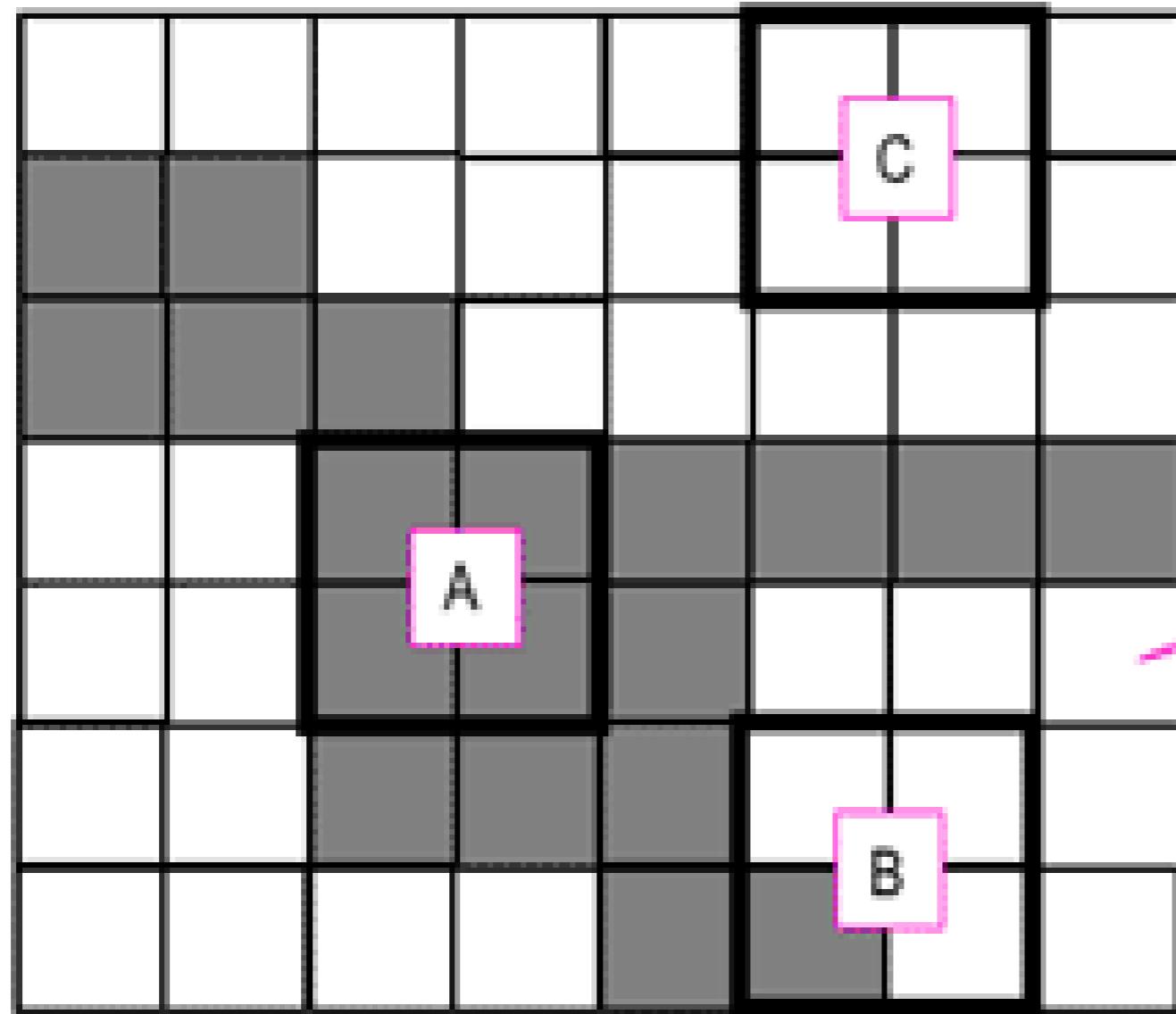
Original



Eroded

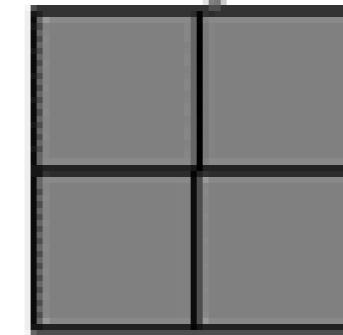


Structuring element



- A - the structuring element fits the image
- B - the structuring element hits (intersects) the image
- C - the structuring element neither fits, nor hits the image

Structuring element



Structuring element

1	1	1	1	1
1	1	1	1	1
1	1	1	1	1
1	1	1	1	1
1	1	1	1	1

Square 5x5 element

0	0	1	0	0
0	1	1	1	0
1	1	1	1	1
0	1	1	1	0
0	0	1	0	0

Diamond-shaped 5x5 element

0	0	1	0	0
0	0	1	0	0
1	1	1	1	1
0	0	1	0	0
0	0	1	0	0

Cross-shaped 5x5 element



1	1	1
1	1	1
1	1	1

Square 3x3 element

Shapes in scikit-image

```
from skimage import morphology
```

```
square = morphology.square(4)
```

```
[[1 1 1 1]
 [1 1 1 1]
 [1 1 1 1]
 [1 1 1 1]]
```

```
rectangle = morphology.rectangle(4, 2)
```

```
[[1 1]
 [1 1]
 [1 1]
 [1 1]]
```

Erosion in scikit-image

```
from skimage import morphology

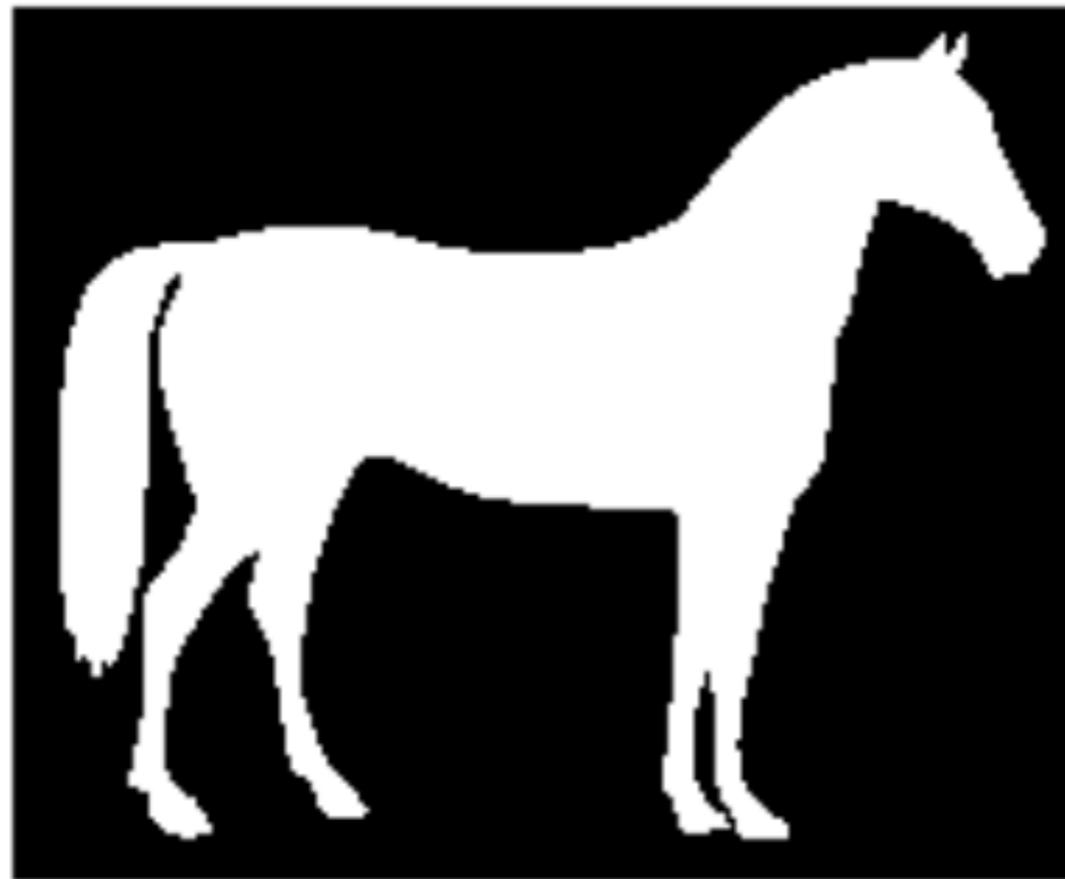
# Set structuring element to the rectangular-shaped
selem = rectangle(12,6)

# Obtain the eroded image with binary erosion
eroded_image = morphology.binary_erosion(image_horse, selem=selem)
```

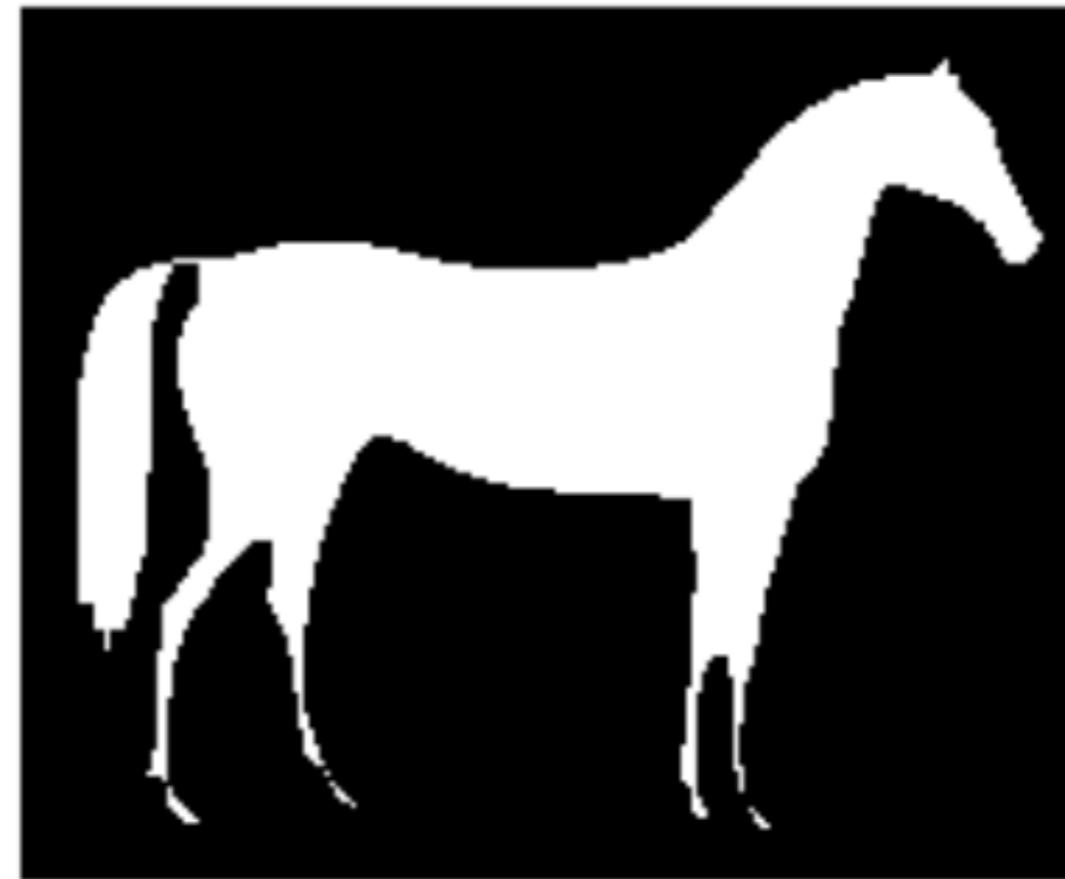
Erosion in scikit-image

```
# Show result  
plot_comparison(image_horse, eroded_image, 'Erosion')
```

original



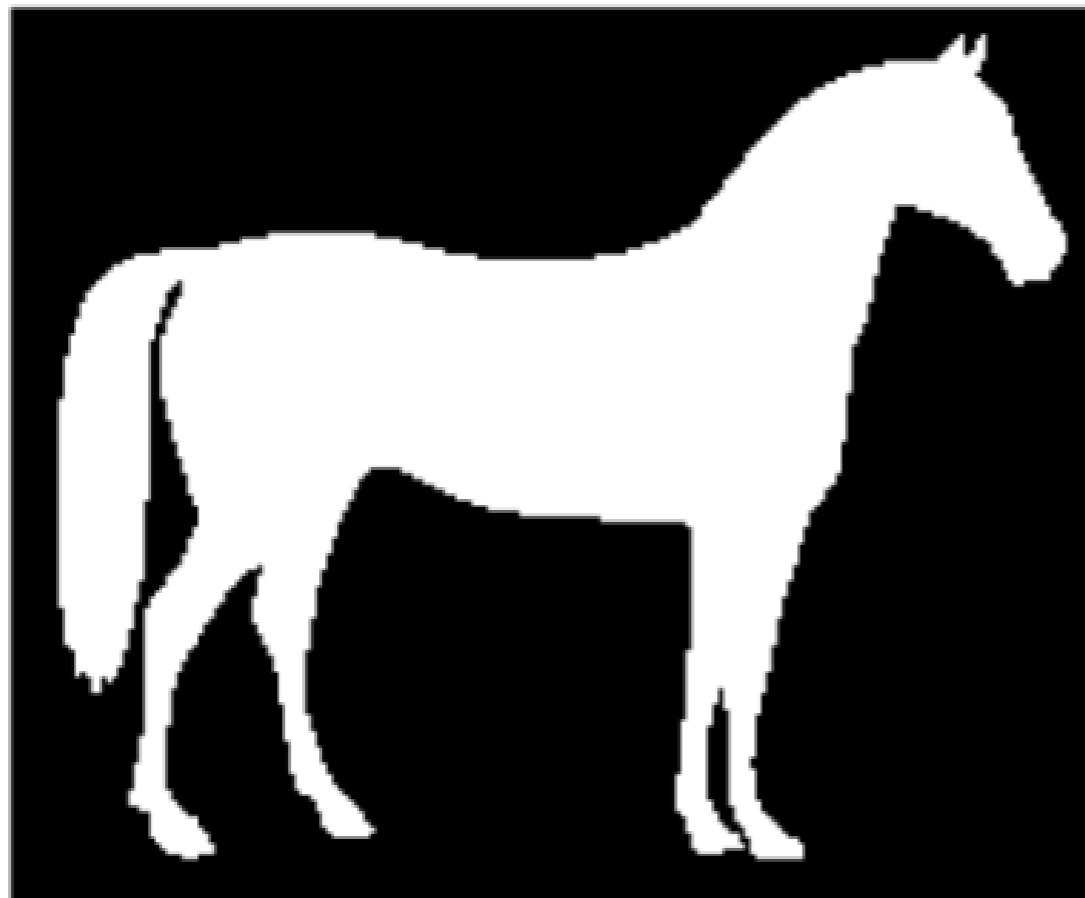
Erosion



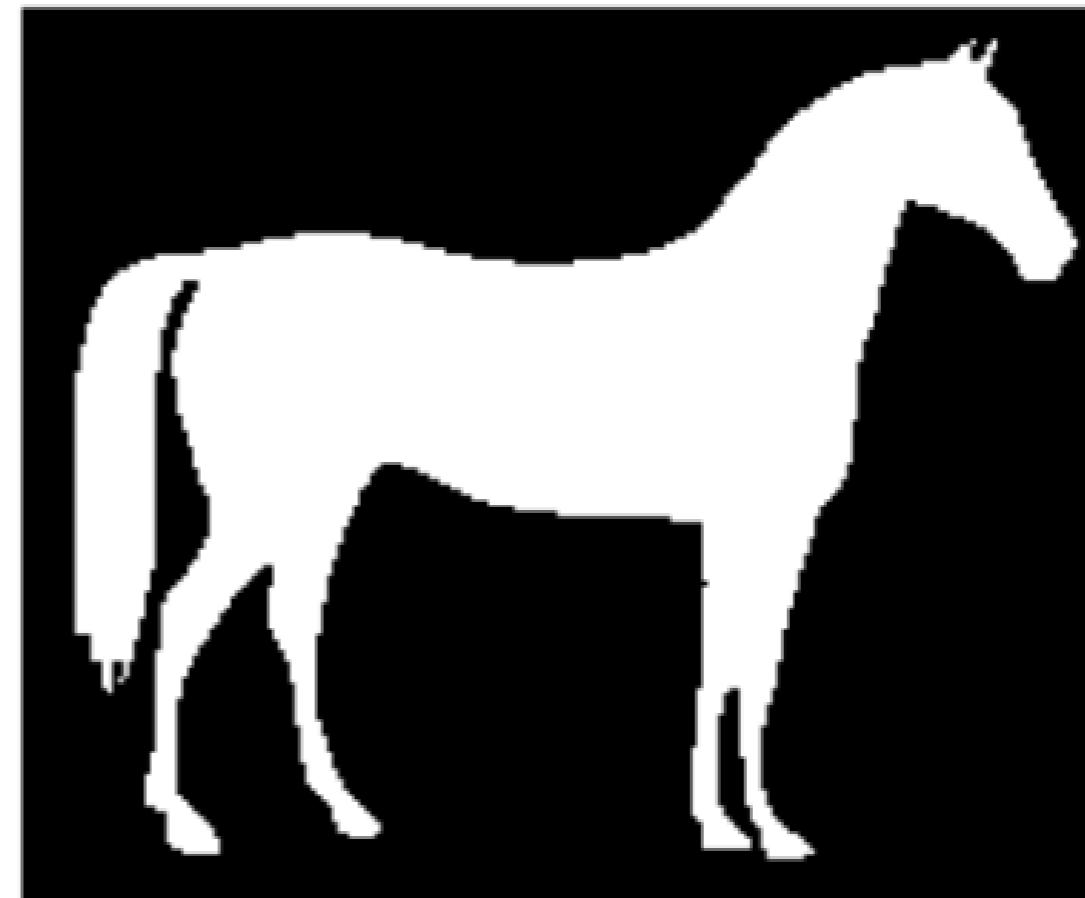
Binary erosion with default selem

```
# Binary erosion with default selem  
eroded_image = morphology.binary_erosion(image_horse)
```

