

QUESTION: Provide your comments on the effectiveness of a *median filter* for the example above? Explain why?

Your answer: Median filter is more effective in removing noise in the example above as the example has salt and pepper noise. In salt and pepper noise, pixels with extreme intensities (black and white) will be eliminated after median filtering. Meanwhile, Gaussian filtering will not eliminate these pixels, but simply blur them out (lower their intensity).

```
In [24]: def myMedianBlur(img, size):
    """
    A implementation of median blur filter.
    """
    out = img.copy()
    w,h = img.shape(0),img.shape(1)
    s = (size - 1)/2
    #####
    # TODO: Implement the median blur.
    # NOTE: Your implementation is NOT necessary to provide the identical
    # output as OpenCV built-in function. However, it should be visually very
    # similar.
    #####
    pad = int(s)
    padout = np.lib.pad(out, (pad,pad, pad, pad), 'edge')
    for i in range(H):
        for j in range(W):
            image_slice = padout[i:i+size,j:j+size]
            out[i][j]=findMedian(image_slice)
    #####
    # END OF YOUR CODE
    #####
    return out

In [25]: img = cv2.imread('imgs/SaltAndPepperNoise.jpg', 0)
myMedian = myMedianBlur(img,5)
median = cv2.medianBlur(img,5)

# Note that your implementation is NOT necessary to provide
# the identical output as OpenCV built-in function. However,
# it should visually very similar.
plt.figure(figsize=(16,8))
plt.subplot(121),plt.imshow(median, 'gray')
plt.title('OpenCV Median Blur'),plt.xticks([],),plt.yticks([],)
plt.subplot(122),plt.imshow(myMedian, 'gray')
plt.title('My Median Blur'),plt.xticks([],),plt.yticks([],)
plt.show()
```

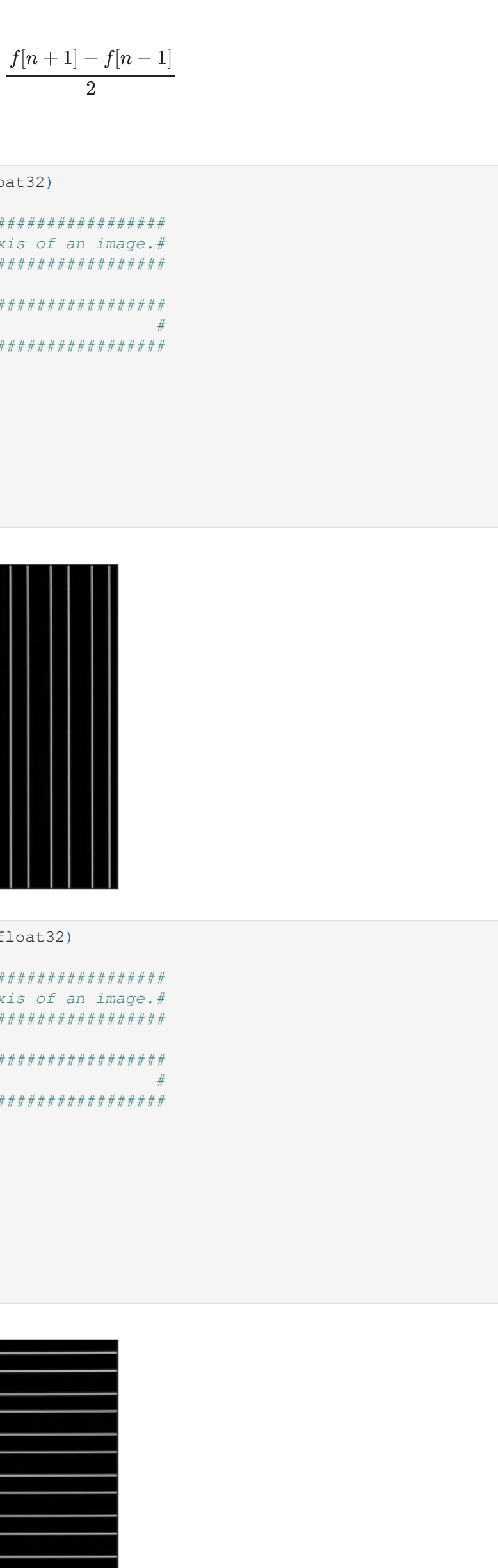


Image gradient

For 1-D continuous function $f(x)$, the gradient is given as:

$$D_x[f(x)] = \frac{d}{dx}f(x) = \lim_{\Delta x \rightarrow 0} \frac{f(x + \Delta x) - f(x)}{\Delta x}, \quad \text{or} \quad \lim_{\Delta x \rightarrow 0} \frac{f(x + \Delta x) - f(x - \Delta x)}{2\Delta x}$$

For 1-D discrete function $f[n]$, the gradient becomes difference.

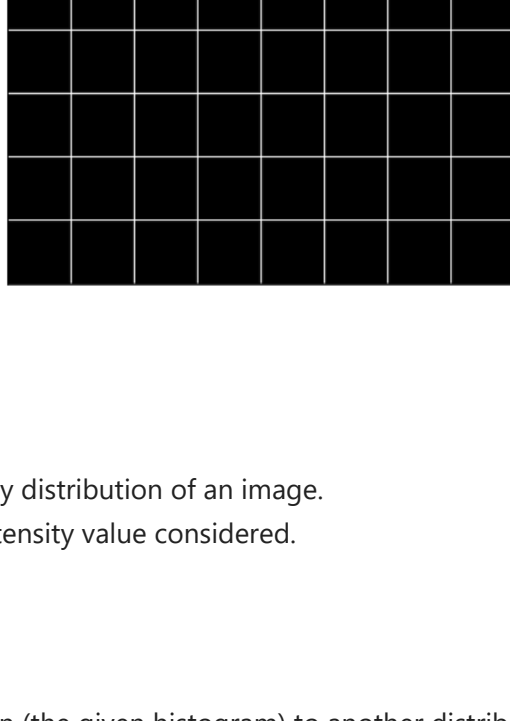
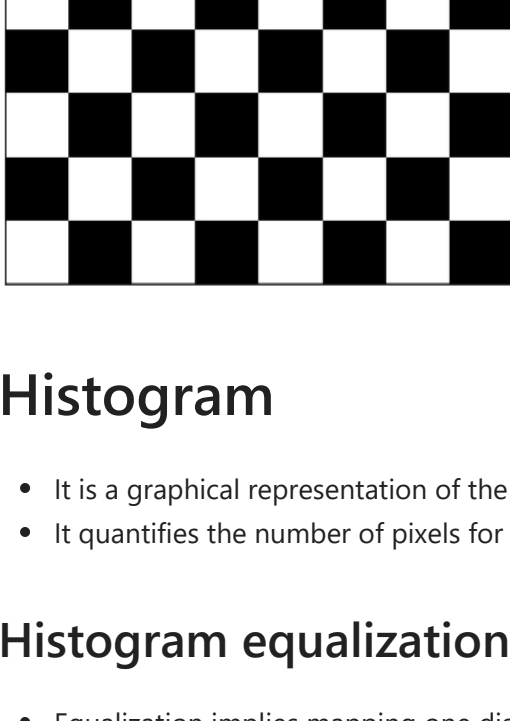
$$D_x[f[n]] = f[n + 1] - f[n], \quad \text{or} \quad \frac{f[n + 1] - f[n - 1]}{2}$$

