

# Make images come alive with scikit- image

IMAGE PROCESSING IN PYTHON

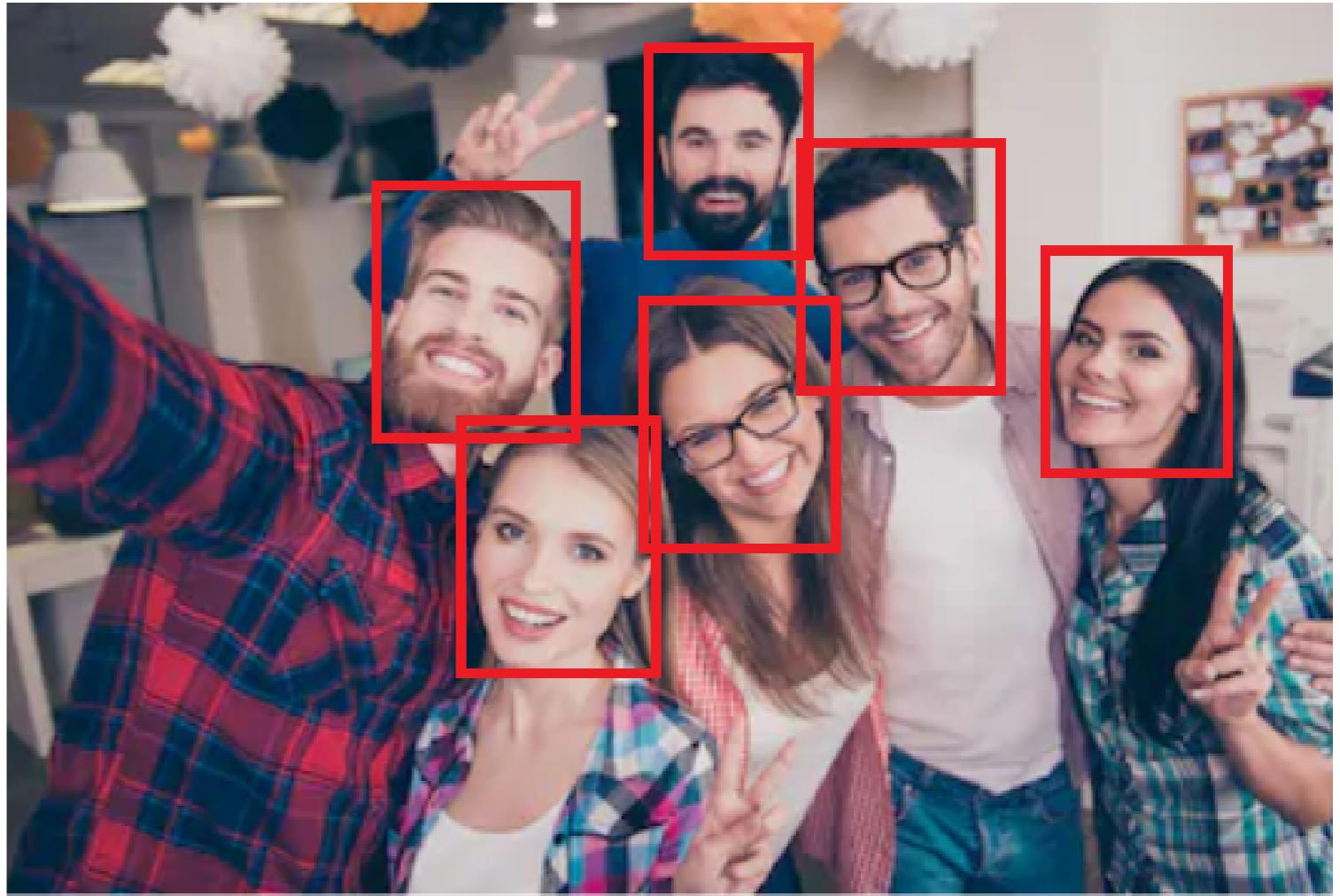


Rebeca Gonzalez  
Data Engineer

# What is image processing?

Operations on images and videos to:

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



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Operations to on images and videos to:

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

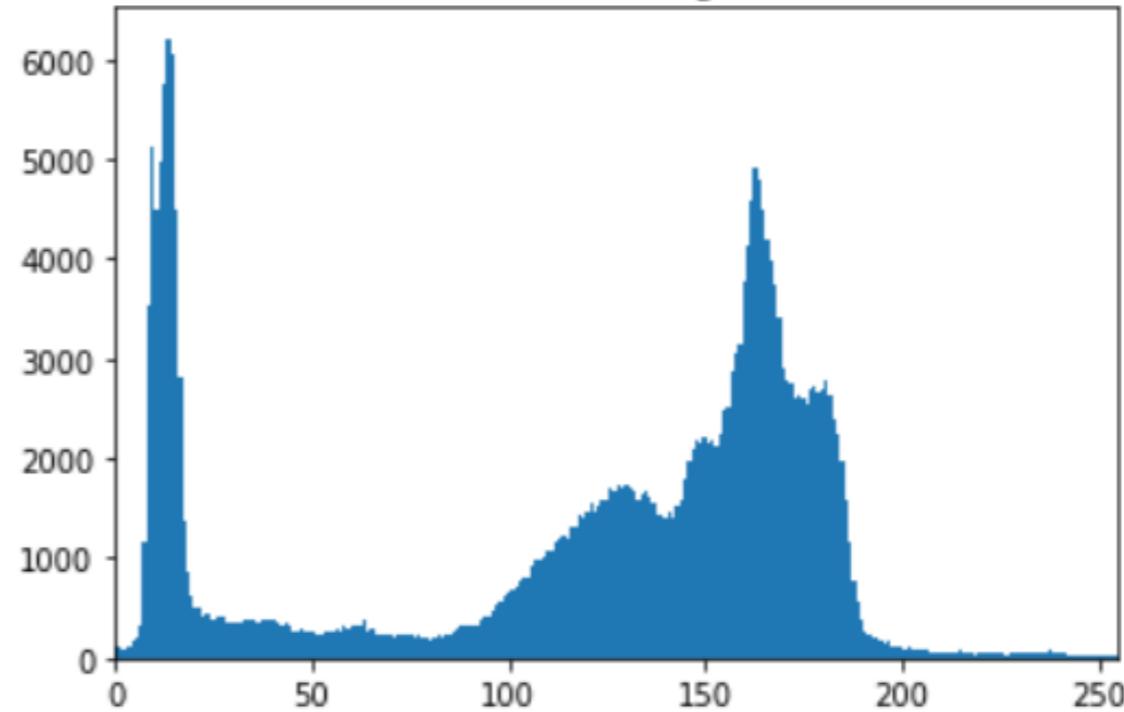
Original Image



Thresholded Image

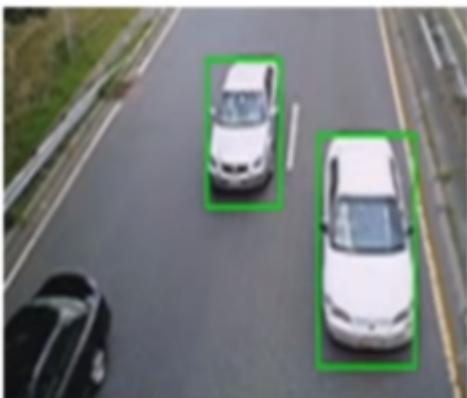
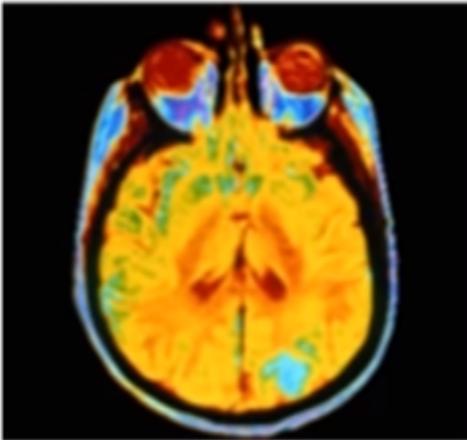


Bimodal histogram



# 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

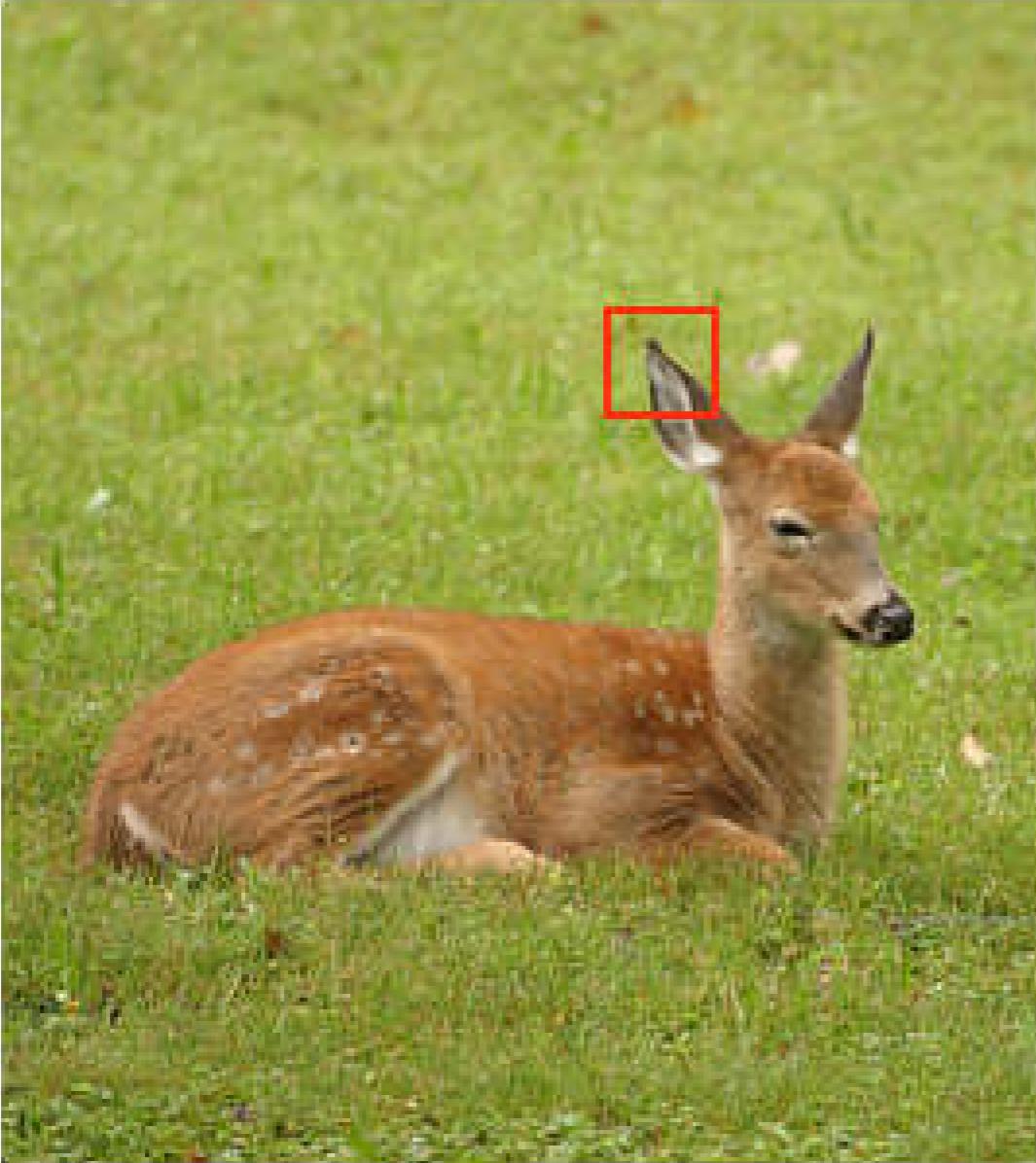
# Intro to scikit-image

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

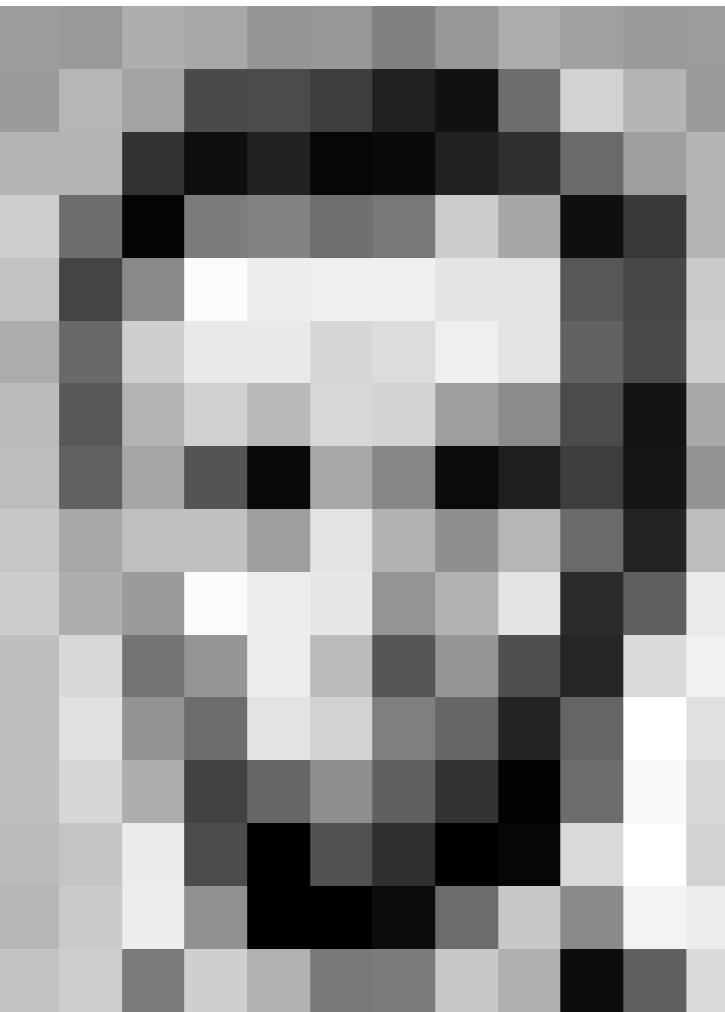


**scikit-image**  
image processing in python

# What is an image?



# What is an image?



157	153	174	168	150	152	129	151	172	161	155	166				
155	182	168	74	75	62	33	17	110	210	180	154				
180	180	50	14	34	6	10	33	48	106	159	181				
206	169	5	124	131	111	120	204	165	15	55	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	25	169				
189	97	165	84	10	168	134	11	31	62	22	148				
199	168	191	193	158	227	178	143	182	106	35	190				
205	174	155	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	98	50	2	109	249	215				
187	196	236	75	1	81	47	0	6	217	255	211				
183	202	237	145	0	0	12	108	209	138	243	236				
196	206	129	207	177	121	123	200	175	13	96	218				

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180	180	50	14	34	6	10	33	48	106	159	181				
206	169	5	124	131	111	120	204	165	15	55	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	25	169				
189	97	165	84	10	168	134	11	31	62	22	148				
199	168	191	193	158	227	178	143	182	106	35	190				
205	174	155	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	98	50	2	109	249	215				
187	196	236	75	1	81	47	0	6	217	255	211				
183	202	237	145	0	0	12	108	209	138	243	236				
196	206	129	207	177	121	123	200	175	13	96	218				

# Images in scikit-image

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



# RGB channels

RGB



Red channel



Green channel



Blue channel



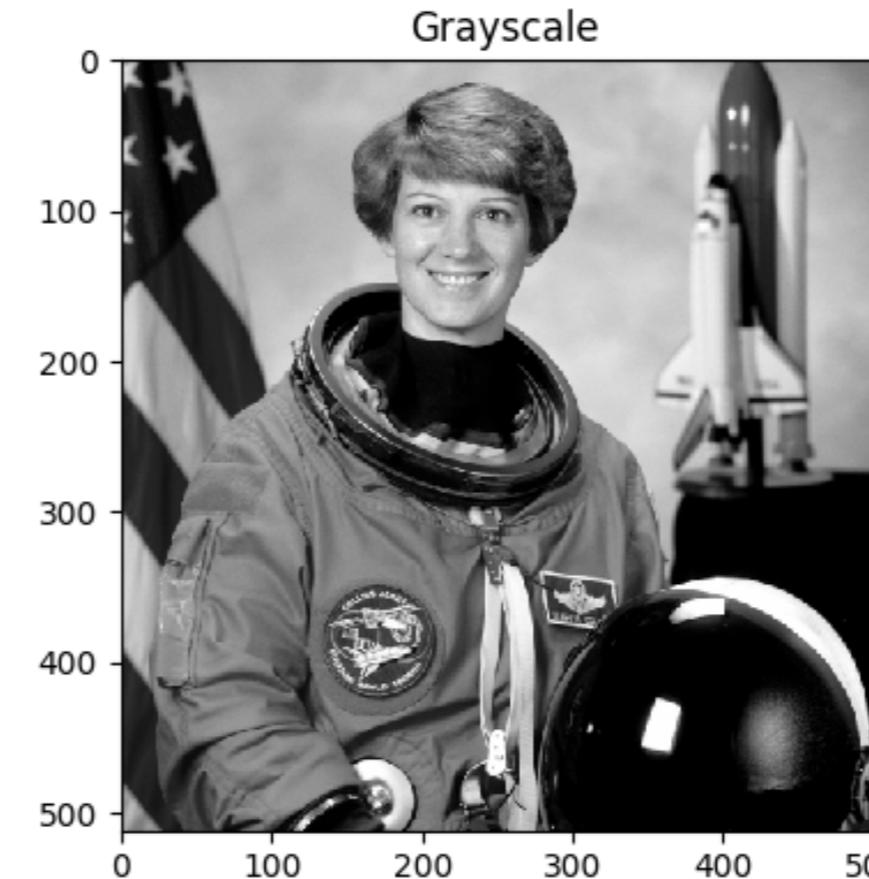
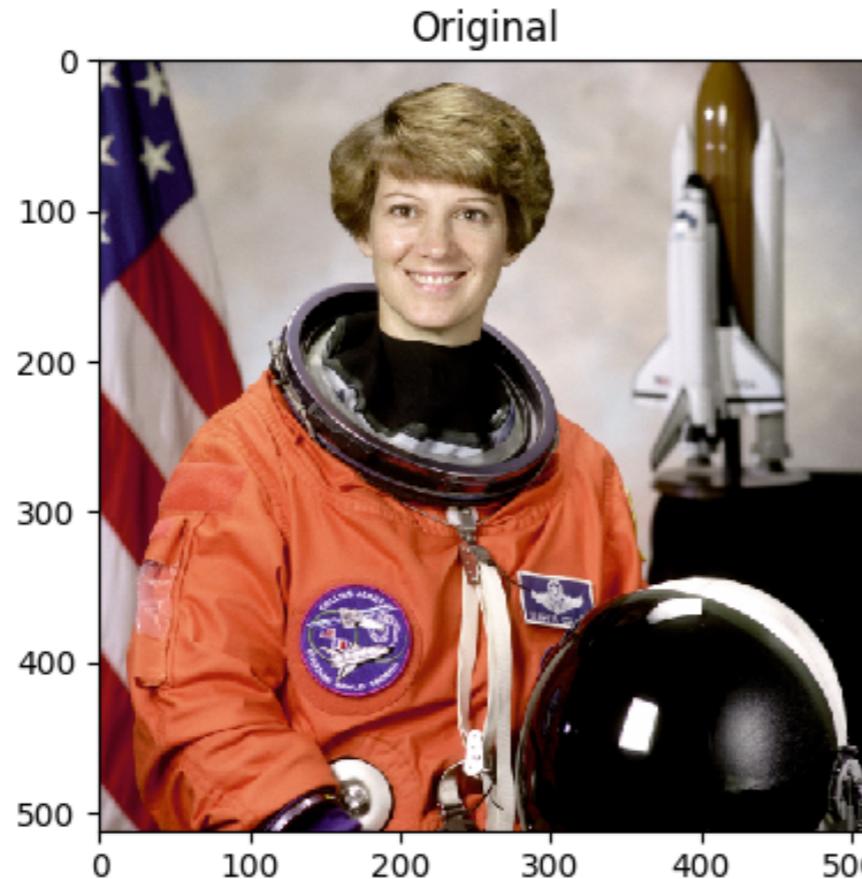
# Grayscaled images



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

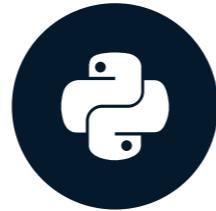


# **Let's practice!**

## **IMAGE PROCESSING IN PYTHON**

# NumPy for images

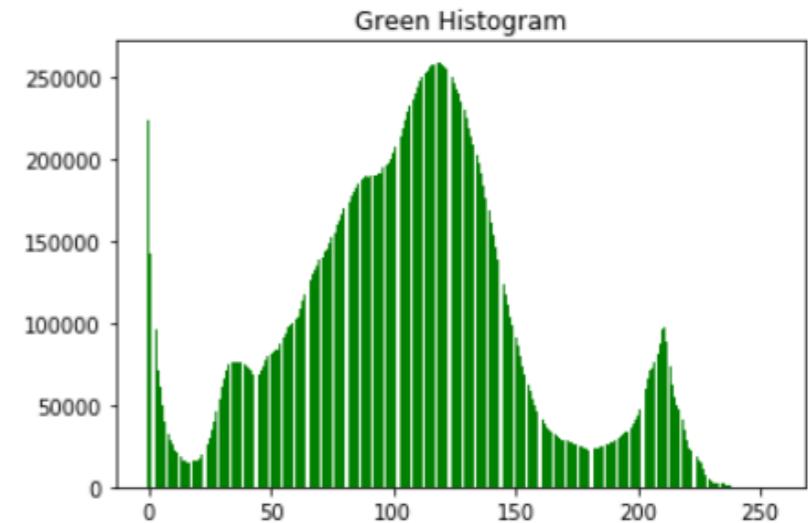
## IMAGE PROCESSING IN PYTHON



**Rebeca Gonzalez**  
Data Engineer

# NumPy for images

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



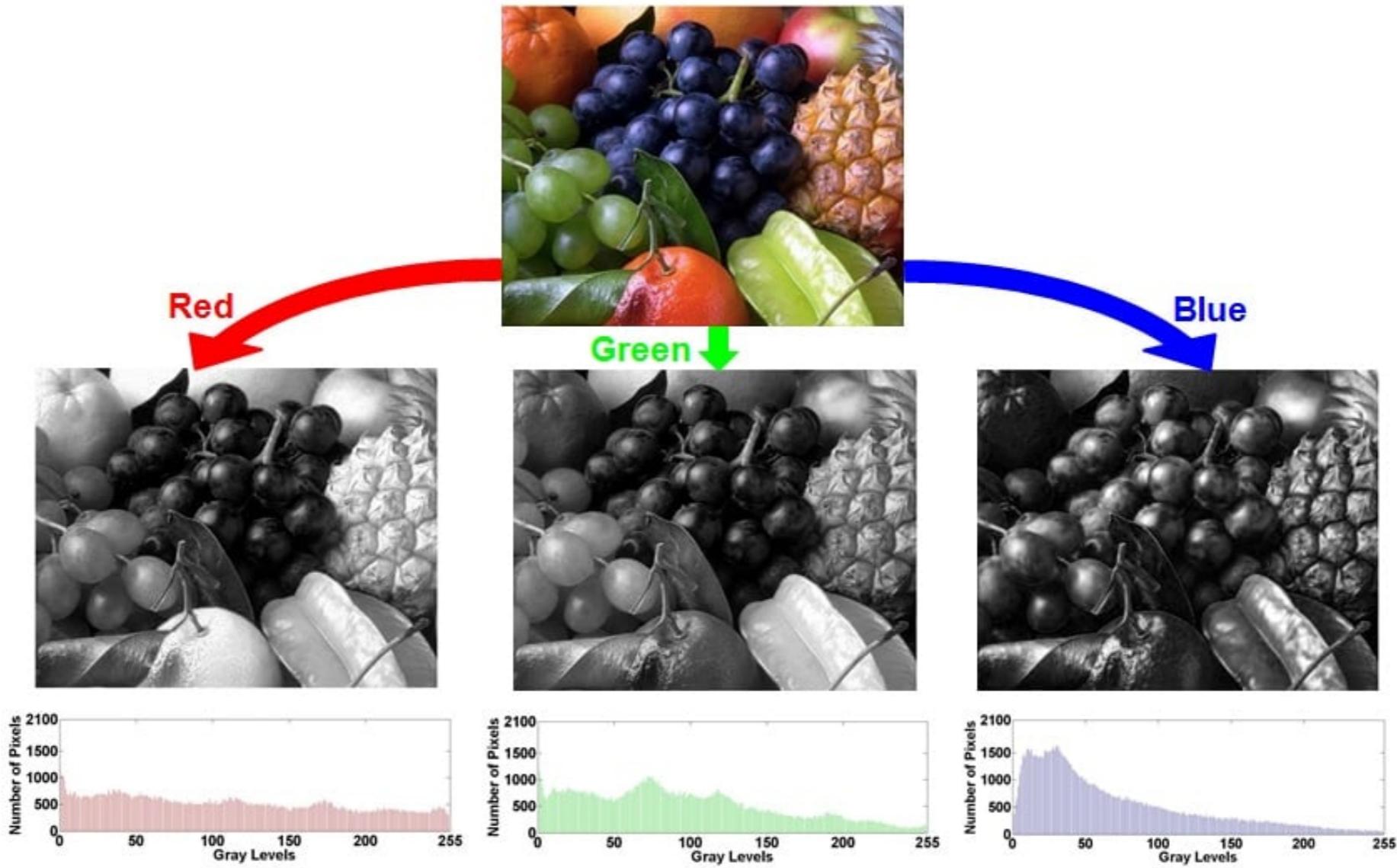
# Images as NdArrays



```
# 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
```

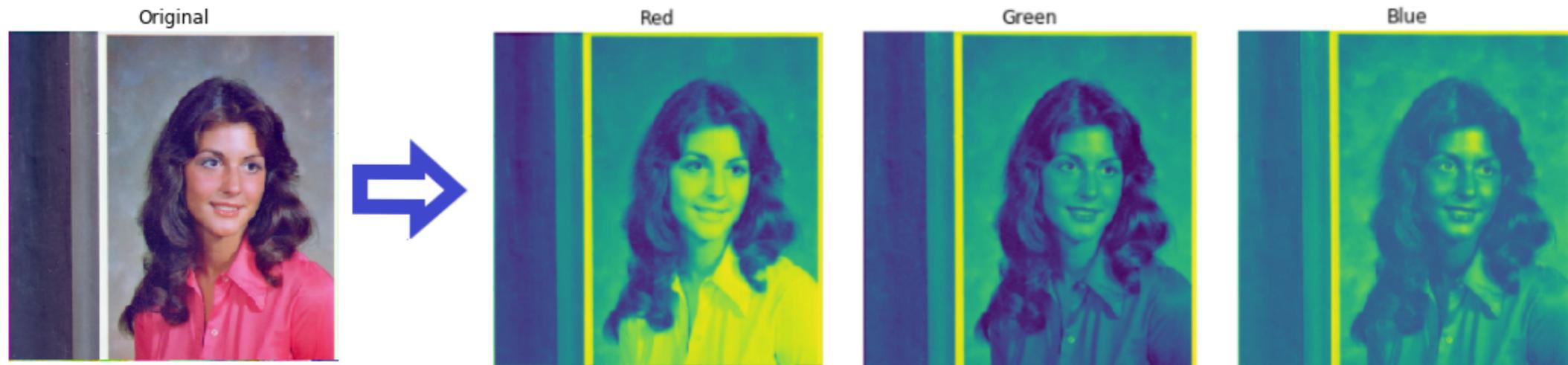
```
red = image[:, :, 0]
```

```
# 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

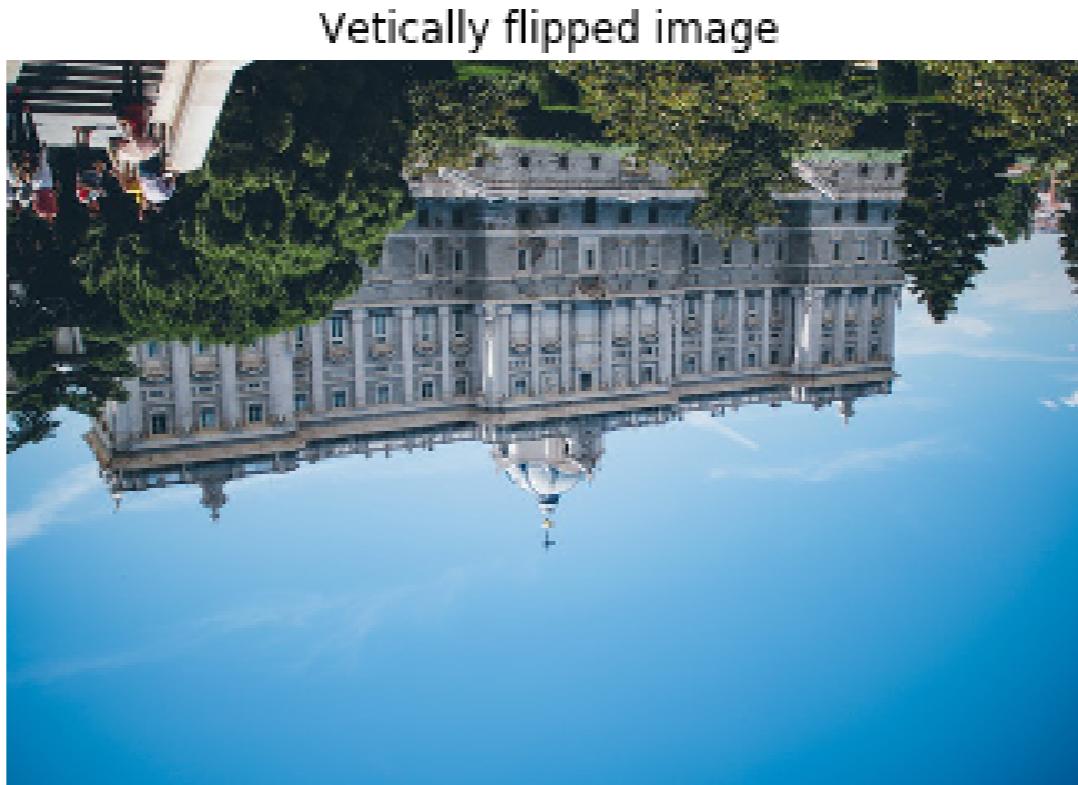


```
# Accessing the shape of the image  
madrid_image.size
```

```
817920
```

# Flipping images: vertically

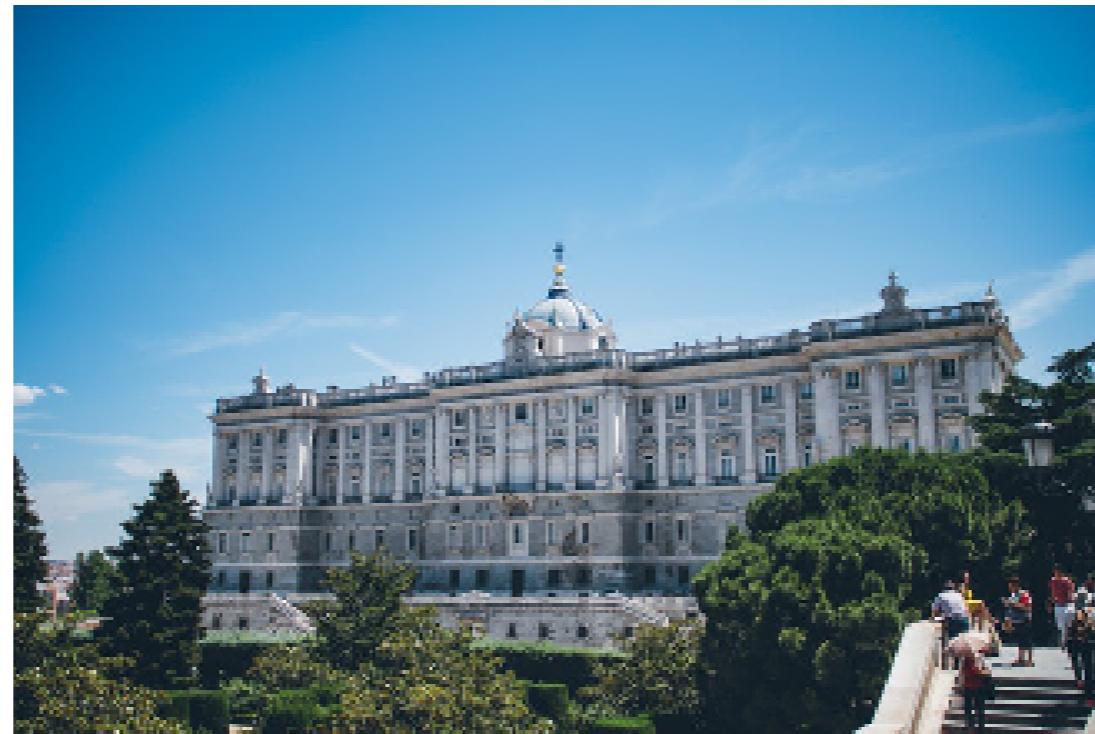
```
# Flip the image in up direction  
vertically_flipped = np.flipud(madrid_image)  
  
show_image(vertically_flipped, 'Vertically flipped image')
```



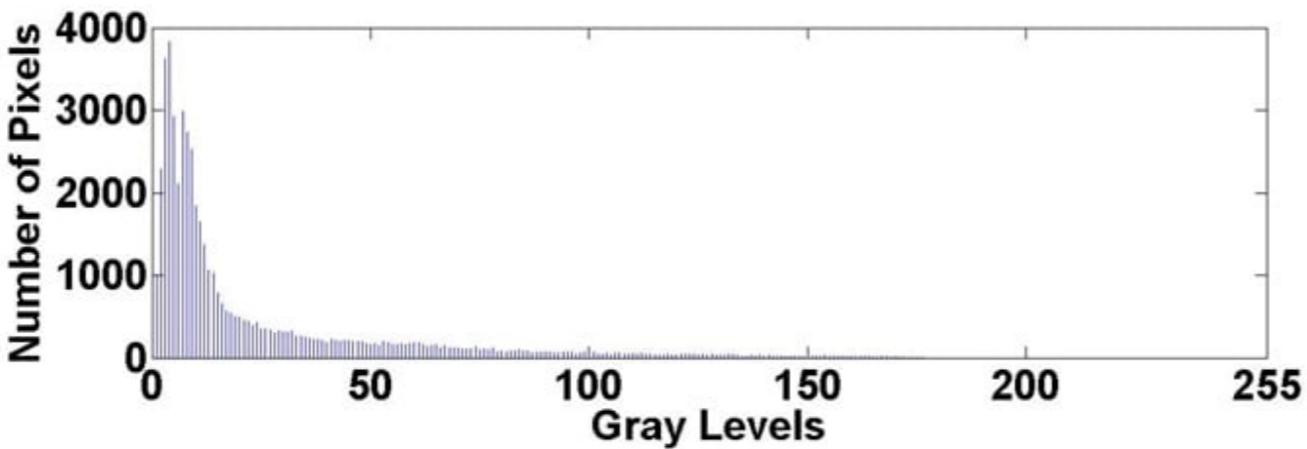
# Flipping images: horizontally

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

Horizontally flipped image



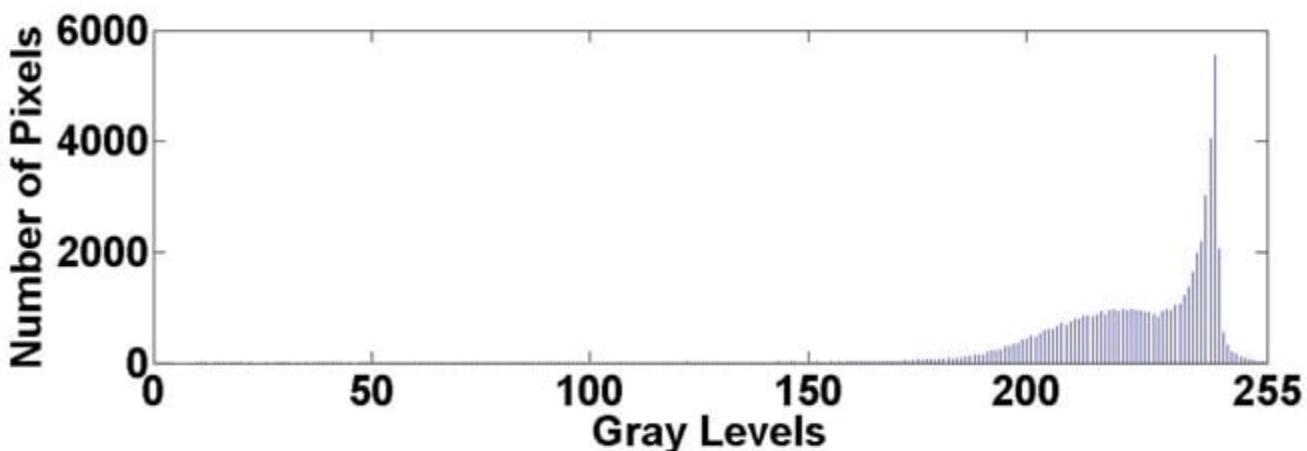
# What is a histogram?



(a)



(b)

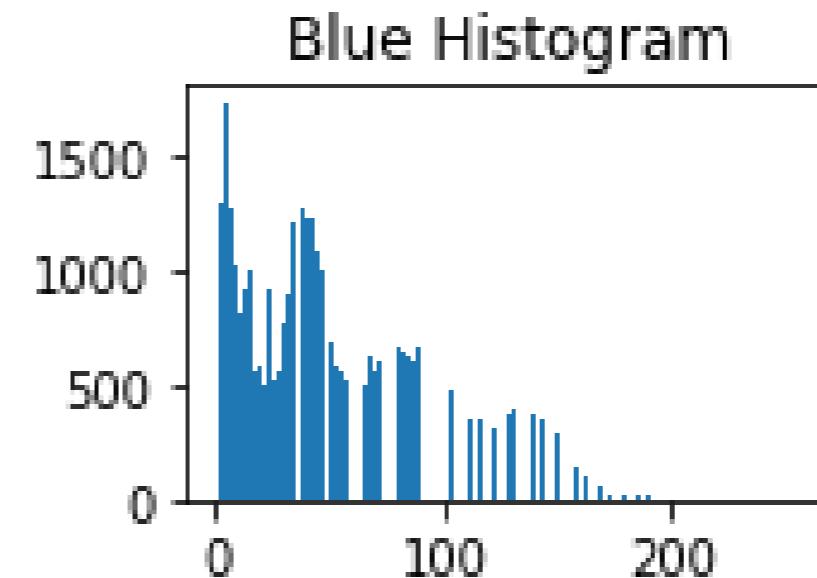
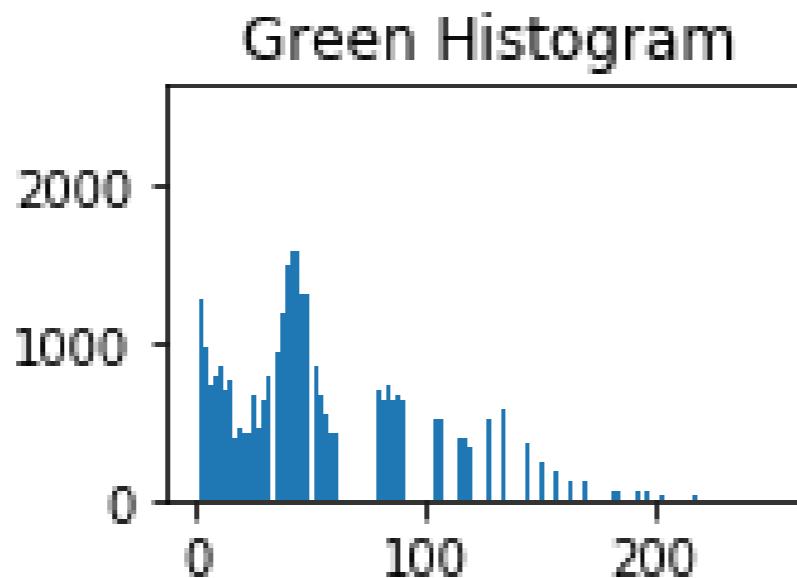
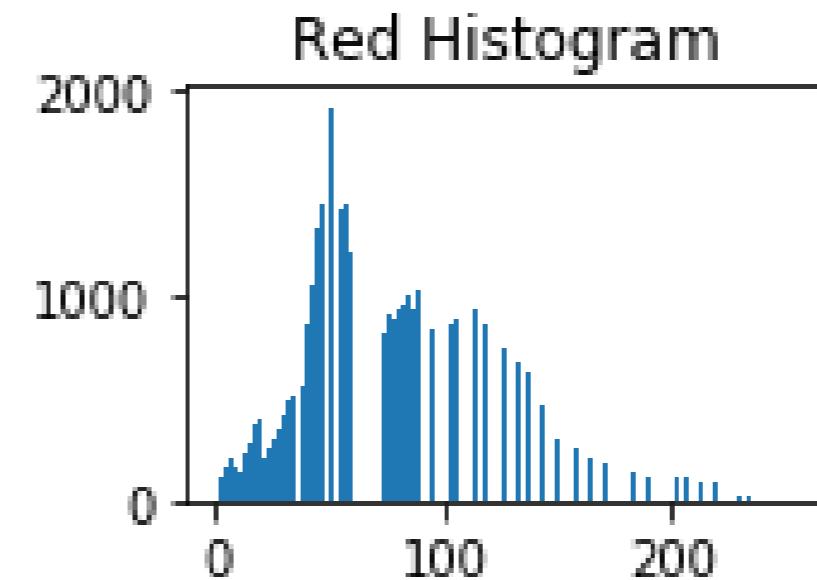
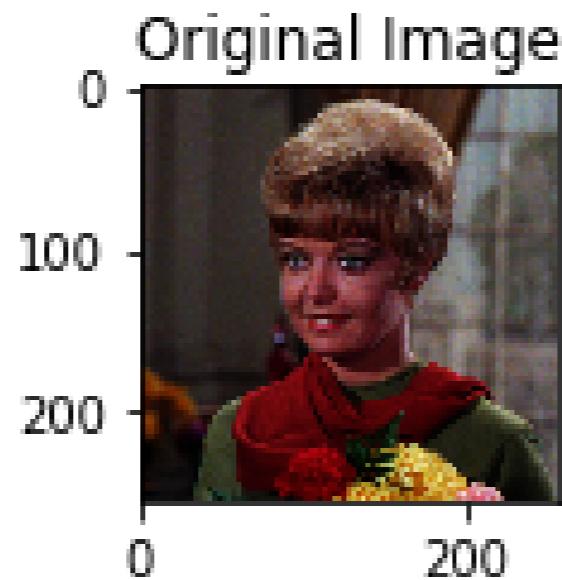


(a)



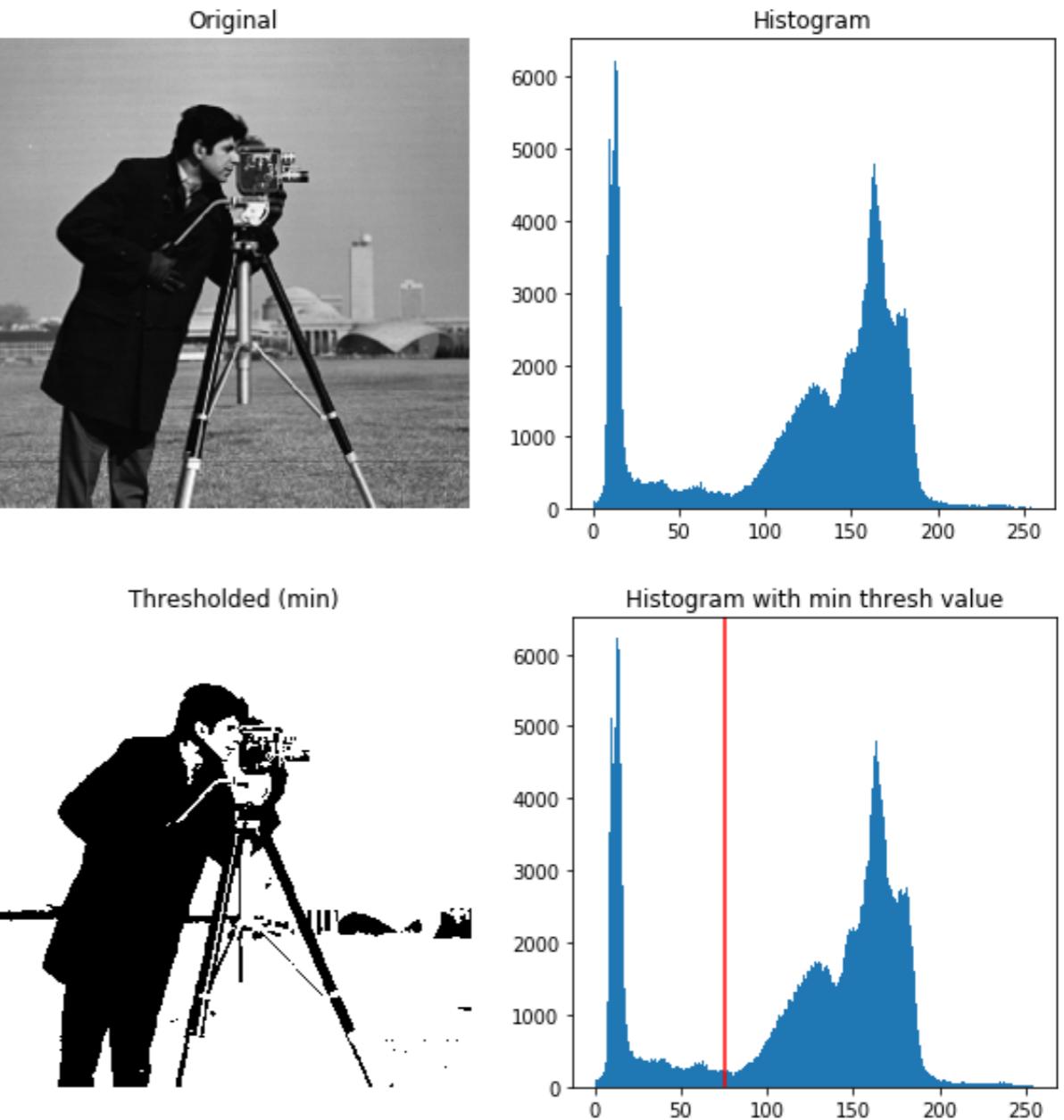
(b)

# Color histograms

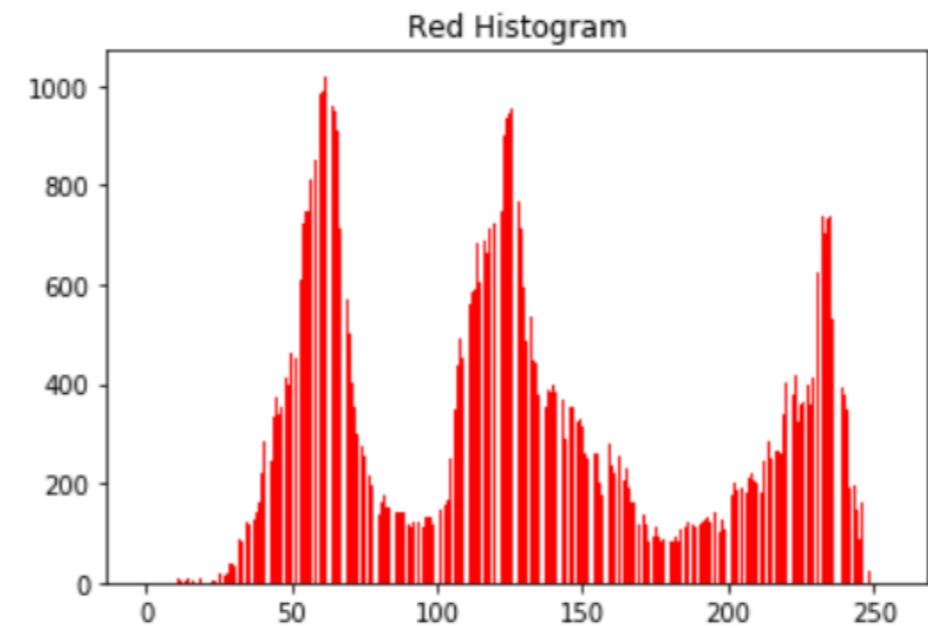


# Applications of histograms

- 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)
```

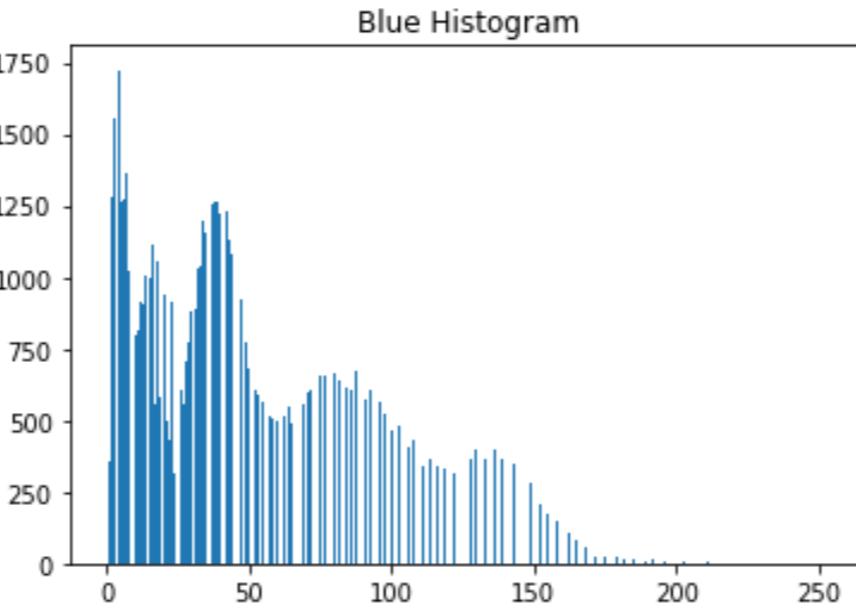
# Visualizing histograms with Matplotlib

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

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

```
import numpy as np

# 2D array
array = np.array([[1, 2],
                  [3, 4]])
print(array.shape) # (2, 2)
print(array.ravel()) # [1, 2, 3, 4]
print(array.ravel().shape) # (4,)
```



# **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:

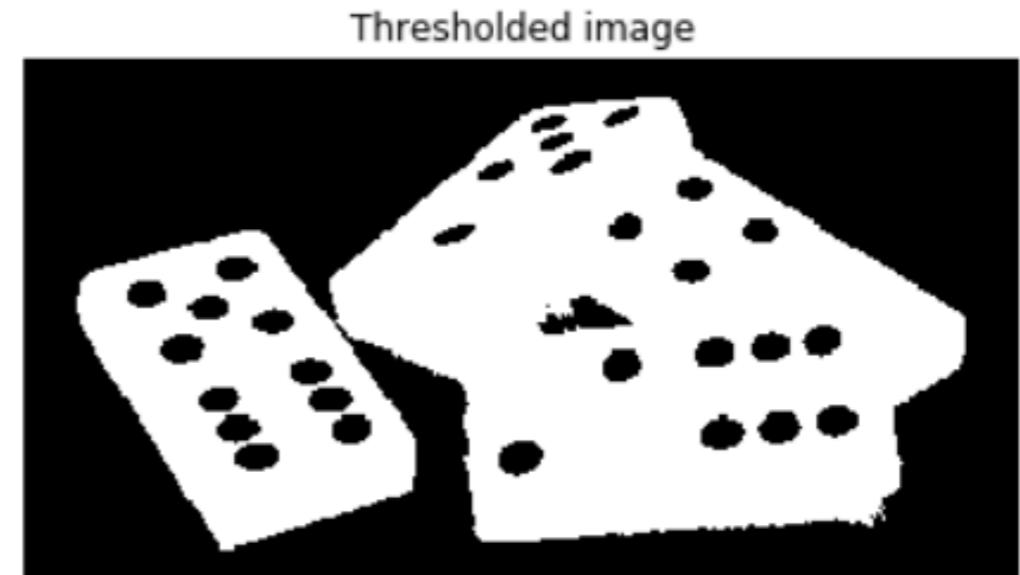
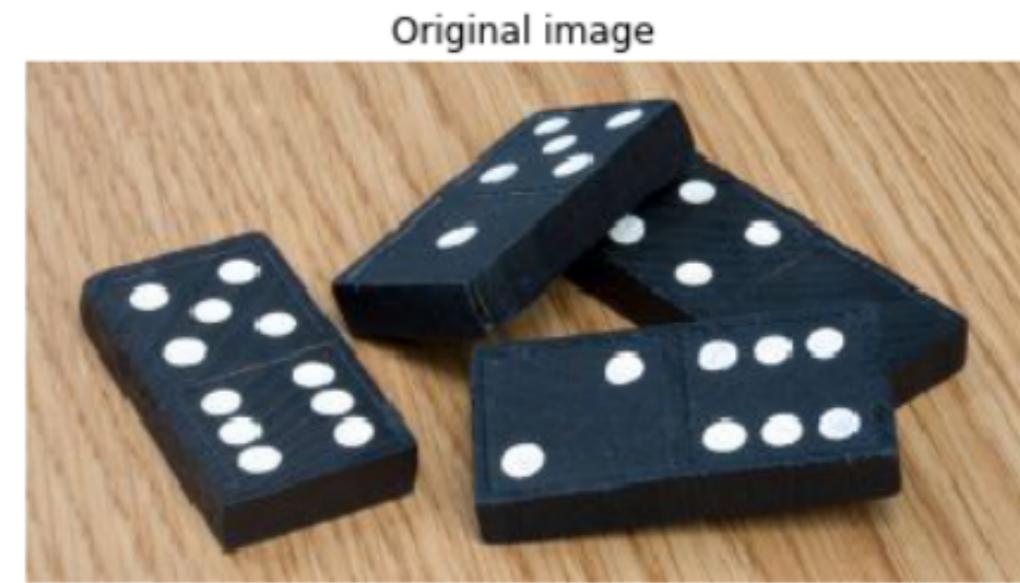
- 255 (white) if  $\text{pixel} > \text{thresh value}$
- 0 (black) if  $\text{pixel} < \text{thresh value}$



# Thresholding

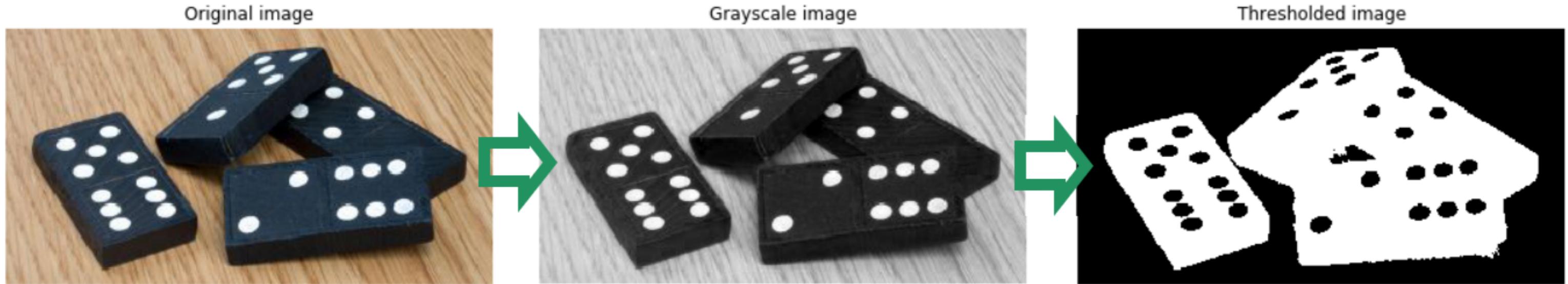
Simplest method of image segmentation

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



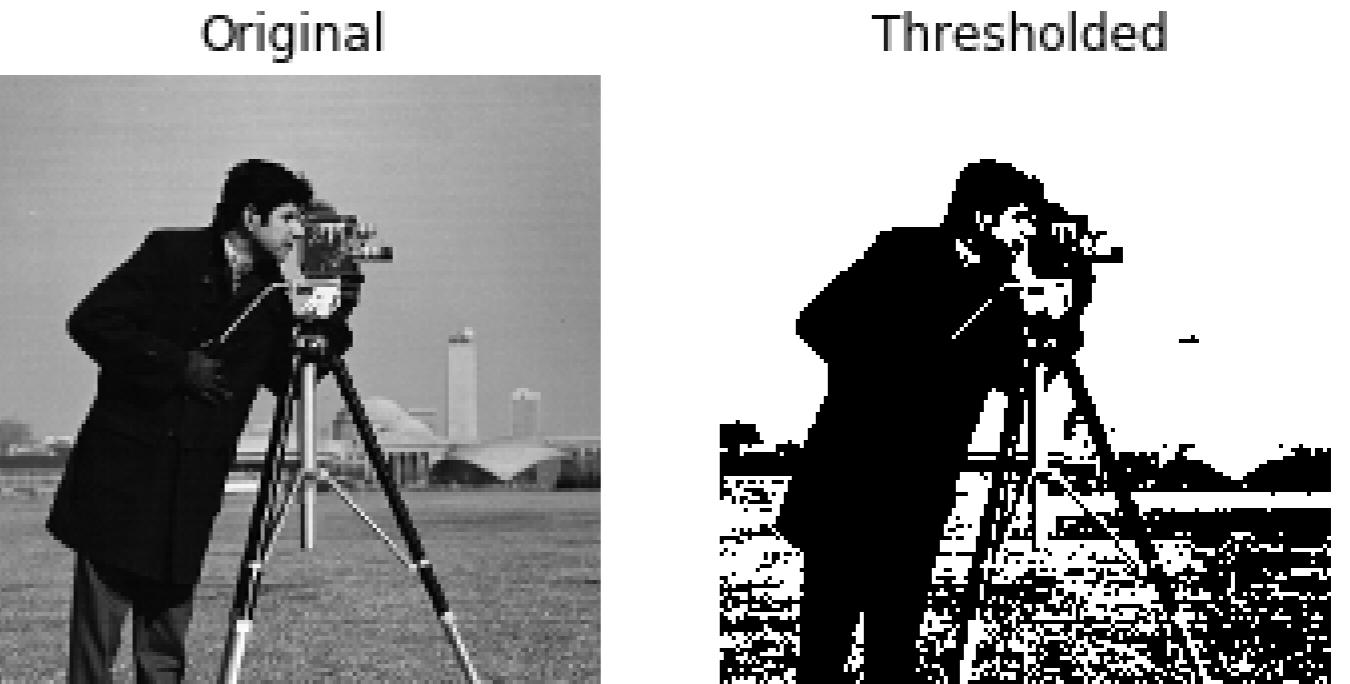
# Thresholding

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:

```
np_markers = np.zeros_like(coins)
```

Global thresholding

## Op-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:

```
np_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 extreme parts of the histogram of grey values:

```
np_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);
```

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);
```

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);
```

# Optimal thresh value

## Global

### Uniform background

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

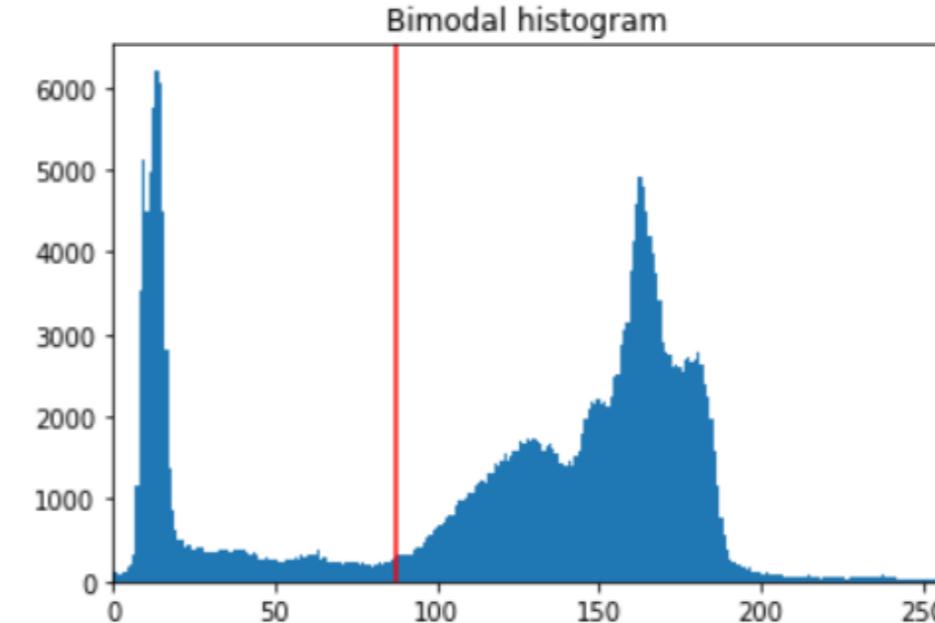
# Obtain the optimal threshold value
thresh = threshold_otsu(image)

# 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(text_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(gray)
```

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(gray)
```

# **Let's practice!**

## **IMAGE PROCESSING IN PYTHON**