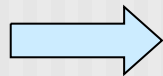

Lecture 2

Pattern Classification

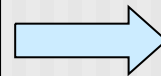
Lecture by: Suthep “Jogie” Madarasmi, Ph.D.

Optical Character Recognition OCR

Input: Scanned
Image of paper
with printed text



**Optical Character
Recognition
(OCR)**



Output: Text
File in UTF-8
encoding

segmentation - find the bounding box



ในช่วงระยะแค่ 5 ปี มีนักท่องเที่ยวเพิ่มขึ้นเรื่อย ๆ ในปี 2534
มีตัวเลขนักท่องเที่ยวประมาณ 220,000 คน ทำกำไรให้กับ
มณฑลถึง 63 ล้านบาทหรือสหรัฐ
อาจจะเป็นความใฝ่ฝันของคนคุณหมิงอยู่พอสมควรว่า
เมื่อกรุงปักกิ่งเป็นตลาดท่องเที่ยวของอเมริกาและยุโรป คุณหมิง
ก็น่าจะเป็นตลาดท่องเที่ยวของชาวเอเชียตะวันออกและตะวันออก
เฉียงใต้



The 5 Steps in OCR Algorithm

1. **Remove image noise.** Use Gaussian Filtering and Median Filter.
2. **Threshold image to foreground/background.** Use Image Histogram and select threshold at valley between 2 peaks.
3. **Segmentation into single characters.** Use Contour Blob Coloring and get bounding box.
4. **Resize each test image to the template size.** Use aspect ratio to guide new image size.
5. **Character Recognition.** Use Template Matching (KNN), ANN, ML, ...

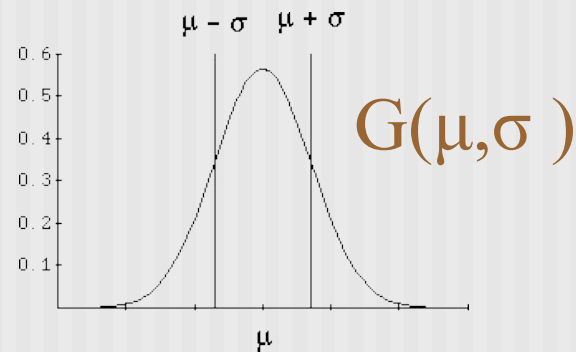
Gaussian Additive Noise

- For example, an ideal white paper

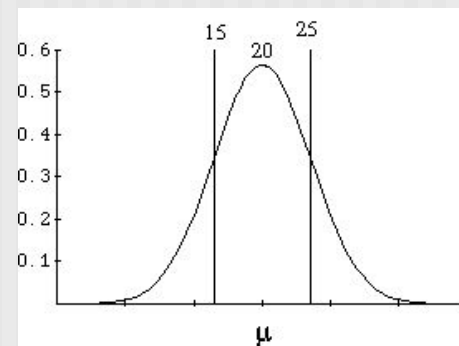
| | | | | |
|-----|-----|-----|-----|-----|
| 220 | 220 | 220 | 220 | 220 |
| 220 | 220 | 220 | 220 | 220 |
| 220 | 220 | 220 | 220 | 220 |
| 220 | 220 | 220 | 220 | 220 |

- Scanned white paper will spread around $220 + 20$:

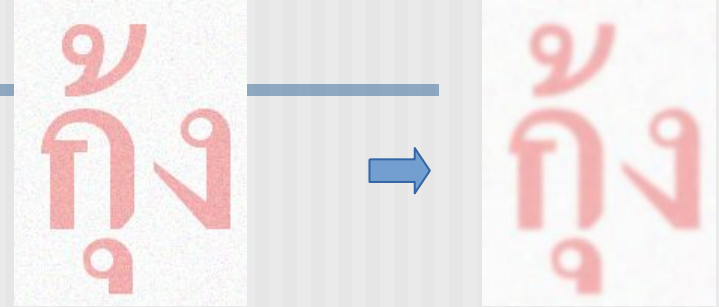
| | | | | |
|-----|-----|-----|-----|-----|
| 242 | 239 | 240 | 220 | 238 |
| 242 | 240 | 240 | 241 | 245 |
| 247 | 237 | 230 | 235 | 238 |
| 244 | 240 | 237 | 232 | 243 |



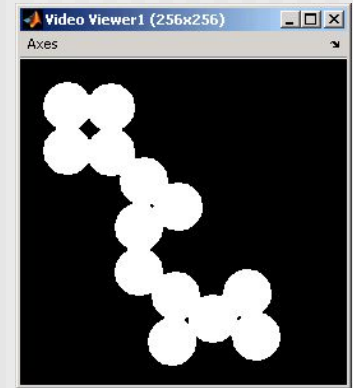
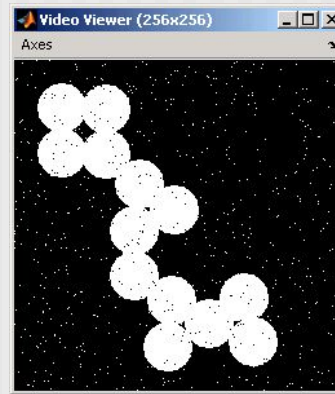
$$G(\mu=20, \sigma=5)$$



The Convolution Filter



- Gaussian Noise
 - Use Gaussian Filter
 - Can also use the Mean (Average) Filter

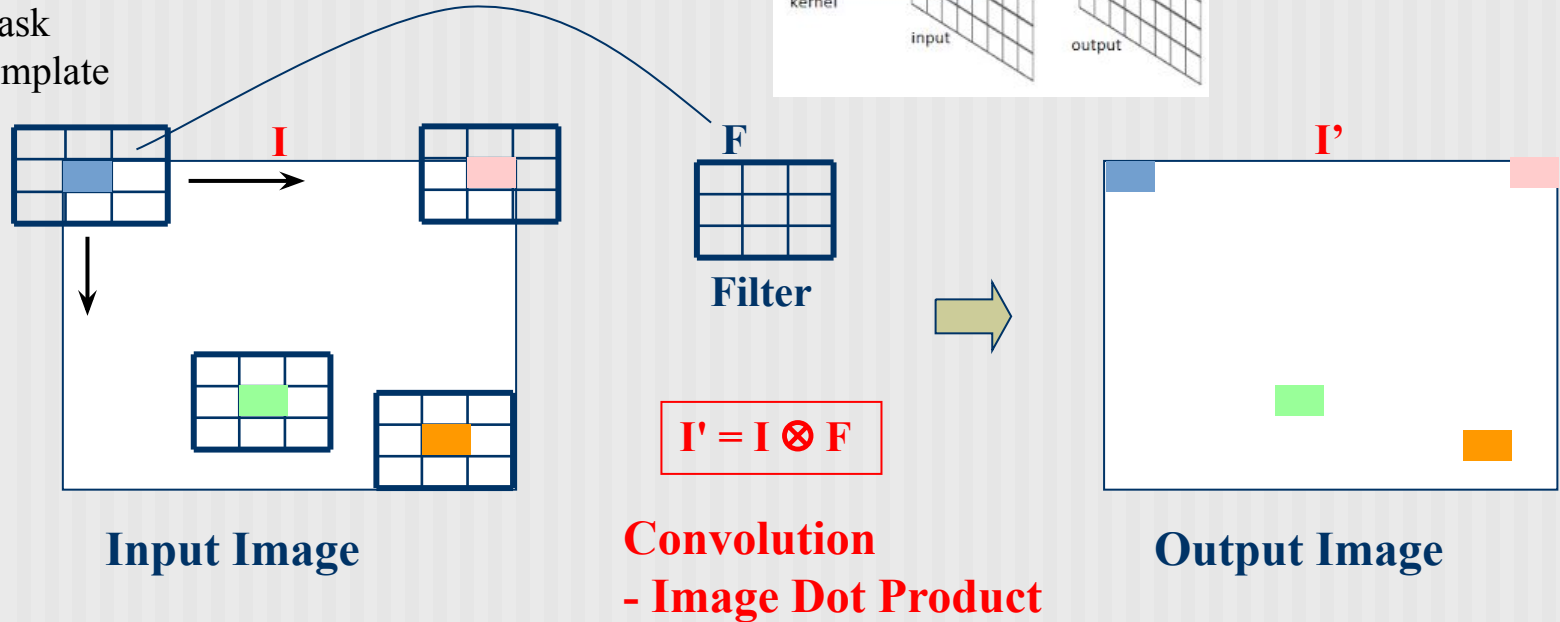
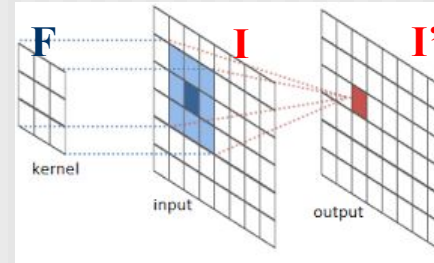


- Salt/Pepper Noise
 - Use Median Filter

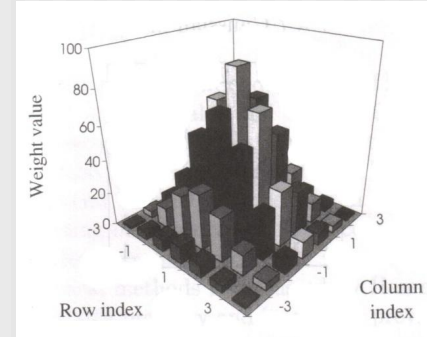
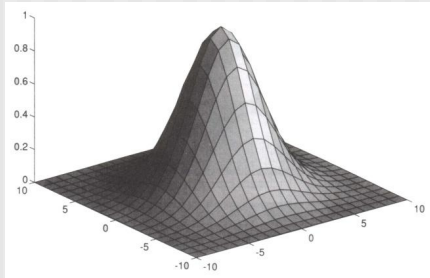
The Convolution Filter

Synonyms for Convolution Matrix

- Kernel
- Filter
- Mask
- Template



The Gaussian Filter (Convolution)



| | | | | | | |
|---|---|---|----|---|---|---|
| 1 | 1 | 2 | 2 | 2 | 1 | 1 |
| 1 | 2 | 2 | 4 | 2 | 2 | 1 |
| 2 | 2 | 4 | 8 | 4 | 2 | 2 |
| 2 | 4 | 8 | 16 | 8 | 4 | 2 |
| 2 | 2 | 4 | 8 | 4 | 2 | 2 |
| 1 | 2 | 2 | 4 | 2 | 2 | 1 |
| 1 | 1 | 2 | 2 | 2 | 1 | 1 |

Step 1. Remove Image Noise

Median Filter: Rids Salt/Pepper Noise

- 20, 21, 32, 23, 17, 19 , 20
- Order by value

17

19

20

20

21

23

32

Use the
middle

- Use 20

- 20, 22, 32, 23, 17, 19 , 20,24
- Order by value

17

19

20

20

22

23

24

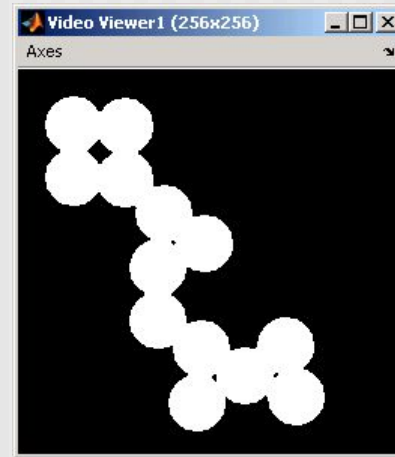
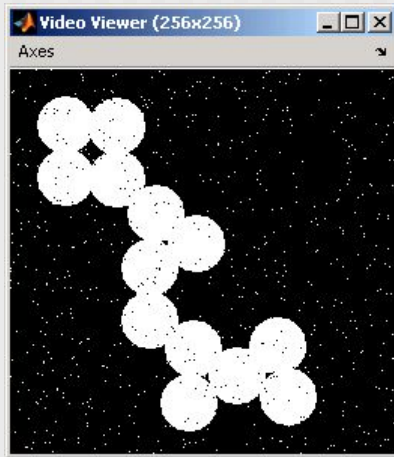
32

Average the middle
 $(20+22)/2 = 21$

- Use 21

Step 1. Remove Image Noise

Salt/Pepper Noise Removal



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2 color images have shades of gray from Gaussian noise

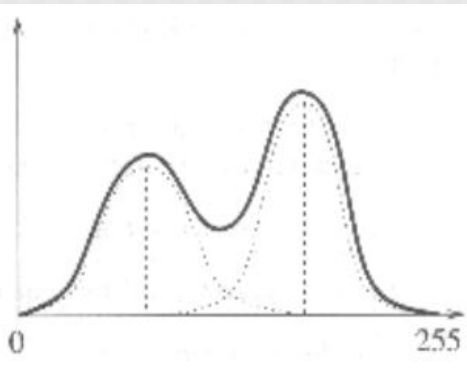
| | | | | | | |
|-----|-----|-----|-----|-----|-----|-----|
| 200 | 200 | 200 | 200 | 200 | 200 | 200 |
| 200 | 200 | 200 | 50 | 50 | 200 | 200 |
| 200 | 200 | 50 | 200 | 200 | 50 | 200 |
| 200 | 50 | 200 | 200 | 200 | 50 | 200 |
| 200 | 200 | 50 | 200 | 200 | 50 | 200 |
| 200 | 200 | 50 | 200 | 200 | 50 | 200 |
| 200 | 200 | 50 | 200 | 200 | 50 | 200 |
| 200 | 200 | 50 | 200 | 200 | 50 | 200 |
| 200 | 200 | 50 | 200 | 200 | 50 | 200 |
| 200 | 200 | 200 | 200 | 200 | 200 | 200 |

IDEAL Binary Image



| | | | | | | |
|-----|-----|-----|-----|-----|-----|-----|
| 205 | 198 | 203 | 200 | 199 | 190 | 203 |
| 195 | 201 | 199 | 48 | 49 | 203 | 202 |
| 197 | 204 | 55 | 196 | 201 | 51 | 197 |
| 204 | 53 | 195 | 201 | 203 | 49 | 203 |
| 197 | 199 | 52 | 200 | 198 | 53 | 197 |
| 198 | 197 | 50 | 197 | 203 | 48 | 200 |
| 197 | 203 | 47 | 201 | 203 | 51 | 198 |
| 197 | 198 | 48 | 197 | 196 | 50 | 197 |
| 201 | 199 | 198 | 199 | 198 | 199 | 197 |