The kernel to find gradient in 1-D discrete function is $[1, 0, -1]$.

```
In [26]: img = cv2.imread('imgs/banded_vertical.jpg', 0).astype(np.float32)

#####
# TODO: Create a 3x3 kernel, Kx, to find the gradient in x-axis of an image.
#####
Kx = np.array([[1,-1,0],[0,0,0],[-1,0,1]])
#####
# END OF YOUR CODE
#####
dstx = cv2.filter2D(img,-1, Kx)

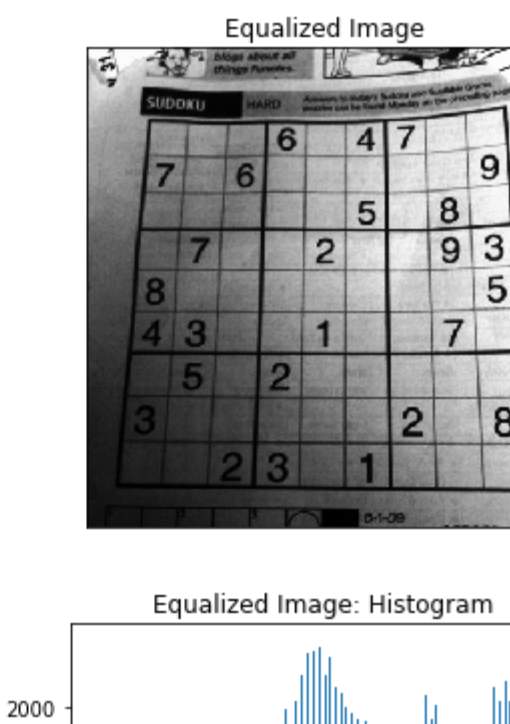
plt.figure(figsize=(10,5))
plt.subplot(121),plt.imshow(img, cmap='gray')
plt.title('Original'),plt.xticks([],),plt.yticks([],)
plt.subplot(122),plt.imshow(np.abs(dstx), cmap='gray')
plt.title('Output 1'),plt.xticks([],),plt.yticks([],)
plt.show()
```



```
In [27]: img = cv2.imread('imgs/banded_horizontal.jpg', 0).astype(np.float32)

#####
# TODO: Create a 3x3 kernel, Ky, to find the gradient in y-axis of an image.
#####
Ky = np.array([[1,-1,-1],[0,0,0],[1,1,1]])
#####
# END OF YOUR CODE
#####
dsty = cv2.filter2D(img,-1,Ky)

plt.figure(figsize=(10,5))
plt.subplot(121),plt.imshow(img, 'gray')
plt.title('Original'),plt.xticks([],),plt.yticks([],)
plt.subplot(122),plt.imshow(np.abs(dsty), 'gray')
plt.title('Output'),plt.xticks([],),plt.yticks([],)
plt.show()
```



Question: What do the kernel K_x and K_y do in image processing?

Answer: The kernels K_x and K_y identify vertical and horizontal edges respectively.

Two directions:

- Find the difference in the two directions:

$$g_x[m,n] = f[m + 1, n] - f[m - 1, n]$$

$$g_y[m,n] = f[m, n + 1] - f[m, n - 1]$$

- Find the magnitude and direction of the gradient vector:

$$||g[m,n]|| = \sqrt{g_x^2[m,n] + g_y^2[m,n]}$$

$$\angle g[m,n] = \tan^{-1} \left(\frac{g_y[m,n]}{g_x[m,n]} \right)$$

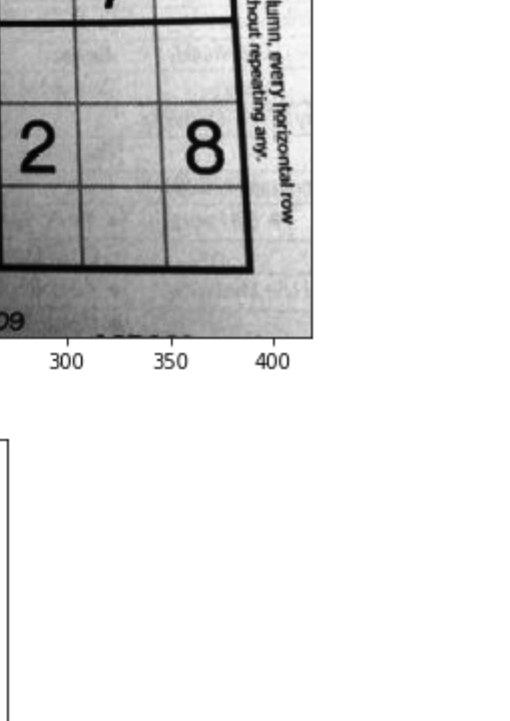
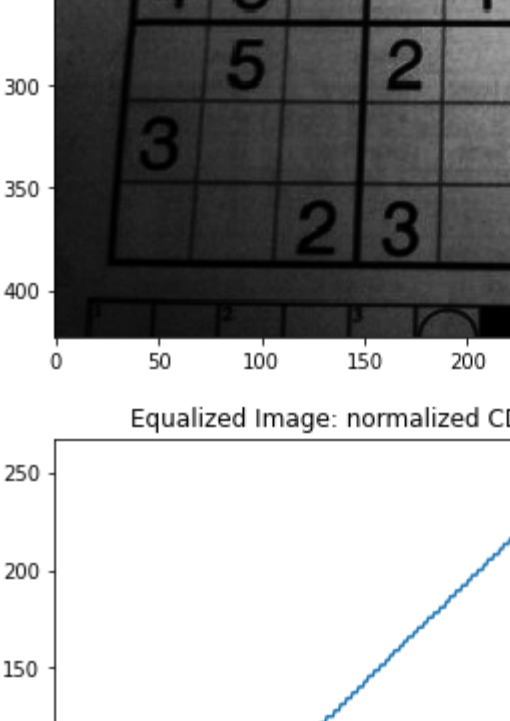
```
In [28]: img = cv2.imread('imgs/chequered.jpg', 0).astype(np.float32)

#####
# TODO: Using the theory provided above, compute the magnitude of 2
# direction image gradient.
#####
Kx = np.array([[0,0,0],[-1,0,1],[0,0,0]])
Ky = np.array([[0,-1,0],[0,0,0],[0,1,0]])

gradx = cv2.filter2D(img,-1,Kx)
grady = cv2.filter2D(img,-1,Ky)

dst1 = (gradx**2 + grady**2)**(0.5)
#####
# END OF YOUR CODE
#####
# You can achieve a similar (NOT identical) output with the following code line.
K = np.array([[1,0,1],[0,1,1],[0,1,0]])
dst2 = cv2.filter2D(img,-1,K)

plt.figure(figsize=(20,10))
plt.subplot(131),plt.imshow(img, 'gray')
plt.title('Original'),plt.xticks([],),plt.yticks([],)
plt.subplot(132),plt.imshow(np.abs(dst1), 'gray')
plt.title('Output 1'),plt.xticks([],),plt.yticks([],)
plt.subplot(133),plt.imshow(np.abs(dst2), 'gray')
plt.title('Output 2'),plt.xticks([],),plt.yticks([],)
plt.show()
```



Histogram


- It is a graphical representation of the intensity distribution of an image.
- It quantifies the number of pixels for each intensity value considered.

Histogram equalization


- Equalization implies mapping one distribution (the given histogram) to another distribution (a wider and more uniform distribution of intensity values) so the intensity values are spreaded over the whole range.
- To accomplish the equalization effect, the remapping should be the cumulative distribution function (cdf) (more details, refer to Learning OpenCV). For the histogram $H(i)$, its cumulative distribution $H'(i)$ is:

$$H'(i) = \sum_{0 \leq j < i} H(j)$$

- To use this as a remapping function, we have to normalize $H'(i)$ such that the maximum value is 255 (or the maximum value for the intensity of the image). From the example above, the cumulative function is:

 cumulative distribution function

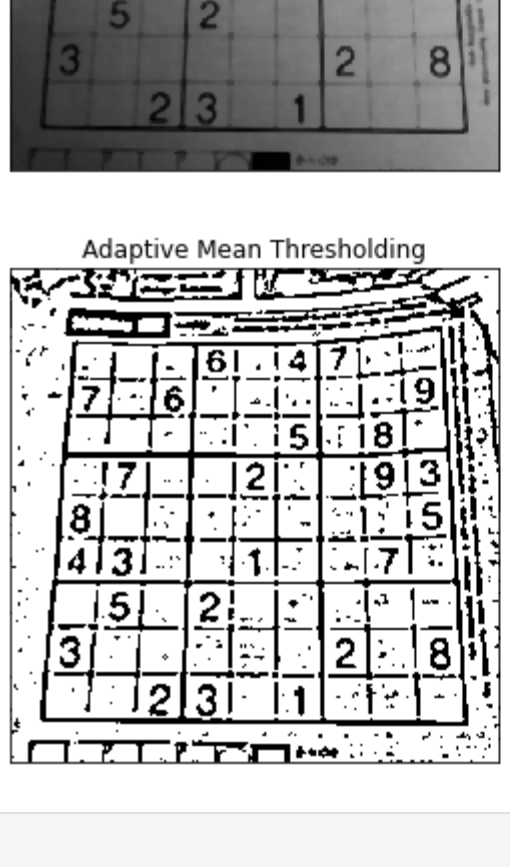
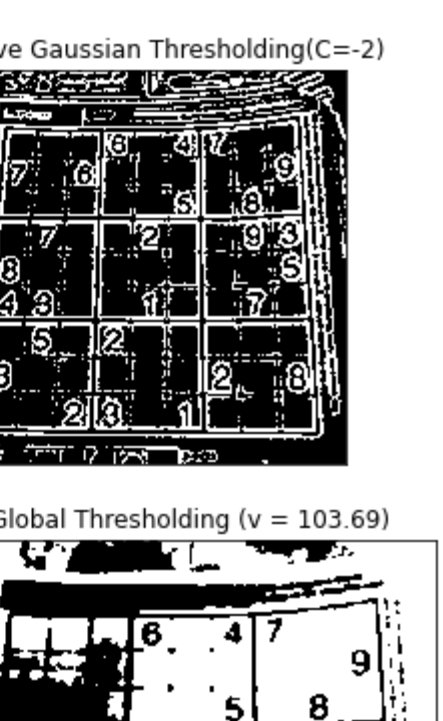
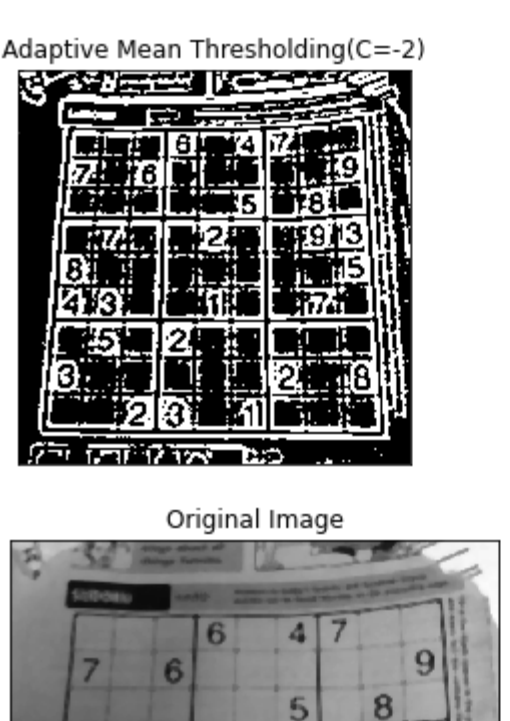
$$equalized(x, y) = H' \left(\frac{src(x, y)}{255} \right)$$

