



# Image Processing (CSE281)

## Fall 2025/2026

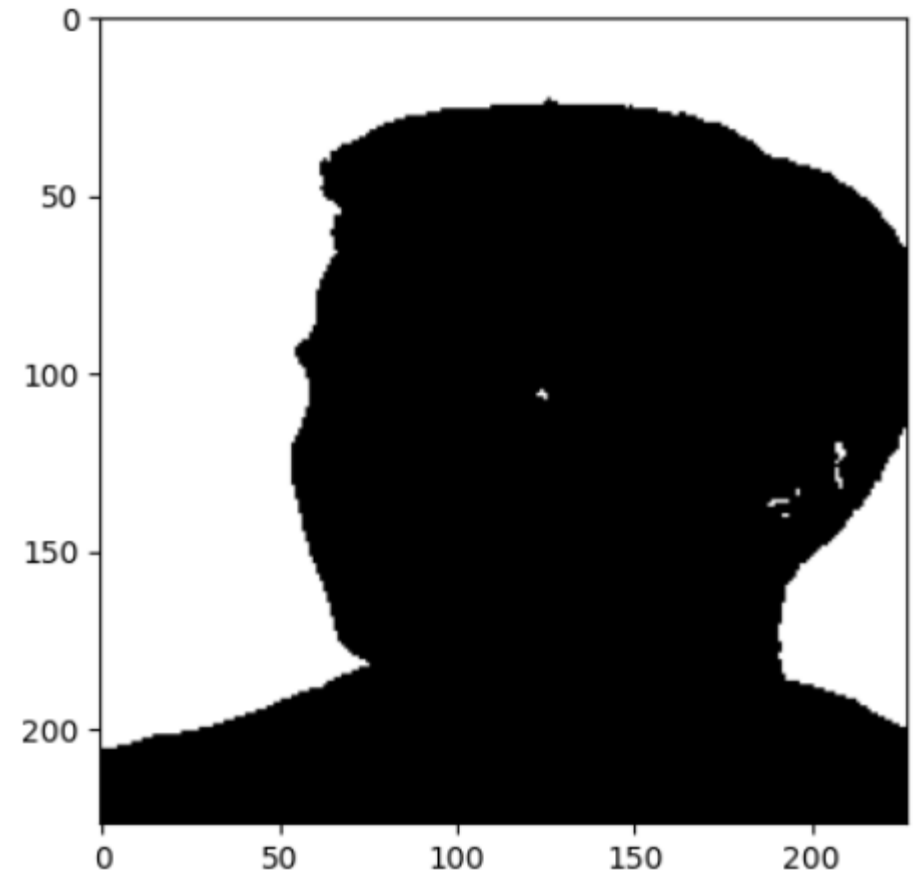
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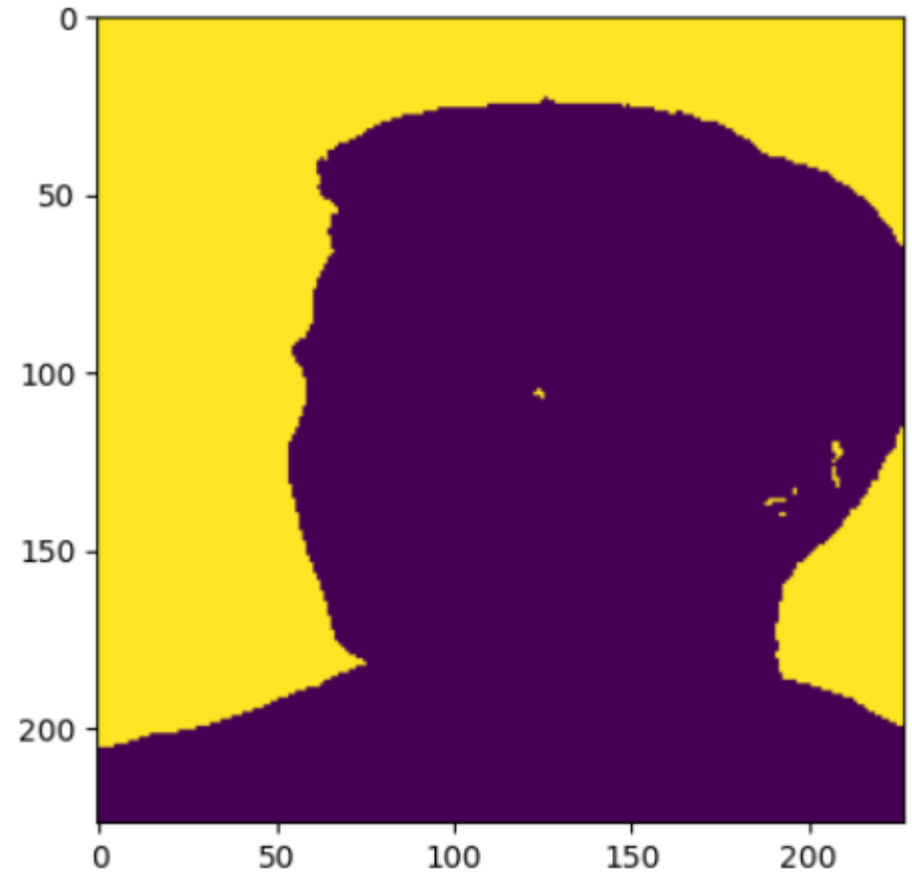
# Binary Segmentation

```
from skimage import io
from skimage.color import rgb2gray
from matplotlib import pyplot as plt
image = io.imread("F:\\13.jpg")
img_gray = rgb2gray(image)
BWimage = img_gray.copy()
for i in range(BWimage.shape[0]):
    for j in range(BWimage.shape[1]):
        if (BWimage[i][j] >= 0.5):
            BWimage[i][j] = 1
        else:
            BWimage[i][j] = 0
plt.figure()
plt.imshow(BWimage, 'gray')
```



# Binary Segmentation

```
from skimage import io
from skimage.color import rgb2gray
from matplotlib import pyplot as plt
image = io.imread("F:\\13.jpg")
img_gray = rgb2gray(image)
BWimage = img_gray.copy()
for i in range(BWimage.shape[0]):
    for j in range(BWimage.shape[1]):
        if (BWimage[i][j] >= 0.5):
            BWimage[i][j] = 1
        else:
            BWimage[i][j] = 0
plt.figure()
plt.imshow(BWimage)
plt.show()
```



# Binary Segmentation

## *plt.imshow(image)*

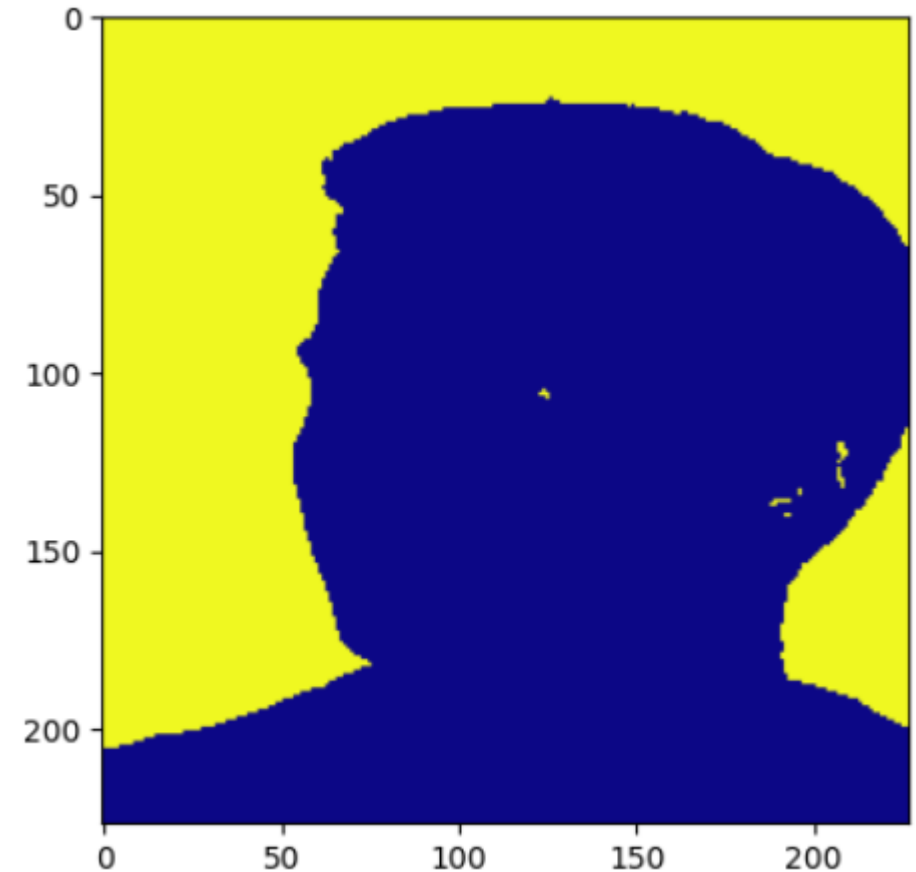
- Uses viridis colormap (default in matplotlib)
- Displays the image in a colorful scale (blue to yellow)
- Good for highlighting patterns and variations
- Can make grayscale images appear in false colors

## *plt.imshow(image, 'gray')*

- Uses grayscale colormap
- Displays the image in black and white

# Binary Segmentation

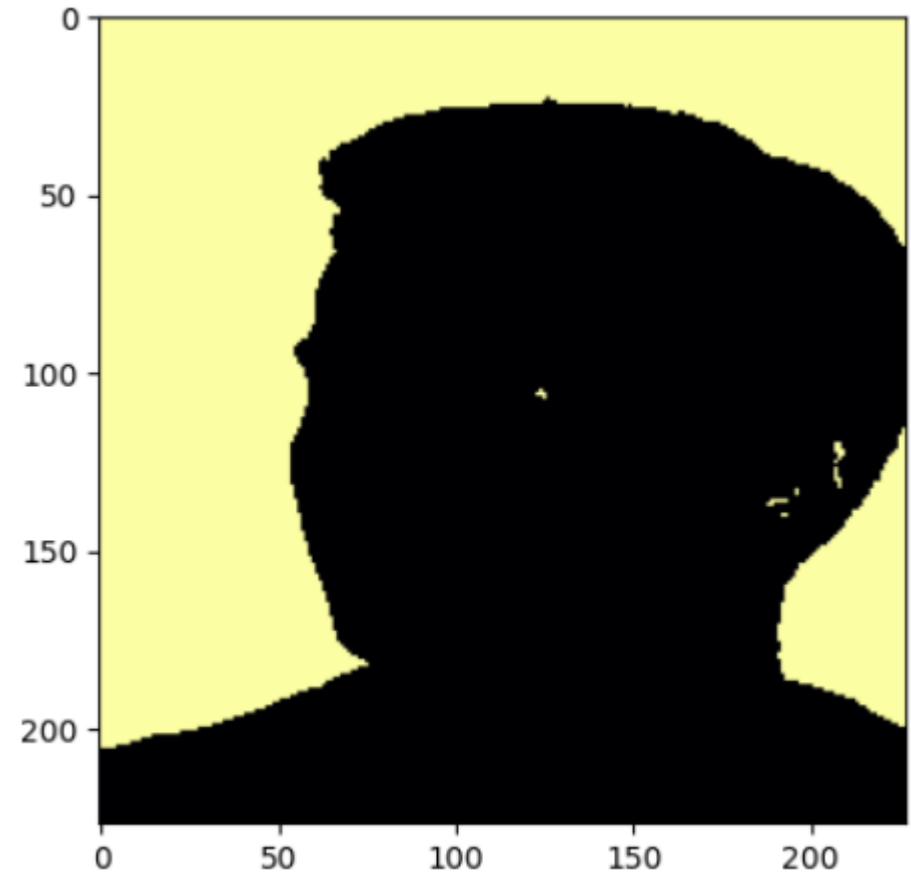
```
from skimage import io
from skimage.color import rgb2gray
from matplotlib import pyplot as plt
image = io.imread("F:\\13.jpg")
img_gray = rgb2gray(image)
BWimage = img_gray.copy()
for i in range(BWimage.shape[0]):
    for j in range(BWimage.shape[1]):
        if BWimage[i][j] >= 0.5:
            BWimage[i][j] = 1
        else:
            BWimage[i][j] = 0
plt.figure()
plt.imshow(BWimage, cmap = 'plasma')
plt.show()
```



Purple-red-yellow

# Binary Segmentation

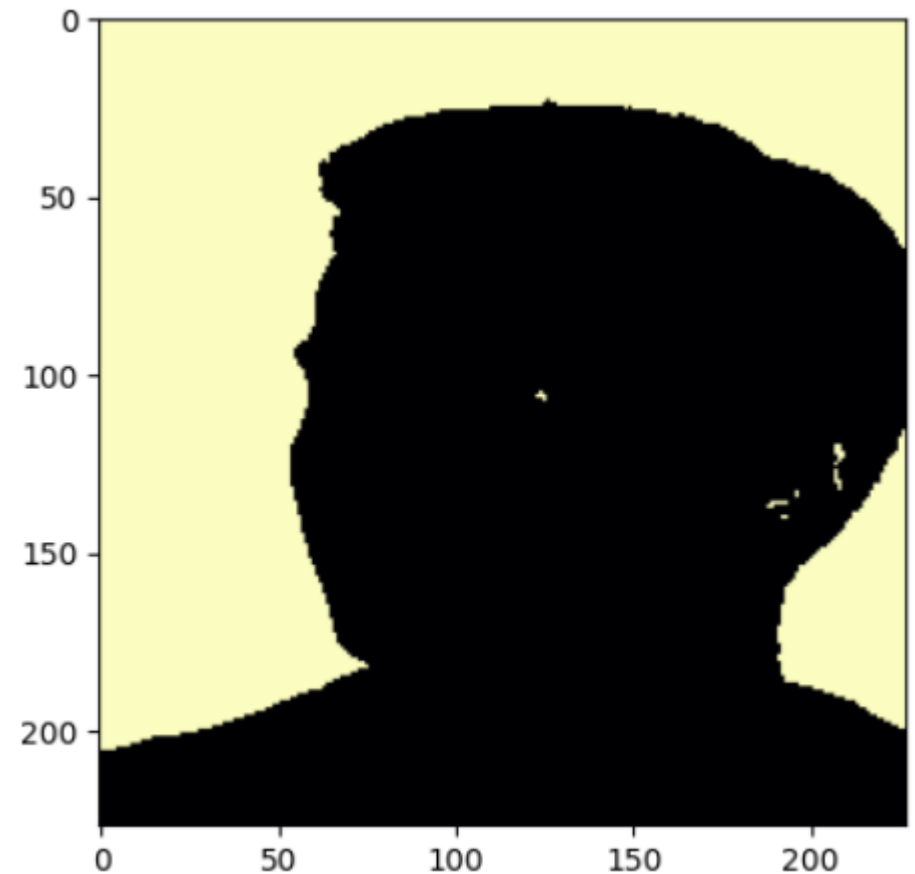
```
from skimage import io
from skimage.color import rgb2gray
from matplotlib import pyplot as plt
image = io.imread("F:\\13.jpg")
img_gray = rgb2gray(image)
BWimage = img_gray.copy()
for i in range(BWimage.shape[0]):
    for j in range(BWimage.shape[1]):
        if BWimage[i][j] >= 0.5:
            BWimage[i][j] = 1
        else:
            BWimage[i][j] = 0
plt.figure()
plt.imshow(BWimage, cmap = 'inferno')
plt.show()
```



Black – yellow – red

# Binary Segmentation

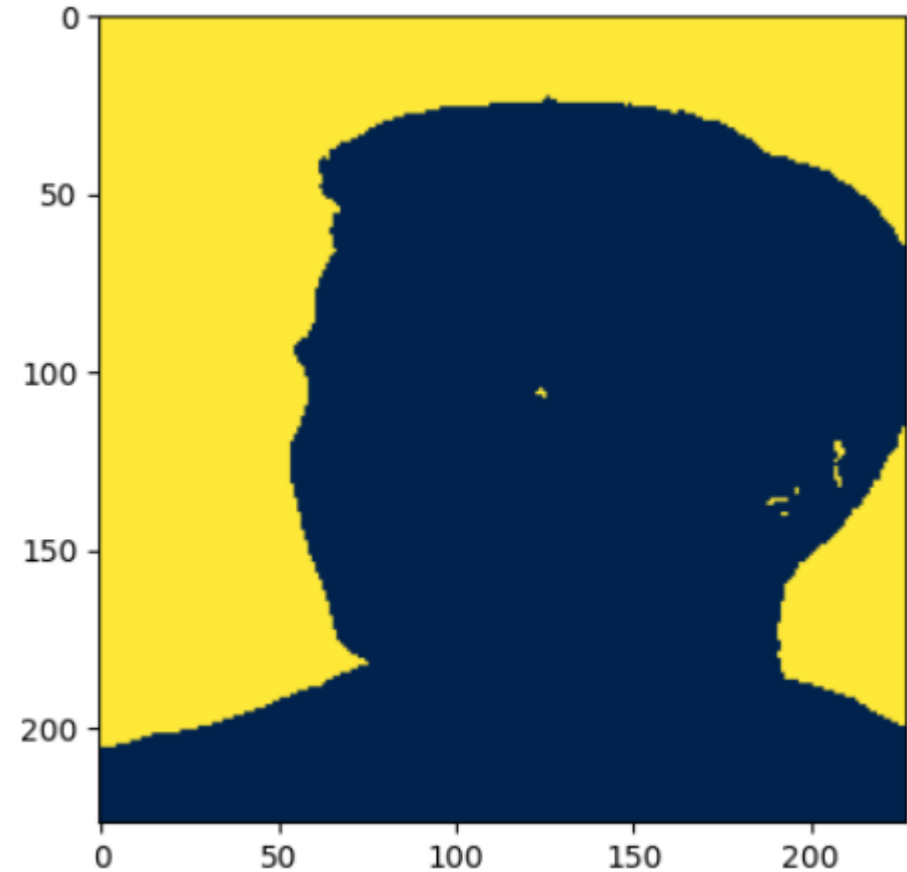
```
from skimage import io
from skimage.color import rgb2gray
from matplotlib import pyplot as plt
image = io.imread("F:\\13.jpg")
img_gray = rgb2gray(image)
BWimage = img_gray.copy()
for i in range(BWimage.shape[0]):
    for j in range(BWimage.shape[1]):
        if BWimage[i][j] >= 0.5:
            BWimage[i][j] = 1
        else:
            BWimage[i][j] = 0
plt.figure()
plt.imshow(BWimage, cmap = 'magma')
plt.show()
```



Black – Purple – pink

# Binary Segmentation

```
from skimage import io
from skimage.color import rgb2gray
from matplotlib import pyplot as plt
image = io.imread("F:\\13.jpg")
img_gray = rgb2gray(image)
BWimage = img_gray.copy()
for i in range(BWimage.shape[0]):
    for j in range(BWimage.shape[1]):
        if BWimage[i][j] >= 0.5:
            BWimage[i][j] = 1
        else:
            BWimage[i][j] = 0
plt.figure()
plt.imshow(BWimage, cmap = 'cividis')
plt.show()
```

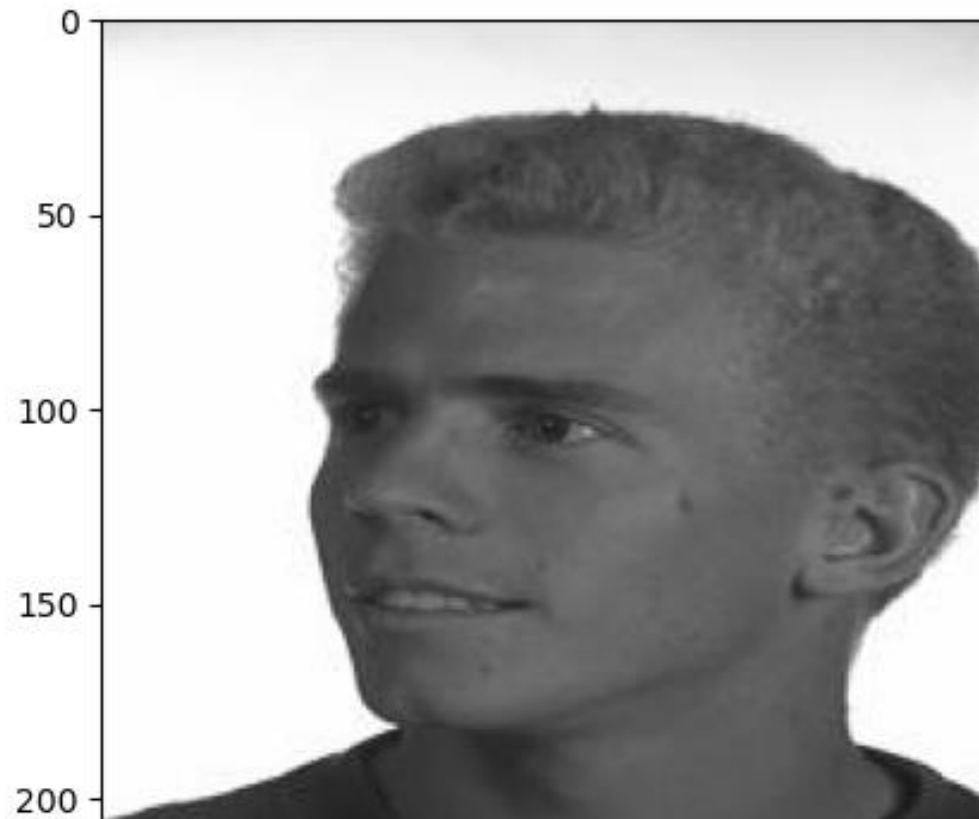


Blue – Yellow



```
from PIL import Image
from matplotlib import pyplot as plt
im = Image.open("F:\\13.jpg")
plt.figure()
plt.imshow(im, 'gray')
```

<matplotlib.image.AxesImage at 0x28db6c81090>



```
from PIL import Image
from matplotlib import pyplot as plt
im = Image.open(r"F:\\13.jpg")
plt.figure()
plt.imshow(im, cmap = 'cividis')
```

<matplotlib.image.AxesImage at 0x14920b3a490>



# Logarithmic transformation

General form:  $s = c * \ln(1 + r)$

- The log transformation maps a narrow range of low input grey level values into a wider range of output values (bright images).
- We add 1 to avoid  $\log(0)$  which is undefined
- If  $r = 0$ ,  $\ln(1+0) = \ln(1) = 0$
- This ensures all pixel values can be processed
- $\ln$  is just a specific type of  $\log$ .
- $\ln(x) = \log(x) / \log(e)$

# Logarithmic transformation

*Example: Low input values get expanded (let  $c = 10$ )*

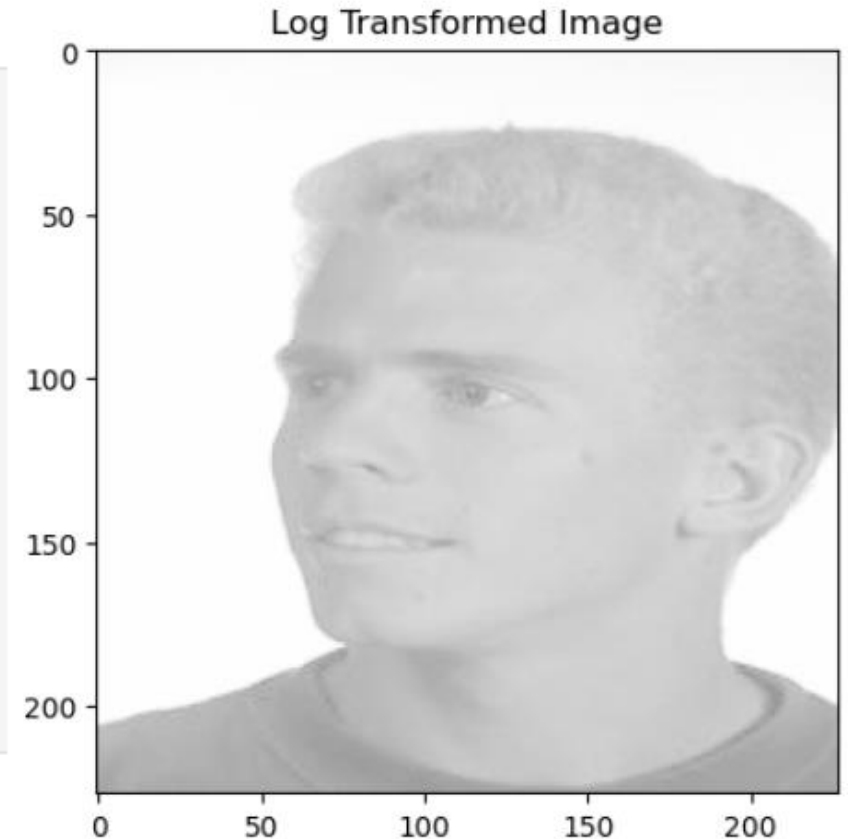
- $r = 10 \rightarrow s = c * \ln(11) = 23.9 \rightarrow s = 10 * \log(11) / \log(e) = 23.9$
- $r = 20 \rightarrow s = c * \ln(21) = 30.4 \rightarrow s = 10 * \log(21) / \log(e) = 30.4$

*Example: High input values get compressed (let  $c = 10$ )*

- $r = 200 \rightarrow s = c * \ln(201) = 53.03 \rightarrow s = 10 * \log(201) / \log(e) = 53.03$
- $r = 250 \rightarrow s = c * \ln(251) = 55.25 \rightarrow s = 10 * \log(250) / \log(e) = 55.25$

# Logarithmic transformation

```
from skimage import io
from matplotlib import pyplot as plt
import numpy as np
my_image = io.imread(r"F:\13.jpg")
image_float = my_image.astype(np.float64)
c = 255 / np.log(1 + 255)
log_transformed = c * np.log(1 + image_float)
log_transformed = log_transformed.astype(np.uint8)
plt.imshow(log_transformed, 'gray')
plt.title('Log Transformed Image')
```



**In Python:** `np.log(x)` or `math.log(x)` means natural logarithm

# Logarithmic transformation

*`image_float = my_image.astype(np.float64)`*

- Converts image pixel values from integers (0-255) to floating-point numbers
- This prevents issues with logarithmic operations on integers

*`log_transformed = log_transformed.astype(np.uint8)`*

- Converts the transformed floating-point values back to 8-bit integers (0-255)

# Power-law (gamma) transformation

It has the following form:  $s = c * r^\gamma$

- Power-law curves with fractional values of  $\gamma$  *map a narrow range of* dark input values into a wider range of output values, with the opposite being true for higher values.

# Power-law (gamma) transformation

```
from skimage import io
from matplotlib import pyplot as plt
import numpy as np
my_image = io.imread("F:\\13.jpg")
image_float = my_image.astype(np.float64) / 255.0
gamma_values = [0.1, 0.5, 1.0, 2.0, 4.0]
c = 1.0
plt.figure(figsize = (15, 10))
for i in range(len(gamma_values)):
    gamma = gamma_values[i]
    power_law_transformed = c * (image_float ** gamma)
    power_law_transformed = (power_law_transformed * 255).astype(np.uint8)
    plt.subplot(2, 3, i+1)
    plt.imshow(power_law_transformed, 'gray')
    plt.title(f'Gamma = {gamma}')
    plt.axis('off')
plt.tight_layout()
plt.show()
```

**`plt.axis('off')`** removes the axes  
**`plt.tight_layout()`** optimizes the spacing  
between subplots

# Power-law (gamma) transformation

Gamma = 0.1



Gamma = 0.5



Gamma = 1.0





# Power-law (gamma) transformation

Gamma = 2.0



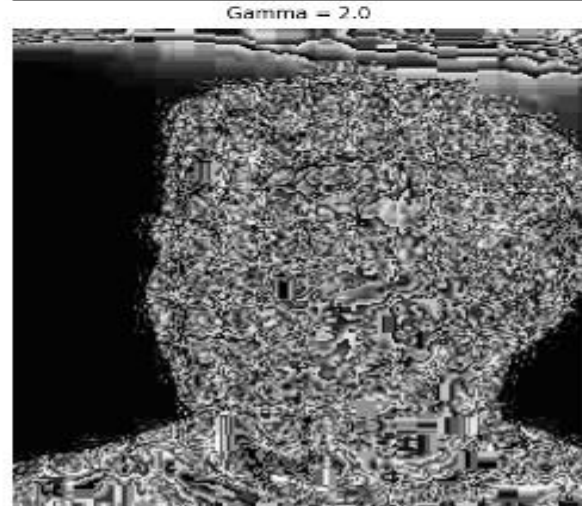
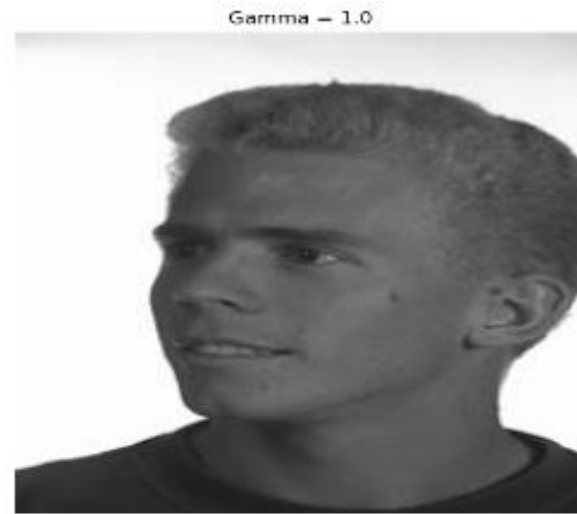
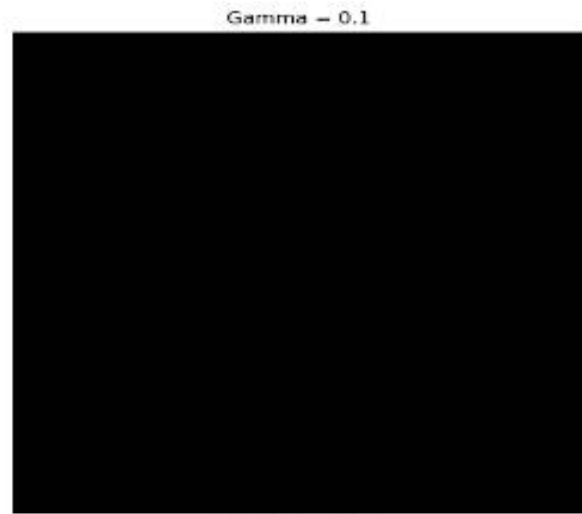
Gamma = 4.0



# Power-law (gamma) transformation

```
from skimage import io
from matplotlib import pyplot as plt
import numpy as np
my_image = io.imread("F:\\13.jpg")
image_float = my_image.astype(np.float64)
gamma_values = [0.1, 0.5, 1.0, 2.0, 4.0]
c = 1.0
plt.figure(figsize = (15, 10))
for i in range(len(gamma_values)):
    gamma = gamma_values[i]
    power_law_transformed = c * (image_float ** gamma)
    power_law_transformed = (power_law_transformed).astype(np.uint8)
    plt.subplot(2, 3, i+1)
    plt.imshow(power_law_transformed, 'gray')
    plt.title(f'Gamma = {gamma}')
    plt.axis('off')
plt.tight_layout()
plt.show()
```

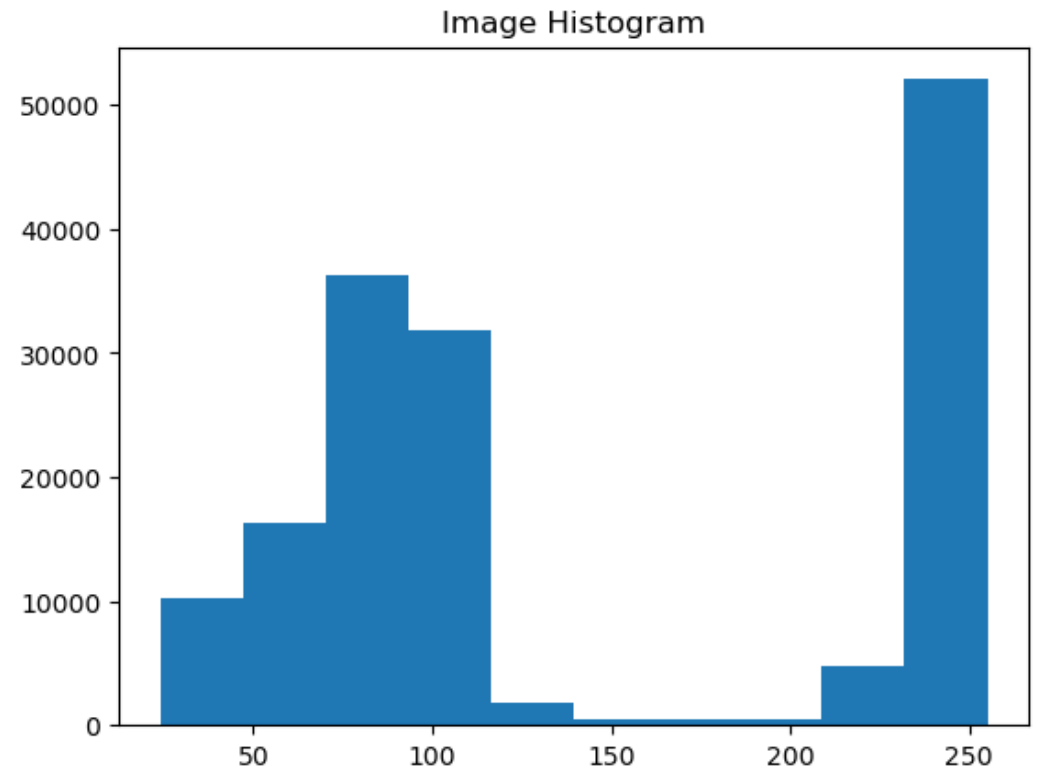
# Power-law (gamma) transformation



# Histogram Processing

An image histogram is a graphical representation of the tonal distribution in a digital image. It plots the number of pixels for each intensity value.

```
from skimage import io
from matplotlib import pyplot as plt
import numpy as np
my_image = io.imread(r"F:\13.jpg")
plt.figure()
plt.hist(my_image.ravel())
plt.title('Image Histogram')
plt.show()
```



# Histogram Processing

**`my_image.ravel ()`** → converts the image pixels into a simple list of values that **`plt.hist()`** can process to count how many pixels have each intensity value.

# Histogram Equalization

*Histogram equalization* is an image enhancement technique that improves contrast by redistributing pixel intensity values so that they cover the entire possible range more evenly.

In a dark or low-contrast image, many pixel values are clustered in a narrow range (*for example, between 50 and 120 out of 255*).

Histogram equalization spreads these pixel values across the full range (0 – 255) → *enhanced contrast*.

# Histogram Equalization

*Compute the PDF (Probability Density Function):*

$$p_r(r_k) = \frac{n_k}{n}$$

***n<sub>k</sub>***: number of pixels with intensity ***r<sub>k</sub>***  
***n***: total number of pixels

*Compute the CDF (Cumulative Distribution Function):*

$$s_k = T(r_k) = \sum_{j=0}^k p_r(r_j)$$

# Histogram Equalization

*Map intensity values:*

$$s'_k = (L - 1) \times s_k$$

This scales the result back to the valid range  $[0, L-1]$ .

Replace each pixel intensity  $r_k$  with  $s'_k$  → This yields the equalized image.



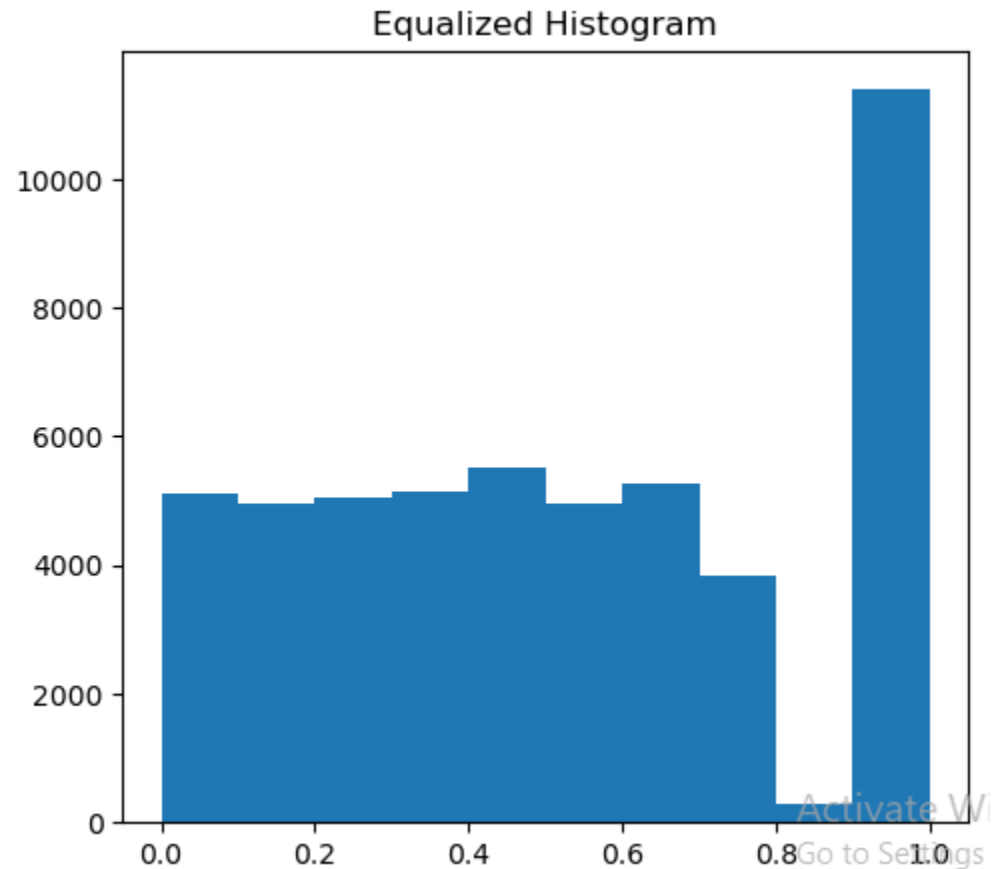
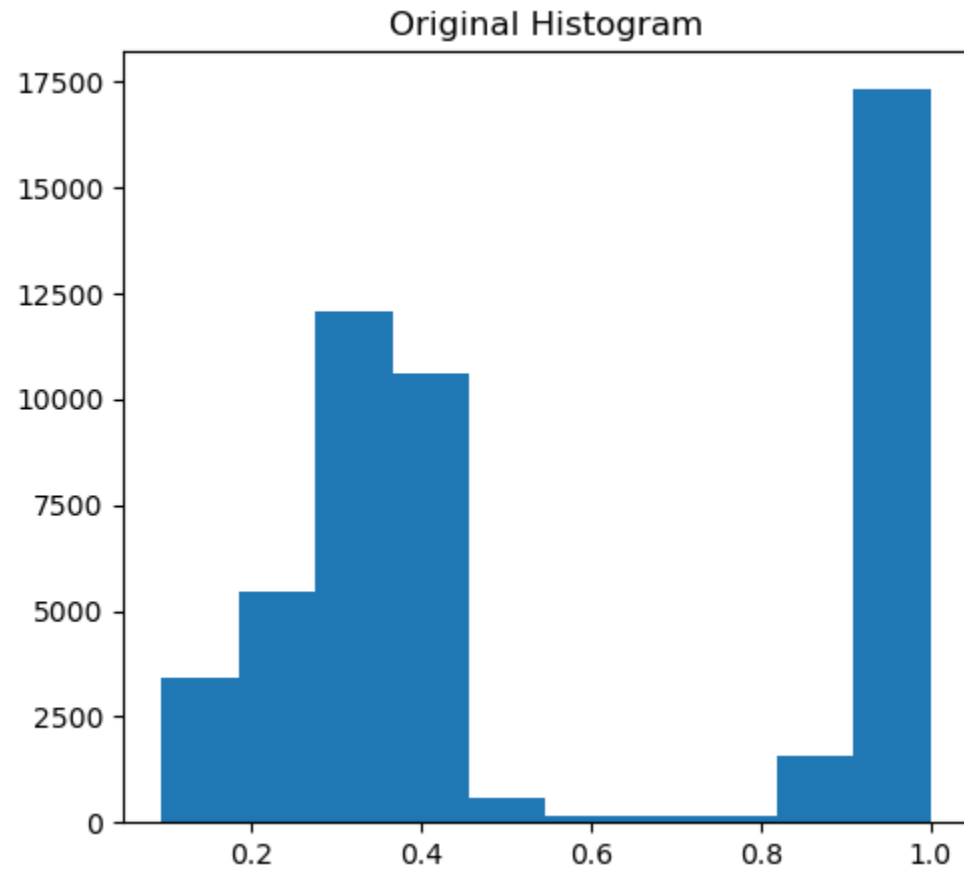
# Histogram Equalization

- ✓ Dark regions become more visible.
- ✓ Light regions gain more contrast.
- ✓ The histogram of the equalized image becomes more uniform (spread out across all intensity levels).

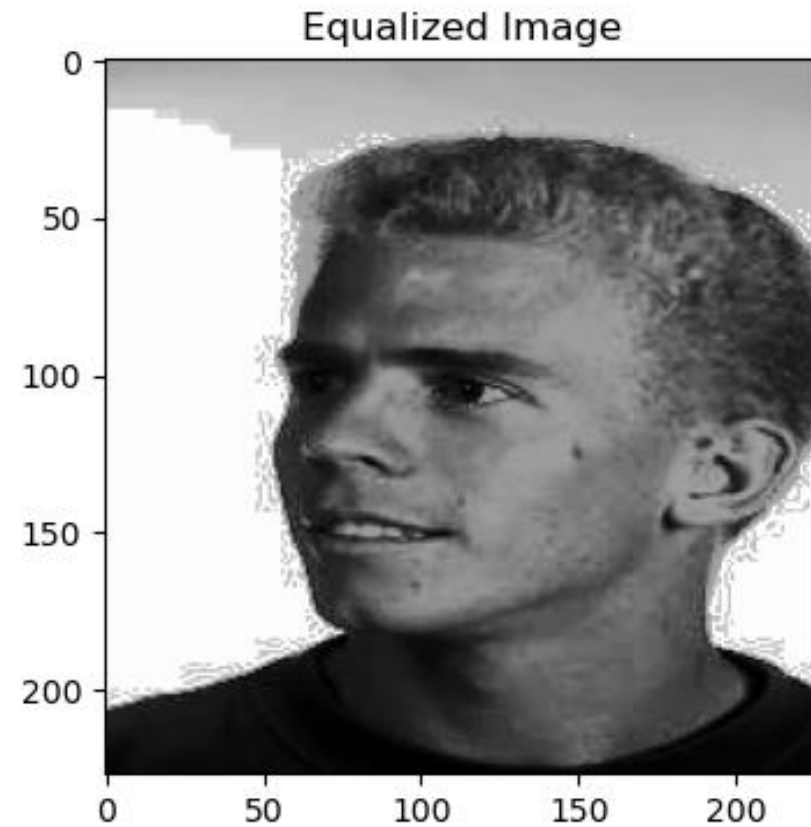
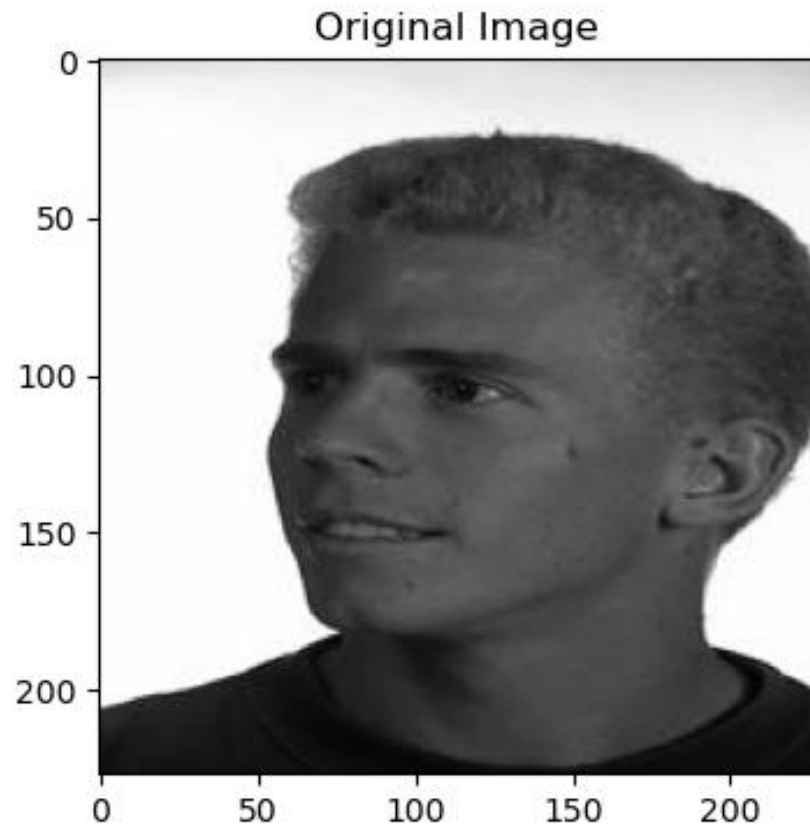
```
from skimage import io, exposure, color
from matplotlib import pyplot as plt
import numpy as np
my_image = io.imread(r"F:\13.jpg")
gray_image = color.rgb2gray(my_image)
plt.figure(figsize = (12, 5))
plt.subplot(1, 2, 1)
plt.hist(gray_image.ravel())
plt.title('Original Histogram')
equalized_image = exposure.equalize_hist(gray_image)
plt.subplot(1,2,2)
plt.hist(equalized_image.ravel())
plt.title('Equalized Histogram')
plt.show()
plt.figure(figsize = (10, 4))
plt.subplot(1,2,1)
plt.imshow(gray_image, cmap='gray')
plt.title('Original Image')
plt.subplot(1,2,2)
plt.imshow(equalized_image, cmap='gray')
plt.title('Equalized Image')
plt.show()
```

**exposure.equalize\_hist (gray\_image) → is a function that performs histogram equalization.**

# Histogram Equalization



# Histogram Equalization



# Example

*Apply histogram equalization to the following image*

3-bit image:  $2^3 = 8$  possible intensity levels (0-7)

Image size:  $4 \times 8 = 32$  pixels

Original intensity values: 0, 1, 2, 3, 4

0	1	1	2	2	3	4	4
0	1	1	2	2	3	4	4
0	1	1	2	2	3	4	4
0	1	1	2	2	3	4	4

# Example

*Calculate Probability Density Function (PDF)*

Intensity ( $r_k$ )	Count ( $n_k$ )	PDF: $P_r(r_k) = n_k/MN$
0	4	$4/32 = 0.125$
1	8	$8/32 = 0.25$
2	8	$8/32 = 0.25$
3	4	$4/32 = 0.125$
4	8	$8/32 = 0.25$

# Example

*Calculate Cumulative Distribution Function (CDF)*

$r_k$	$P_r(r_k)$	Cumulative Sum	CDF
0	0.125	0.125	0.125
1	0.25	$0.125+0.25=0.375$	0.375
2	0.25	$0.375+0.25=0.625$	0.625
3	0.125	$0.625+0.125=0.75$	0.75
4	0.25	$0.75+0.25=1.0$	1.0

# Example

*Apply Histogram Equalization Transform*

$r_k$	CDF	$s_k = 7 \times \text{CDF}$	Rounded $s_k$
0	0.125	0.875	1
1	0.375	2.625	3
2	0.625	4.375	4
3	0.75	5.25	5
4	1.0	7.0	7



# Histogram Equalization

*Example:* Apply the histogram transformation to a 3-bit image ( $L = 8$ ) of size  $64 \times 64$  pixels ( $MN = 4096$ ).

Intensity	Pixel Count
0	800
1	600
2	500
3	400
4	500
5	600
6	400
7	296

# Histogram Equalization

*Calculate Probability Density Function (PDF)*

$r_k$	$n_k$	$P_r(r_k)$
0	800	0.195
1	600	0.146
2	500	0.122
3	400	0.098
4	500	0.122
5	600	0.146
6	400	0.098
7	296	0.072

# Histogram Equalization

*Calculate Cumulative Distribution Function (CDF)*

$r_k$	$P_r(r_k)$	CDF( $r_k$ )
0	0.195	0.195
1	0.146	0.341
2	0.122	0.463
3	0.098	0.561
4	0.122	0.683
5	0.146	0.829
6	0.098	0.927
7	0.072	1.000

# Histogram Equalization

*Apply the Mapping to Original Image*

$r_k$	CDF( $r_k$ )	$s_k = 7 \times \text{CDF}$	Rounded $s_k$
0	0.195	1.365	1
1	0.341	2.387	2
2	0.463	3.241	3
3	0.561	3.927	4
4	0.683	4.781	5
5	0.829	5.803	6
6	0.927	6.489	6
7	1.000	7.000	7