original



Erosion

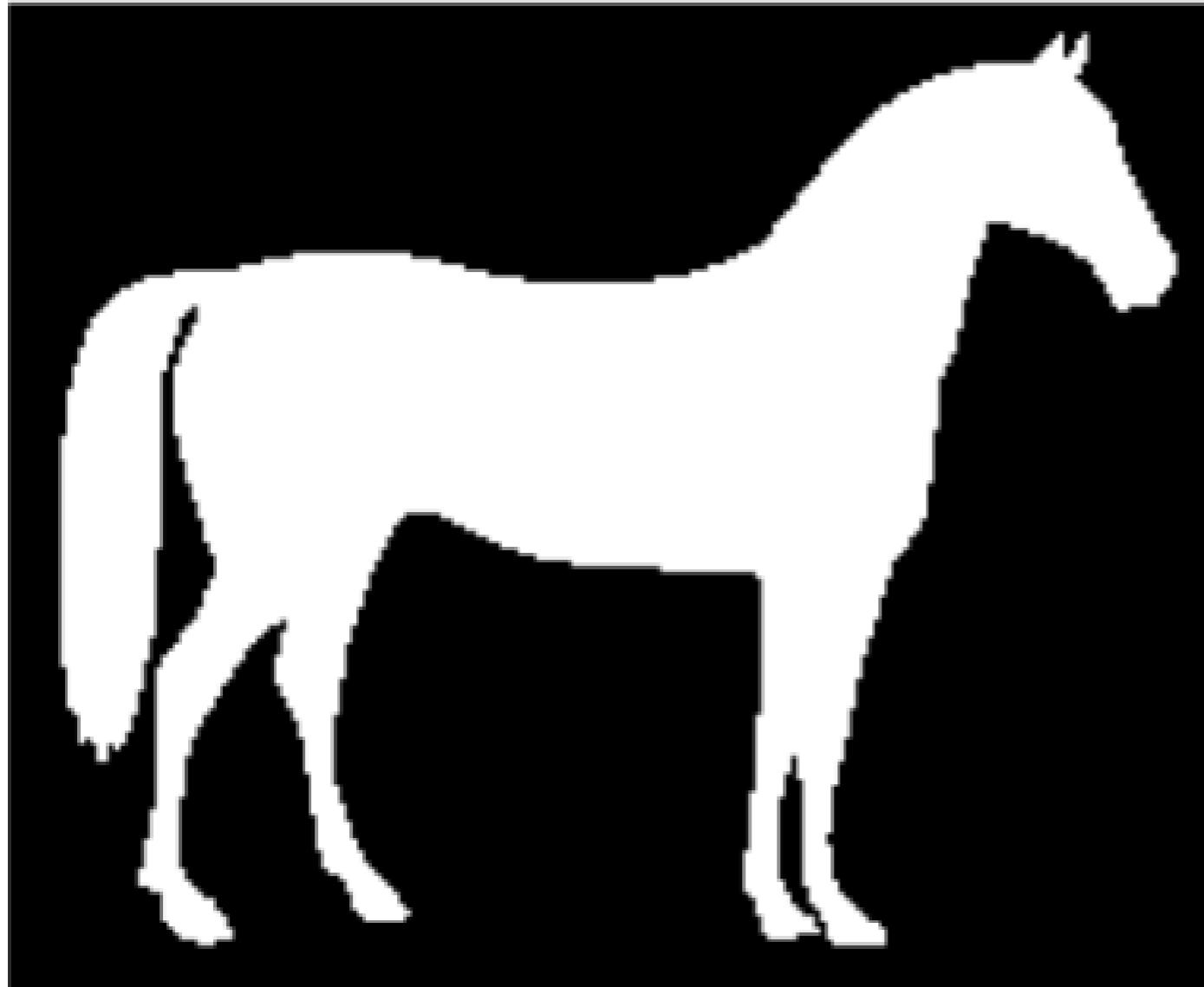


Dilation in scikit-image

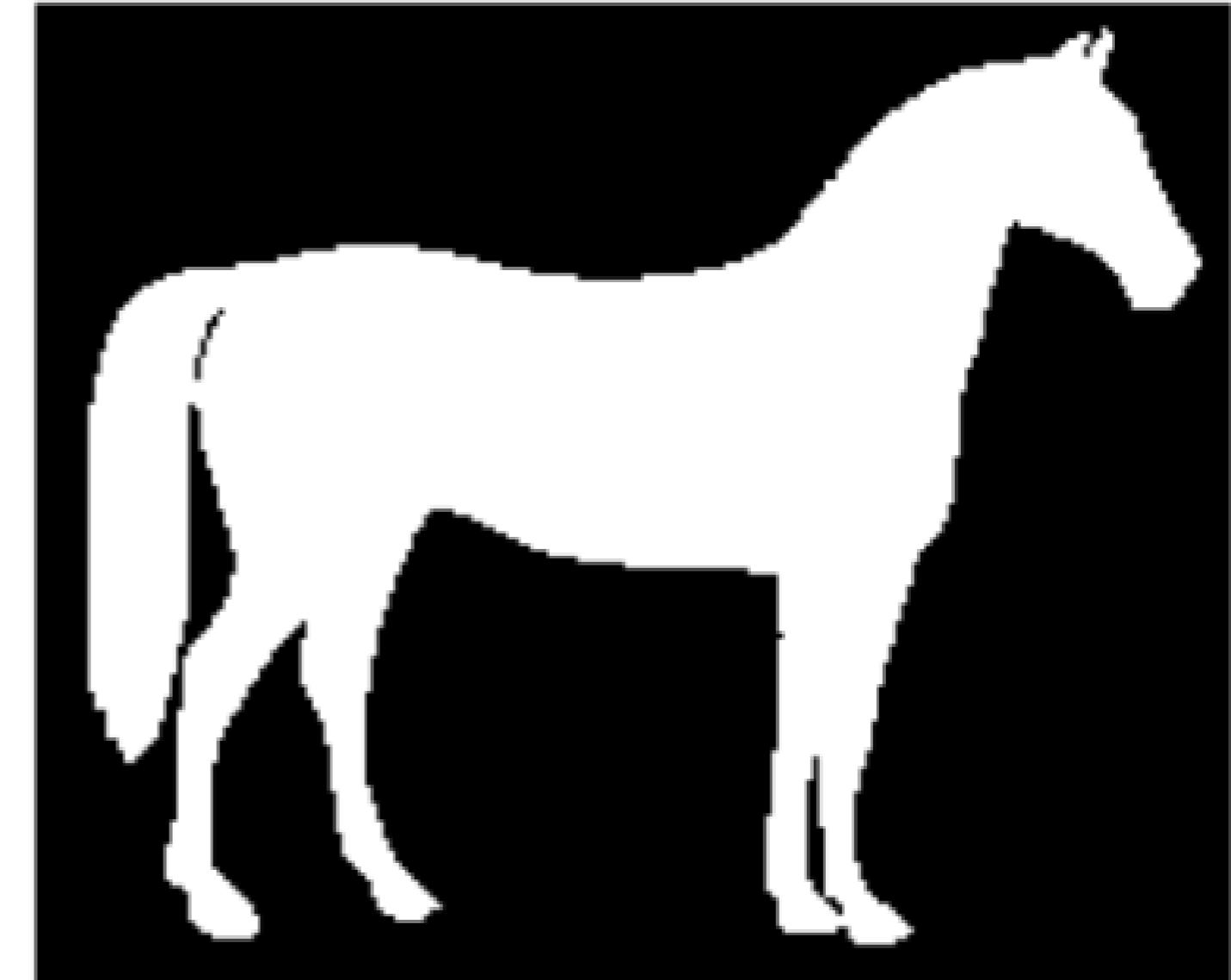
```
from skimage import morphology  
  
# Obtain dilated image, using binary dilation  
dilated_image = morphology.binary_dilation(image_horse)  
  
# See results  
plot_comparison(image_horse, dilated_image, 'Erosion')
```

Dilation in scikit-image

original



Dilation

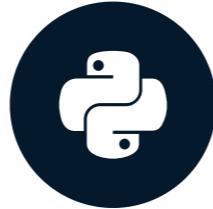


Let's practice!

IMAGE PROCESSING IN PYTHON

Image restoration

IMAGE PROCESSING IN PYTHON



Rebeca Gonzalez

Data Engineer

Restore an image

Image to restore



Image restored



Image reconstruction

- Fixing damaged images
- Text removing
- Logo removing
- Object removing



Image reconstruction

Inpainting

- Reconstructing lost parts of images
- Looking at the non-damaged regions

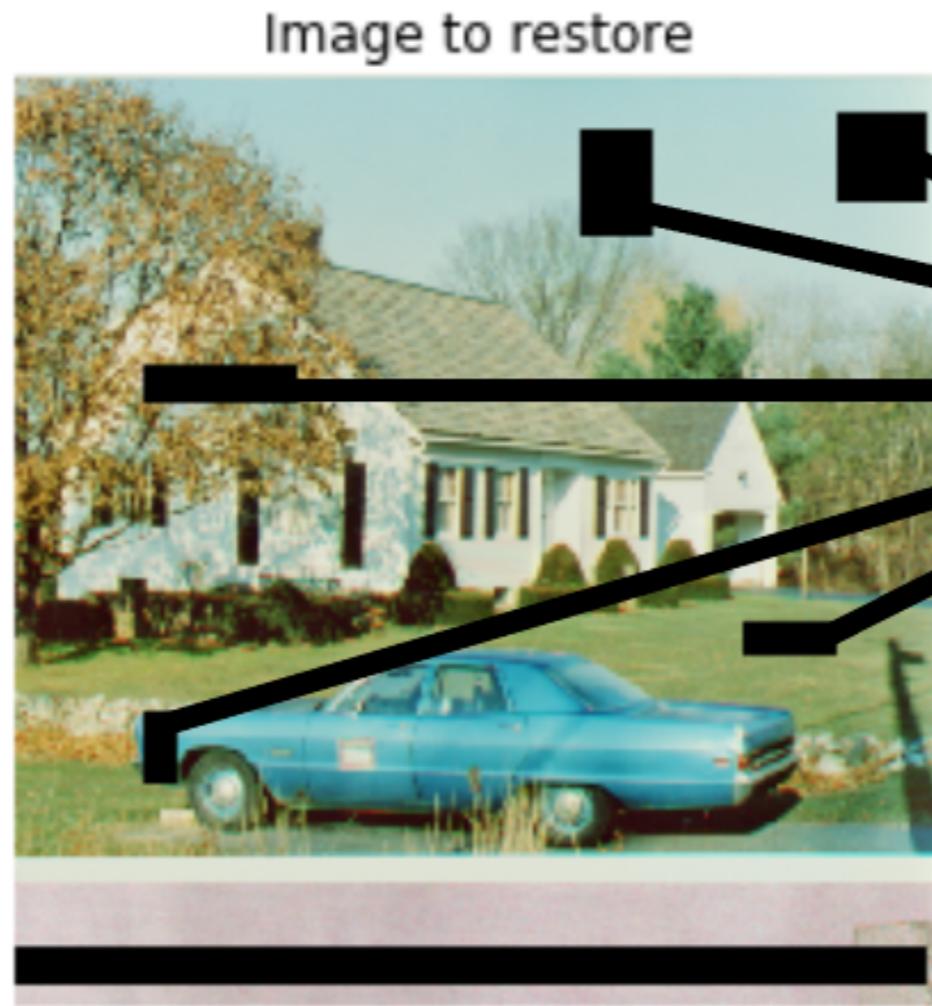


Inpainting

A large black arrow points from the 'Image to restore' on the left to the 'Image restored' on the right, indicating the direction of the inpainting process.



Image reconstruction



Damaged pixels



Set as a mask

Image reconstruction in scikit-image

```
from skimage.restoration import inpaint

# Obtain the mask
mask = get_mask(defect_image)

# Apply inpainting to the damaged image using the mask
restored_image = inpaint.inpaint_biharmonic(defect_image,
                                              mask,
                                              multichannel=True)

# Show the resulting image
show_image(restored_image)
```

Image reconstruction in scikit-image

```
# Show the defect and resulting images  
show_image(defect_image, 'Image to restore')  
show_image(restored_image, 'Image restored')
```

Image to restore



Image restored



Masks

Image to restore



Mask



Masks

```
def get_mask(image):
    ''' Creates mask with three defect regions '''
    mask = np.zeros(image.shape[:-1])

    mask[101:106, 0:240] = 1

    mask[152:154, 0:60] = 1
    mask[153:155, 60:100] = 1
    mask[154:156, 100:120] = 1
    mask[155:156, 120:140] = 1

    mask[212:217, 0:150] = 1
    mask[217:222, 150:256] = 1

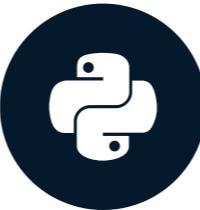
    return mask
```

Let's practice!

IMAGE PROCESSING IN PYTHON

Noise

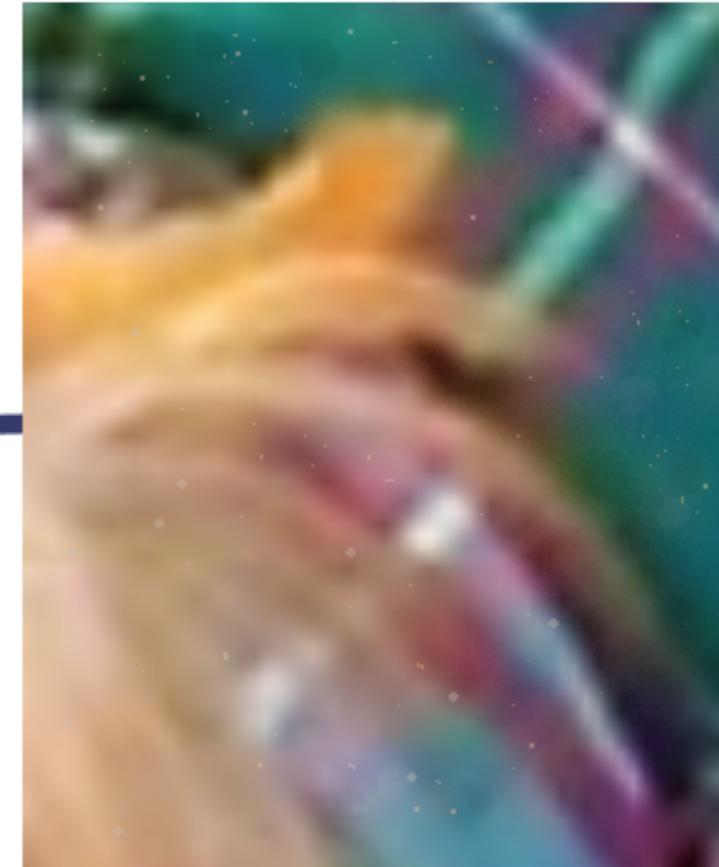
IMAGE PROCESSING IN PYTHON



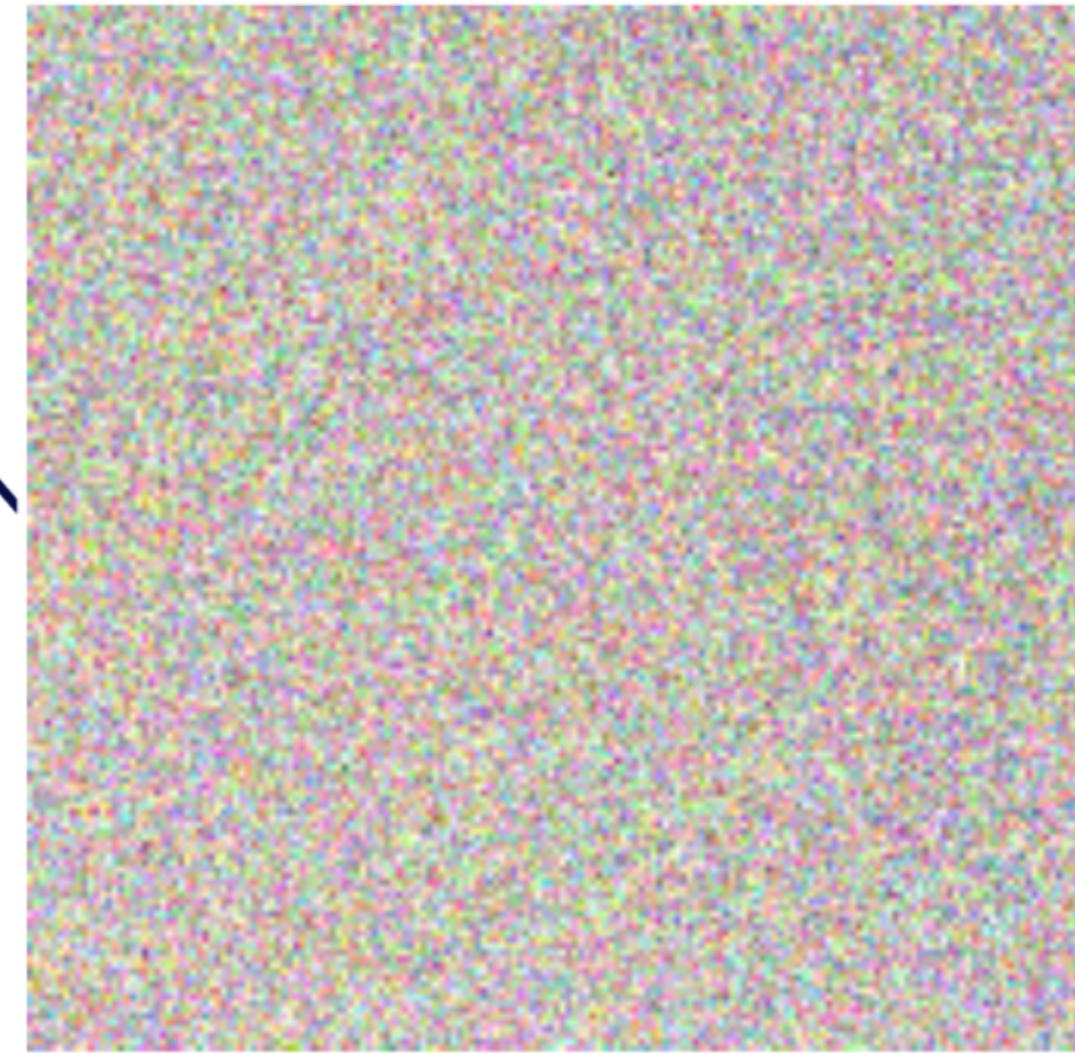
Rebeca Gonzalez

Data Engineer

Noise



Noise



Apply noise in scikit-image

```
# Import the module and function  
from skimage.util import random_noise  
  
# Add noise to the image  
noisy_image = random_noise(dog_image)  
  
# Show original and resulting image  
show_image(dog_image)  
show_image(noisy_image, 'Noisy image')
```

Apply noise in scikit-image

Original



Noisy image



Reducing noise

Noisy image

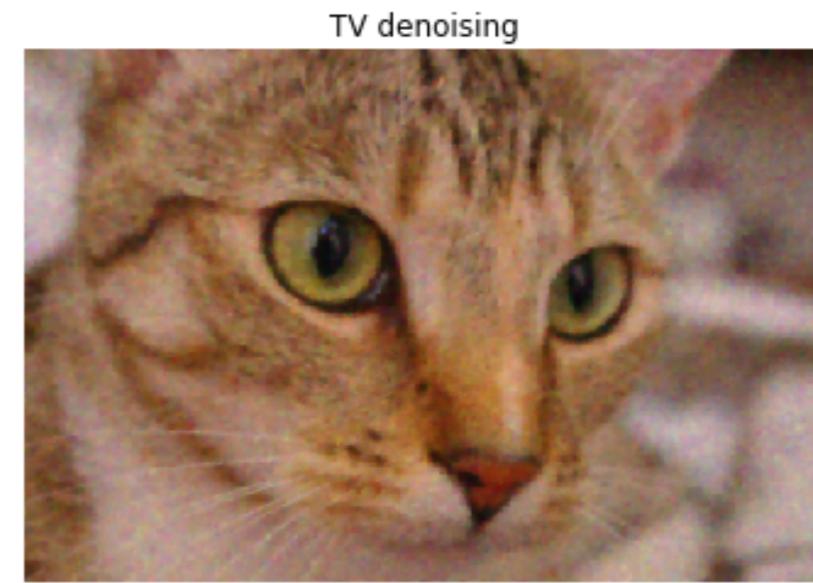


Denoised



Denoising types

- Total variation (TV)
- Bilateral
- Wavelet denoising
- Non-local means denoising



Denoising

Using total variation filter denoising

```
from skimage.restoration import denoise_tv_chambolle

# Apply total variation filter denoising
denoised_image = denoise_tv_chambolle(noisy_image,
                                         weight=0.1,
                                         multichannel=True)

# Show denoised image
show_image(noisy_image, 'Noisy image')
show_image(denoised_image, 'Denoised image')
```

Denoising

Total variation filter

Noisy image



Denoised image



Denoising

Bilateral filter

```
from skimage.restoration import denoise_bilateral

# Apply bilateral filter denoising
denoised_image = denoise_bilateral(noisy_image, multichannel=True)

# Show original and resulting images
show_image(noisy_image, 'Noisy image')
show_image(denoised_image, 'Denoised image')
```

Denoising

Bilateral filter

Noisy image



Denoised image



Let's practice!