 Histogram Equalization

```
In [29]: img = cv2.imread('imgs/sudoku-original.jpg',0)
W,H = img.shape
img_eq = cv2.equalizeHist(img)

hist = np.histogram(img, bins=256, range=(0.0, 255.0))
hist_eq = np.histogram(img_eq, bins=256, range=(0.0, 255.0))

plt.figure(figsize=(10,15))
plt.subplot(321),plt.imshow(img, cmap='gray'),plt.title('Original Image'),plt.xticks([],),plt.yticks([],)
plt.subplot(322),plt.imshow(img_eq, cmap='gray'),plt.title('Equalized Image'),plt.xticks([],),plt.yticks([],)
plt.subplot(323),plt.hist(img_eq.ravel(), bins=256, range=(0.0, 255.0),plt.title('Original Image: Histogram')
plt.subplot(324),plt.hist(img_eq.ravel(), bins=256, range=(0.0, 255.0),plt.title('Equalized Image: Histogram')
plt.subplot(325),plt.plot(range(0,256),np.cumsum(hist_eq[0])*255/(W*H)),plt.title('Original Image: normalized CDF')
plt.subplot(326),plt.plot(range(0,256),np.cumsum(hist_eq[0])*255/(W*H)),plt.title('Equalized Image: normalized CDF')
plt.show()
```



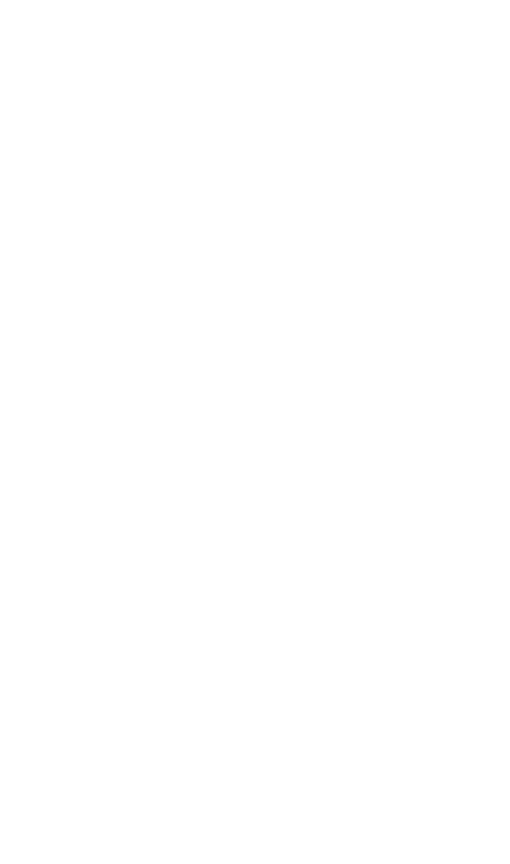
QUIZ: Is histogram equalization reversible?

Your answer: It is not reversible.

```
In [30]: def myQualizeHist(img):
    """
    A implementation of a histogram equalization for image of 'uint8' data type.
    """
    out = img
    #####
    # TODO: Implement the histogram equalization function.
    #####
    hist,bins = np.histogram(img.flatten(),256,[0,256])
    cdf = hist.cumsum()
    cdf_m = np.ma.masked_equal(cdf,0)
    cdf_m = (cdf_m - cdf_m.min())*255/(cdf_m.max()-cdf_m.min())
    cdf = np.ma.filled(cdf_m,0).astype('uint8')
    out = cdf[img]
    plt.imshow(out)
    plt.show()
    #####
    # END OF YOUR CODE
    #####
    return out

In [31]: # Verify the correctness of your implementation by plotting the
# exactly the same as the one OpenCV built-in function does.
img = cv2.imread('imgs/sudoku-original.jpg',0)
W,H = img.shape
img_myeq = myQualizeHist(img)

# Your implementation may NOT need to return an image that is
# exactly the same as the one OpenCV built-in function does.
# However, the normalized CDF should make sense.
hist_myeq = np.histogram(img_myeq, bins=256, range=(0.0, 255.0))
plt.plot(range(0,256),np.cumsum(hist_myeq[0])*255/(W*H))
plt.title('Equalized Image: normalized CDF')
plt.show()
```