Actual Image with Gaussian Noise

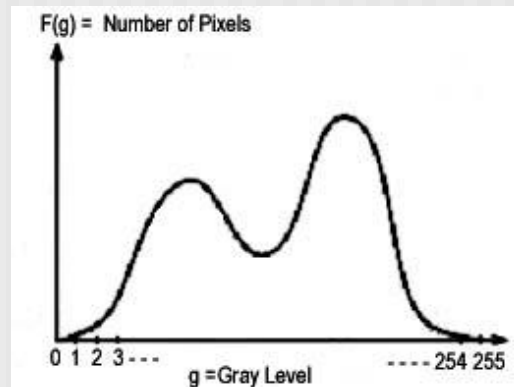


Histogram: Good summary of an Image

- g - gray level 0..255. (Use values or luminance channel, but can be each of RGB)
- $F(g)$ - Represents frequency of gray level (g)
- $F(1)$ - how many 1s (black) are there in image
- $F(100)$ – how many 100 (gray) are there in image

ในช่วงระยะแค่ 5 ปี มีนักท่องเที่ยวเพิ่มขึ้นเรื่อย ๆ ในปี 2534 มีตัวเลขนักท่องเที่ยวประมาณ 220,000 คน ทำกำไรให้กับมณฑลถึง 63 ล้านบาทเลยทีเดียว

อาจจะเป็นความใฝ่ฝันของคนคุณหมิงอยู่พอสมควรว่า เมื่อกรุงปักกิ่งเป็นตลาดท่องเที่ยวของอเมริกาและยุโรป คุณหมิงก็น่าจะเป็นตลาดท่องเที่ยวของชาวเอเชียตะวันออกและตะวันออกเฉียงใต้

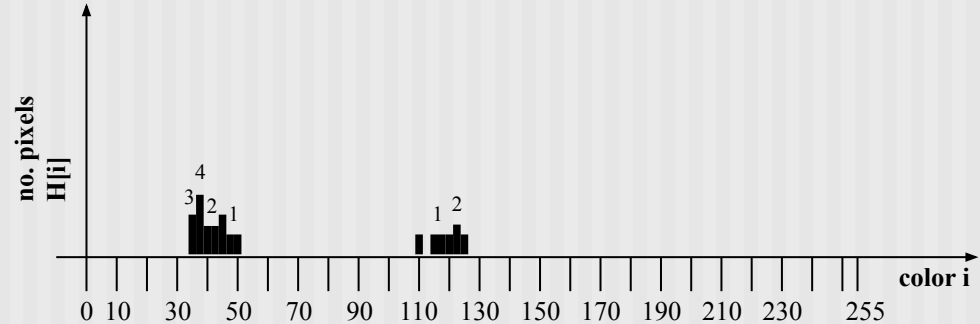


Step 2. Image Thresholding to get binary image

Histogram shows count of each color

Input Gray Image:

| | | | | |
|----|----|-----|-----|-----|
| 40 | 38 | 120 | 110 | 123 |
| 42 | 41 | 115 | 118 | 124 |
| 39 | 44 | 119 | 121 | 123 |
| 43 | 38 | 42 | 42 | 38 |
| 39 | 40 | 39 | 41 | 39 |



Histogram above Image:

| | | | | | | | | | | | | | | | | | | | | | | | | | | | |
|--------|---|----|---|---|---|---|---|---|---|-----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|-----|----|
| [i]: | 0 | .. | 3 | 3 | 4 | 4 | 4 | 4 | 4 | ... | 11 | 11 | 11 | 11 | 11 | 11 | 11 | 11 | 11 | 11 | 12 | 12 | 12 | 12 | 12 | ... | 25 |
| | 0 | . | 8 | 9 | 0 | 1 | 2 | 3 | 4 | | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 0 | 1 | 2 | 3 | 4 | | 5 |
| H [i]: | 0 | .. | 3 | 4 | 2 | 2 | 3 | 1 | 1 | ... | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 2 | 1 | ... | 0 |
| | | . | | | | | | | | | | | | | | | | | | | | | | | | | |

Note that the histogram of a gray scale image of any size can be represented by an integer array of 256 dimensions

Histogram of 2 color image

- Generally looking for 2 peaks
- Look for the gray in between

Grayscale



T = 128



Black/White



Step 2. Image Thresholding to get binary image

Automatic Threshold Example

Automatic Threshold Algorithm

1. Select an initial estimate of threshold T

$$T = \text{Av. Image Intensity}$$

2. Use T to partition image into R_1, R_2

3. Calculate mean $I : \mu_1, \mu_2$ for R_1, R_2

4. New $T = 1/2 (\mu_1 + \mu_2)$

5. Repeat 2-4 until μ_1, μ_2 do not change. T is your answer.

$$T_1 = 69.72 = 70$$

$$R1_1 \leq 70$$

$$R2_1 > 70$$

$$\mu_{R1} = 40$$

$$\mu_{R2} = 119$$

$$T_2 = 80$$

Input Gray Image:

| | | | | |
|----|----|-----|-----|-----|
| 40 | 38 | 120 | 110 | 123 |
| 42 | 41 | 115 | 118 | 124 |
| 39 | 44 | 119 | 121 | 123 |
| 43 | 38 | 42 | 42 | 38 |
| 39 | 40 | 39 | 41 | 39 |

Output Binary Image:

| | | | | |
|---|---|---|---|---|
| 0 | 0 | 1 | 1 | 1 |
| 0 | 0 | 1 | 1 | 1 |
| 0 | 0 | 1 | 1 | 1 |
| 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 |

$$R1_2 \leq 80$$

$$R2_2 > 80$$

$$\mu_{R1} = 40$$

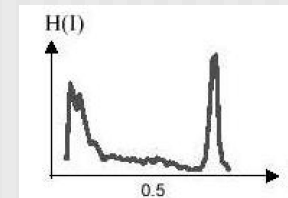
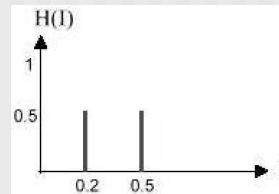
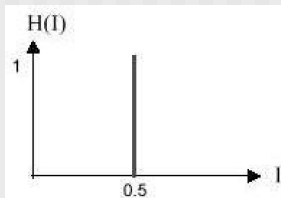
$$\mu_{R2} = 119$$

$$T_3 = 80$$

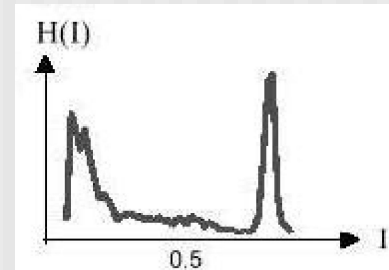
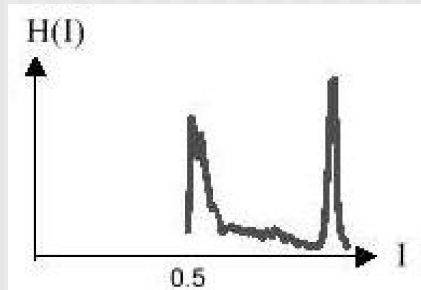
ANSWER: Threshold = 80.

Histogram Examples

- Represent the number of pixels according to gray levels



Modification of histogram



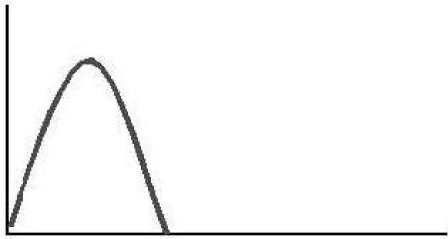
$$\text{new} = (\text{old} - \text{min}) / (\text{max} - \text{min})$$

Example:

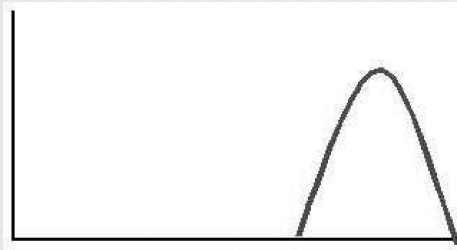
$$\text{new} = (\text{old} - 0.5) / (1 - 0.5)$$

Brightness

- Brightness is the average pixel value



– Brightness

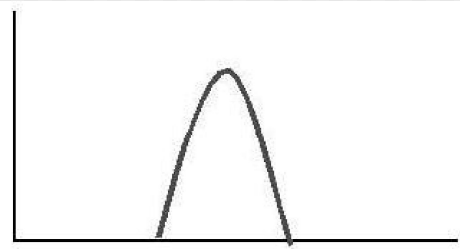


+ Brightness



Contrast

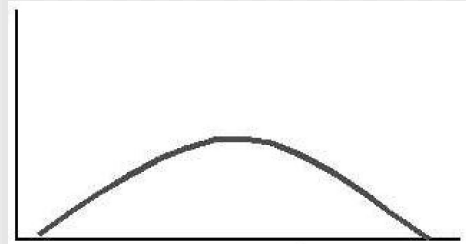
- relative differences in image



– Contrast



$$\text{new} = (\text{old} - \text{min}) / (\text{max} - \text{min})$$



+ Contrast



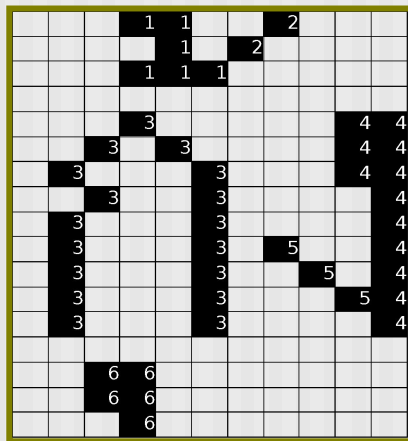
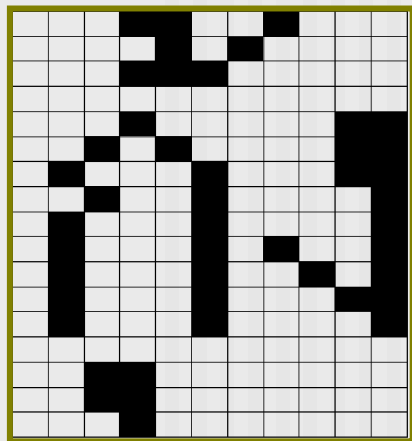
The 5 Steps in OCR Algorithm

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Character Extraction via Connected Components



Equivalence table:

| | |
|---|---|
| 1 | 2 |
| 4 | 5 |
| | |

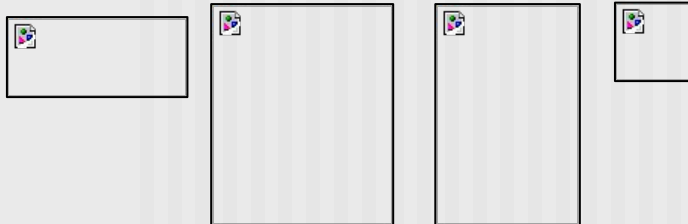
Template for Contour Coloring:

| | | |
|----|---|----|
| NW | N | NE |
| W | O | |

Template for Region Coloring:

| | |
|---|---|
| | N |
| W | O |

Characters extracted using same color bounding box:

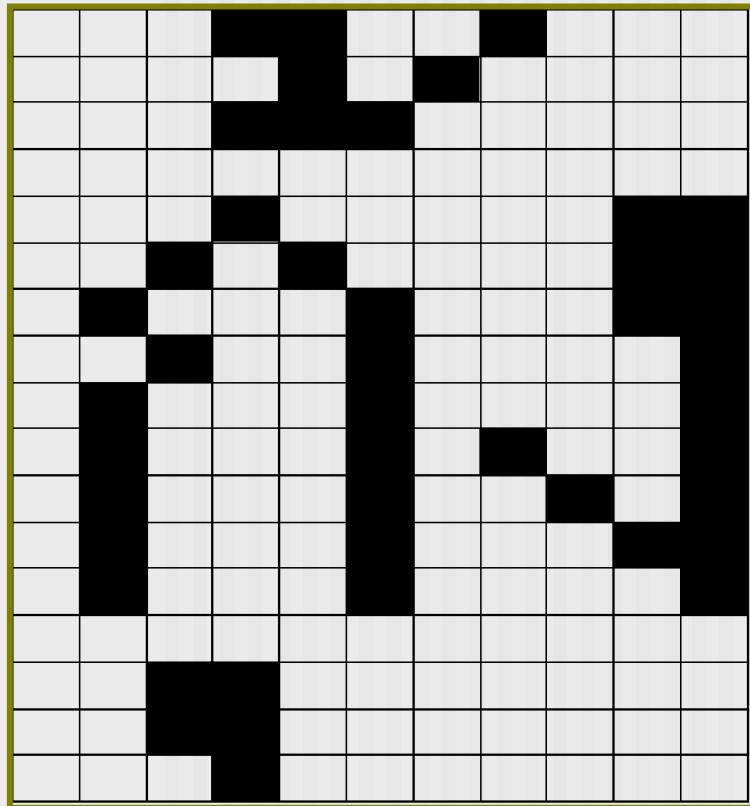


Step 3. Character Segmentation by Contour Coloring

Let's Try

| | | |
|----|---|----|
| NW | N | NE |
| W | ○ | |

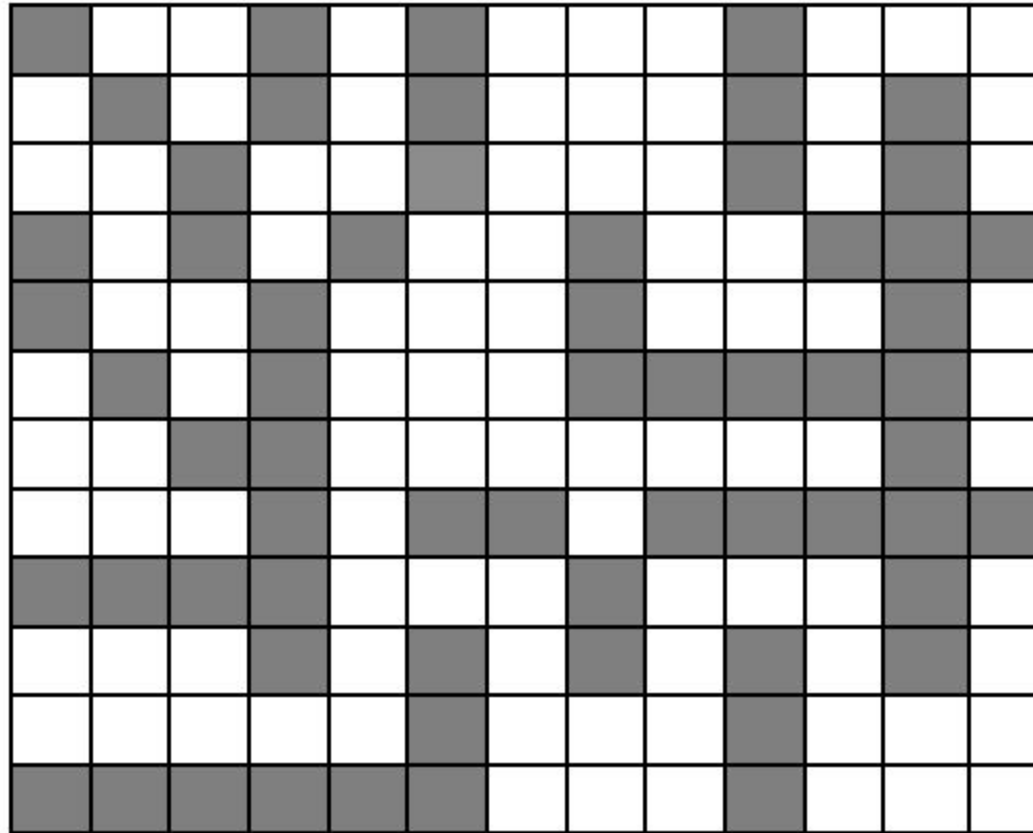
| | |
|---|---|
| | N |
| W | ○ |



Let's Try

| | | |
|----|---|----|
| NW | N | NE |
| W | ○ | |

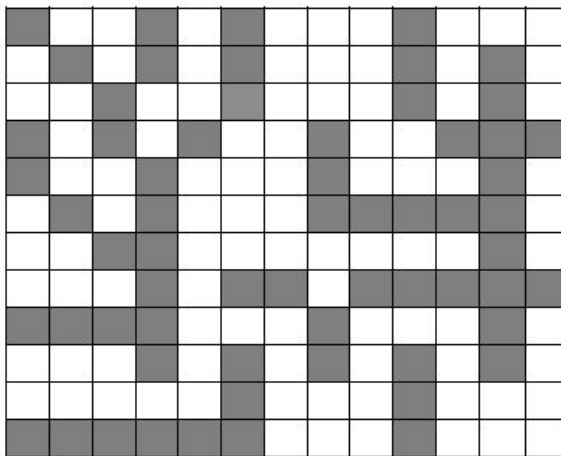
| | |
|---|---|
| | N |
| W | ○ |



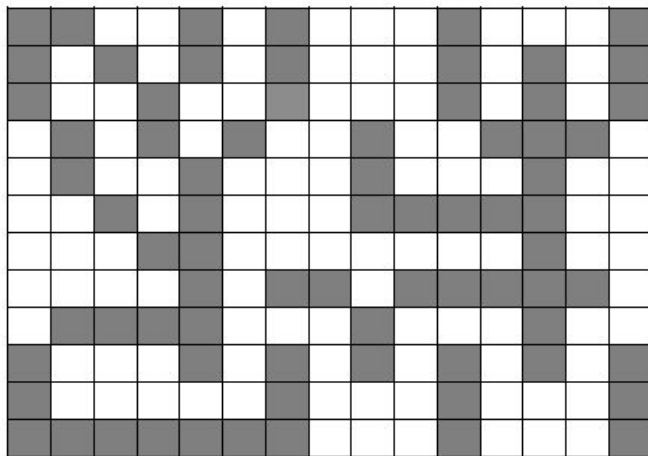
Quiz 3

1. **Connected Components.** Non-programming exercise. Label the following image with colors starting 1.
 - a. 5 points. 0.5 hrs. Use 4 connected to label the background (white) regions. Show the equivalence table and the final color in each box.

Your Output for 4-connected Labeling:





Your Output for 8-connected Labeling:



- b. 5 points. 0.5 hrs. Use 8 connected to label foreground (black) regions. Show the equivalence table and the final color in each box.

Learning Exercise on Thresholding, Connected Components

← → ↺ colab.research.google.com/drive/14YpQBGAfktwgchZVD2FwMYvPcXpVyBi4#scrollTo=7GuA9f6gUA-P

  Thresholding and Blob Coloring.ipynb ☆

File Edit View Insert Runtime Tools Help All changes saved

+ Code + Text

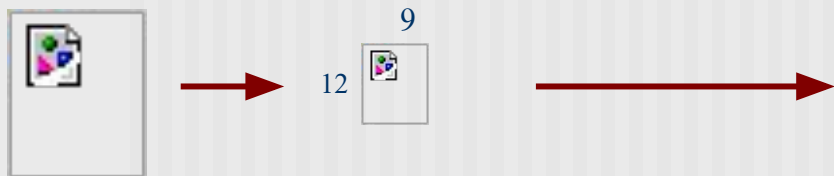
```
[ ] #From https://learnopencv.com/histogram-of-orient
[ ] #upload component_testing.jpg, 4_5_digits_crop.p
[ ] #!pip install opencv-contrib-python==4.5.5.62 #in
[ ] import cv2
    import numpy as np
```

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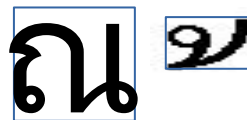
Image scaling needed for OCR

**Resize based on aspect ratio
width/height**



**Template Matching within
the same aspect ratio group.**

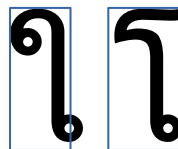
Templates by Aspect Ratio



Ratio 1.2-1.5

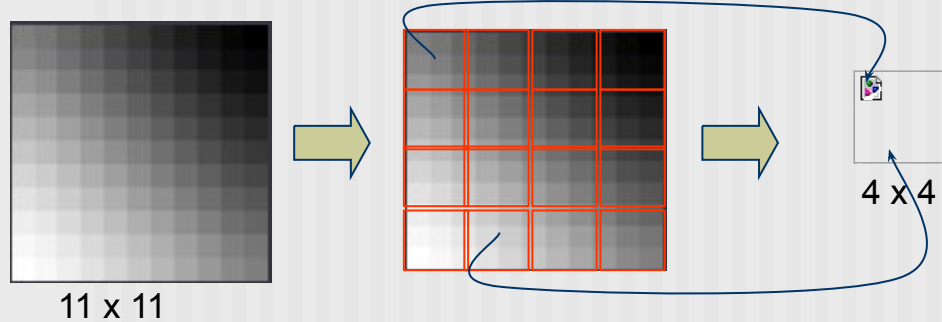


Ratio 0.7 – 0.9



Ratio 0.2 – 0.4

How to reduce image size (raster images)?



Box Size = $11/4 = (2.75x, 2.75y)$

Use Grayscale color average weighted by area of window.

Use Box Sampling to Reduce Image Size:

Consider above example of reducing input 11 x 11 image to an output 4 x 4 image. You can do this by taking the 11 x 11 image and overlaying it with a 4 x 4 tile as shown in middle image above. That means each output tile will take up about 2.75 pixels of the input. So, you can do a weighted average of the input based on pixel area covered to get the output. Thus, the (row, column) pixel output $I(1,1)$ will come from input's weighted average based on areas occupied by the input pixel

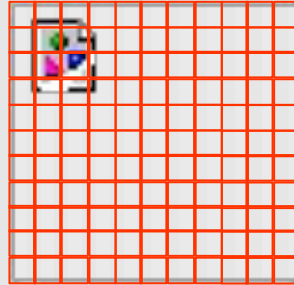
$$I_{new}(1,1) = \frac{1 * 1 * I(1,1) + 1 * 1 * I(1,2) + 1 * 0.75 * I(1,3) + 1 * 1 * I(2,1) + 1 * 1 * I(2,2) + 1 * 0.75 * I(2,3) + 0.75 * 1 * I(3,1) + 0.75 * 1 * I(3,2) + 0.75 * 0.75 * I(3,3)}{1 + 1 + 0.75 + 1 + 1 + 0.75 + 0.75 + 0.75 + 0.75 * 0.75}$$

The output's $I(1, 2)$ will have influence from 16 pixels because the box (1,2) touches 16 pixels. And so on.

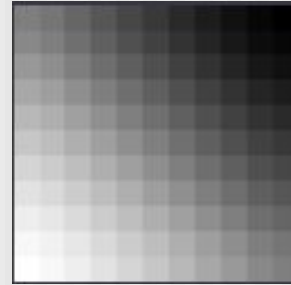
How to increase image size?



4 x 4



11 x 11



11 x 11

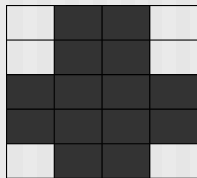
$$\text{Box Size} = 11/4 = (2.75x, 2.75y)$$

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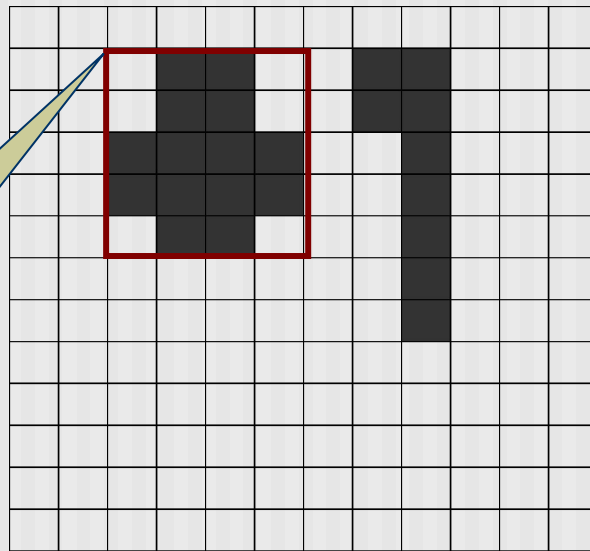
Template matching to image

- Given this template:



- Place template, do sum square difference.
- Move throughout image.
- Low number means a good match

Number = 0
in this window



Step 5. Character recognition (template match, NN, ML, ...)

Min Template Match = Max Convolution

$$\begin{aligned}
 &\underset{\text{minimize}}{SSD} = \sum_k \sum_l (f(k, l) - h(i + k, j + l))^2 \quad \text{Sum of Squares Difference} \\
 &\underset{\text{minimize}}{SSD} = \sum_k \sum_l (f(k, l)^2 - 2h(i + k, j + l)f(k, l) + h(i + k, j + l)^2) \\
 &\underset{\text{minimize}}{SSD} = \sum_k \sum_l (-2h(i + k, j + l)f(k, l)) \\
 &\underset{\text{maximize}}{SSD} = \sum_k \sum_l (2h(i + k, j + l)f(k, l))
 \end{aligned}$$

$f(k, l)$ is template image. $h(i, j)$ is input image.

Template matching is done at $h(i, j)$.

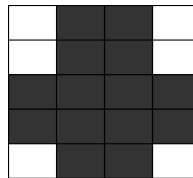
Range of k is template height, range of l is image width.

Min Template Match = Max Convolution

$$SSD = \sum_k \sum_l (f(k, l) - h(i + k, j + l))^2 \text{ Sum of Squares Difference}$$

```
for i = 1 .. 13
for j = 1.. 12
    r(i,j) = 0
    for k = -2 .. 2
        for l = -2.. 2
            r(i,j) += (f(k, l) - h(i+k, j+1))^2
```

f(i,j):



h(i,j):

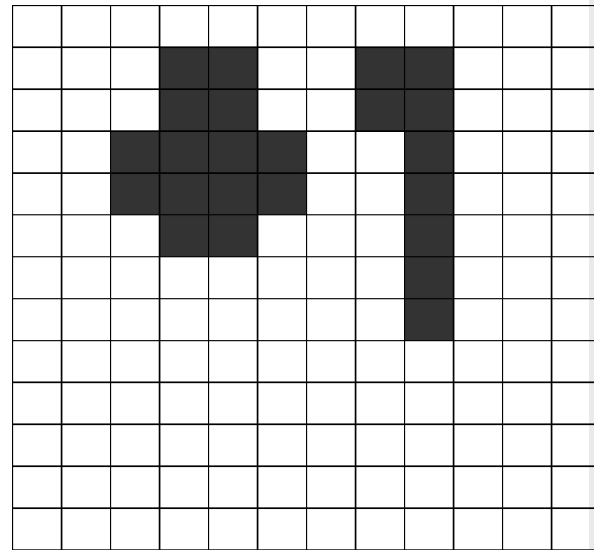


Image Invariant Features

Invariance to:

- Lighting
- Position
- Scale
- Orientation

ก

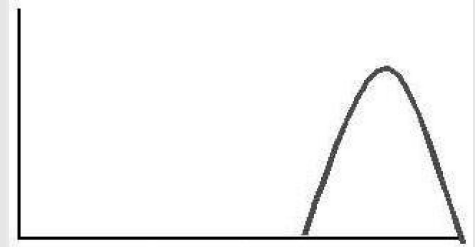
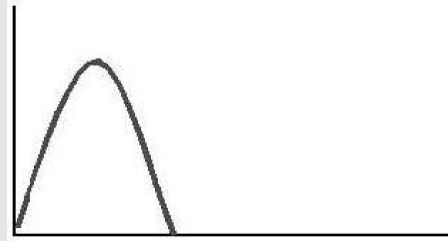
เรียนคุณครู

ขอกราบเรียนเชิญให้เข้าร่วม

เรียนคุณครู

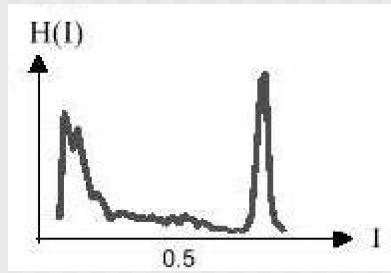
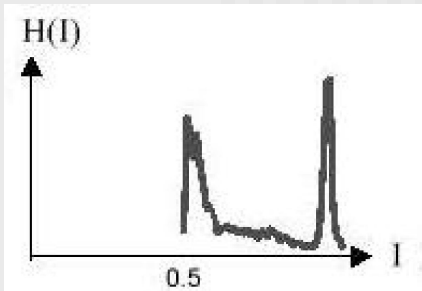
ขอกราบเรียนเชิญให้เข้าร่วม

Histograms are somewhat lighting invariant



– Brightness

+ Brightness



Color Invariant Features: Edges

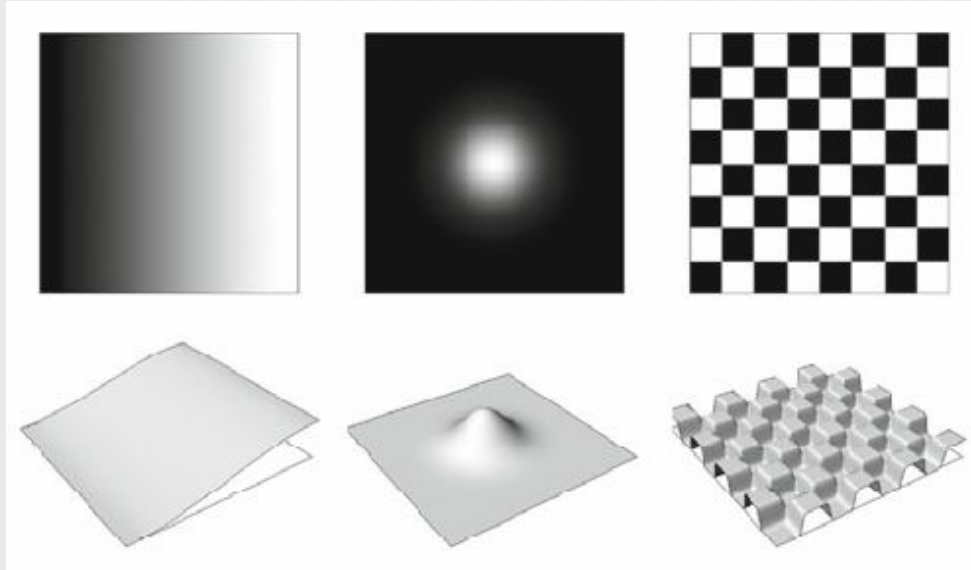
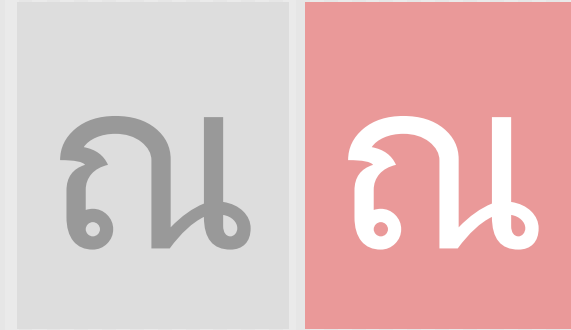


Image $I(x,y)$ viewed as a surface plot $Z(x, y)$



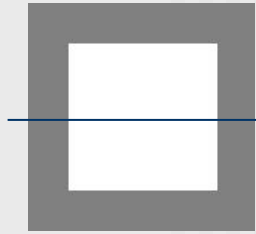
Same Edges



Edges will not get you contour strokes

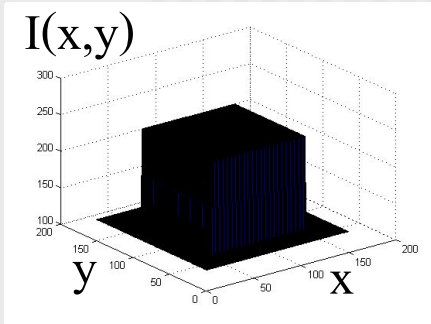
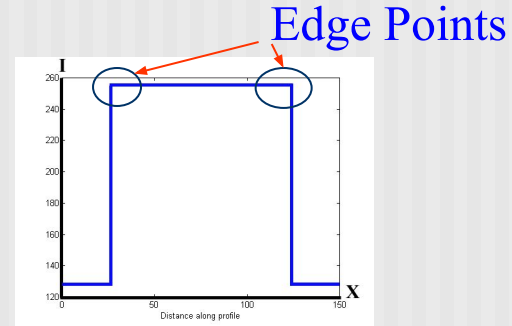
An Edge Point

Edge - Points in image with a big change in intensity



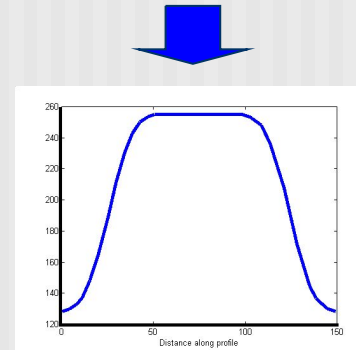
A Scan Line

Step Edge



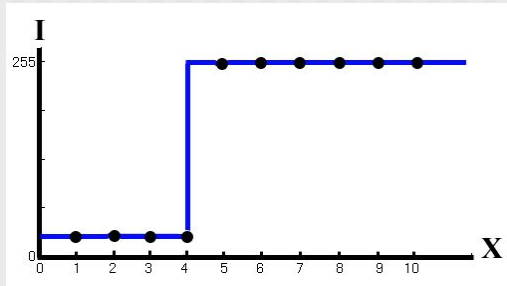
Intensity Profile (Surface)

Step Edge Blurring
(Noise Reduction)

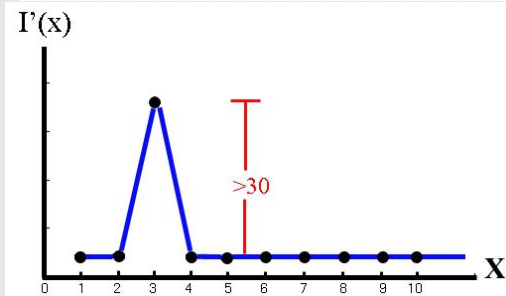


A simple Edge Detector

Edge if $\Delta I / \Delta X > 30$



The Input Image



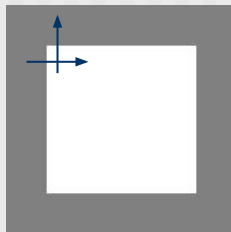
The First Difference Image

A step edge in X and Y

If $|dx| > T$ or $|dy| > T$ then edge. $T = 15$.

Problem when there is Gaussian noise, you can get undesired edges.

So, best to Gaussian blur before taking first difference



| | | | | |
|-----|-----|-----|-----|-----|
| 240 | 240 | 240 | 240 | 240 |
| 240 | 240 | 240 | 240 | 240 |
| 240 | 240 | 240 | 240 | 240 |
| 240 | 240 | 240 | 240 | 240 |

Just $\sigma = 5$, can cause a problem

| | | | | |
|-----|-----|-----|-----|-----|
| 235 | 249 | 248 | 230 | 238 |
| 242 | 240 | 240 | 241 | 245 |
| 247 | 237 | 230 | 251 | 238 |
| 232 | 240 | 237 | 232 | 243 |

Use Gaussian Filter (Blur) to Reduce Noise

- We should blur the image first, because first difference in image with Gaussian noise can lead to a false edge. Consider

$$I = 200 \pm G(0, 20)$$

Edge is when $|dI/dx| \geq 30$. 4 edges due to noise!

| | | | | | | |
|--|------------|-----|------------|------------|------------|-----------|
| I(x): | 170 | 210 | 220 | 180 | 210 | 160 |
| dI(x)/dx = $\Delta I = I_{x+1} - I_x$: | 40 | 10 | -40 | 30 | -50 | undefined |
| I_av(x): | 200 | 200 | 203 | 203 | 183 | 183 |
| dI_av(x)/dx | 0 | 3 | 0 | -20 | 0 | undefined |

Common Edge Masks: Prewitt

Prewitt Edge Operator

$$G = G_x^2 + G_y^2 > T \Rightarrow \text{Edge}$$

G_x

| | | |
|-----------|----------|----------|
| -1 | 0 | 1 |
| -1 | 0 | 1 |
| -1 | 0 | 1 |

G_y

| | | |
|-----------|-----------|----------|
| 1 | 1 | 1 |
| 0 | 0 | 0 |
| -1 | -1 | 1 |

$$I(x+1) - I(x-1)$$

Common Edge Detection: Sobel

Sobel Operator. Based on 1st derivative. Better because more blurring.

$$G = G_x^2 + G_y^2 > T \Rightarrow \text{Edge}$$

$$G_x$$

| | | |
|-----------|----------|----------|
| -1 | 0 | 1 |
| -2 | 0 | 2 |
| -1 | 0 | 1 |

$$G_y$$

| | | |
|-----------|-----------|-----------|
| 1 | 2 | 1 |
| 0 | 0 | 0 |
| -1 | -2 | -1 |

Gradient Magnitude G and Direction θ

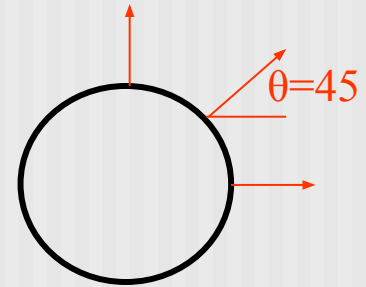
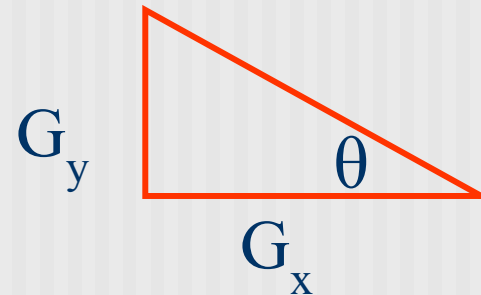
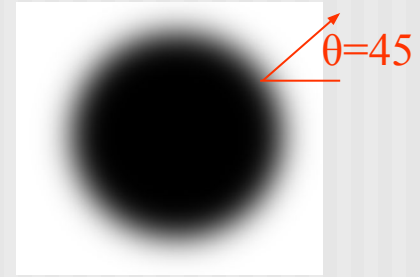
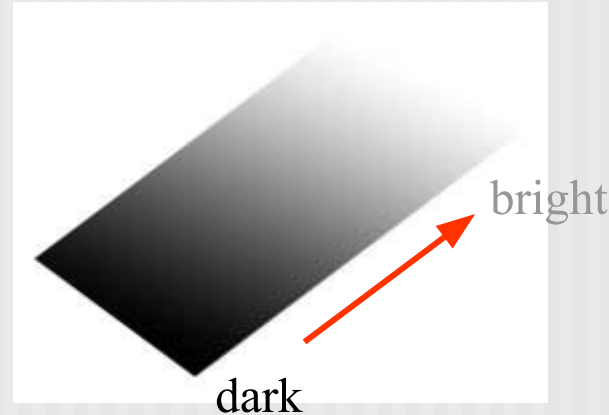
Gradient Direction is perpendicular to edge direction, from dark to bright.

$$\tan\theta = G_y / G_x$$

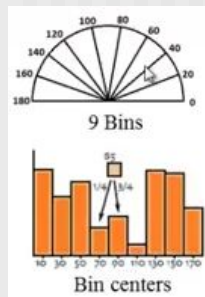
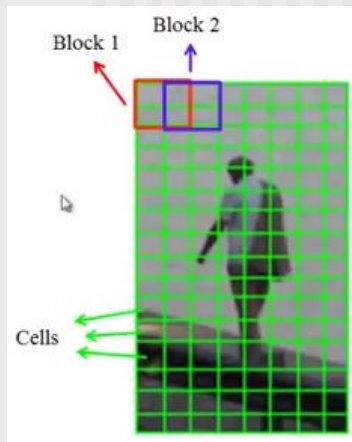
$$\theta = \arctan(G_y / G_x)$$

$$G^2 = G_x^2 + G_y^2$$

In python use **atan2**
to get -180 to 180 degrees.

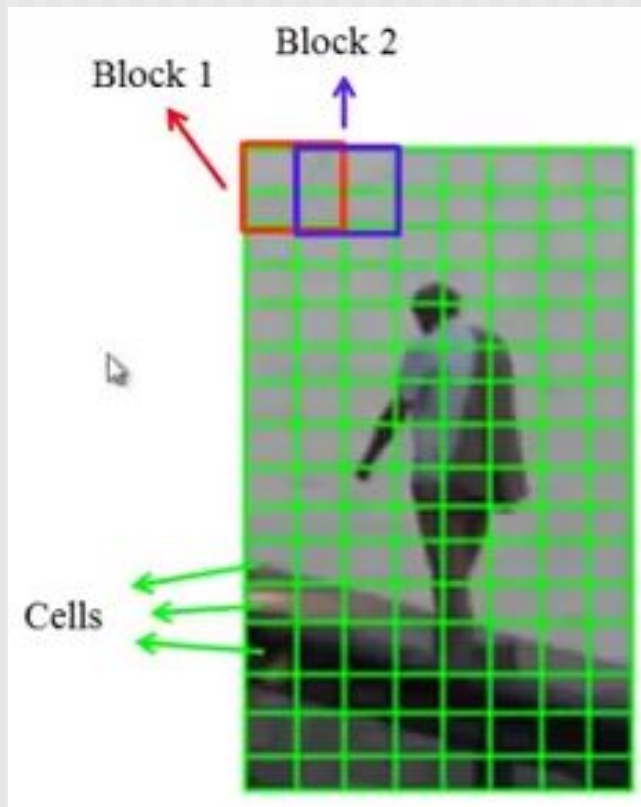
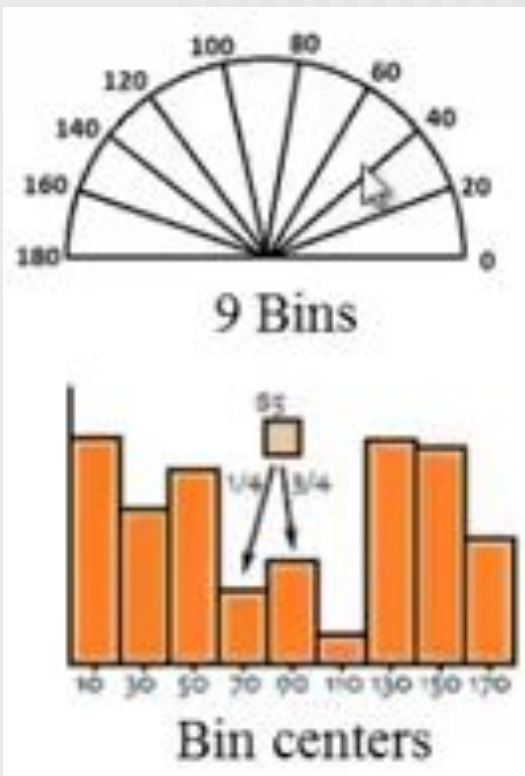


Histogram of Oriented Gradients HOG Feature



- A global descriptor
- For 64×128 image, we divide into 16×16 blocks with 50% overlap. That is 7×15 blocks = 105 blocks. $7 = (64/16)*2 - 1$; $15 = (128/16)*2 - 1$.
- Each block is 2×2 cell with 8×8 pixels.
- Quantize gradient orientation $[0, 180)$ degrees for each 8×8 to 9 bins (20 degrees each). So, 9 histogram values. **Non-Directional Gradients.**
- Feature for full image is $105 \times 4 \times 9 = 3,780$. Concatenated to a huge feature vector.
- Very popular, used in human detection.

HOG Feature



Gradient
Histogram vs.
Gray-Scale
Histogram?

Gradient Magnitude G and Direction θ

Gradient Direction is perpendicular to edge direction, from dark to bright.

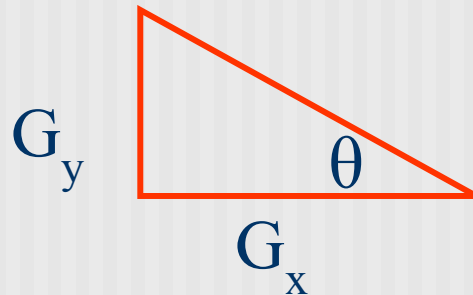
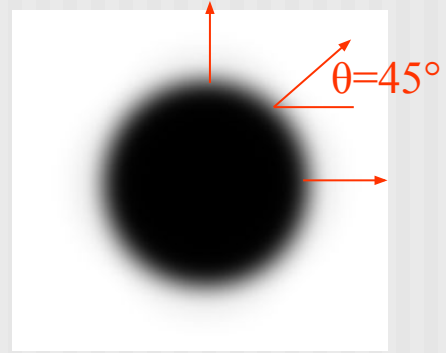
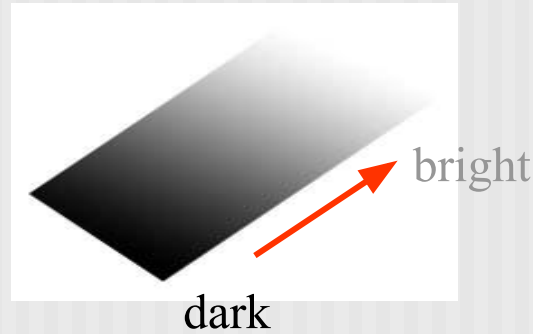
$$\tan\theta = G_y / G_x$$

$$\theta = \arctan(G_y / G_x)$$

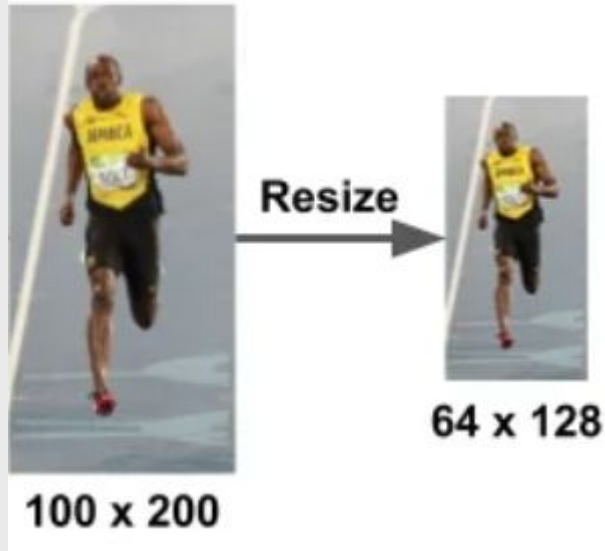
$$G^2 = G_x^2 + G_y^2$$

In python **atan(x)** gives angle value between -90° and 90° (add 90 to get 0 to 180).

atan2(x) gives angle value between -180° and 180° (add 180 to get 0 to 360).



HOG. Fixed Image Size. Gradient θ and $\|G\|$



Left : Absolute value of x-gradient. Center : Absolute value of y-gradient. Right : Magnitude of gradient.

$$\tan\theta = G_y / G_x$$

$$\theta = \arctan(G_y / G_x)$$

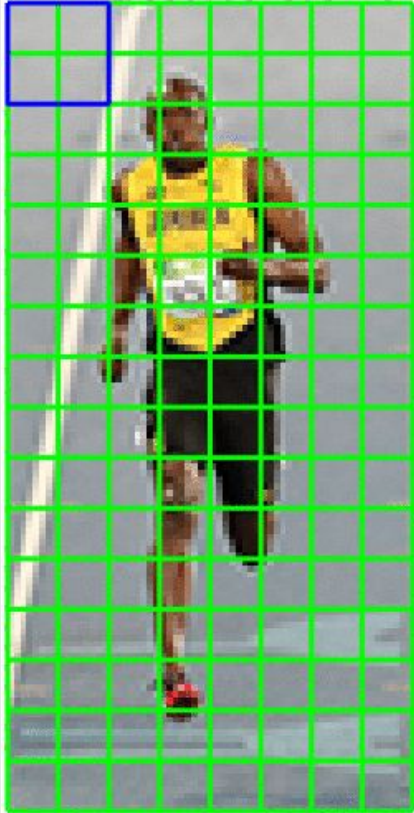
$$G^2 = G_x^2 + G_y^2$$

$$\|G\| = \|(G_x, G_y)\|$$

$$G_x \begin{array}{|c|c|c|} \hline -1 & 0 & 1 \\ \hline -2 & 0 & 2 \\ \hline -1 & 0 & 1 \\ \hline \end{array}$$

$$G_y \begin{array}{|c|c|c|} \hline 1 & 2 & 1 \\ \hline 0 & 0 & 0 \\ \hline -1 & -2 & -1 \\ \hline \end{array}$$

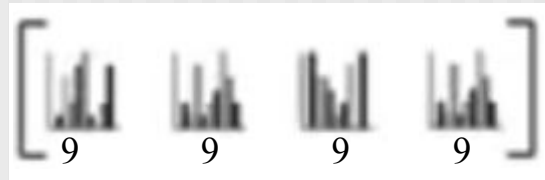
Histogram of Oriented Gradients



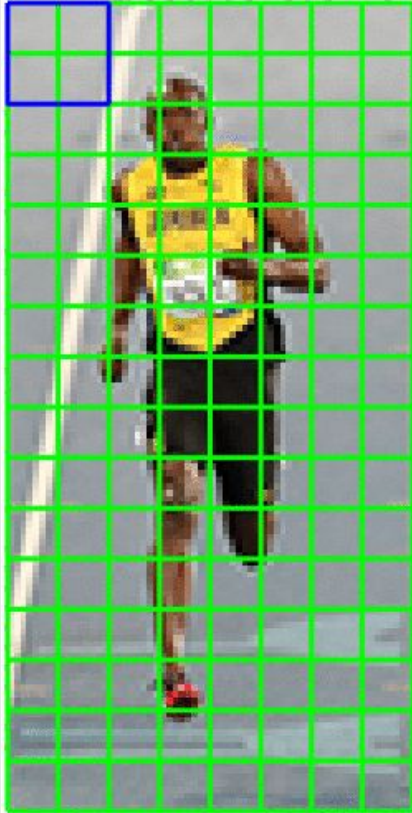
A feature from each blue window, each having 4 cells, **each cell** is a green window with 8x8 pixels.

Each cell outputs 1 histogram which is an array of 9 values. One blue window has **4 cells**.

Each blue window feature is, thus, an array of 9 values per cell \times 4 cells = 36 values.



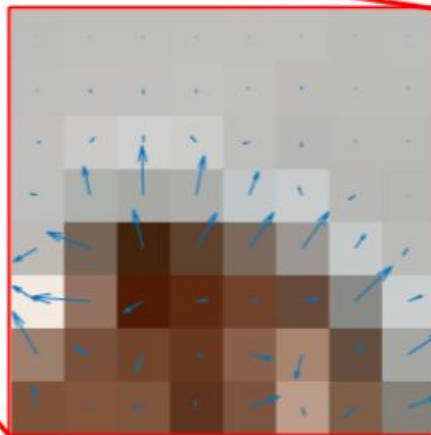
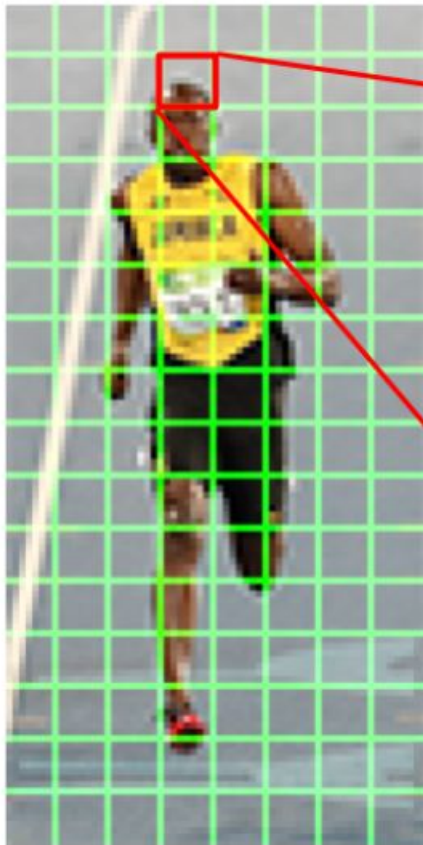
Histogram of Oriented Gradients



- There are 7 horizontal and 15 vertical blue windows, making a total of $7 \times 15 = 105$ positions or blocks.
- Each 16×16 blue block is represented by a 36×1 vector (2×2 green cells, each of 8×8 pixels, each green cell having 9 histograms)
- The HOG feature for this image is a concatenation of 105 such blue box features to get a vector of dimension $3,780 \times 1$ from 105×36 .



Histogram of Oriented Gradients



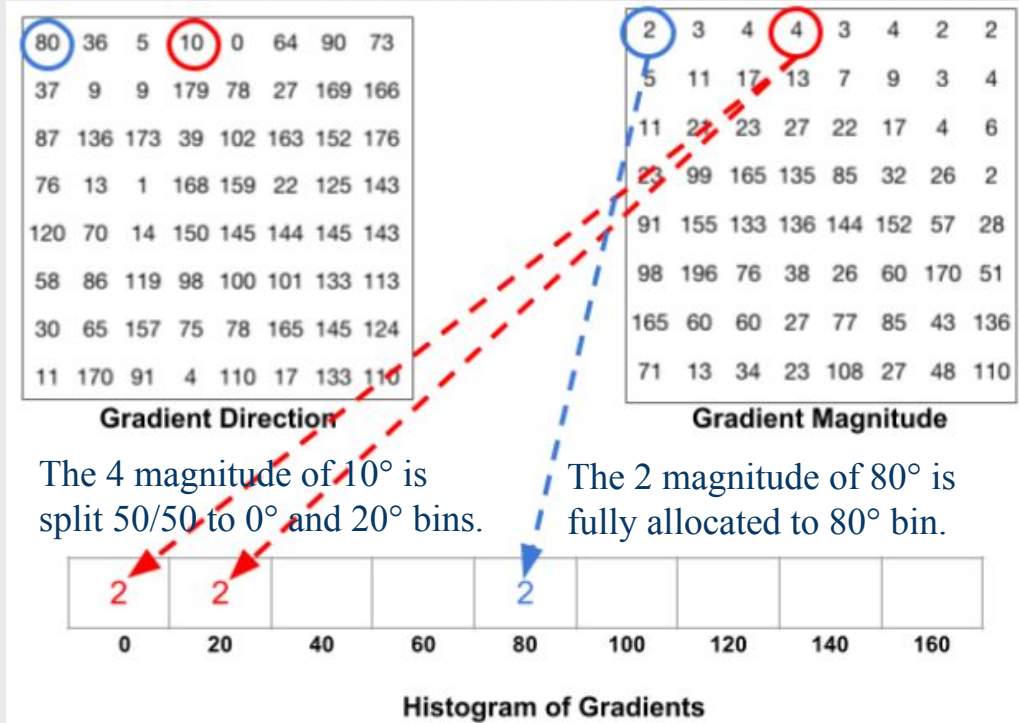
| | | | | | | | |
|-----|-----|-----|-----|-----|-----|-----|-----|
| 2 | 3 | 4 | 4 | 3 | 4 | 2 | 2 |
| 5 | 11 | 17 | 13 | 7 | 9 | 3 | 4 |
| 11 | 21 | 23 | 27 | 22 | 17 | 4 | 6 |
| 23 | 99 | 165 | 135 | 85 | 32 | 26 | 2 |
| 91 | 155 | 133 | 136 | 144 | 152 | 57 | 28 |
| 98 | 196 | 76 | 38 | 26 | 60 | 170 | 51 |
| 165 | 60 | 60 | 27 | 77 | 85 | 43 | 136 |
| 71 | 13 | 34 | 23 | 108 | 27 | 48 | 110 |

Gradient Magnitude

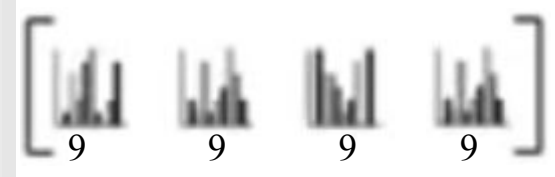
| | | | | | | | |
|-----|-----|-----|-----|-----|-----|-----|-----|
| 80 | 36 | 5 | 10 | 0 | 64 | 90 | 73 |
| 37 | 9 | 9 | 179 | 78 | 27 | 169 | 166 |
| 87 | 136 | 173 | 39 | 102 | 163 | 152 | 176 |
| 76 | 13 | 1 | 168 | 159 | 22 | 143 | 143 |
| 120 | 70 | 14 | 150 | 145 | 144 | 145 | 143 |
| 58 | 86 | 119 | 98 | 100 | 101 | 133 | 113 |
| 30 | 65 | 157 | 75 | 78 | 165 | 145 | 124 |
| 11 | 170 | 91 | 4 | 110 | 17 | 133 | 110 |

Gradient Direction

Histogram of Oriented Gradients



Each histogram feature vector from 2×2 concatenation or 36×1 vector is normalized to have a length of 1, but dividing by sqrt of sum squared.

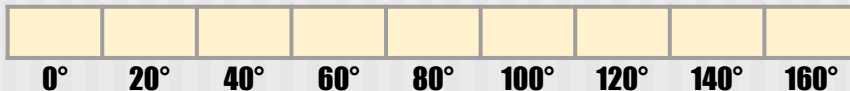


0-180 degree gradients are non-directional gradients. 0 to 360 degrees are directional.

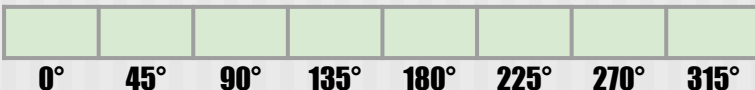
HOG: bin size and what they mean

For each 8x8 region:

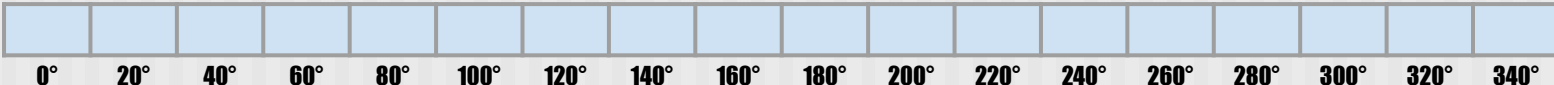
- Quantize gradient orientation $[0, 180)$ to **9 bins** (20 degrees each).
Non-Directional Gradients. Use $\text{atan}(x) + 90$ to get $[0^\circ, 180^\circ)$



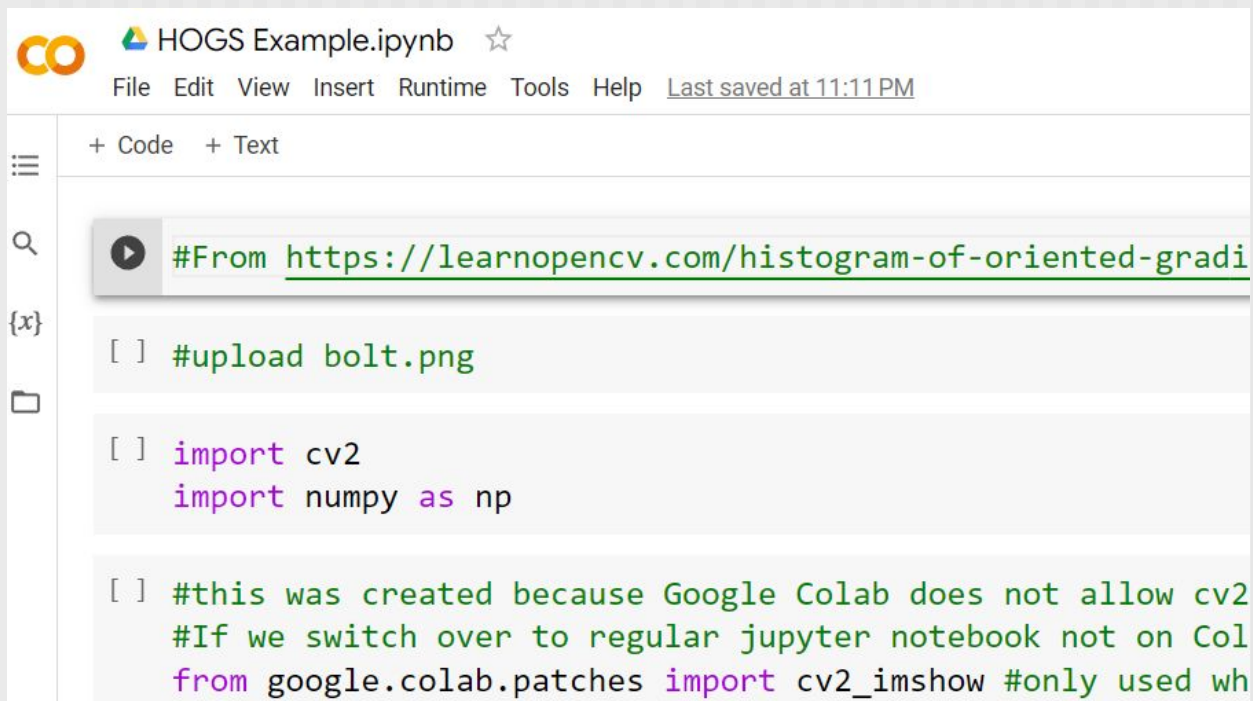
- Quantize gradient orientation $[0, 360)$ to **8 bins** (45 degrees each).
Directional Gradients. Use $\text{atan2}(x) + 180$ to get $[0^\circ, 360^\circ)$.



- Quantize gradient orientation $[0, 360)$ to **18 bins** (20 degrees each).
Directional Gradients. Use $\text{atan2}(x) + 180$ to get $[0^\circ, 360^\circ)$.



HOG Examples



The screenshot shows a Jupyter Notebook titled "HOGS Example.ipynb" with a star icon. The interface includes a menu bar with "File", "Edit", "View", "Insert", "Runtime", "Tools", and "Help", and a status bar indicating "Last saved at 11:11 PM". On the left, there is a sidebar with icons for a menu, search, and file explorer. The main area displays three code cells. The first cell is a comment starting with a play button icon. The second cell contains a comment about uploading a file. The third cell contains import statements for cv2 and numpy, followed by a comment about Google Colab and a line of code to import cv2_imshow from google.colab.patches.

```
#From https://learnopencv.com/histogram-of-oriented-gradi
```

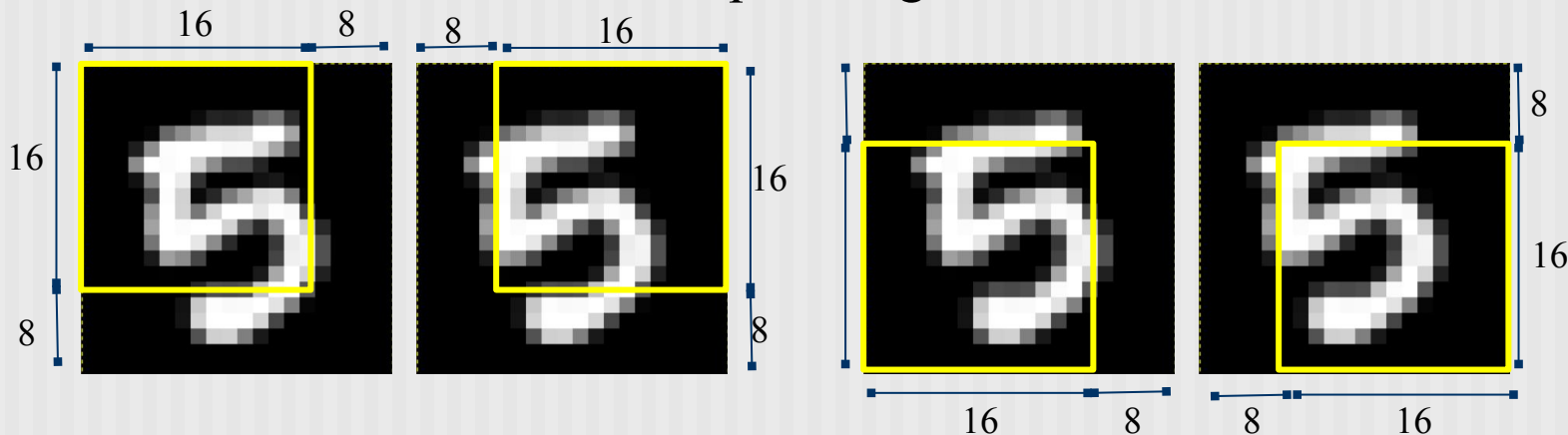
```
[ ] #upload bolt.png
```

```
[ ] import cv2
import numpy as np
```

```
[ ] #this was created because Google Colab does not allow cv2
#If we switch over to regular jupyter notebook not on Col
from google.colab.patches import cv2_imshow #only used wh
```

Quiz 3 to use OpenCV HOG library

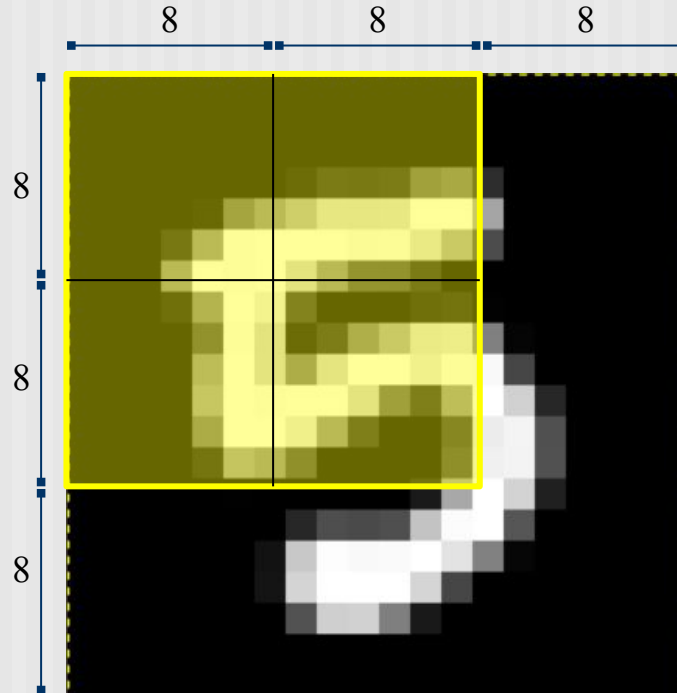
- Scale all 20×20 training and testing data into 24×24 to start with. Then use 16×16 blocks of 4 cells, each 8×8 . You will have 4 such blocks per image.



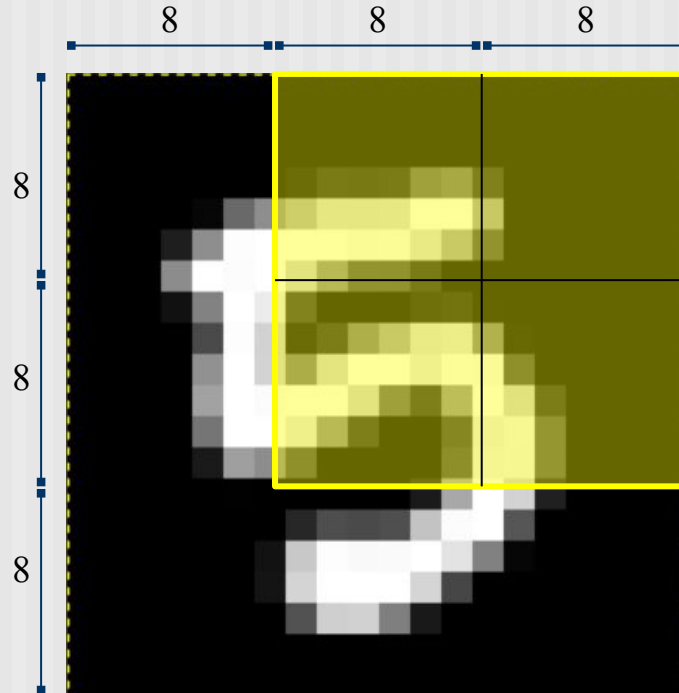
Your HOG Feature vector will have:

- 9 bins per 8×8 cell * 4 cells per block * 4 blocks per image
- Total: 144 values.

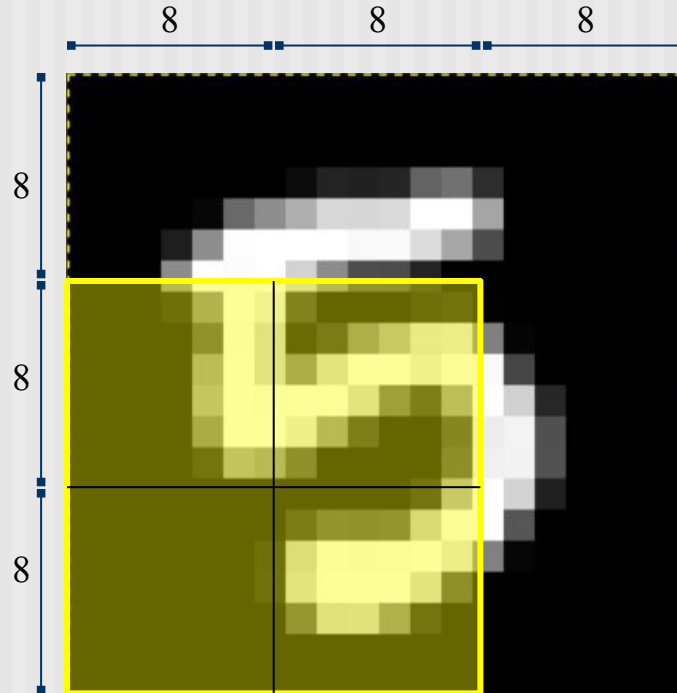
Quiz 3 to use OpenCV HOG library



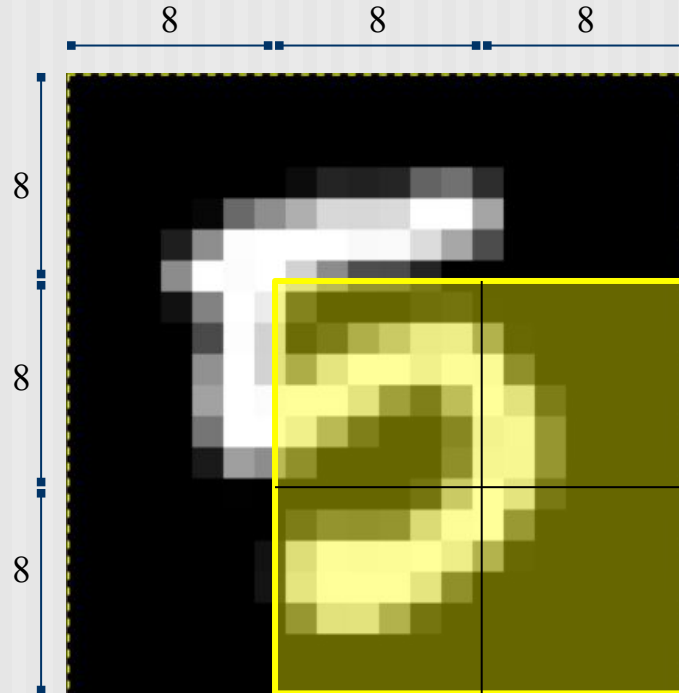
Quiz 3 to use OpenCV HOG library




Quiz 3 to use OpenCV HOG library



Quiz 3 to use OpenCV HOG library




Example of 1 Character HOG


HOGS for OCR.ipynb ☆

File Edit View Insert Runtime Tools Help [Last edited on January 31](#)

+ Code + Text

 #From <https://learnopencv.com/histogram-of-oriented-gradients/>

```
[ ] import cv2
import numpy as np
```

```
[ ] #upload 4_20x20.png
```

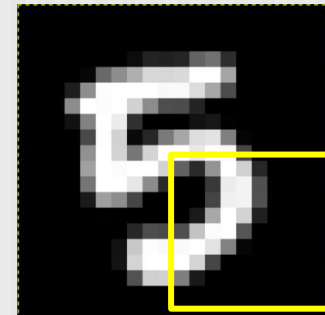
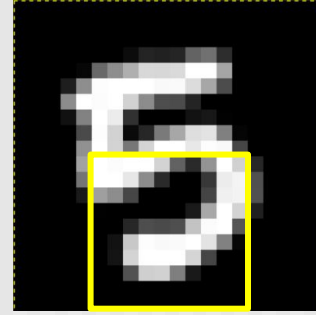
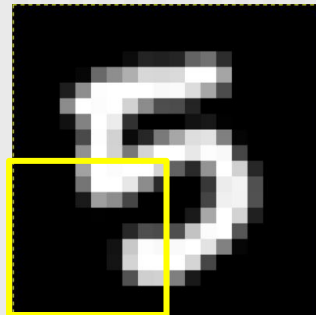
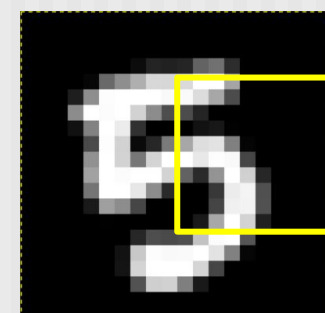
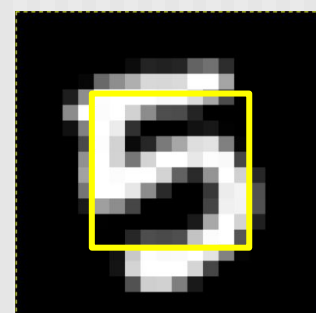
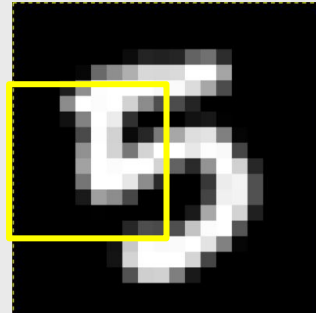
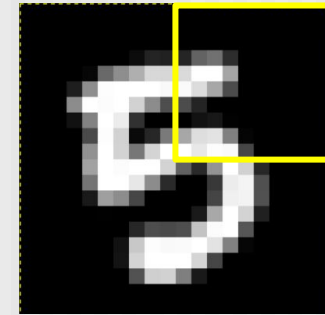
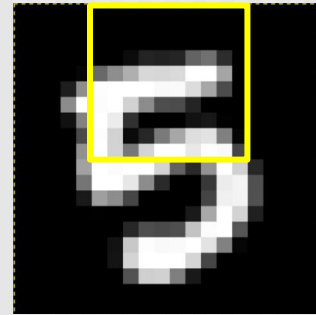
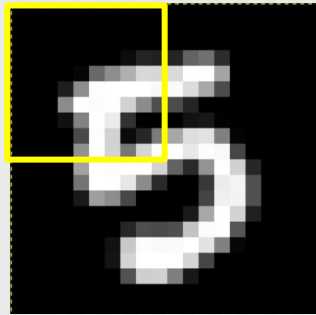
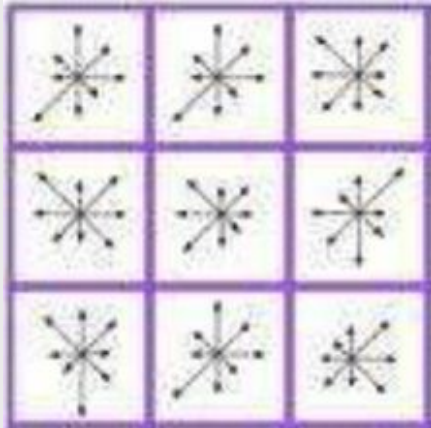
```
[ ] #this was created because Google Colab does not allow cv2.imshow
#If we switch over to regular jupyter notebook not on Colab, we
from google.colab.patches import cv2_imshow #only used when running
def my_imshow(title, img):
    print(title)
```

HOG in OpenCV vs. sklearn

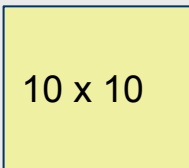
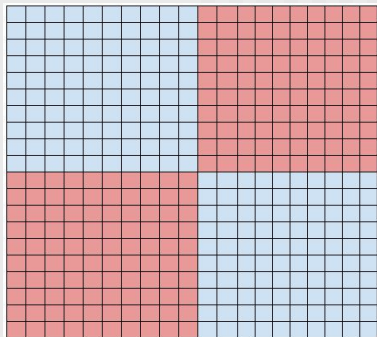
- The OpenCV HOG is restricted to 8x8 with 9 bins.
- The sklearn HOG is more generalizable to try 10x10 with 8 bins.

10 x 10 box

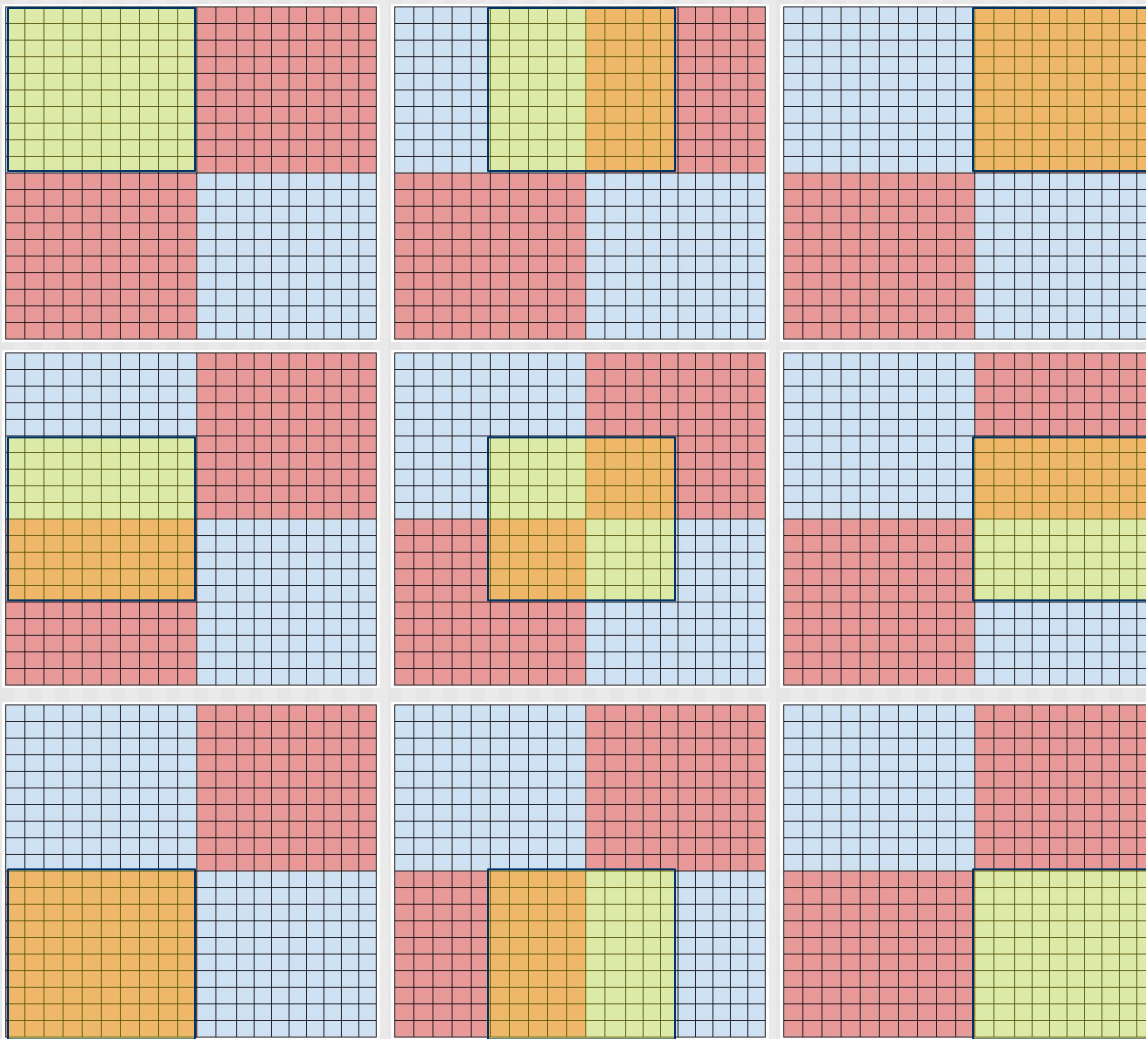
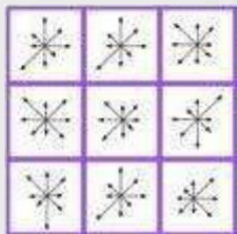
3 x 3 boxes, each
10 x 10 pixels



Total: 9
configurations



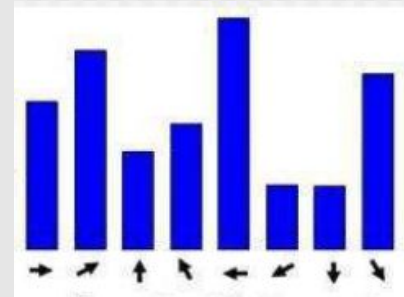
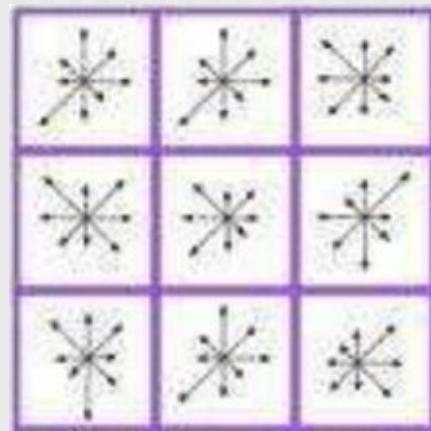
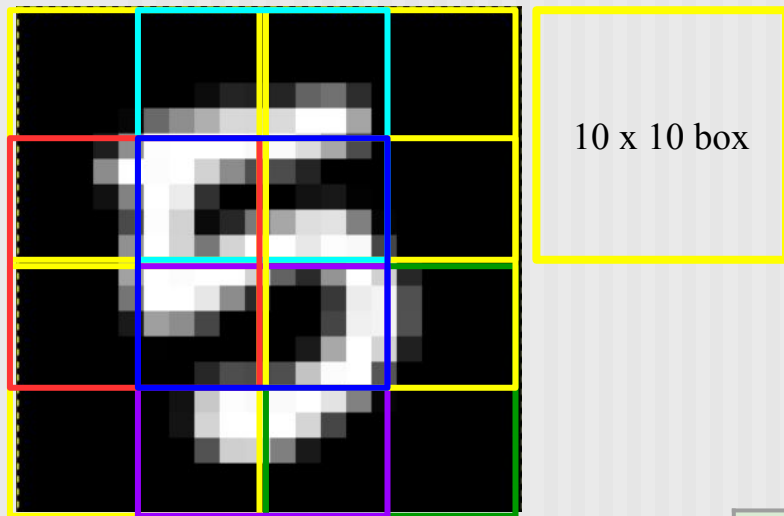
Output HOG Feature:



HOG if image were 20 x 20 (use sklearn)

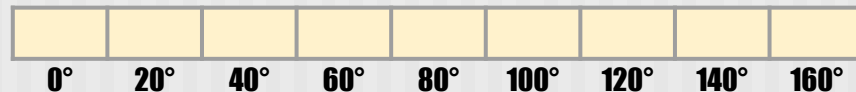
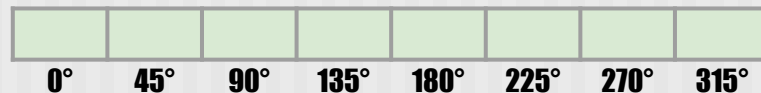
20 x 20 features into 10 x 10 overlapping boxes (shifted by 5 pixels), so 3 x 3 grid. Each grid has 9 bins.

Thus, the 400-pixel color feature vector is now a $3 \times 3 \times 9 = 81$ dimensional feature vector of histogram probability.

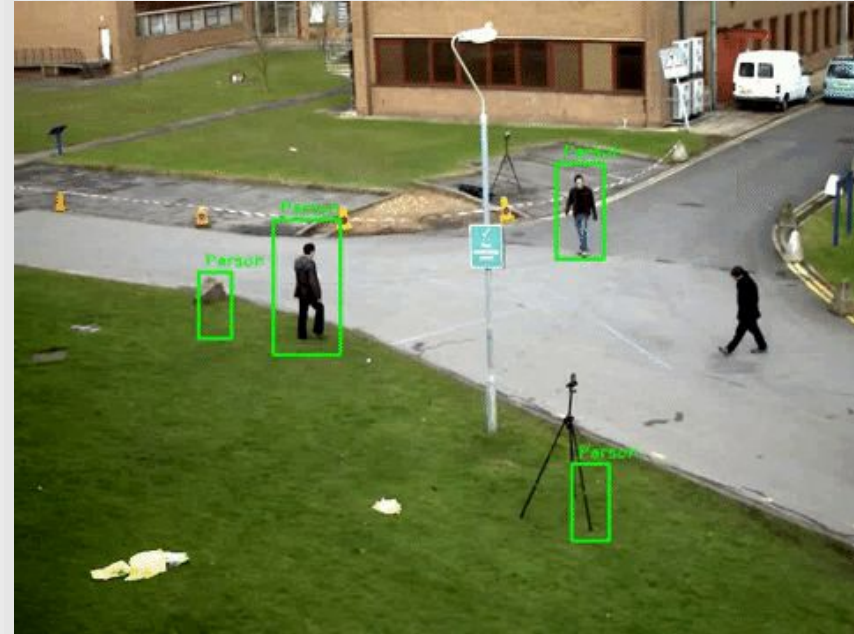
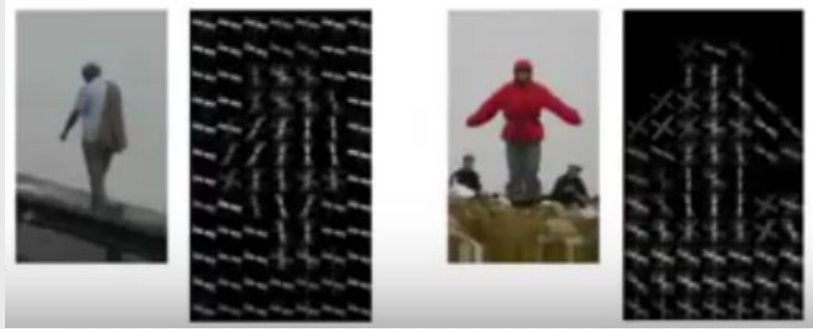


$72 = 3 \text{ rows} \times 3 \text{ columns} \times 8 \text{ gradient directions}$

$81 = 3 \text{ rows} \times 3 \text{ columns} \times 9 \text{ gradient directions}$

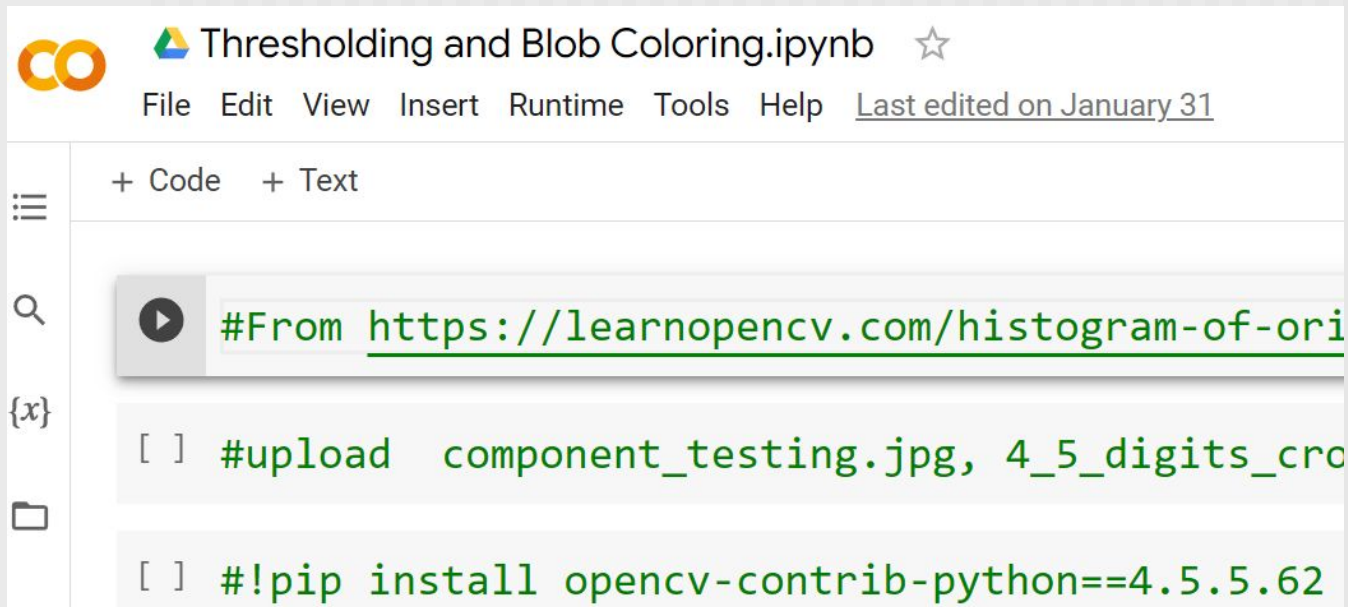


HOG still need to determine how to segment



- Disadvantage of HOG is it covers entire object in the image (global).
How to Segment part of the image?

Use Segmentation to Improve OCR




The screenshot shows a Jupyter Notebook interface. At the top, the title is "Thresholding and Blob Coloring.ipynb" with a star icon. Below the title is a menu bar with "File", "Edit", "View", "Insert", "Runtime", "Tools", and "Help". To the right of the menu bar, it says "Last edited on January 31". On the left side, there is a sidebar with icons for a menu, search, and a file explorer. The main area shows a code cell with the following code:

```
#From https://learnopencv.com/histogram-of-ori  
[ ] #upload component_testing.jpg, 4_5_digits_cro  
[ ] #!pip install opencv-contrib-python==4.5.5.62
```

We can get a bounding box for each training image and scale them to 20 x 20. Do the same for each test image. Then do template matching using gray-scale or using HOG.

New Shared Folder on Google Drive

drive.google.com/drive/folders/1udbuEoMuroczMJFTscgz9aWn88M4Pi9Y


Drive

+

New









- My Drive
- Computers
- Shared with me
- Recent
- Starred
- Bin

Storage (86% full)

13.03 GB of 15 GB used

[Buy storage](#)

My Drive > ... > Share Among ML Students > Lecture 1, Quiz 1-2 material, co...

| Name | Owner | Last modified | File |
|---|-------|---------------|------|
|  Naive Bayes and KNN Iris and Cancer.ipynb | me | 31 Jan 2023 | 67 K |
|  ML Course Outline (MEE673 Only).pdf | me | 10:13 am | 164 |
|  ML Course Outline (CPE393 Only).pdf | me | 10:11 am | 165 |
|  Lenna.png | me | 16 Jan 2023 | 463 |
|  Lecture 1.pdf | me | 10:08 am | 5.6 |
|  Lecture 0 (MEE673 Only).pdf | me | 9:00 am | 1.1 |
|  Lecture 0 (CPE393 Only).pdf | me | 10:10 am | 1.1 |
|  knn plot.ipynb | me | 17 Jan 2023 | 22 K |

Quiz 3

2. **Handwritten Digit Recognition.** Use the **digits.png** file as templates for digits 0, 1, ..., 9. Write a python program to cut out each digit as a labeled dataset from 0..9, each of which is 20x20. Note: You may also use this *exact same dataset* with 100 samples of each digit 0..9 using 20 x 20 pixels from the internet along with libraries to read/load the dataset, if that's easier for you.

Load all the character data into a python class. Then rescale each character from 20 x 20 to 24 x 24 using OpenCV. Use 80% of the data as the training set, reserving 20% for testing.

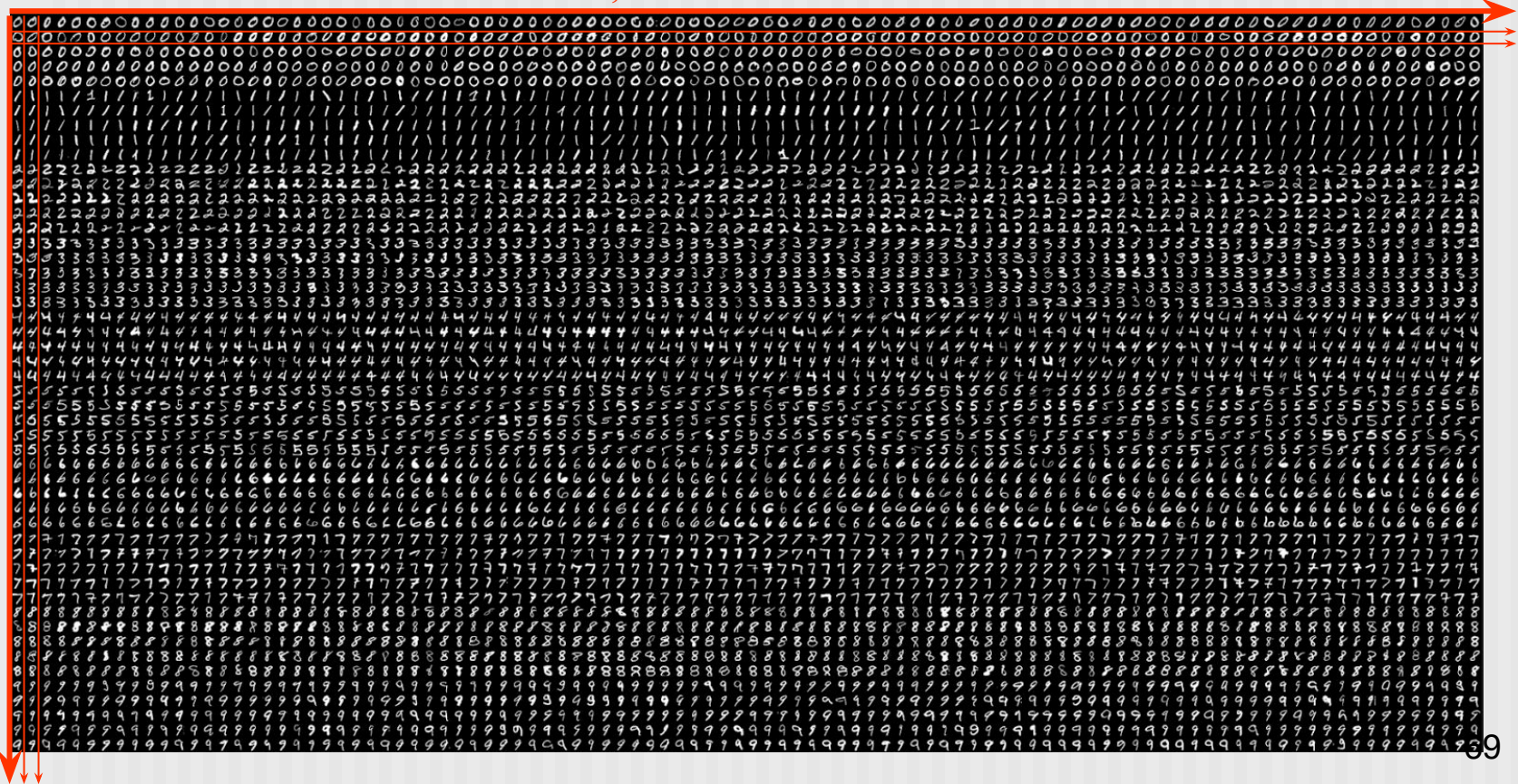
- a. *10+10+10+10 pts.* 5 hrs. Then try recognition by using the test images and report the accuracy percent for these 4 (classifier, feature type) combinations: (KNN K = 5, gray scale features), (KNN K = 5, HOG features), (KNN K = 1, gray scale features), (KNN K = 1, HOG features). For HOG, use 20° histogram orientations of non-directional gradients (ie., 9 bins) with 16 x 16 overlapping pixel windows for each 24 x 24 digit. Each digit will, thus, have 144 HOG features from 4 x 4 x 9, with 9 histogram values x 4 per 16 by 16 block x 4 such blocks per 24 x 24 image.

digits.png - 500 samples per digit each is 20x20 pixels

1..100 chars. TOTAL = 100 x 50 = 5,000 chars.

- 0: Uses rows 1-5 ($i = 0..99$), each 100 characters, each 20 x 20.
- 1: Uses rows 6-10 ($i = 100..199$), each 100 characters, each 20 x 20.
- ...
- 9: Uses rows 46..50 ($i = 900..999$), each 100 characters, each 20 x 20.

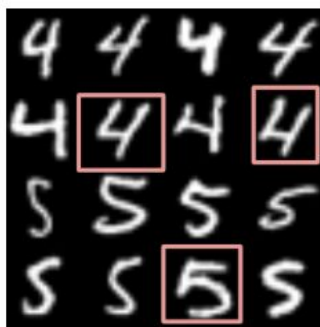
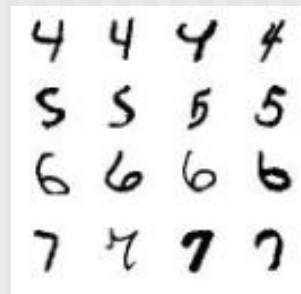
1..50
chars



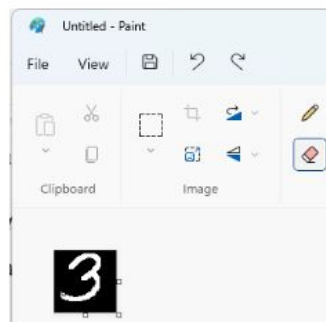
Quiz 3

b. Use KNN $K = 1$ with HOG features to report:

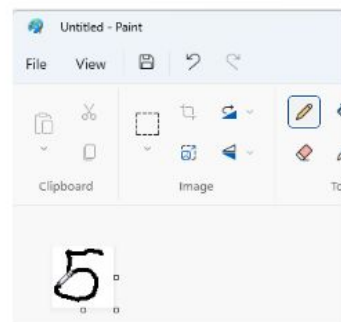
- i. 5 pts. 1.0 hrs. Result for 2 test images *per digit 0..9* cropped out from **digits.png** but not aligned at the original 20 x 20 image, so you may have smaller or bigger input image sizes. You must rescale each test image to 24 x 24 because HOG requires this scaling.
- ii. 5 pts. 1.0 hrs. Result for 2 test images *per digit 0..9* you create in a Paint program to see if you can find your character. Each test image should be big to start with such as 50x50, but you should rescale it to 24 x 24 before testing.
- iii. 5 pts. 1.0 hrs. Result for 4 test images of digit 5 you create in Paint with white background.



2. b. i. Cut digits at different sizes



2. b. ii. Create your own digits 0-9.



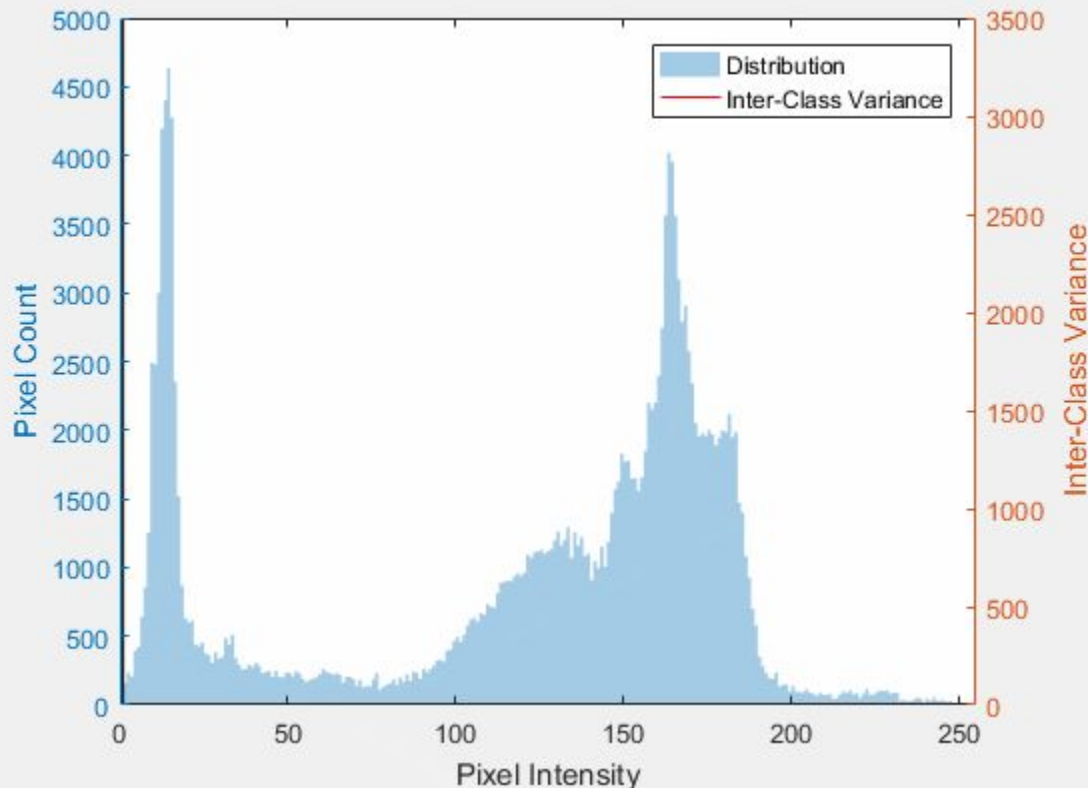
2. c. ii. "5" in white background.

Quiz 3

- c. 20 pts. 2 hrs. For each 0..9 digit in your dataset of 100 characters, use OpenCV's auto threshold (Otsu's algorithm) and then the connected components to find the bounding box. Use that bounding box to cut out each **original** gray-scale image (not the thresholded image) and resize each back to 24 x 24. This will be your new dataset (training and testing, combined). Report the accuracy percent for KNN $K = 1$ using HOG features. Is the result here better than in problem 2a for KNN = 1 using HOG features?

Otsu's auto thresholding

https://en.wikipedia.org/wiki/Otsu%27s_method



“Look for the biggest valley”
 - area between 2 big mountains.

Uses image histogram:
 efficient for all image sizes.

Find threshold that will result
 in the highest inter-class
 variance.