IMAGE PROCESSING IN PYTHON

Superpixels & segmentation

IMAGE PROCESSING IN PYTHON



Rebeca Gonzalez

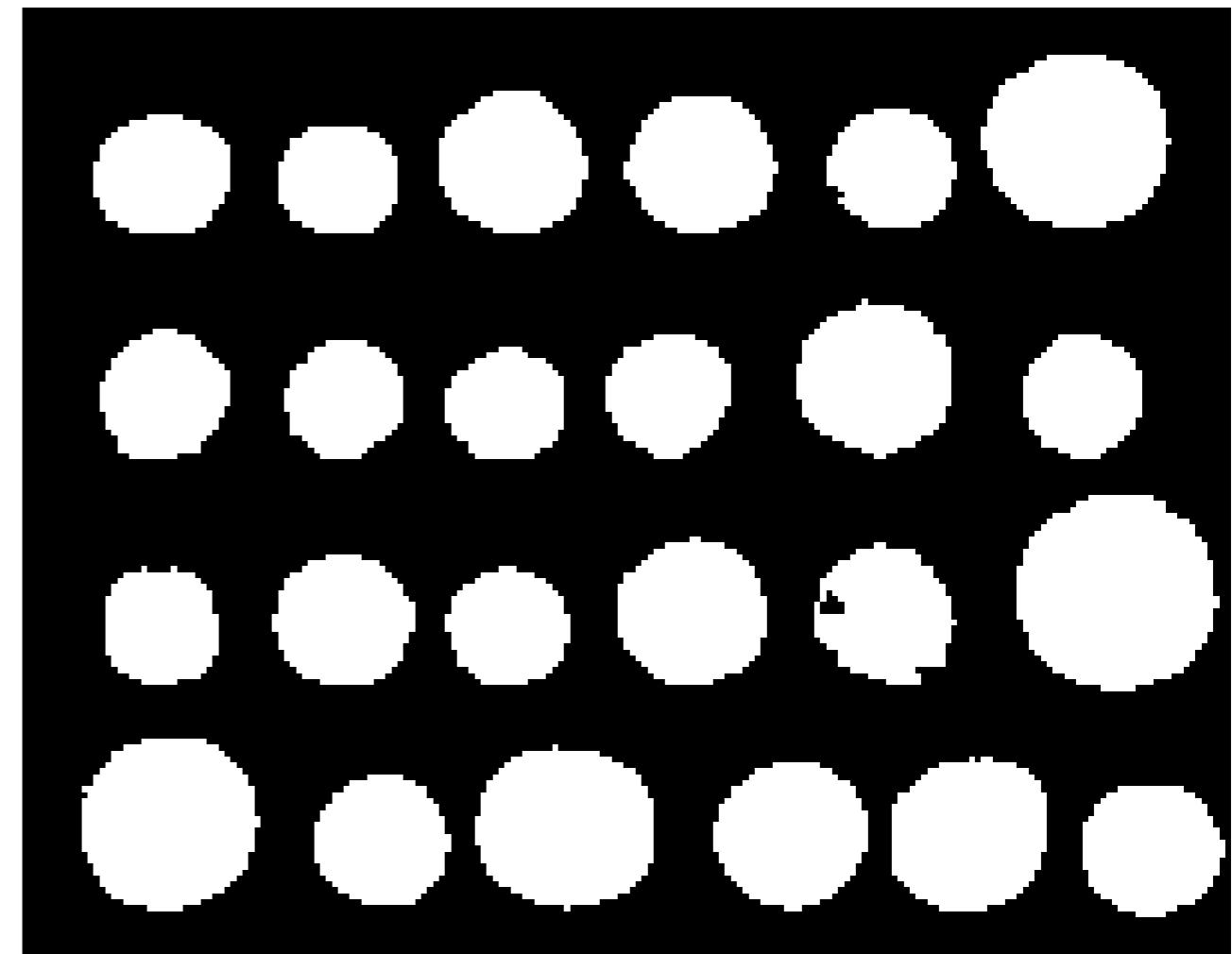
Data Engineer

Segmentation

Original

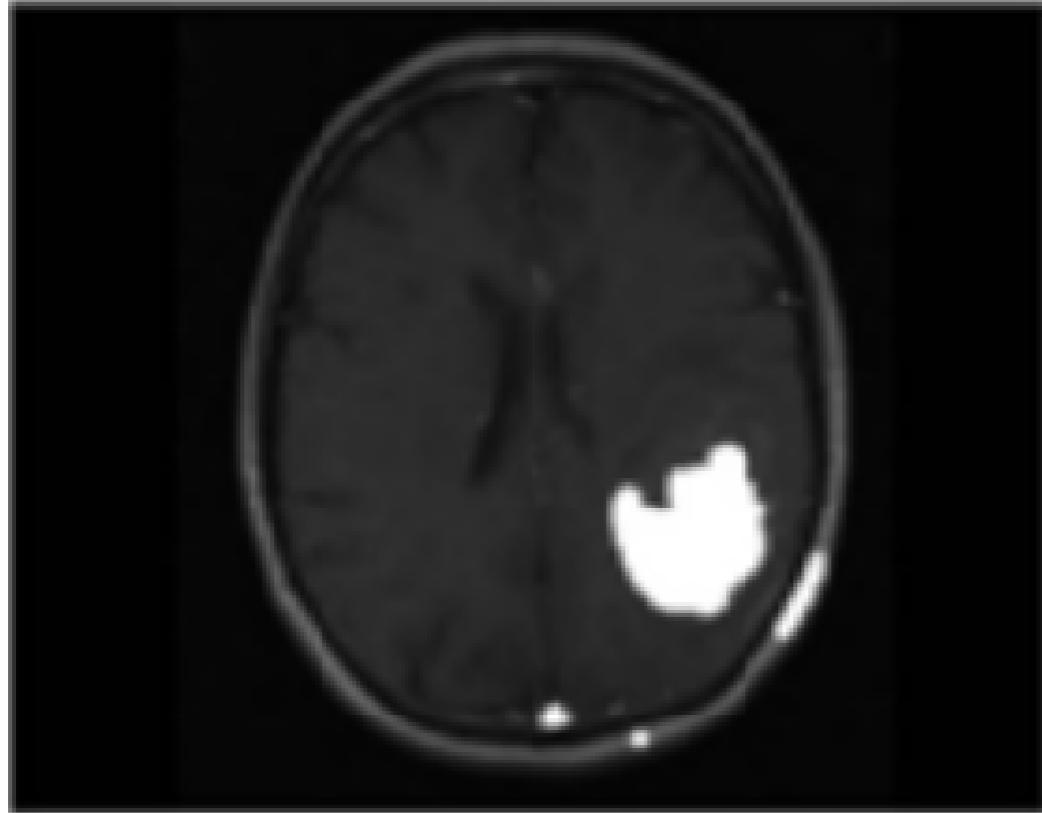


Segmented image



Segmentation

Segmented



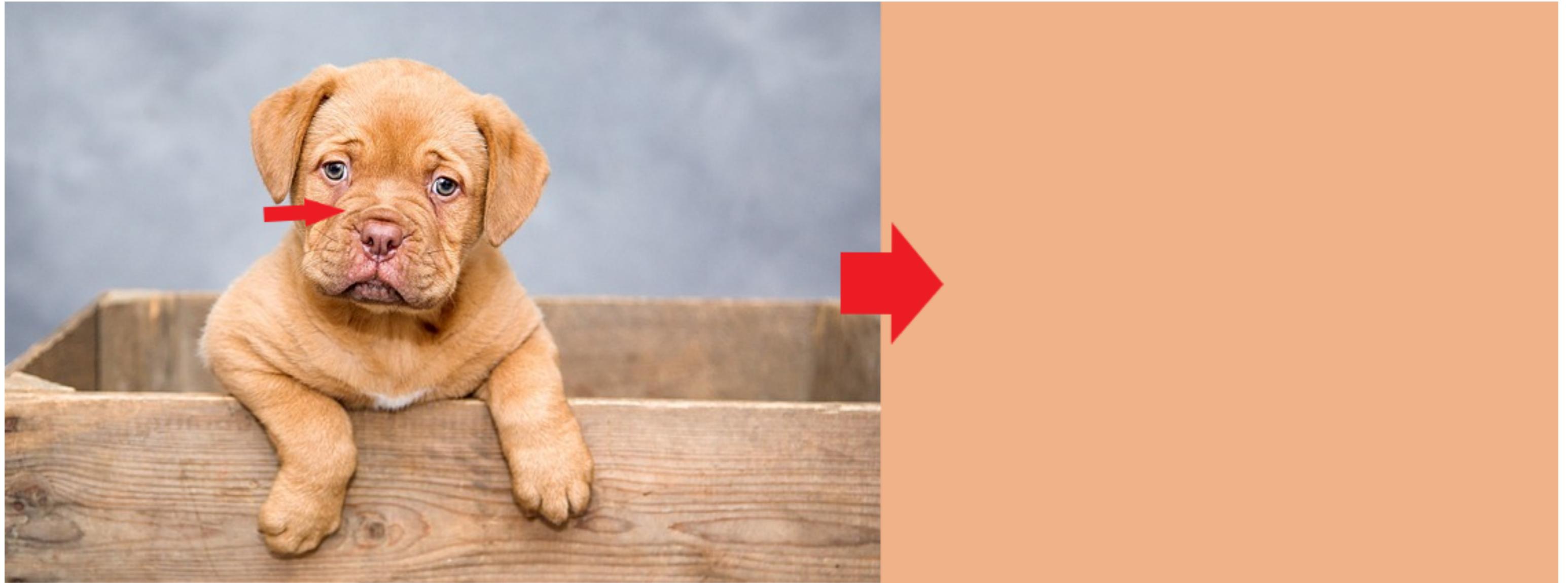
Original



Segmented

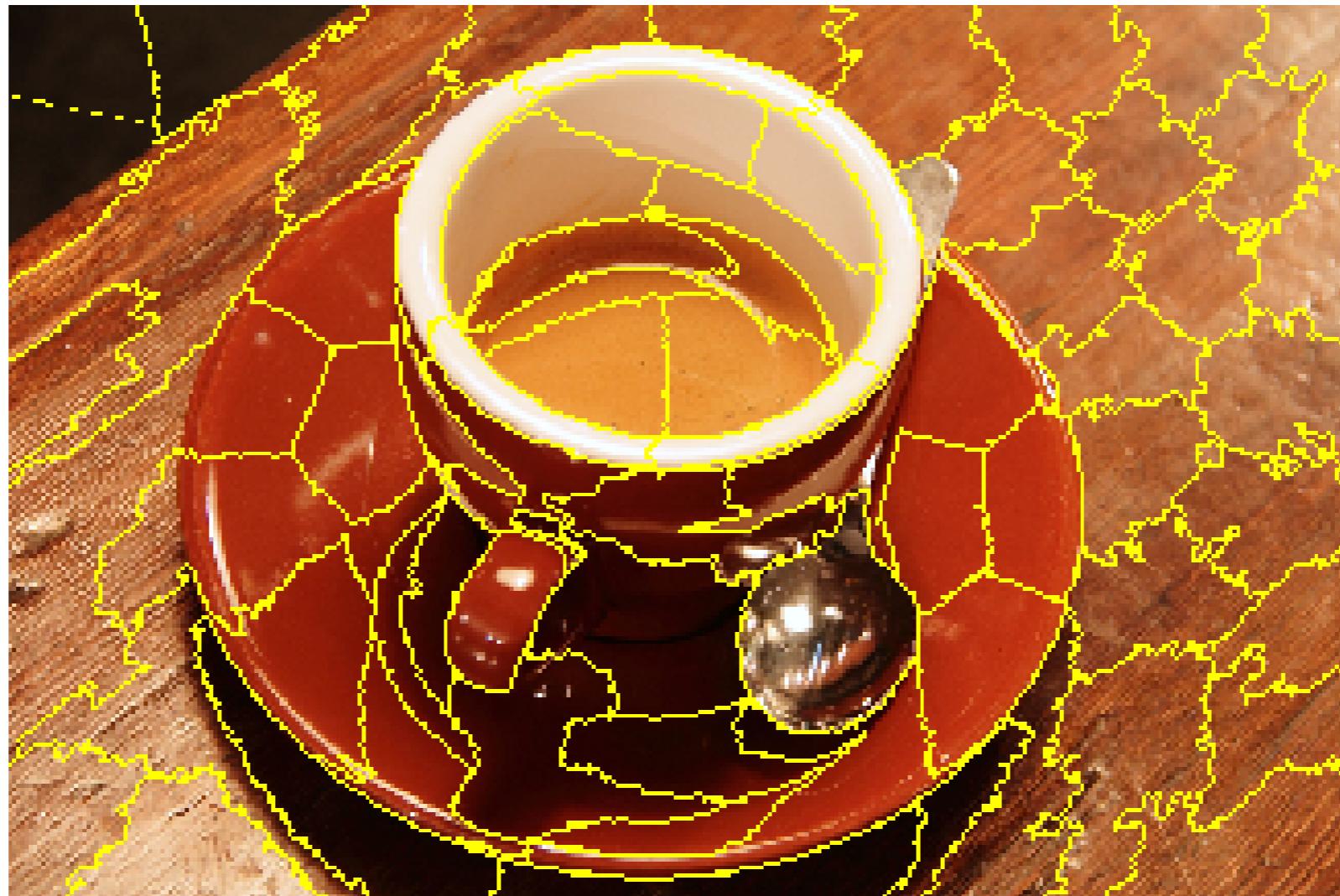


Image representation



Superpixels

Superpixel segmentation, 100 segments



Benefits of superpixels

- More meaningful regions
- Computational efficiency

Segmentation

- Supervised
- Unsupervised



Unsupervised segmentation

Simple Linear Iterative Clustering (SLIC)

Superpixel segmentation, 100 segments



Unsupervised segmentation (SLIC)

```
# Import the modules
from skimage.segmentation import slic
from skimage.color import label2rgb

# Obtain the segments
segments = segmentation.slic(image)

# Put segments on top of original image to compare
segmented_image = label2rgb(segments, image, kind='avg')

show_image(image)
show_image(segmented_image, "Segmented image")
```

Unsupervised segmentation (SLIC)

Original



Segmented image



More segments

```
# Import the modules
from skimage.segmentation import slic
from skimage.color import label2rgb

# Obtain the segmentation with 300 regions
segments = slic(image, n_segments= 300)

# Put segments on top of original image to compare
segmented_image = label2rgb(segments, image, kind='avg')

show_image(segmented_image)
```

More segments

Original



Segmented image



Let's practice!

IMAGE PROCESSING IN PYTHON

Finding contours

IMAGE PROCESSING IN PYTHON



Rebeca Gonzalez

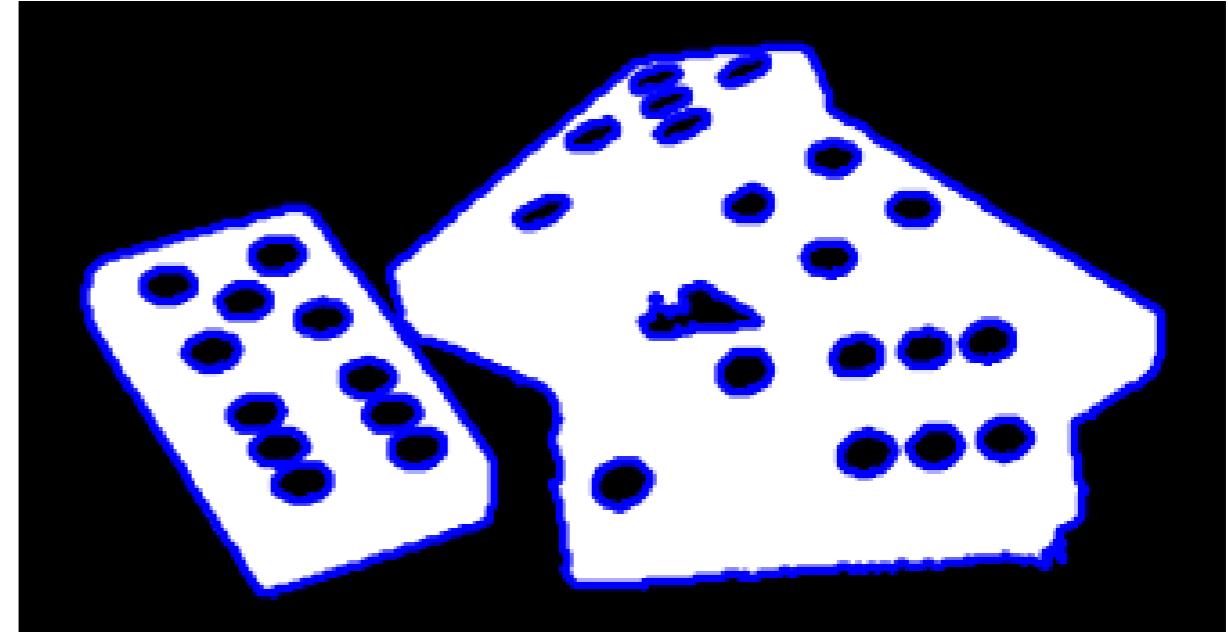
Data Engineer

Finding contours

Original image



Contours



- Measure size
- Classify shapes
- Determine the number of objects

Total points in domino tokens: 29.

Binary images

Thresholded Image



Contours



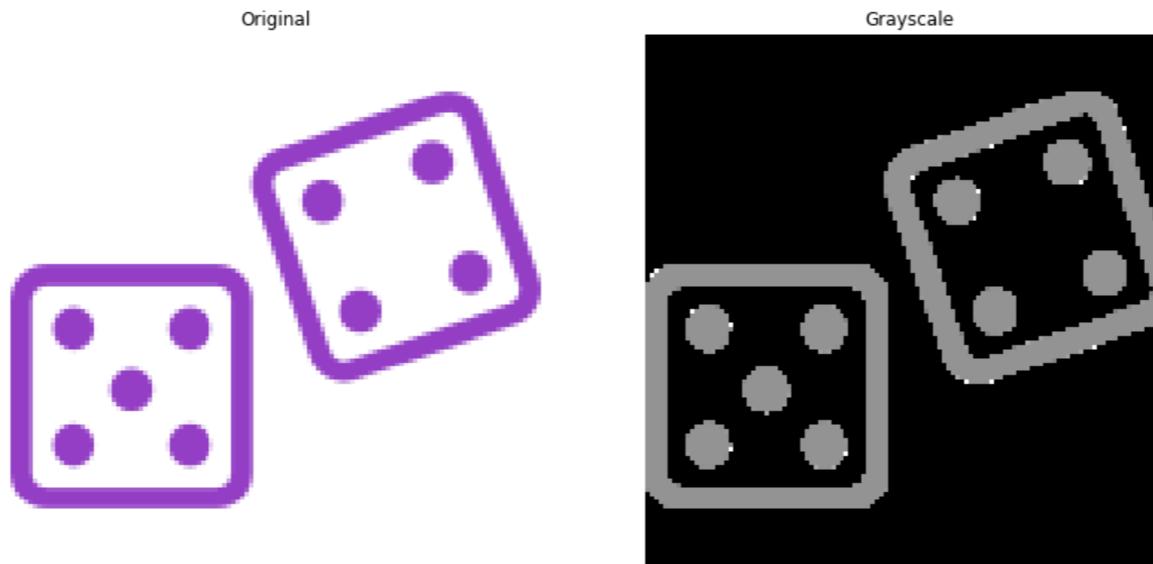
We can obtain a binary image applying
thresholding or using **edge detection**

Find contours using scikit-image

PREPARING THE IMAGE

Transform the image to 2D grayscale.

```
# Make the image grayscale  
image = color.rgb2gray(image)
```



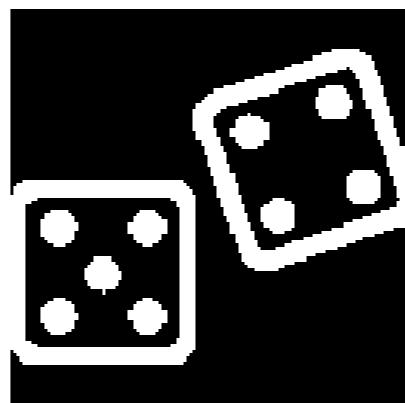
Find contours using scikit-image

PREPARING THE IMAGE

Binarize the image

```
# Obtain the thresh value  
thresh = threshold_otsu(image)  
  
# Apply thresholding  
thresholded_image = image > thresh
```

Thresholded



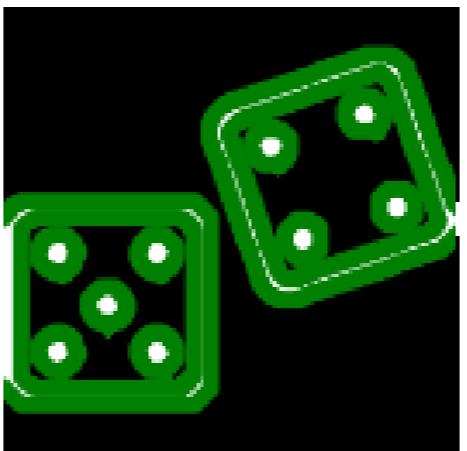
Find contours using scikit-image

And then use `findContours()`.

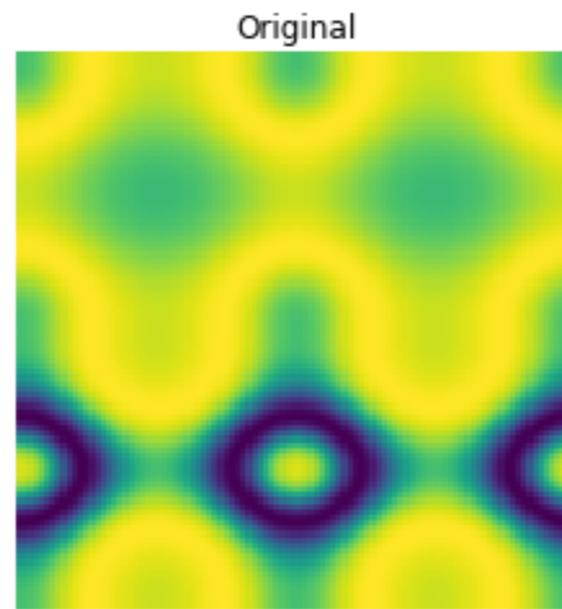
```
# Import the measure module
from skimage import measure

# Find contours at a constant value of 0.8
contours = measure.find_contours(thresholded_image, 0.8)
```

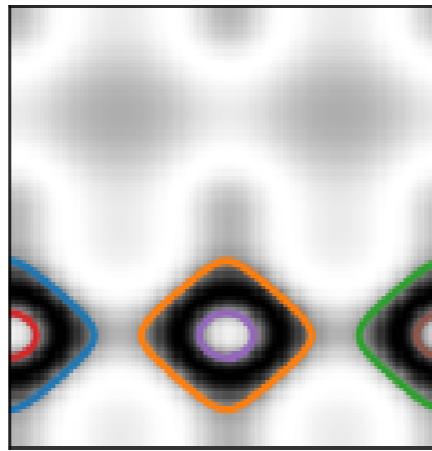
Contours



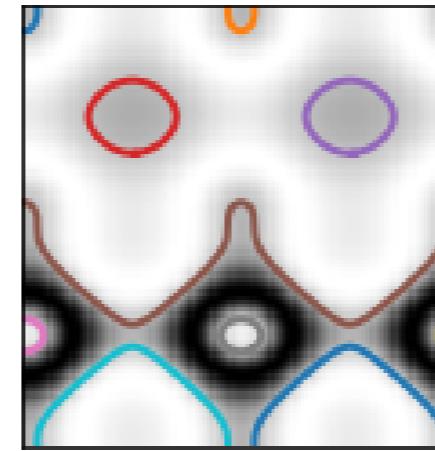
Constant level value



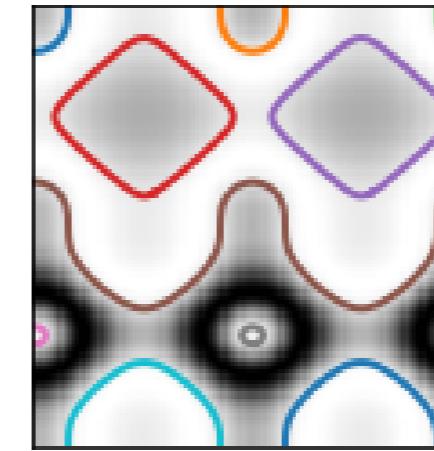
Level value of 0.1



Level value of 0.5



Level value of 0.8



The steps to spotting contours

```
from skimage import measure
from skimage.filters import threshold_otsu

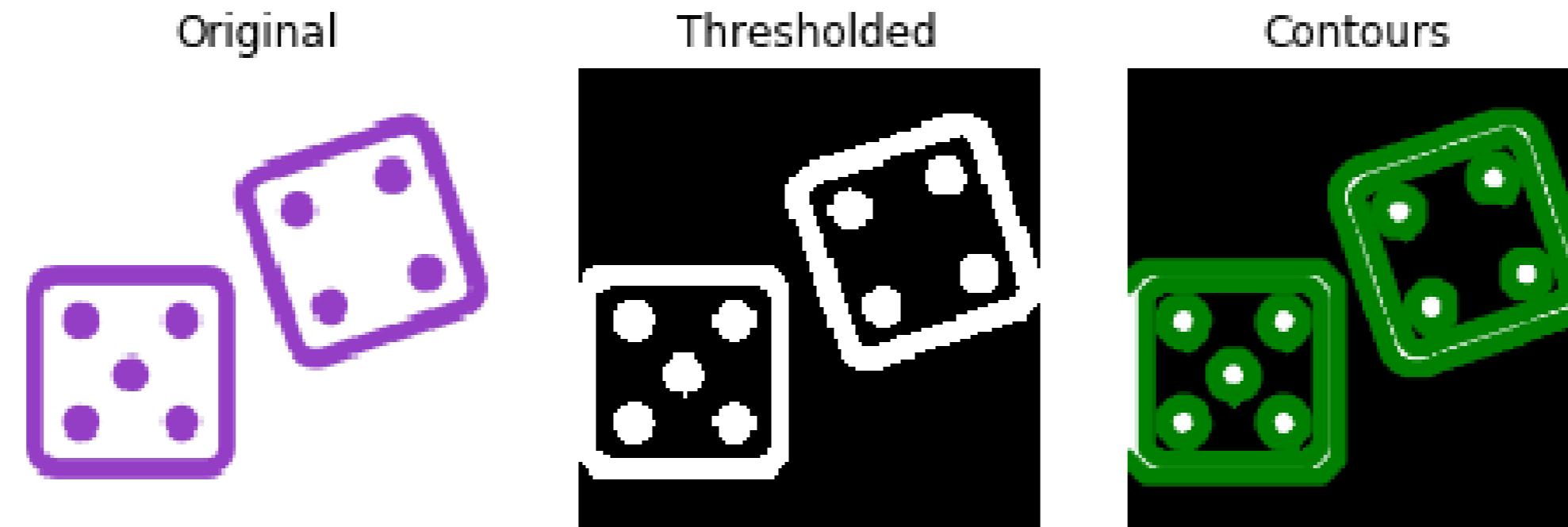
# Make the image grayscale
image = color.rgb2gray(image)
# Obtain the optimal thresh value of the image
thresh = threshold_otsu(image)

# Apply thresholding and obtain binary image
thresholded_image = image > thresh

# Find contours at a constant value of 0.8
contours = measure.find_contours(thresholded_image, 0.8)
```

The steps to spotting contours

Resulting in



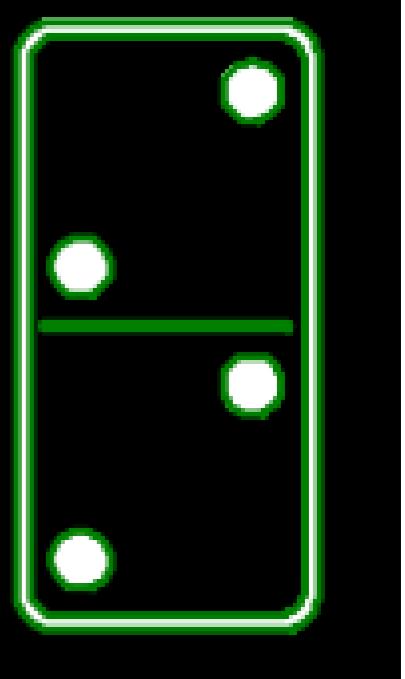
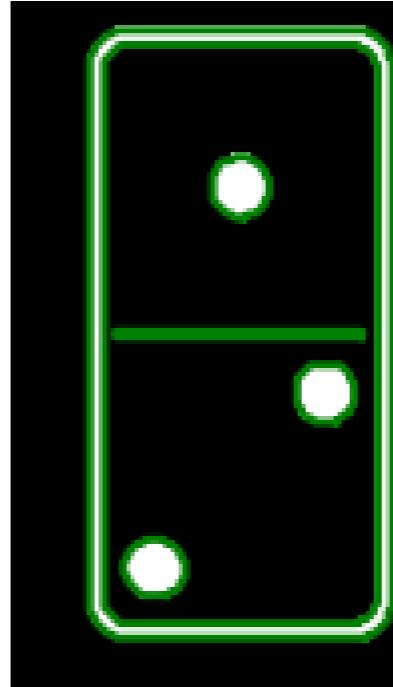
A contour's shape

Contours: list of (n,2) - ndarrays.

```
for contour in contours:  
    print(contour.shape)
```

```
(433, 2)  
(433, 2)  
(401, 2)  
(401, 2)  
(123, 2)  
(123, 2)  
(59, 2)  
(59, 2)  
(59, 2)  
(57, 2)  
(57, 2)  
(59, 2)
```

Contours

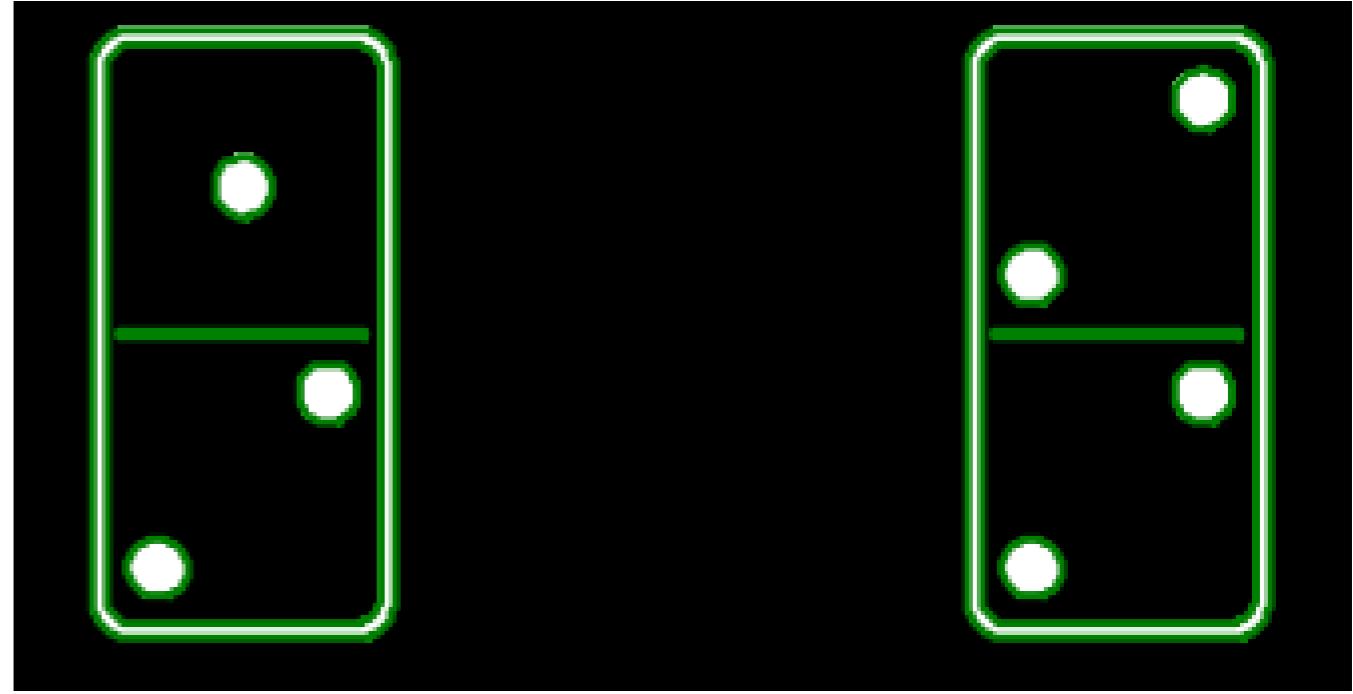


A contour's shape

```
for contour in contours:  
    print(contour.shape)
```

```
(433, 2)  
(433, 2) --> Outer border  
(401, 2)  
(401, 2)  
(123, 2)  
(123, 2)  
(59, 2)  
(59, 2)  
(59, 2)  
(57, 2)  
(57, 2)  
(59, 2)  
(59, 2)
```

Contours

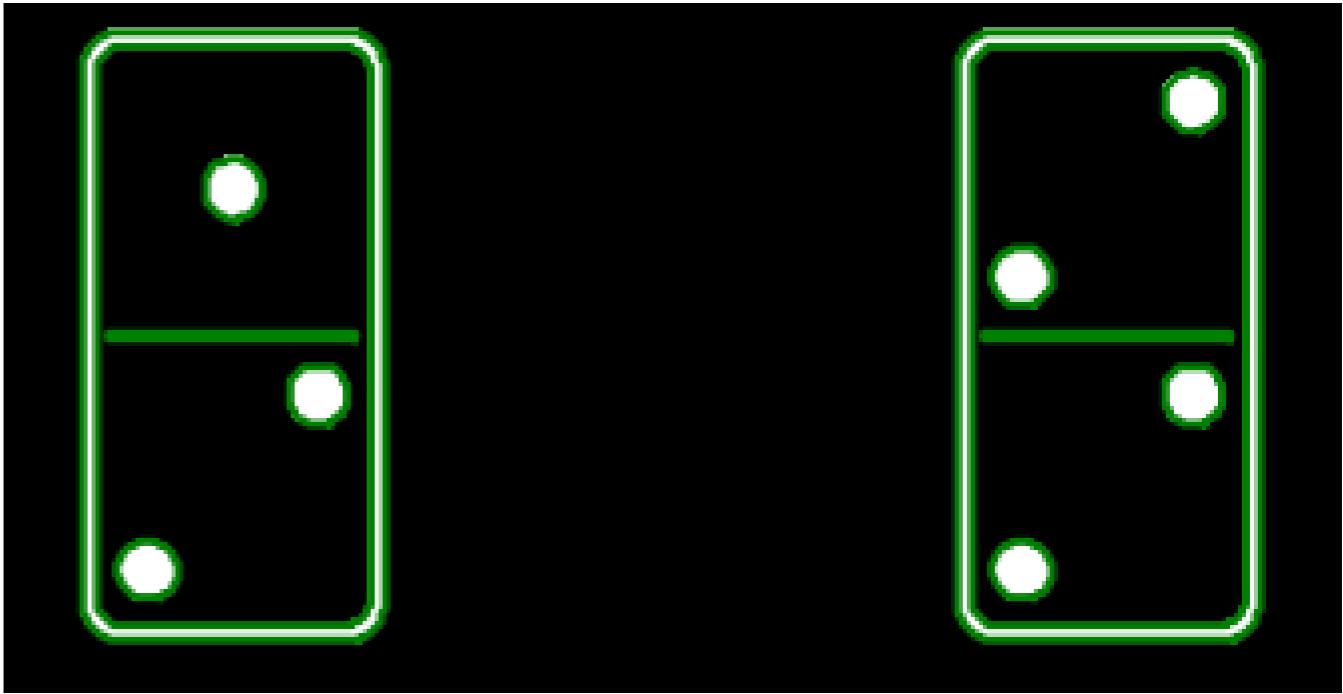


A contour's shape

```
for contour in contours:  
    print(contour.shape)
```

```
(433, 2)  
(433, 2) --> Outer border  
(401, 2)  
(401, 2) --> Inner border  
(123, 2)  
(123, 2)  
(59, 2)  
(59, 2)  
(59, 2)  
(57, 2)  
(57, 2)  
(59, 2)  
(59, 2)
```

Contours

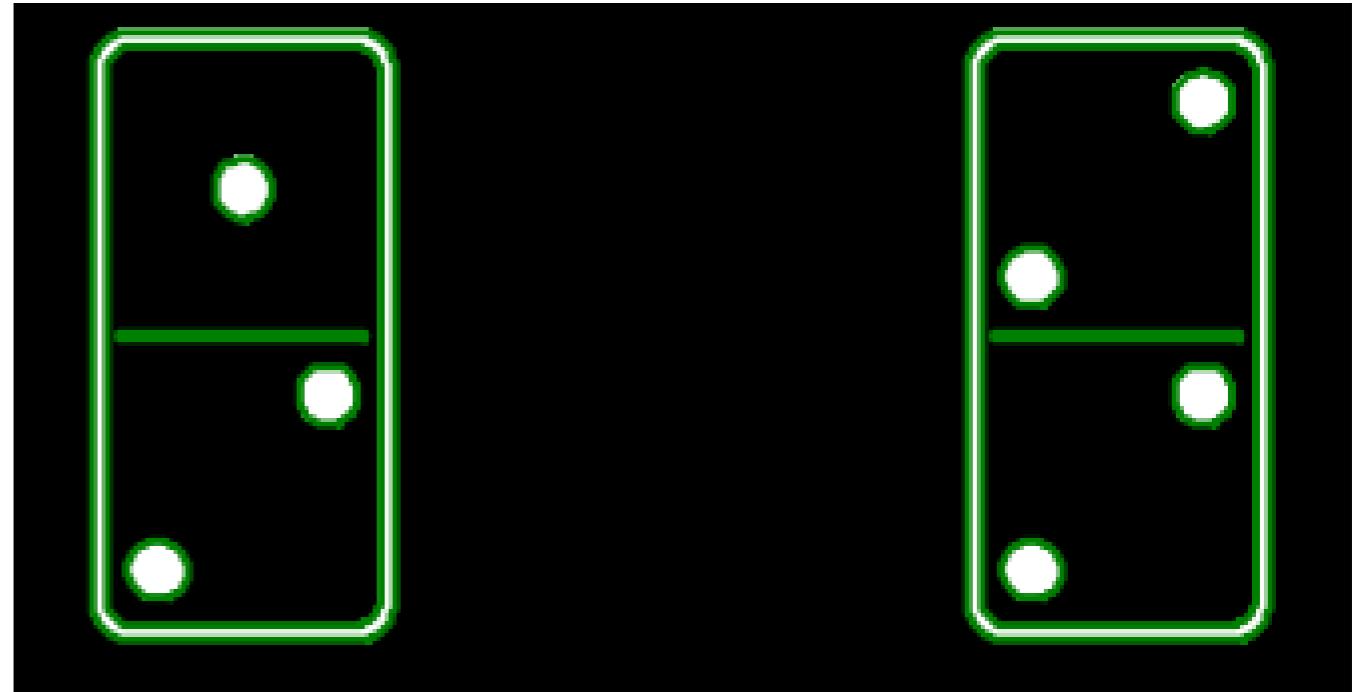


A contour's shape

```
for contour in contours:  
    print(contour.shape)
```

```
(433, 2)  
(433, 2) --> Outer border  
(401, 2)  
(401, 2) --> Inner border  
(123, 2)  
(123, 2) --> Divisory line of tokens  
(59, 2)  
(59, 2)  
(59, 2)  
(57, 2)  
(57, 2)  
(59, 2)  
(59, 2)
```

Contours

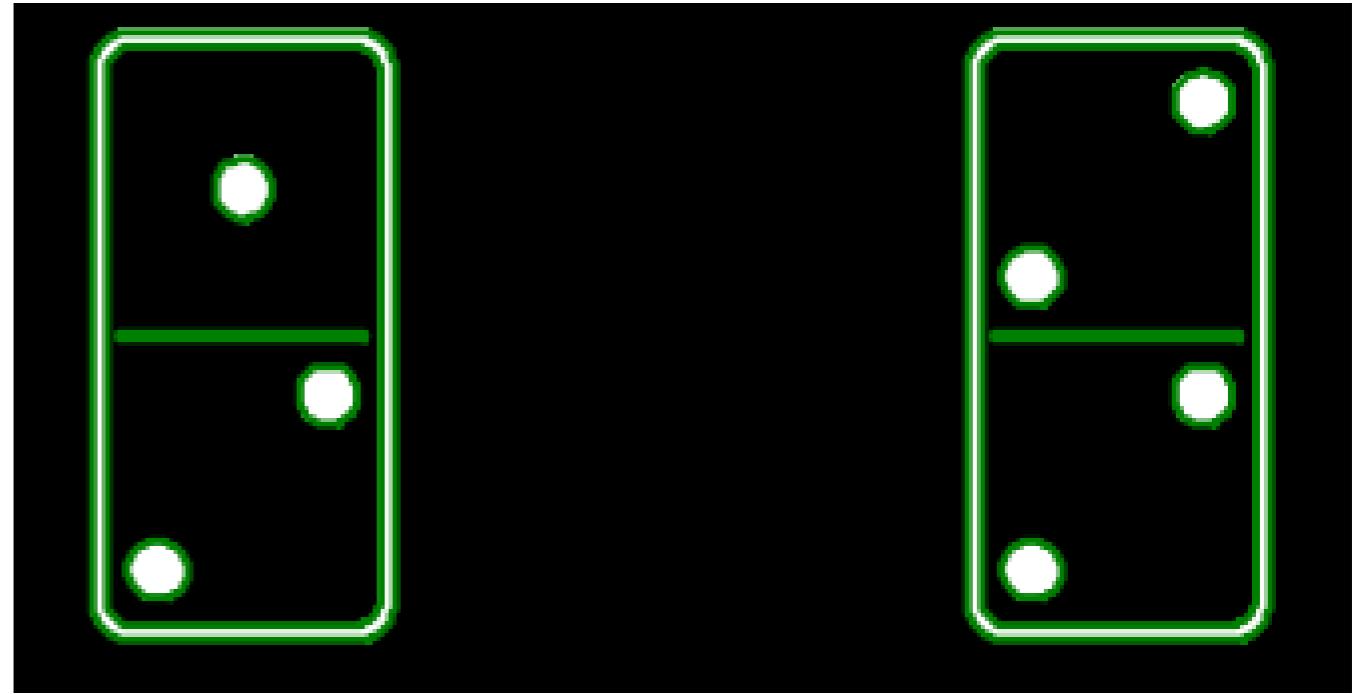


A contour's shape

```
for contour in contours:  
    print(contour.shape)
```

```
(433, 2)  
(433, 2) --> Outer border  
(401, 2)  
(401, 2) --> Inner border  
(123, 2)  
(123, 2) --> Divisory line of tokens  
(59, 2)  
(59, 2)  
(59, 2)  
(57, 2)  
(57, 2)  
(59, 2)  
(59, 2) --> Dots
```

Contours



Number of dots: 7.

Let's practice!

IMAGE PROCESSING IN PYTHON

Finding the edges with Canny

IMAGE PROCESSING IN PYTHON



Rebeca Gonzalez

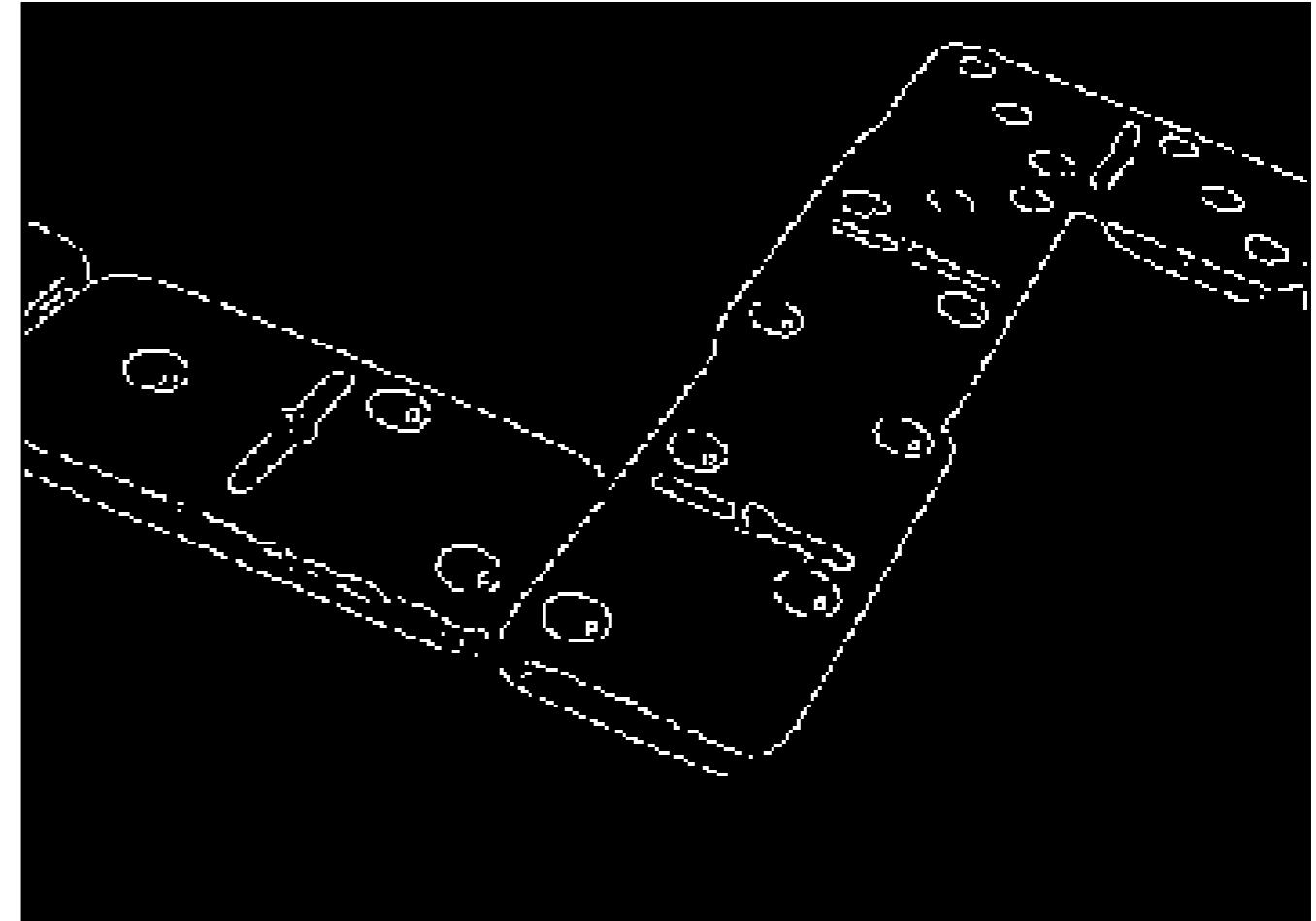
Data Engineer

Detecting edges

Original

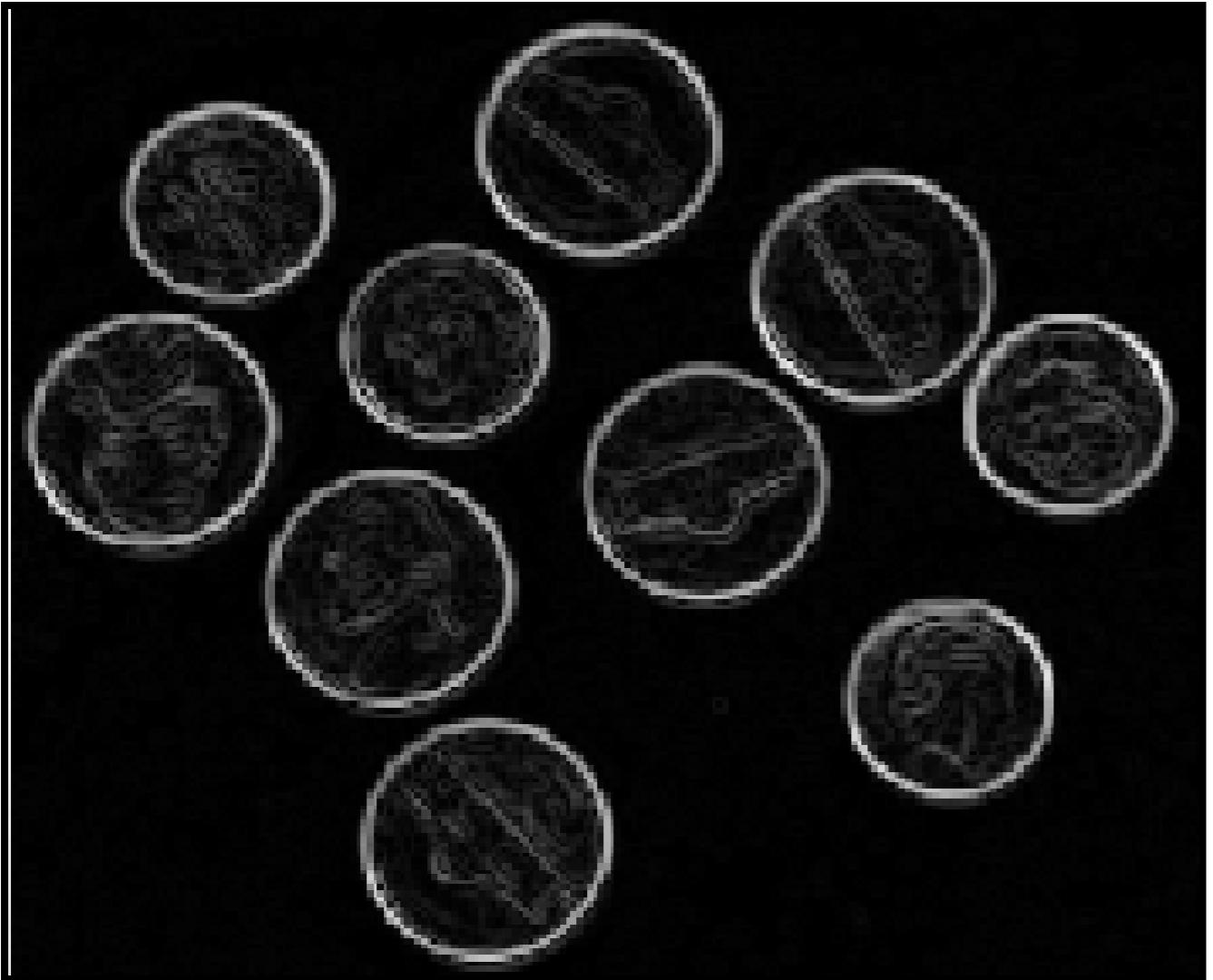


Edges with Canny

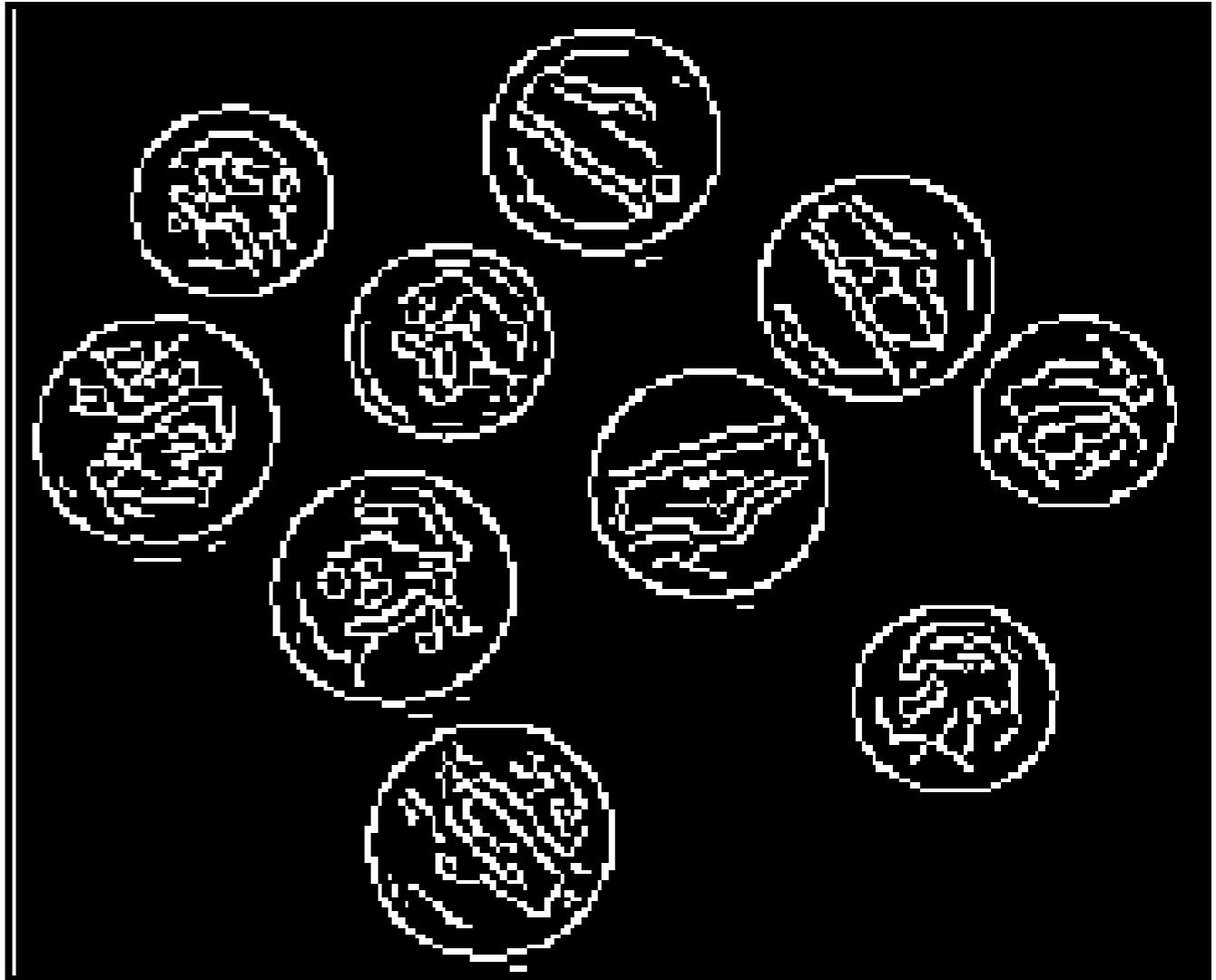


Edge detection

Edges with Sobel



Edges with Canny



Edge detection

```
from skimage.feature import canny

# Convert image to grayscale
coins = color.rgb2gray(coins)

# Apply Canny detector
canny_edges = canny(coins)

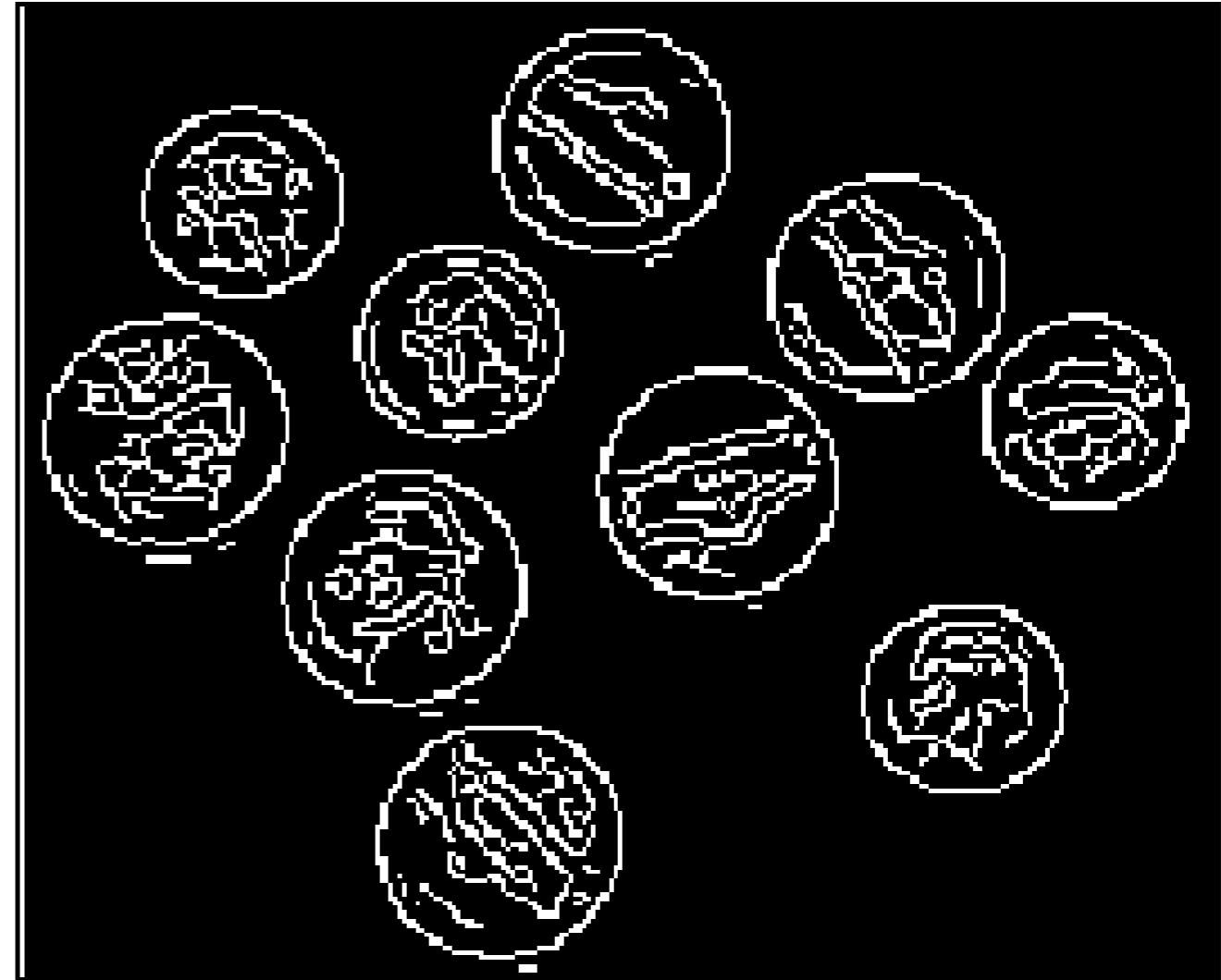
# Show resulted image with edges
show_image(canny_edges, "Edges with Canny")
```

Edge detection

Original



Edges with Canny

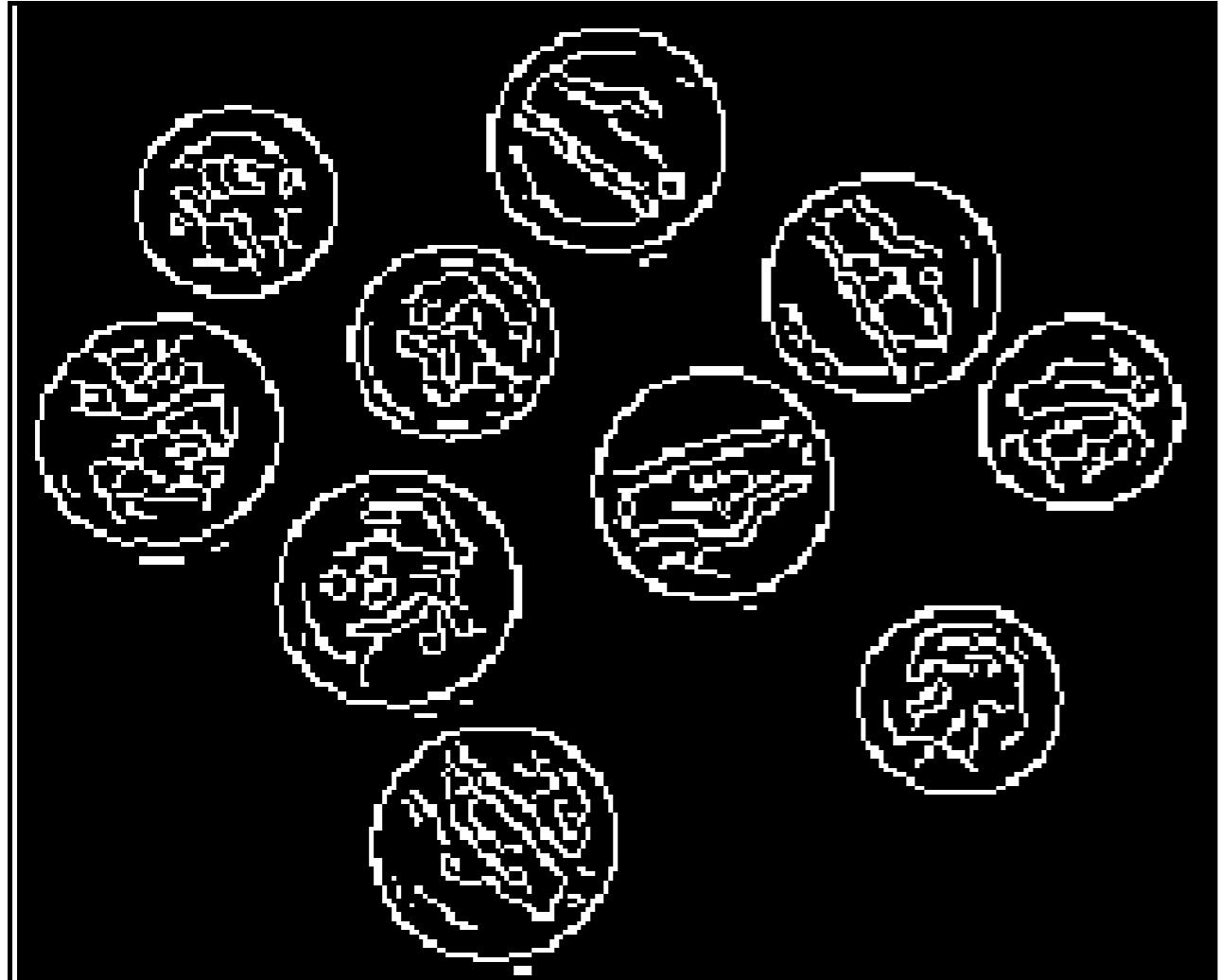


Canny edge detector

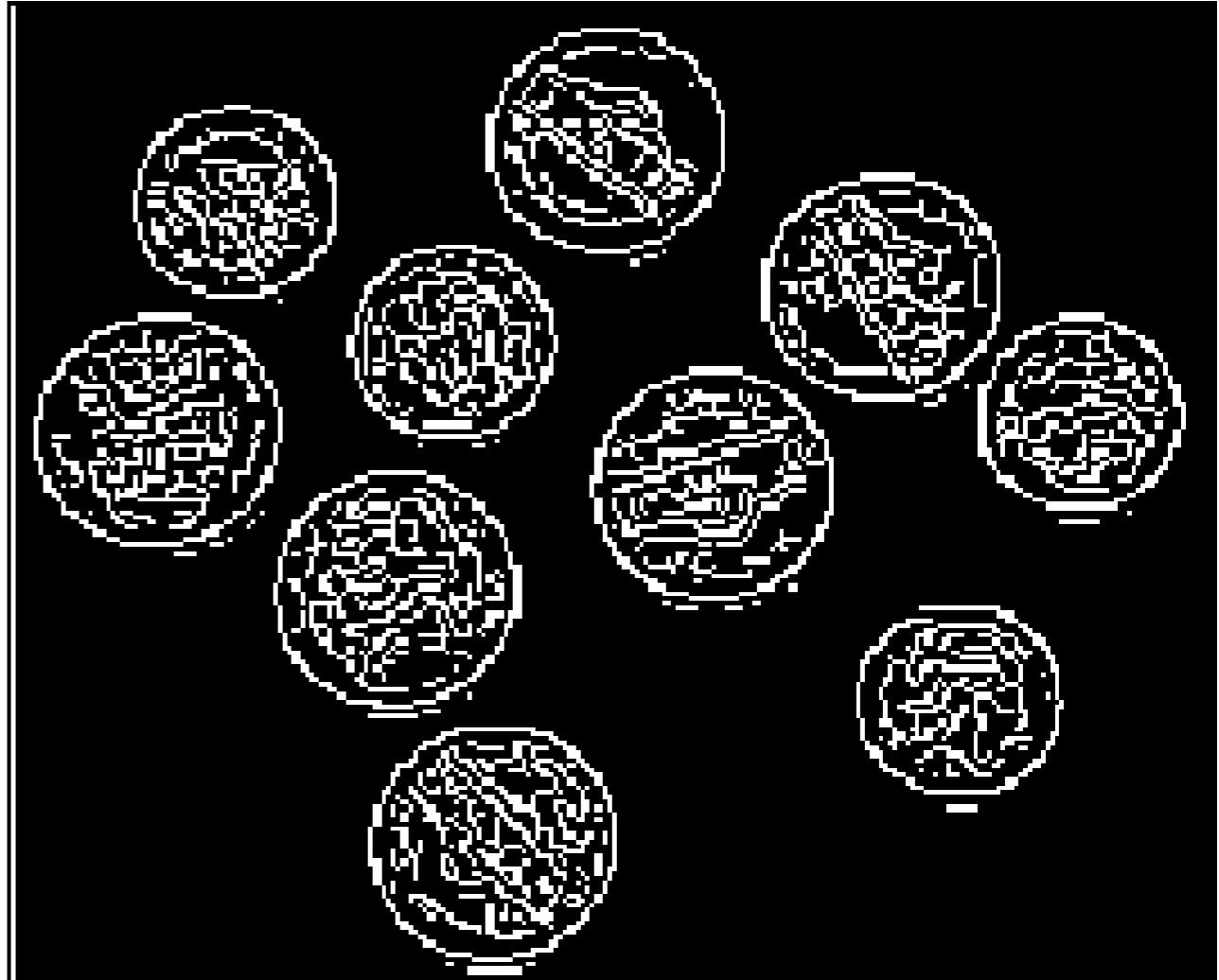
```
# Apply Canny detector with a sigma of 0.5  
canny_edges_0_5 = canny(coins, sigma=0.5)  
  
# Show resulted images with edges  
show_image(canny_edges, "Sigma of 1")  
show_image(canny_edges_0_5, "Sigma of 0.5")
```

Canny edge detector

Sigma of 1



Sigma of 0.5

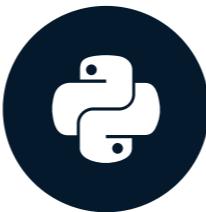


Let's practice!

IMAGE PROCESSING IN PYTHON

Right around the corner

IMAGE PROCESSING IN PYTHON

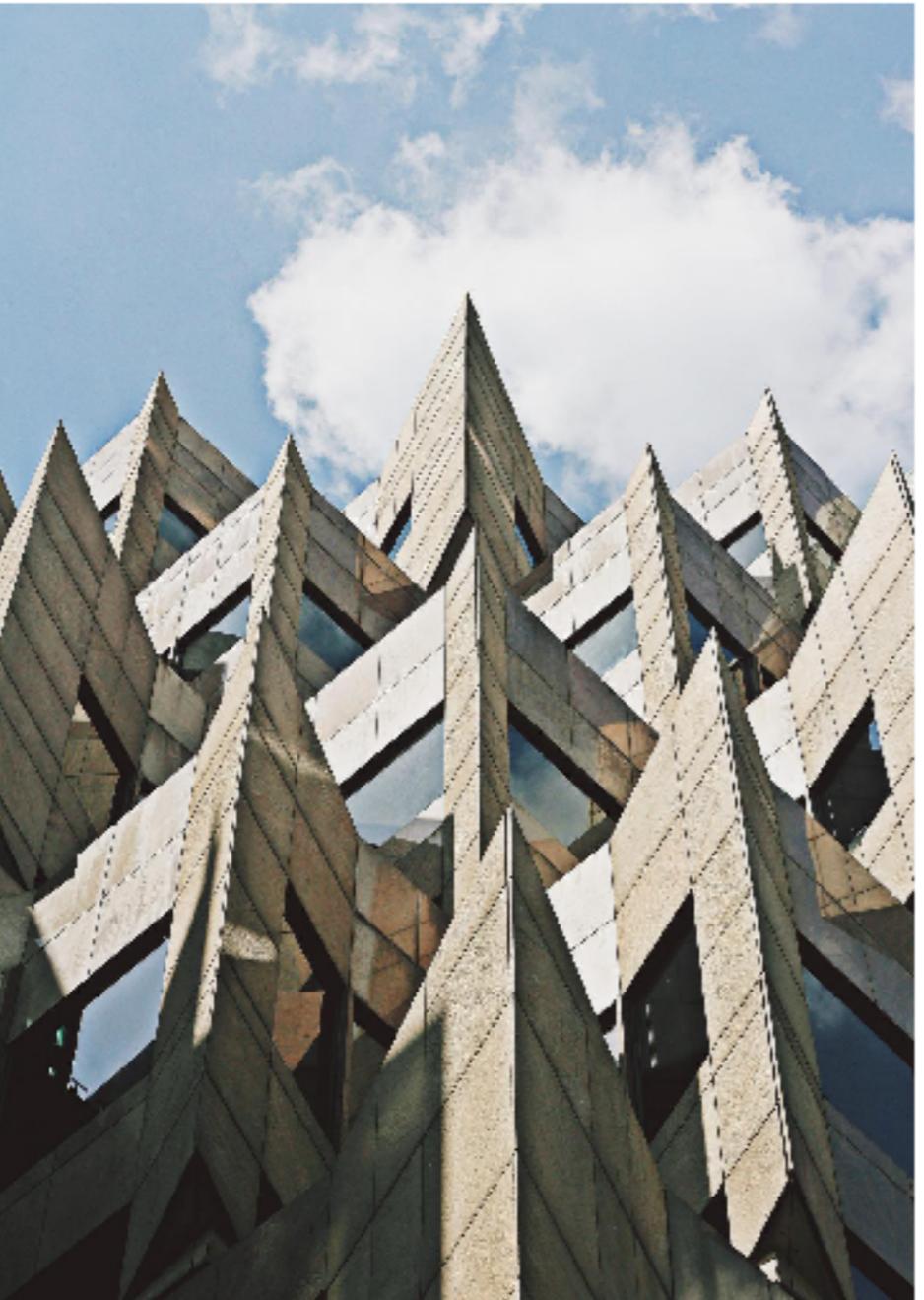


Rebeca Gonzalez

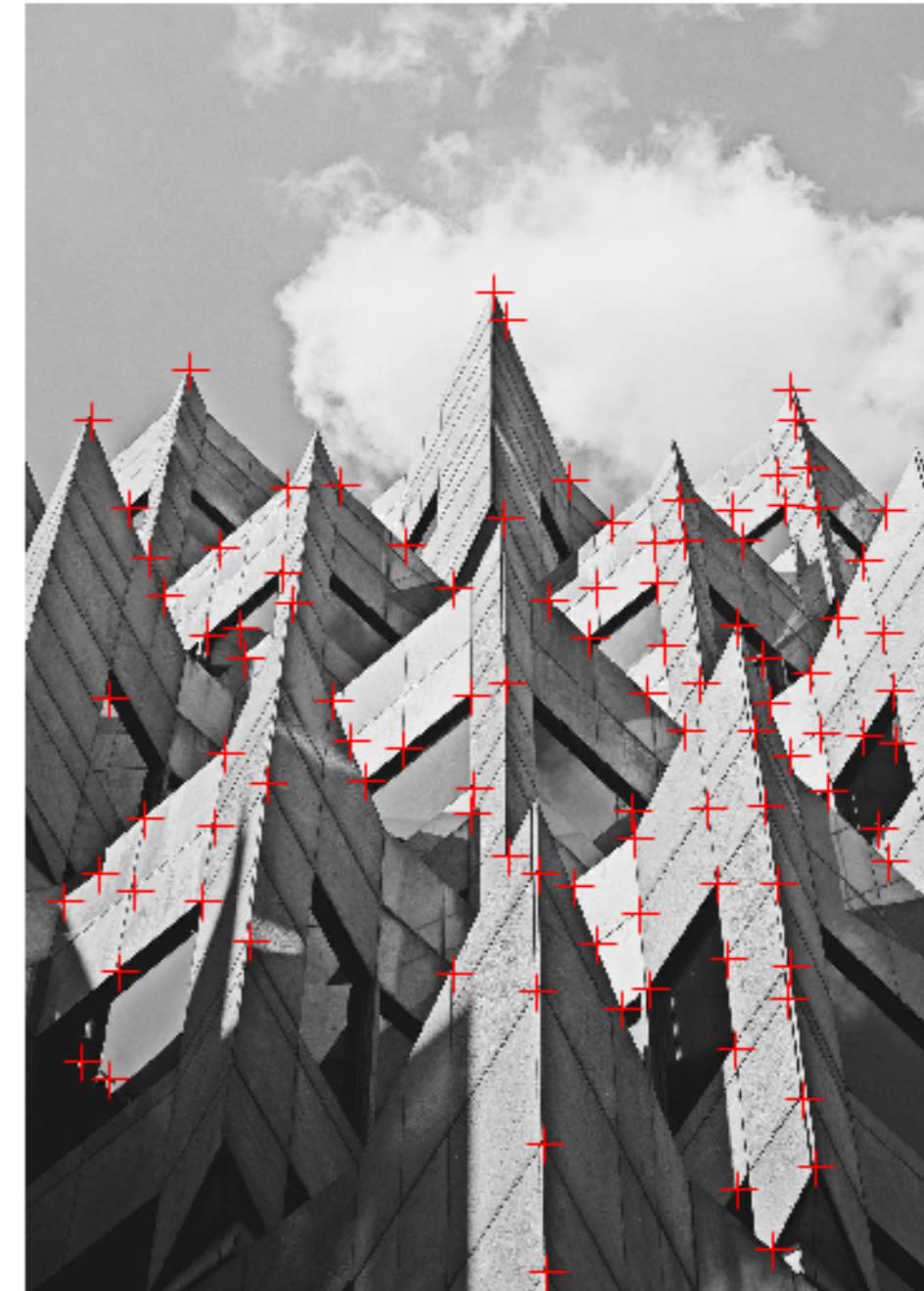
Data Engineer

Corner detection

Original image

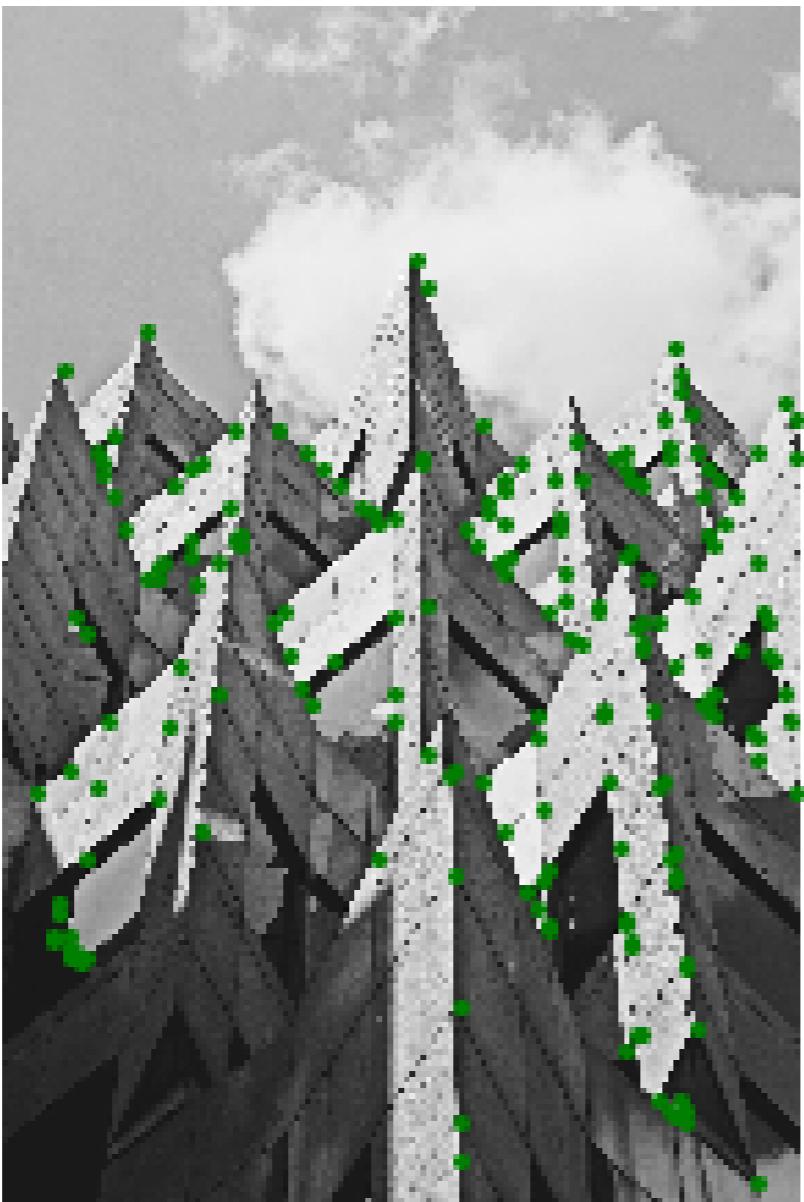


Corners detected



Points of interest

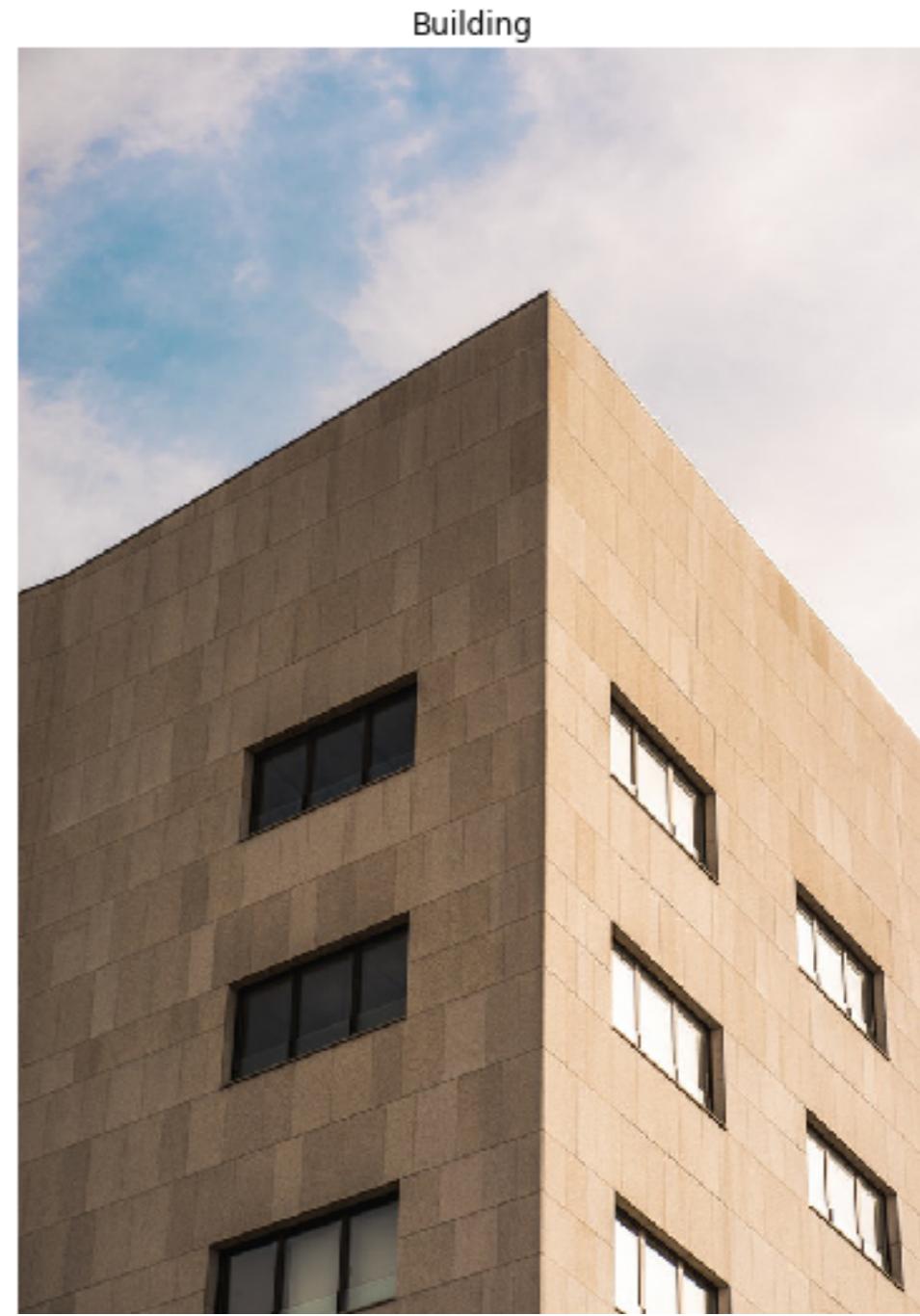
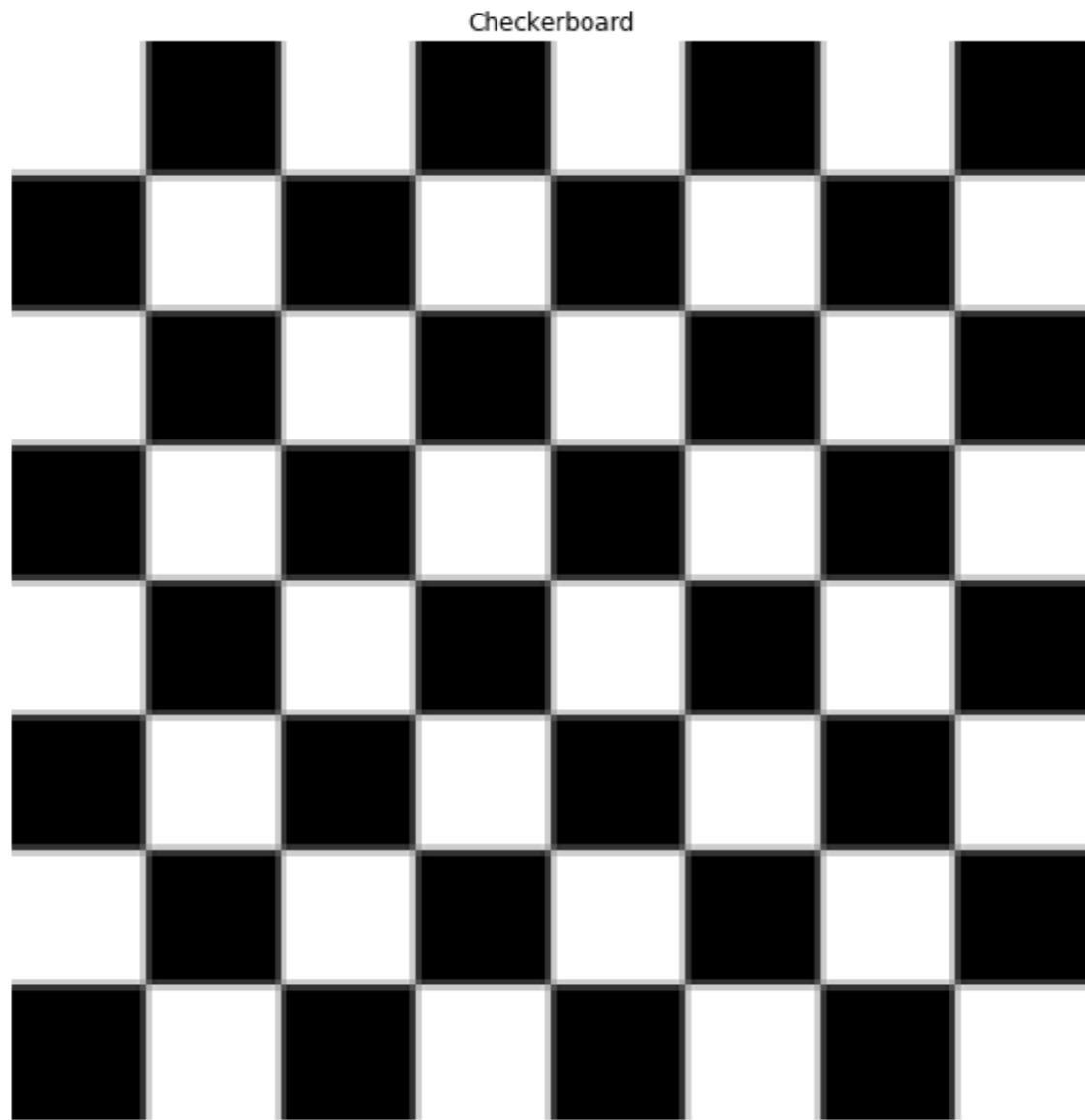
Points of interest



Edges with Sobel

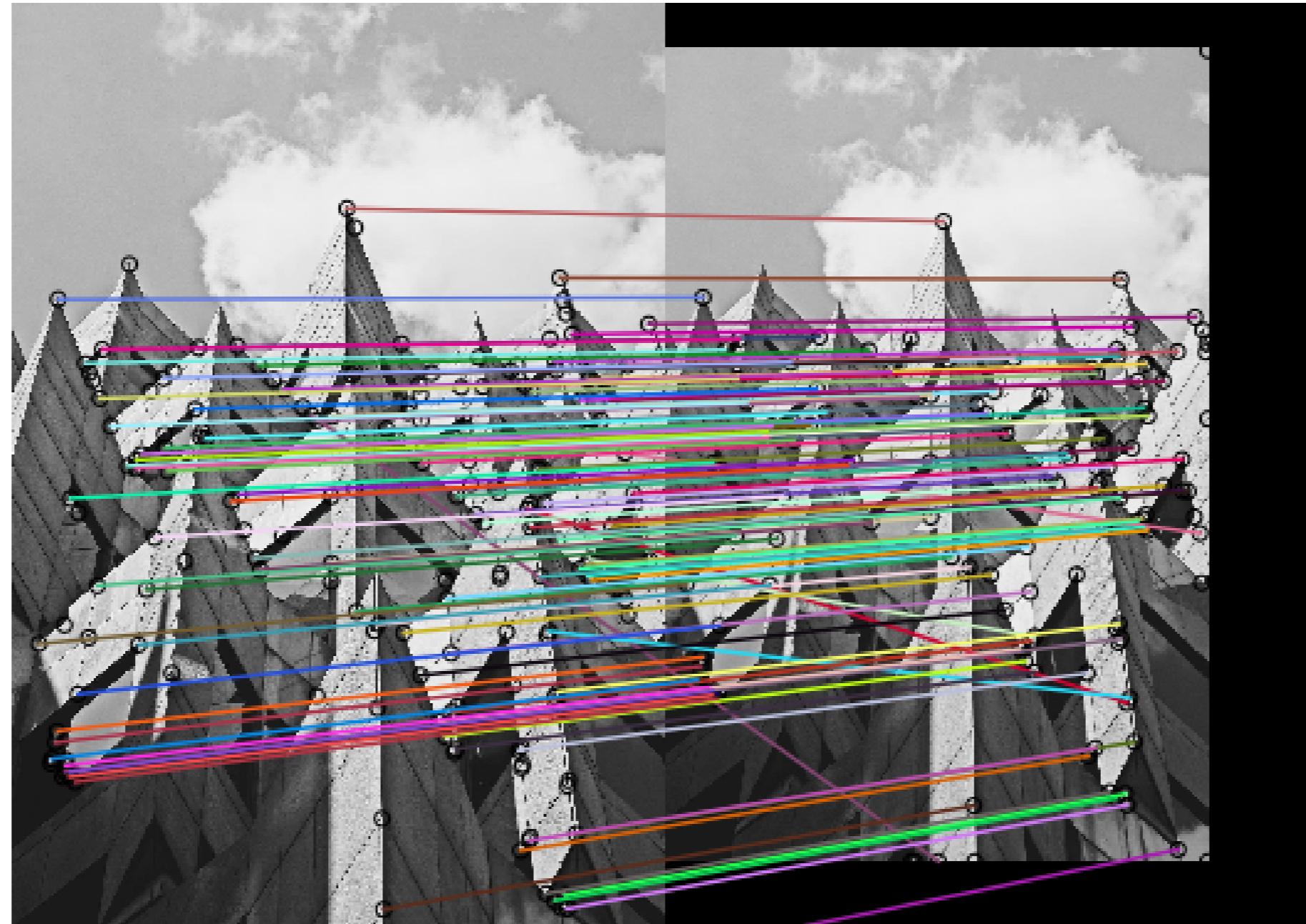


Corners



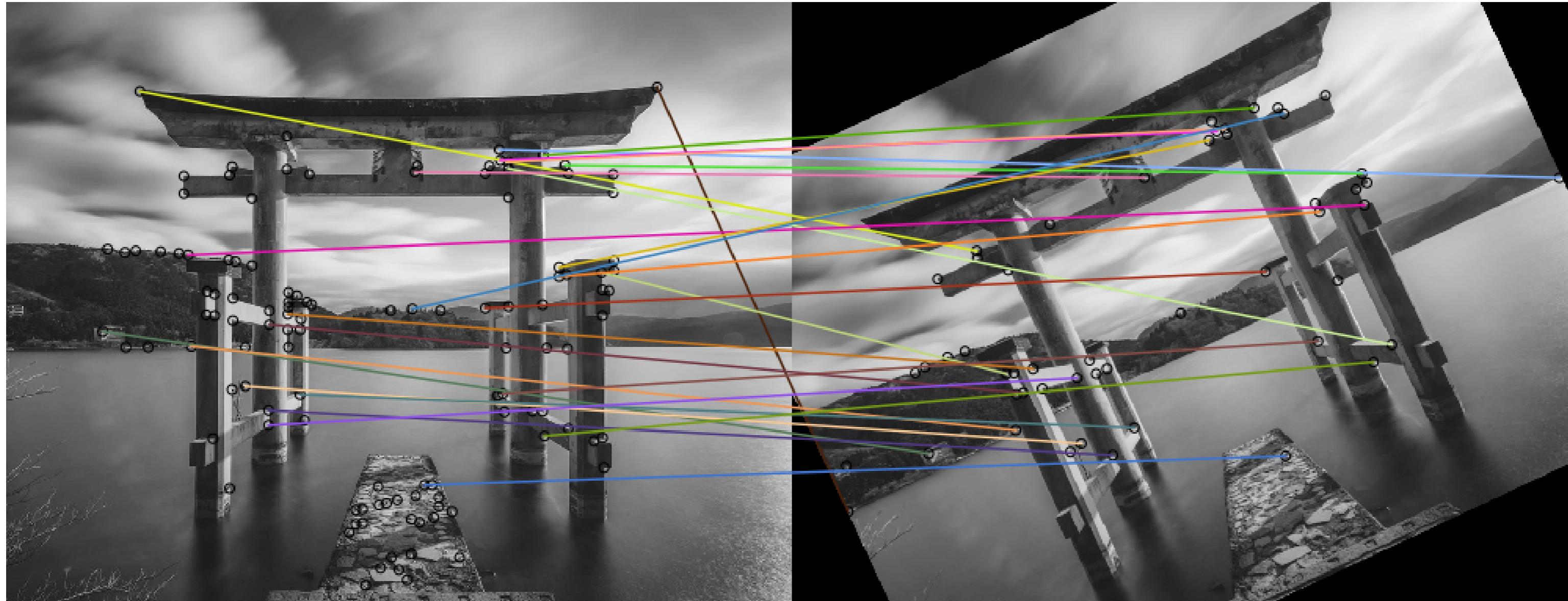
Matching corners

Original Image vs. Transformed Image



Matching corners

Original Image vs. Transformed Image

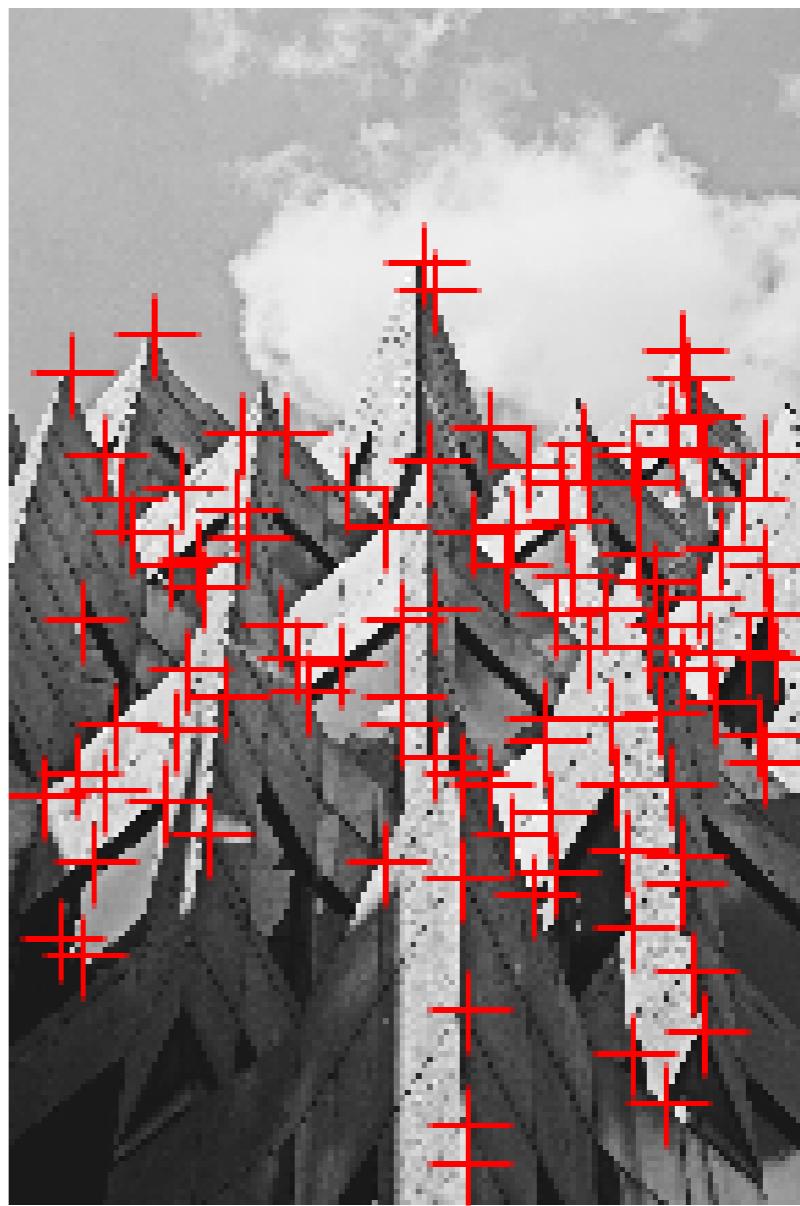


Harris corner detector

Original image



Corners detected



Harris corner detector



Harris corner detector

```
from skimage.feature import corner_harris

# Convert image to grayscale
image = rgb2gray(image)

# Apply the Harris corner detector on the image
measure_image = corner_harris(image)

# Show the Harris response image
show_image(measure_image)
```

Harris corner detector

Harris response image



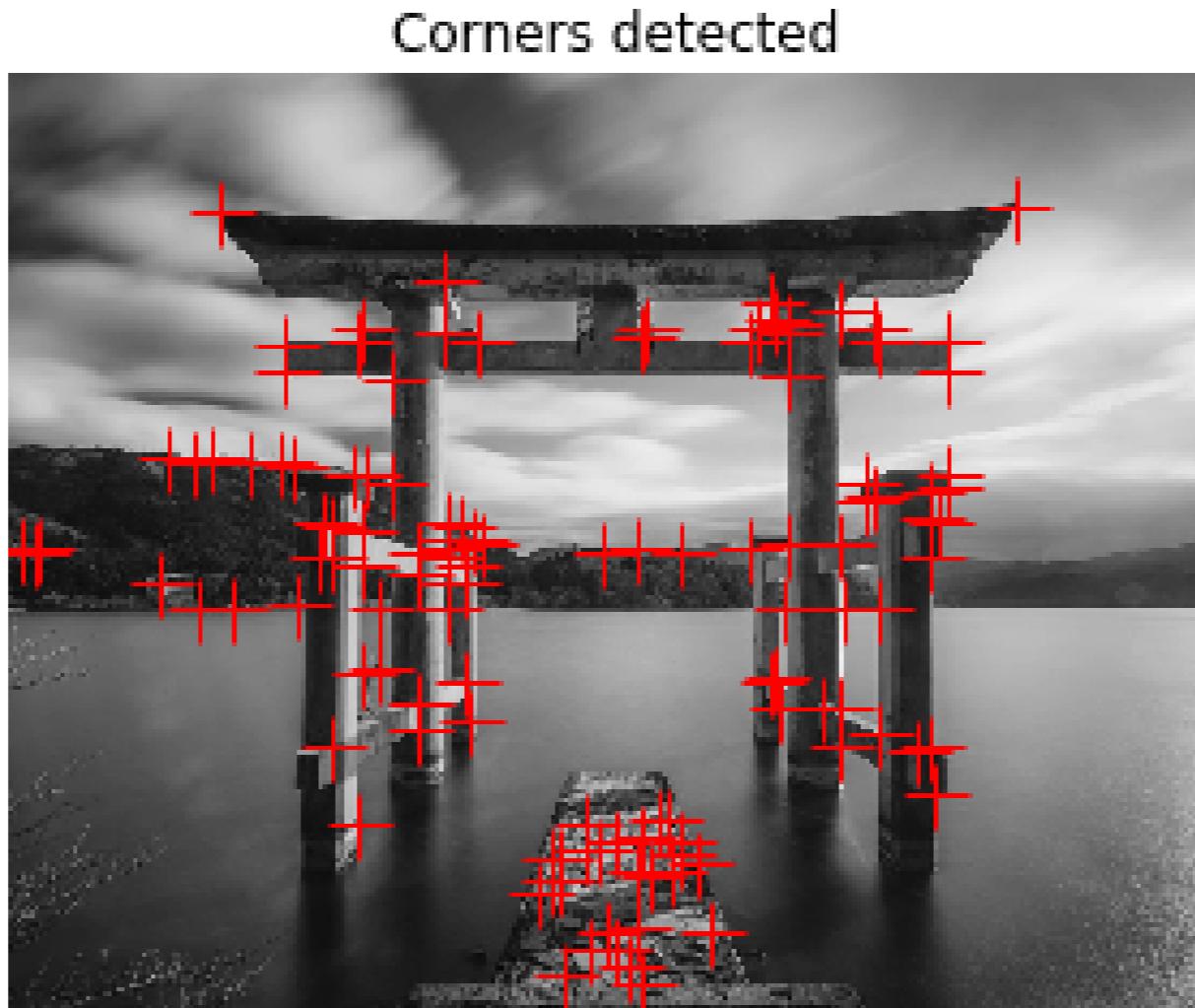
Harris corner detector

```
# Finds the coordinates of the corners  
coords = corner_peaks(corner_harris(image), min_distance=5)  
  
print("A total of", len(coords), "corners were detected.")
```

A total of 122 corners were found from measure response image.

Corners detected

```
# Show image with marks in detected corners  
show_image_with_detected_corners(image, coords)
```



Show image with contours

```
def show_image_with_corners(image, coords, title="Corners detected"):  
    plt.imshow(image, interpolation='nearest', cmap='gray')  
    plt.title(title)  
    plt.plot(coords[:, 1], coords[:, 0], '+r', markersize=15)  
    plt.axis('off')  
    plt.show()
```

Let's practice!

IMAGE PROCESSING IN PYTHON

Face detection

IMAGE PROCESSING IN PYTHON



Rebeca Gonzalez
Data Engineer

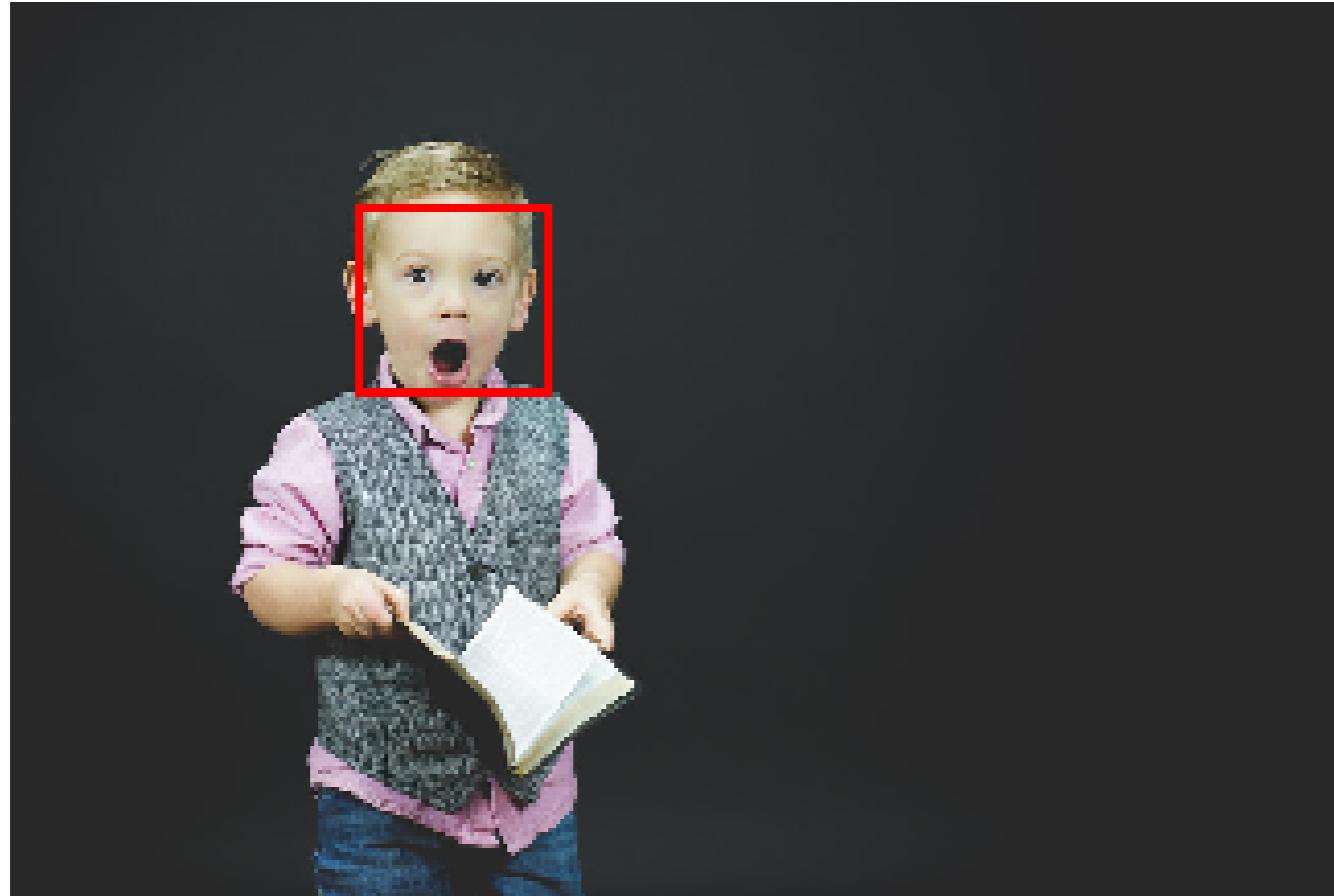
Face detection use cases

- Filters
- Auto focus
- Recommendations
- Blur for privacy protection
- To recognize emotions later on

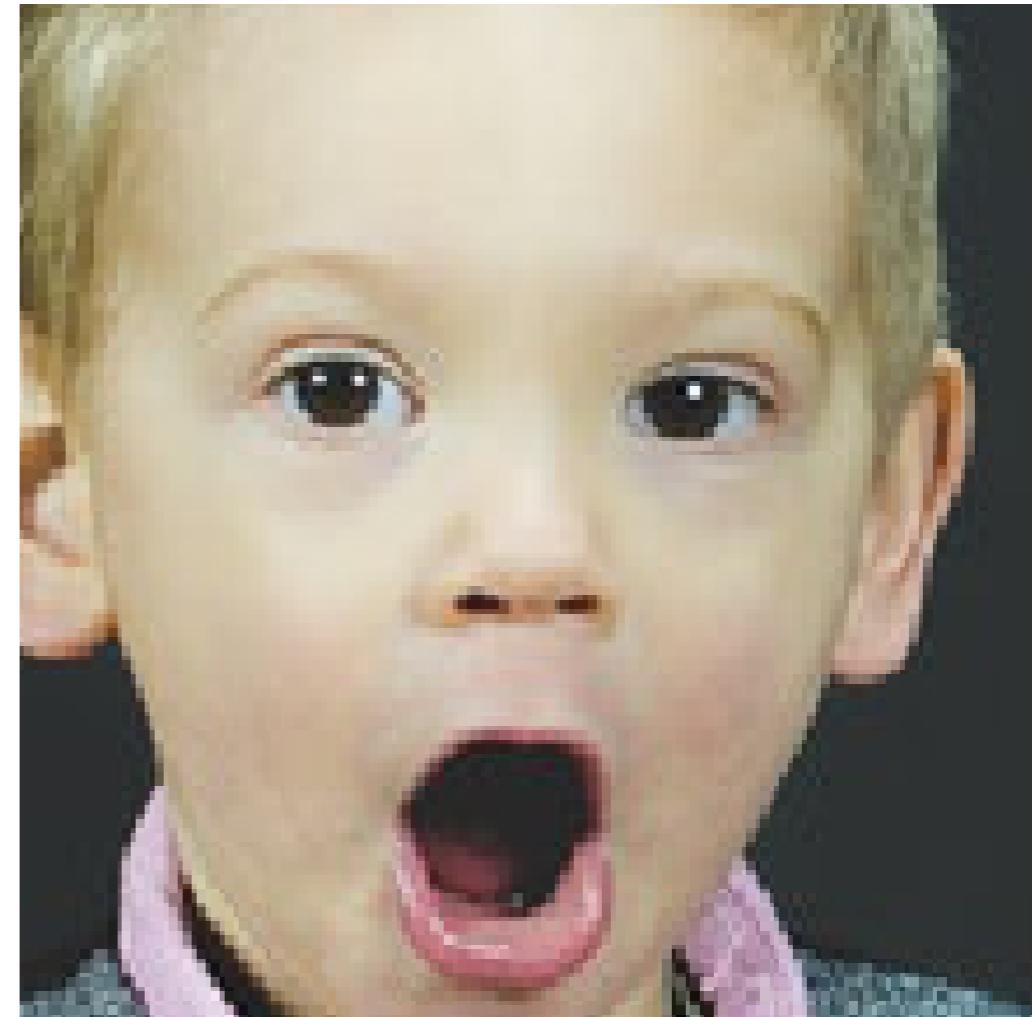


Detecting faces with scikit-image

Face image



Face detected



Detecting faces with scikit-image

```
# Import the classifier class  
from skimage.feature import Cascade  
  
# Load the trained file from the module root.  
trained_file = data.lbp_frontal_face_cascade_filename()  
  
# Initialize the detector cascade.  
detector = Cascade(trained_file)
```

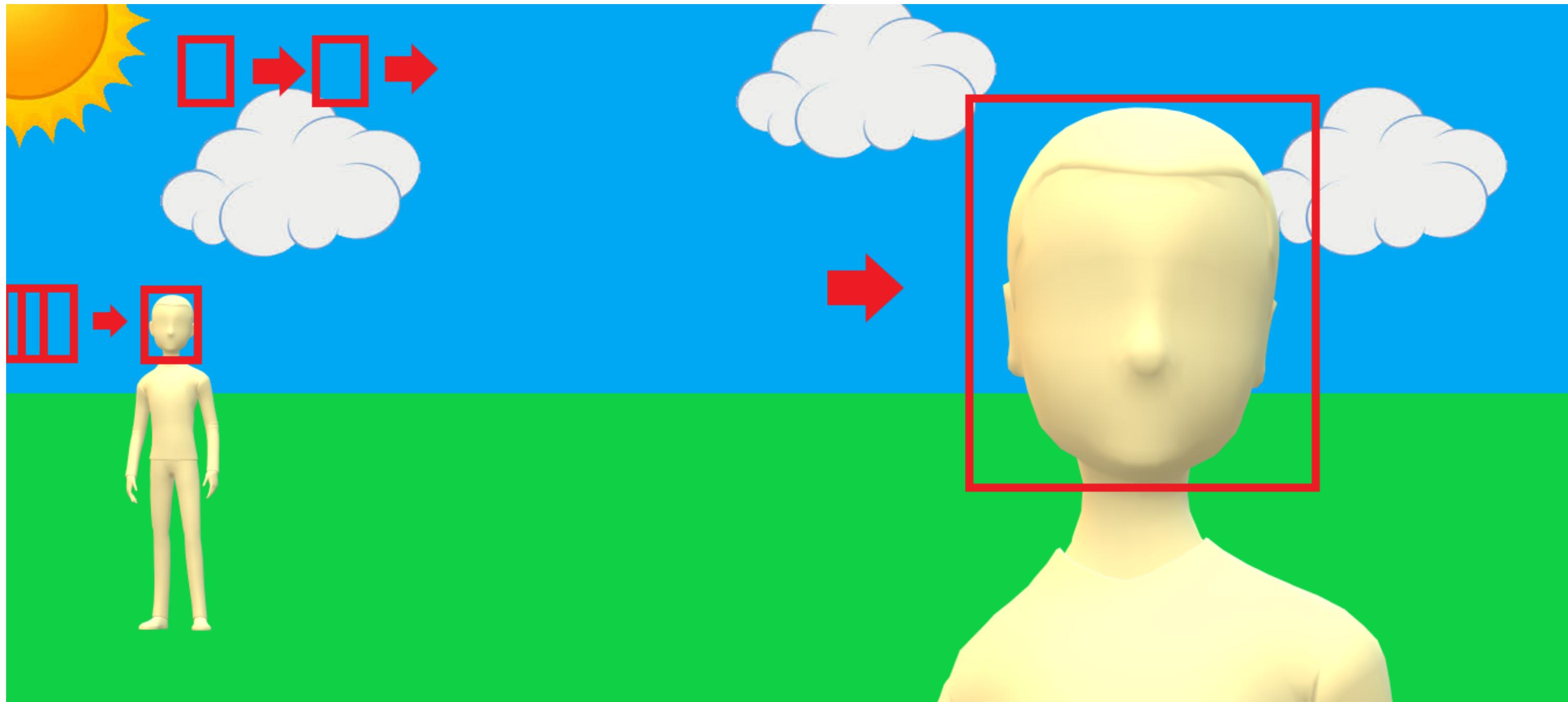
Let's try it



Detecting faces



Detecting faces



Detecting faces

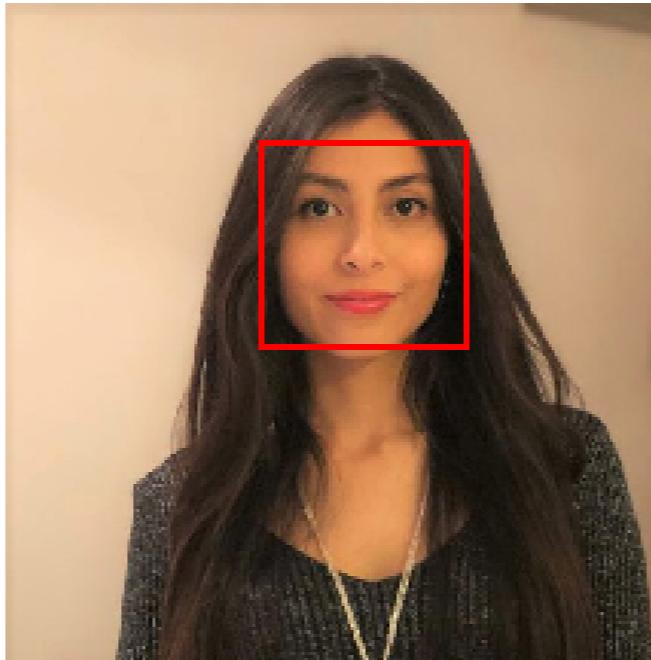
```
# Apply detector on the image  
detected = detector.detect_multi_scale(img=image,  
                                         scale_factor=1.2,  
                                         step_ratio=1,  
                                         min_size=(10, 10),  
                                         max_size=(200, 200))
```

Detected faces

```
print(detected)
# Show image with detected face marked
show_detected_face(image, detected)
```

Detected face: [{'r': 115, 'c': 210, 'width': 167, 'height': 167}]

Face image



Show detected faces

```
def show_detected_face(result, detected, title="Face image"):  
    plt.imshow(result)  
    img_desc = plt.gca()  
    plt.set_cmap('gray')  
    plt.title(title)  
    plt.axis('off')  
  
    for patch in detected:  
        img_desc.add_patch(  
            patches.Rectangle(  
                (patch['c'], patch['r']),  
                patch['width'],  
                patch['height'],  
                fill=False,color='r',linewidth=2)  
        )  
    plt.show()
```

Let's practice!

IMAGE PROCESSING IN PYTHON

Real-world applications

IMAGE PROCESSING IN PYTHON

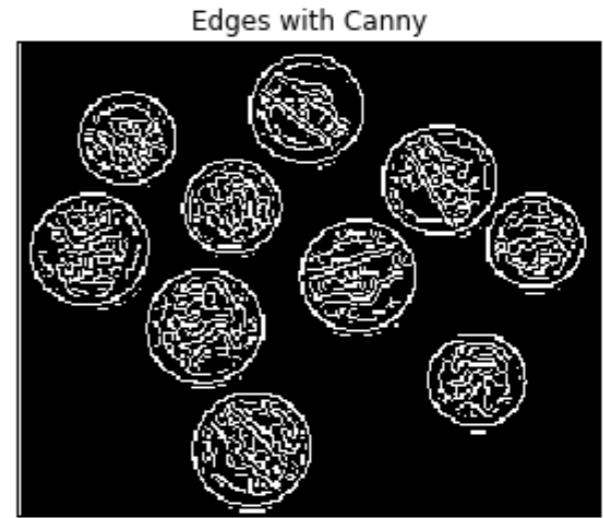


Rebeca Gonzalez

Data engineer

Applications

- Turning to grayscale before detecting edges/corners
- Reducing noise and restoring images
- Blurring faces detected
- Approximation of objects' sizes



Privacy protection



Privacy protection

```
# Import Cascade of classifiers and gaussian filter
from skimage.feature import Cascade
from skimage.filters import gaussian
```

Privacy protection

```
# Detect the faces
detected = detector.detect_multi_scale(img=image,
                                         scale_factor=1.2, step_ratio=1,
                                         min_size=(50, 50), max_size=(100, 100))

# For each detected face
for d in detected:
    # Obtain the face cropped from detected coordinates
    face = getFace(d)
```

Privacy protection

```
def getFace(d):
    ''' Extracts the face rectangle from the image using the
    coordinates of the detected.'''
    # X and Y starting points of the face rectangle
    x, y = d['r'], d['c']

    # The width and height of the face rectangle
    width, height = d['r'] + d['width'], d['c'] + d['height']

    # Extract the detected face
    face= image[x:width, y:height]
    return face
```

Privacy protection

```
# Detect the faces
detected = detector.detect_multi_scale(img=image,
                                         scale_factor=1.2, step_ratio=1,
                                         min_size=(50, 50), max_size=(100, 100))

# For each detected face
for d in detected:
    # Obtain the face cropped from detected coordinates
    face = getFace(d)

    # Apply gaussian filter to extracted face
    gaussian_face = gaussian(face, multichannel=True, sigma = 10)

    # Merge this blurry face to our final image and show it
    resulting_image = mergeBlurryFace(image, gaussian_face)
```

Privacy protection

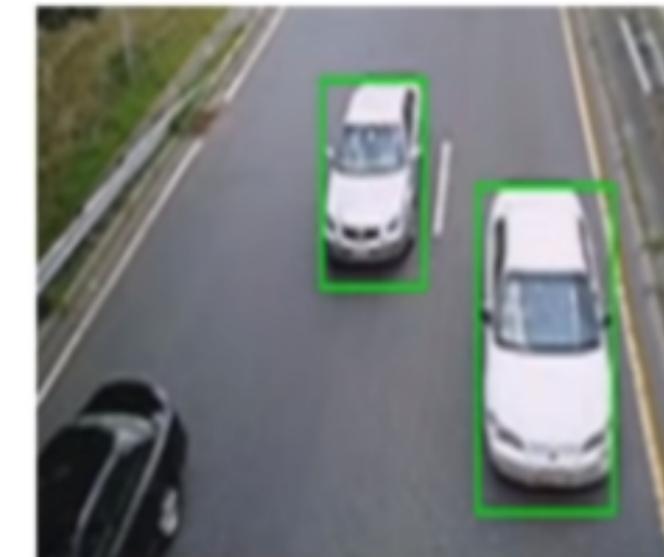
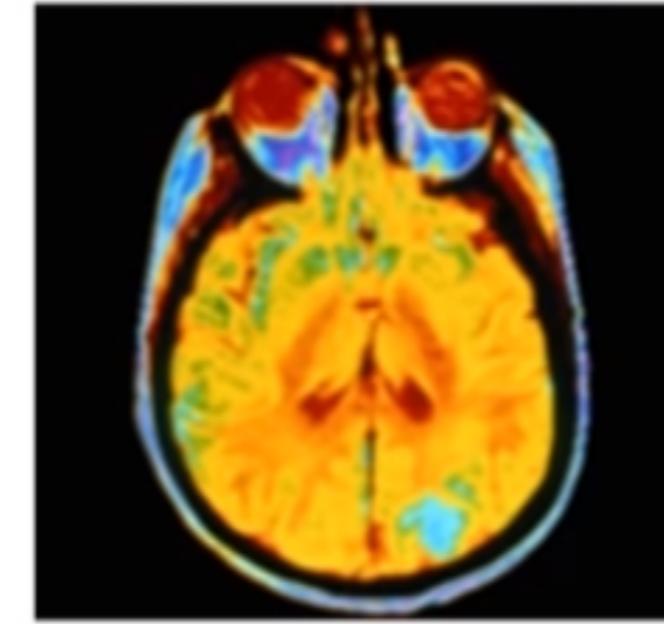
```
def mergeBlurryFace(original, gaussian_image):  
    # X and Y starting points of the face rectangle  
    x, y = d['r'], d['c']  
    # The width and height of the face rectangle  
    width, height = d['r'] + d['width'], d['c'] + d['height']  
  
    original[ x:width, y:height] = gaussian_image  
    return original
```

Privacy protection

Blurred faces



More cases

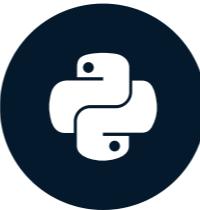


Let's practice!

IMAGE PROCESSING IN PYTHON

Amazing work!

IMAGE PROCESSING IN PYTHON



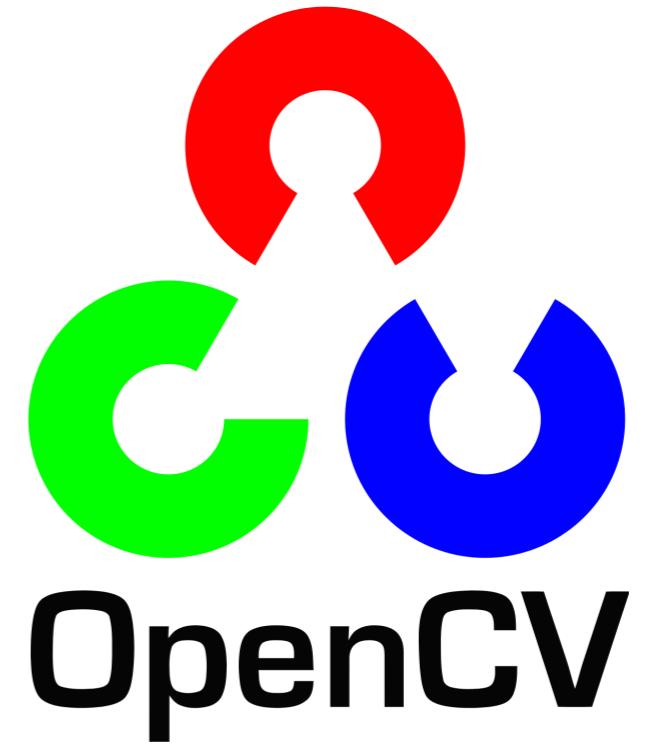
Rebeca Gonzalez
Data Engineer

Recap: What you have learned

- Improved contrast
- Restored images
- Applied filters
- Rotated, flipped and resized!
- Segmented: supervised and unsupervised
- Applied morphological operators
- Created and reduced noise
- Detected edges, corners and faces
- And mixed them up to solve problems!

What's next?

- Tinting gray scale images
- Matching
- Approximation
- Many others!



Congrats!

IMAGE PROCESSING IN PYTHON