Threshold

Simple Threshold

If pixel value is greater than a threshold value, it is assigned one value (may be white), else it is assigned another value (may be black). The function used is `cv2.threshold`.

```
In [32]: # Get list of available flags for thresholding styles
flags = [i for i in dir(cv2) if i.startswith('THRESH_')]
print(flags)

['THRESH_BINARY', 'THRESH_BINARY_INV', 'THRESH_MASK', 'THRESH_OTSU', 'THRESH_TOZERO', 'THRESH_TOZERO_INV', 'THRESH_TRIANGLE', 'THRESH_TRUNC']

Adaptive Method

It decides how thresholding value is calculated. The function used is cv2.adaptiveThreshold.
```

- `cv2.ADAPTIVE_THRESH_MEAN_C`: threshold value is the mean of neighbourhood area.
- `cv2.ADAPTIVE_THRESH_GAUSSIAN_C`: threshold value is the weighted sum of neighbourhood values where weights are a gaussian window.

```
In [33]: img = cv2.imread('imgs/sudoku-original.jpg',0)
img = cv2.medianBlur(img,5)
img_mean = np.mean(img)

C = 2
ret,th1 = cv2.threshold(img,img_mean,255,cv2.THRESH_BINARY)
th2 = cv2.adaptiveThreshold(img,255,cv2.ADAPTIVE_THRESH_MEAN_C,\
                           cv2.THRESH_BINARY,11,C)

th3 = cv2.adaptiveThreshold(img,255,cv2.ADAPTIVE_THRESH_GAUSSIAN_C,\
                           cv2.THRESH_BINARY,11,C)

#####
# TODO:
# Trying several value of constant C and observing how the output
# thresholded images change.
#####
C0 = 0
C2 = 2
th4 = cv2.adaptiveThreshold(img,255,cv2.ADAPTIVE_THRESH_MEAN_C,\
                           cv2.THRESH_BINARY,11,C0)

th5 = cv2.adaptiveThreshold(img,255,cv2.ADAPTIVE_THRESH_GAUSSIAN_C,\
                           cv2.THRESH_BINARY,11,C0)

th6 = cv2.adaptiveThreshold(img,255,cv2.ADAPTIVE_THRESH_MEAN_C,\
                           cv2.THRESH_BINARY,11,C2)

th7 = cv2.adaptiveThreshold(img,255,cv2.ADAPTIVE_THRESH_GAUSSIAN_C,\
                           cv2.THRESH_BINARY,11,C2)

my_titles = ['Adaptive Mean Thresholding (C=0)', 'Adaptive Gaussian Thresholding (C=0)', 'Adaptive Mean Thresholding (C=2)', 'Adaptive Gaussian Thresholding (C=2)']
my_images = [th4,th5,th6,th7]
for i in range(4):
    plt.subplot(2,2,i+1)
    plt.imshow(my_images[i], 'gray')
    plt.title(my_titles[i])
    plt.xticks([],)
    plt.yticks([],)
#####
# END OF YOUR CODE
#####
titles = ['Original Image', 'Global Thresholding (v = 12.2f)'].format(img_mean,
        'Adaptive Mean Thresholding', 'Adaptive Gaussian Thresholding')
images = [img, th1, th2, th3]

fig = plt.figure(figsize=(10, 10))
for i in range(4):
    plt.subplot(2,2,i+1)
    plt.imshow(images[i], 'gray')
    plt.title(titles[i])
    plt.xticks([],)
    plt.yticks([],)
plt.show()
```


In []: