Computer Vision

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2022/3/3

What's Computer Vision

Computer Vision vs. Computer Graphics

電腦視覺　　計算機圖學

[following Slides from CSE/EE 576, @cs.washington.edu]

Every picture tells a story

Goal of computer vision is to write computer programs that can interpret images

Can computers match (or beat) human vision?

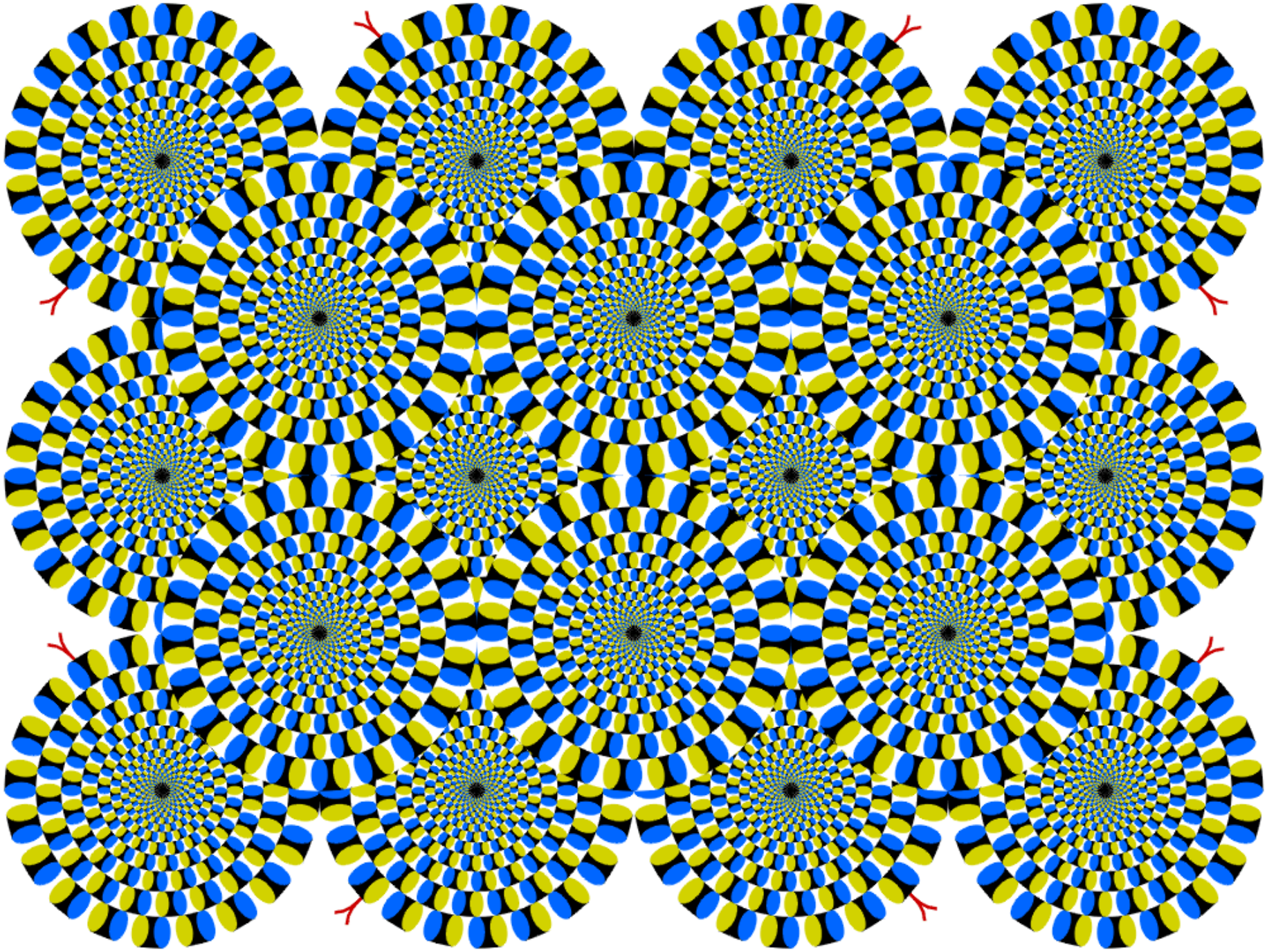
Yes and no (but mostly no!)

- humans are much better at “hard” things
- computers can be better at “easy” things

Human perception has its shortcomings…

Human perception has its shortcomings…

Source: Sinha, Pawan, and Tomaso Poggio. "I Think I Know That Face..." *Nature* 384 (1996): 404. © 1996.



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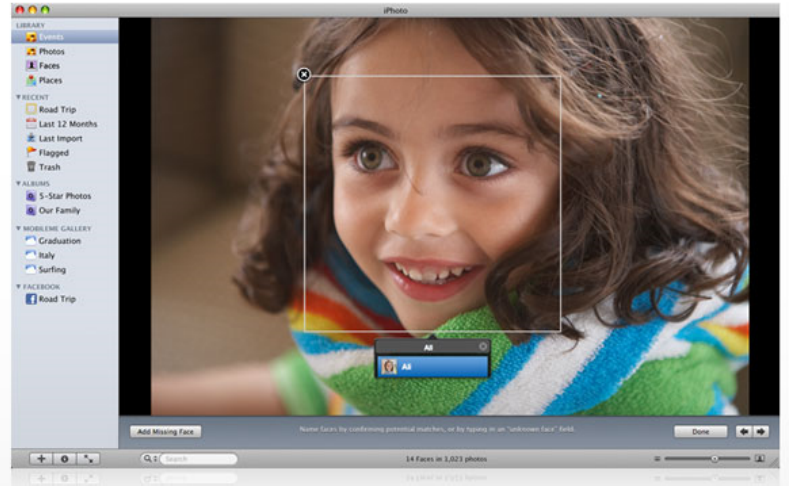
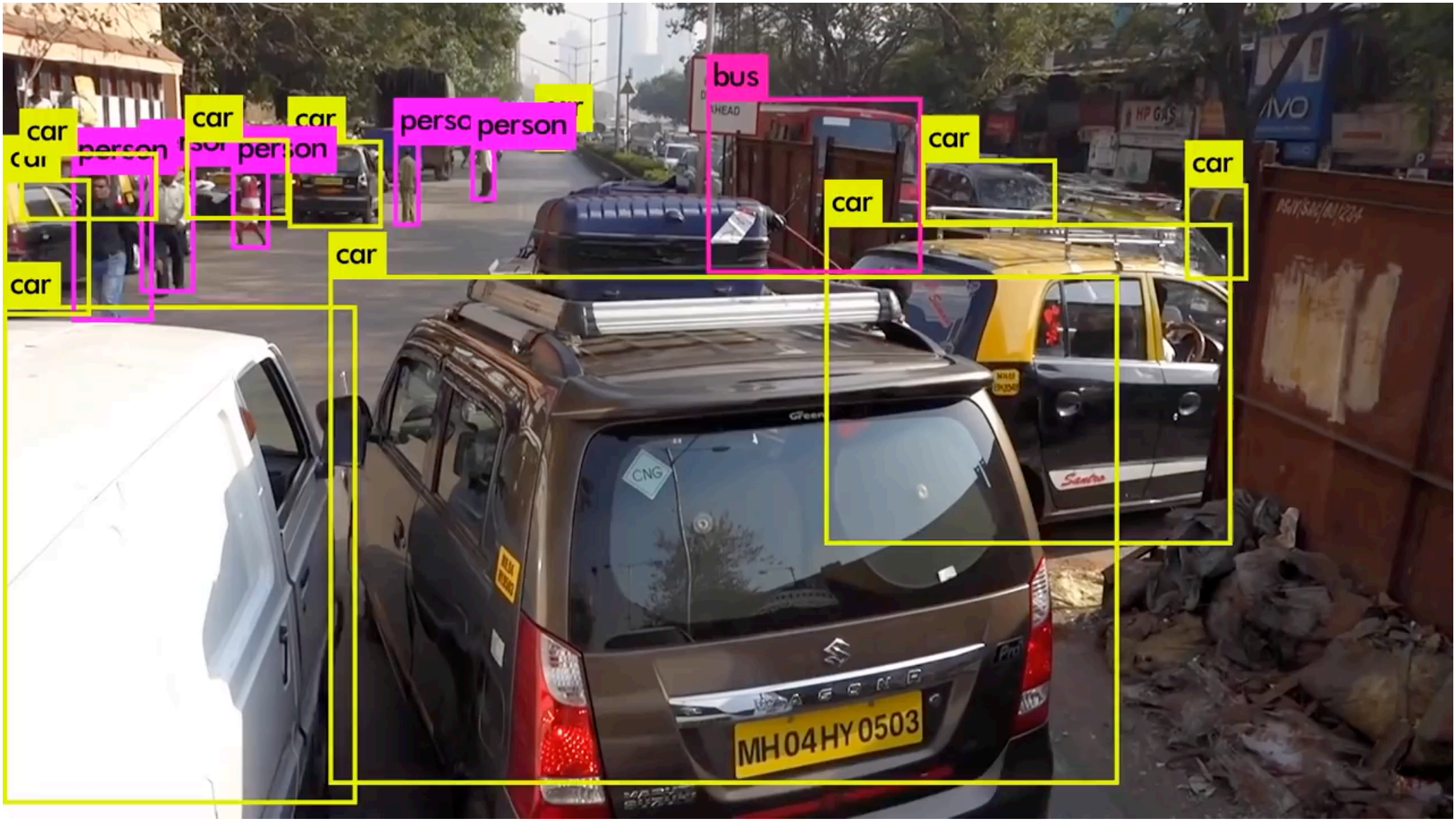
What Works Today?

Face detection and recognition, Biometrics



Object detection and recognition



Self-driving Car

Binary Machine Vision

Introduction

- binary value 1: considered part of object
- binary value 0: background pixel
- binary machine vision: generation and analysis of binary image

Thresholding

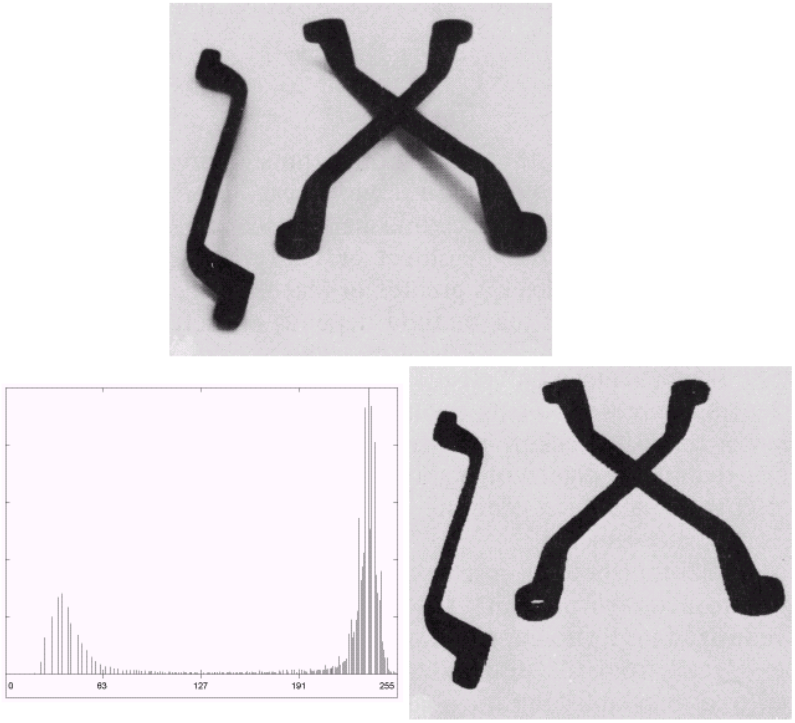
- $B(r,c) = 1$ if $I(r,c) \geq T$
- $B(r,c) = 0$ if $I(r,c) < T$

- *r*: row, *c*: column
- *I*: grayscale intensity, *B*: binary intensity
- *T*: intensity threshold

Thresholding

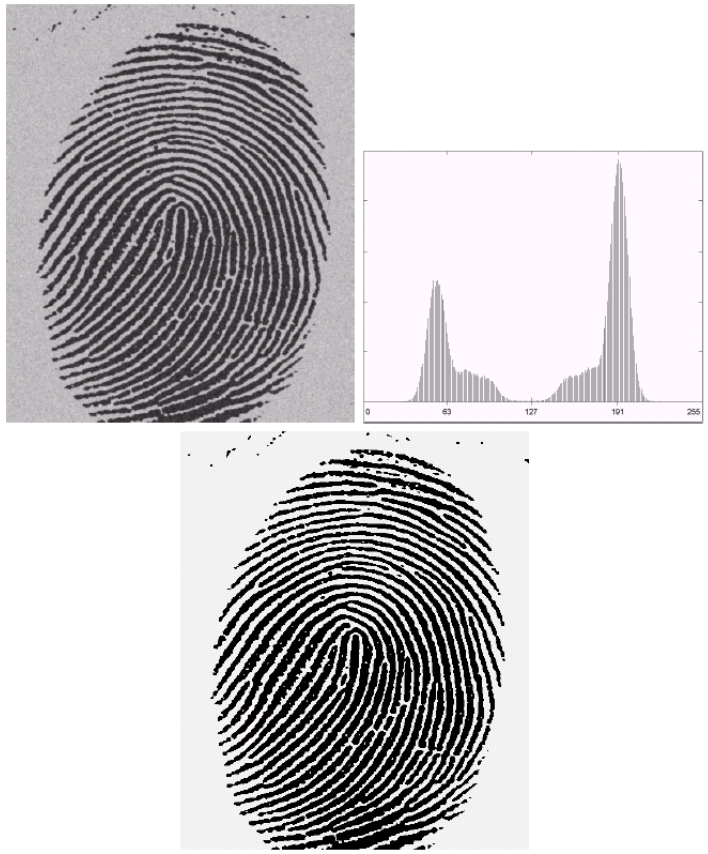
how to choose *T*?

Histogram Analysis for Image Thresholding



a
b c

FIGURE 10.28
(a) Original image. (b) Image histogram. (c) Result of global thresholding with T midway between the maximum and minimum gray levels.



a b
c

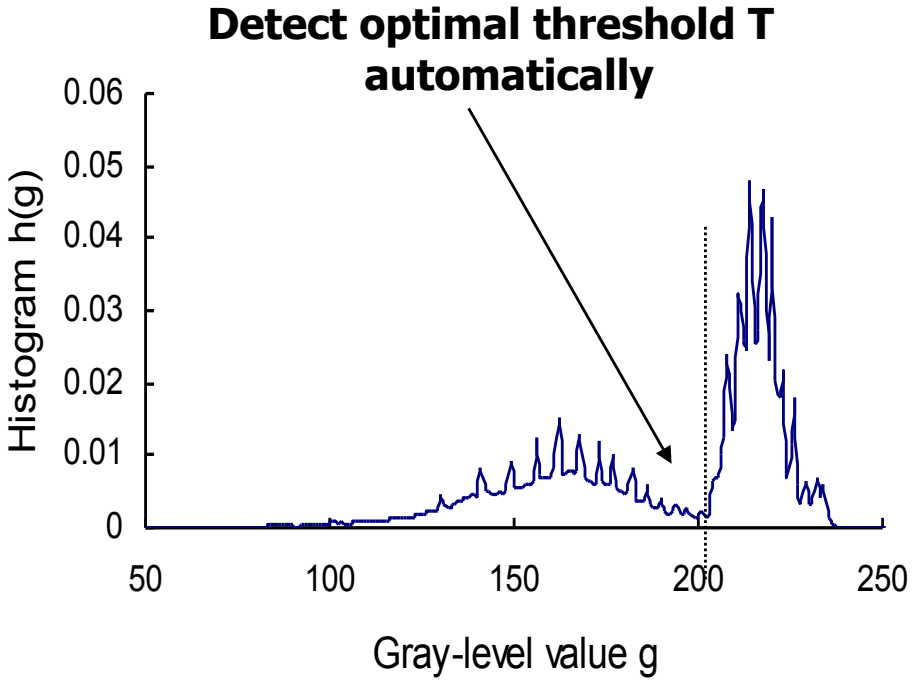
FIGURE 10.29
(a) Original image. (b) Image histogram. (c) Result of segmentation with the threshold estimated by iteration. (Original courtesy of the National Institute of Standards and Technology.)

Histogram Analysis for Image Thresholding

Example:

Image *X*

Histogram



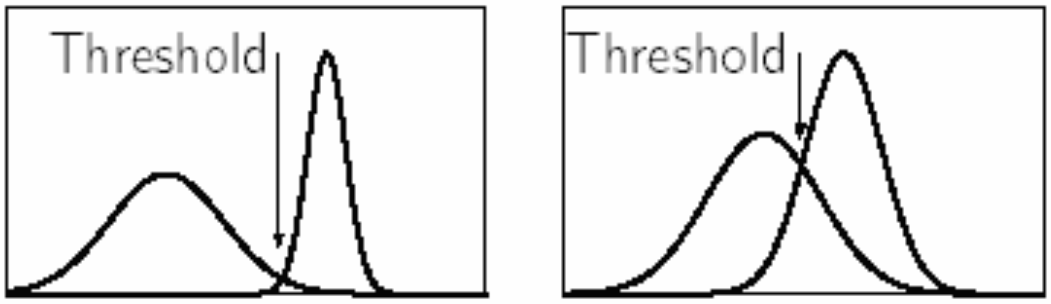
Thresholding at T=200

Binary image *Y*

Thresholding

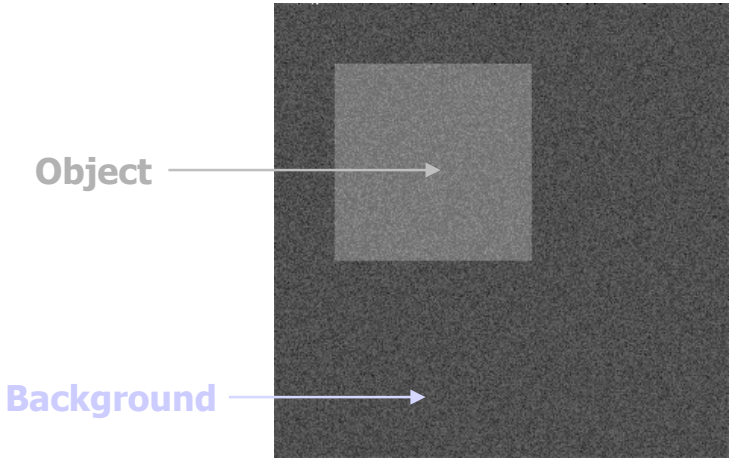
- Histogram shape can be useful in locating the threshold.
  - However it is not reliable for threshold selection when peaks are not clearly resolved.

- Choosing a threshold in the valley between two overlapping peaks, and inevitably some pixels will be incorrectly classified by the thresholding.

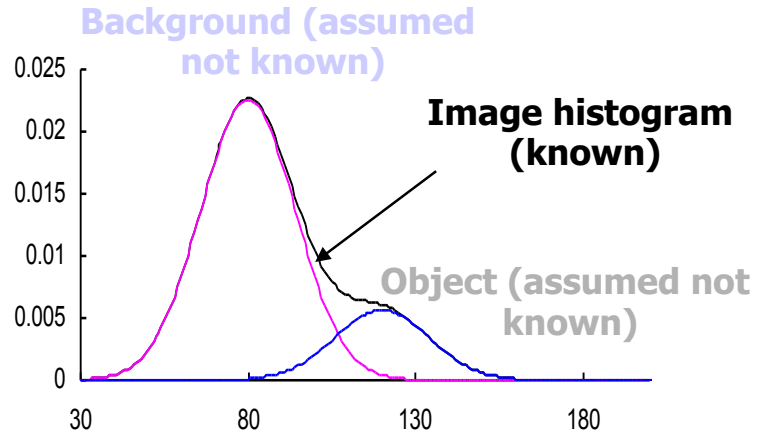


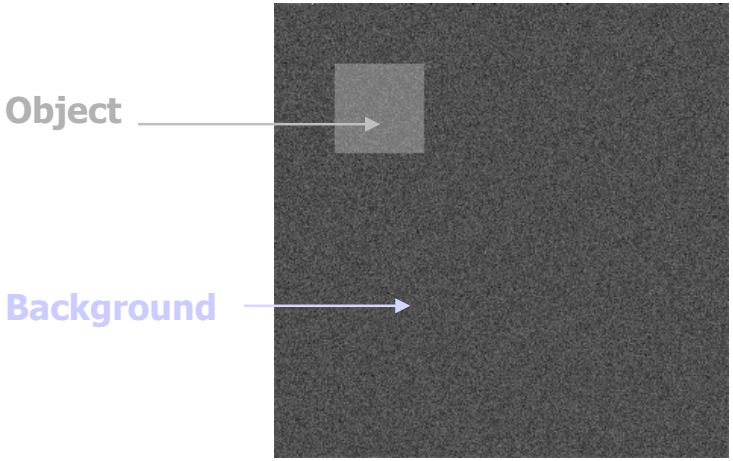
The determination of peaks and valleys is a non-trivial problem

Sensitivity to object size

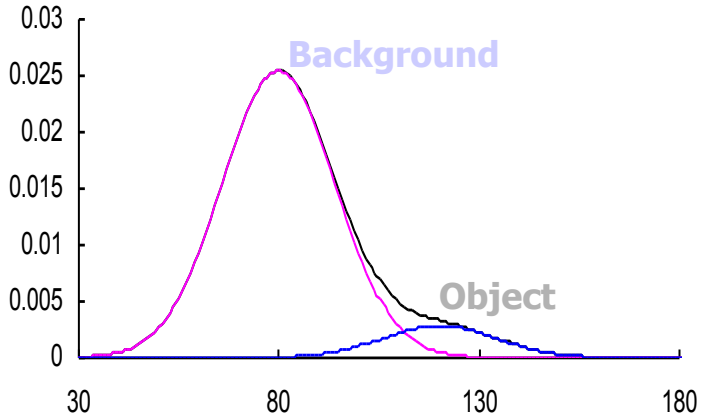


histogram



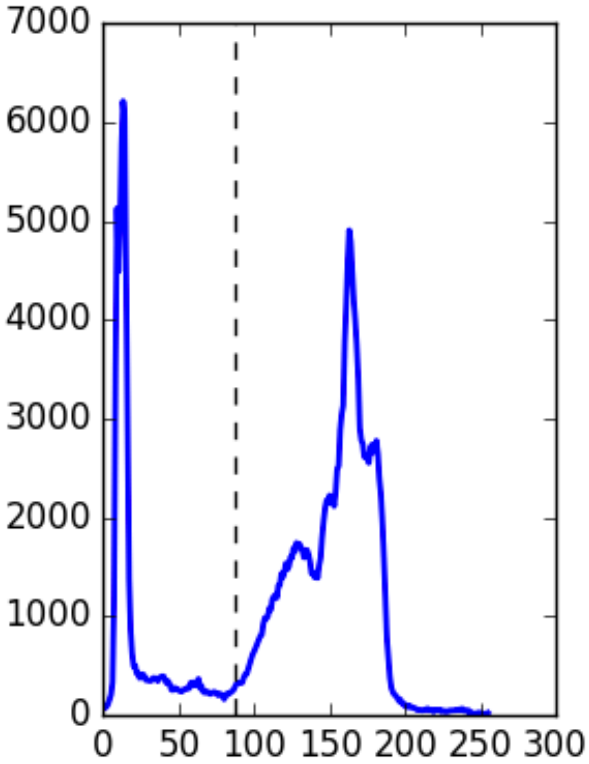


histogram



Otsu Thresholding

Select a threshold that minimize the **within-class variance**



Otsu Thresholding

- define the *within-class* variance as the weighted sum of the variances of each cluster:

$$\sigma^2_{\text{Within}}(T) = n_B(T)\sigma^2_B(T) + n_O(T)\sigma^2_O(T)$$

Minimize

$$n_B(T) = \sum_{i=0}^{T-1} p(i)$$

$$n_O(T) = \sum_{i=T}^{N-1} p(i)$$

$\sigma^2_B(T)$ = the variance of the pixels in the background (below threshold)

$\sigma^2_O(T)$ = the variance of the pixels in the foreground (above threshold)

Otsu Thresholding

Minimize

$$\sigma^2_{\text{Between}}(T) = \sigma^2 - \sigma^2_{\text{Within}}(T)$$
$$= n_B(T)\left[\mu_B(T) - \mu\right]^2 + n_O(T)\left[\mu_O(T) - \mu\right]^2$$

$$\mu = n_B(T)\mu_B(T) + n_O(T)\mu_O(T)$$

$$\sigma^2_{\text{Between}}(T) = n_B(T)n_O(T)[\mu_B(T) - \mu_O(T)]^2$$

Maximize

Algorithm of Otsu Thresholding

Goal: select a T that maximizes $n_B(T)n_O(T)[\mu_B(T) - \mu_O(T)]^2$

- For each potential threshold T ,
  1. Separate the pixels into two clusters according to the threshold.
  2. Find the mean of each cluster.
  3. Square the difference between the means.
  4. Multiply by the number of pixels in one cluster times the number in the other.

An Computational Issue

- The computations aren't independent as we change from one threshold to another.

- We can incrementally update with the following equations:

$$n_B(T+1) = n_B(T) + n_T$$
$$n_O(T+1) = n_O(T) - n_T$$
$$\mu_B(T+1) = \frac{\mu_B(T)n_B(T) + n_T T}{n_B(T+1)}$$
$$\mu_O(T+1) = \frac{\mu_O(T)n_O(T) - n_T T}{n_O(T+1)}$$

Connected Components Labeling

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- **Connected components analysis**:
  - connected components labeling of the binary-1 pixels
  - property measurement of the component regions
  - decision making

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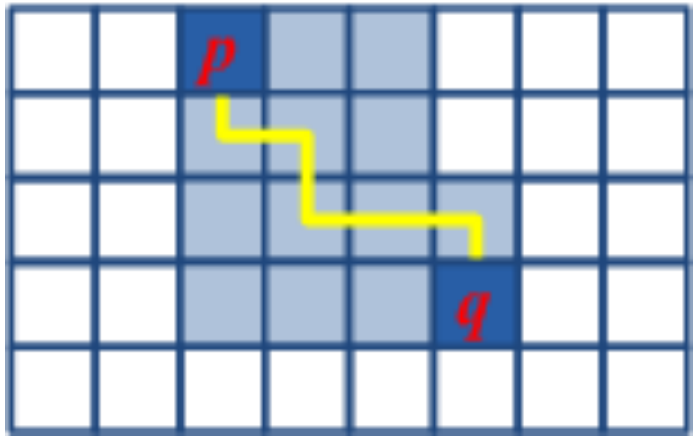
- connected components labeling: a grouping operation

- pixel property: position, gray level or brightness level
- region property: shape, bounding box, position, intensity statistics

Connected Components Operators

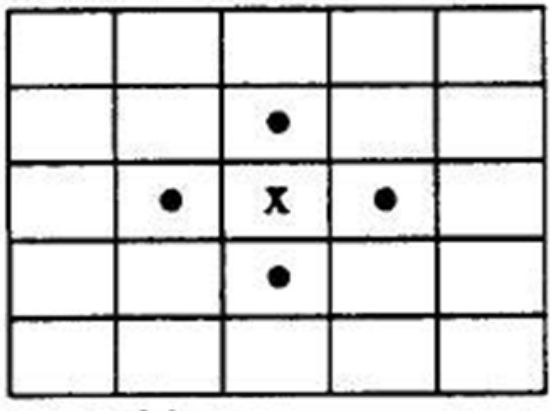
- Definition of Connected Component
  - Two pixels p and q belong to the same connected component C if there is a sequence of 1-pixels $(p_0, p_1, \ldots p_n)$, where
    - $p_0 = p$
    - $p_n = q$
    - $p_{i-1}, p_i : i = 1, \ldots, n$ are neighbor



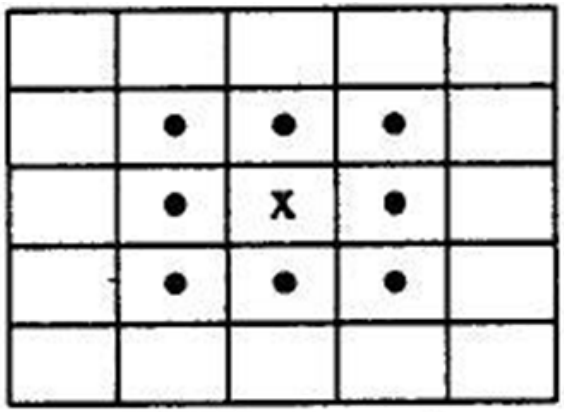
?

Connected Components Operators

- 4-connected: north, south, east, west
- 8-connected: north, south, east, west,
  northeast, northwest, southeast, southwest



4-connected



8-connected

Border: subset of 1-pixels also adjacent to 0-pixels

Connected Components Operators

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

Original Image

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

Connected Components

Connected Components Algorithms

- Common Features
  - Process a row of image at a time
  - Assign a new labels to the first pixel of each component.
  - Propagate the label of a pixel to its neighbors to the right or below it.

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

0	0	1	0	0	0	2
0	0	1	1	0	0	2
0	0	1	1	1	0	2
0	0	1	1	1	1	A

Connected Components Algorithms

- Common Features

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

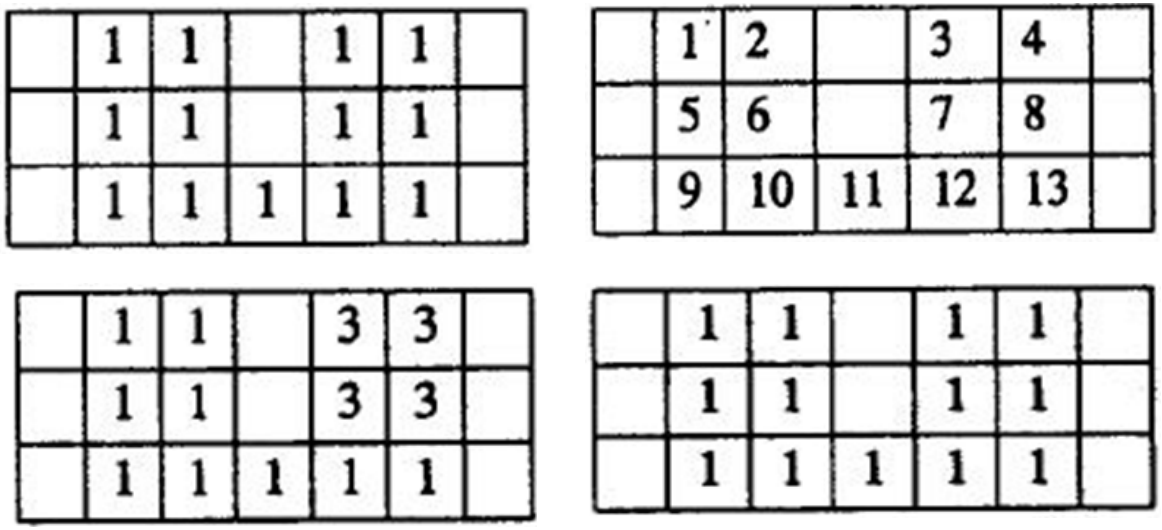
0	0	1	0	0	0	2
0	0	1	1	0	0	2
0	0	1	1	1	0	2
0	0	1	1	1	1	A

- What label should be assigned to *A*
- How does the algorithm keep track of the equivalence of two labels
- How does the algorithm use the equivalence information to complete the processing

Algorithm 1: Iterative Algorithm

- Use no auxiliary storage
- Computational Expensive

- Algorithm Steps
  - Step1 (Initialization): Assign an unique label to each pixel.
  - Step2 (Iteration) : Perform a sequence of top-down and bottom-up label propagation.

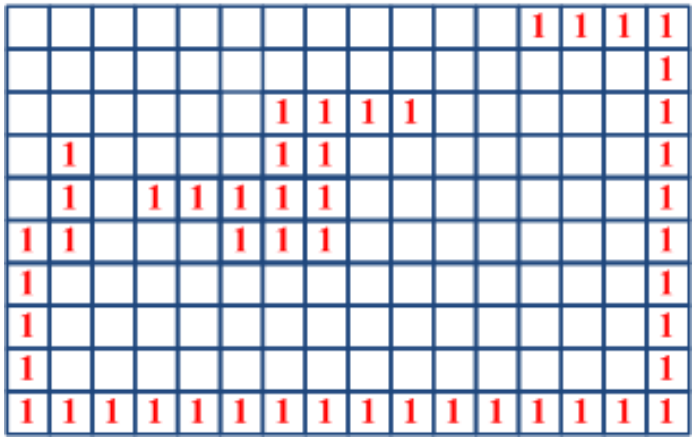


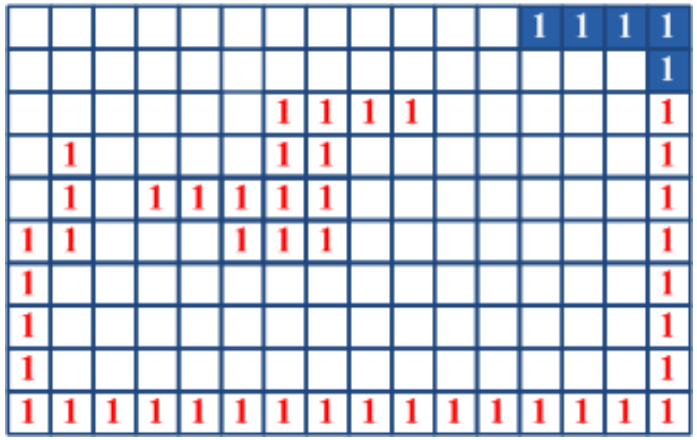
Algorithm 2: Classic Algorithm

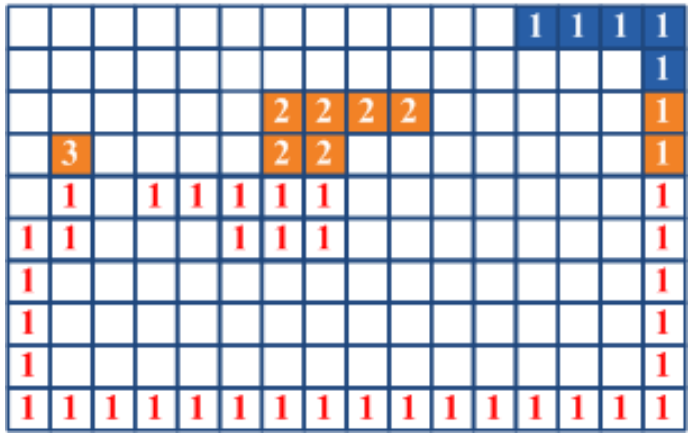
- Two-Pass Algorithm
  - Pass 1:
    - Perform label assignment and label propagation
    - Construct the equivalence relations between labels when two different labels propagate to the same pixel.
    - Apply resolve function to find the transitive closure of all equivalence relations.
  - Pass 2:
    - Perform label translation.

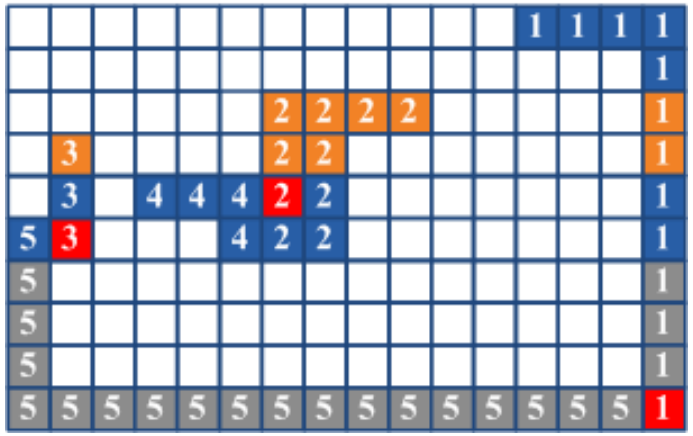
Algorithm 2: Classic Algorithm

- Example:









{2=4}

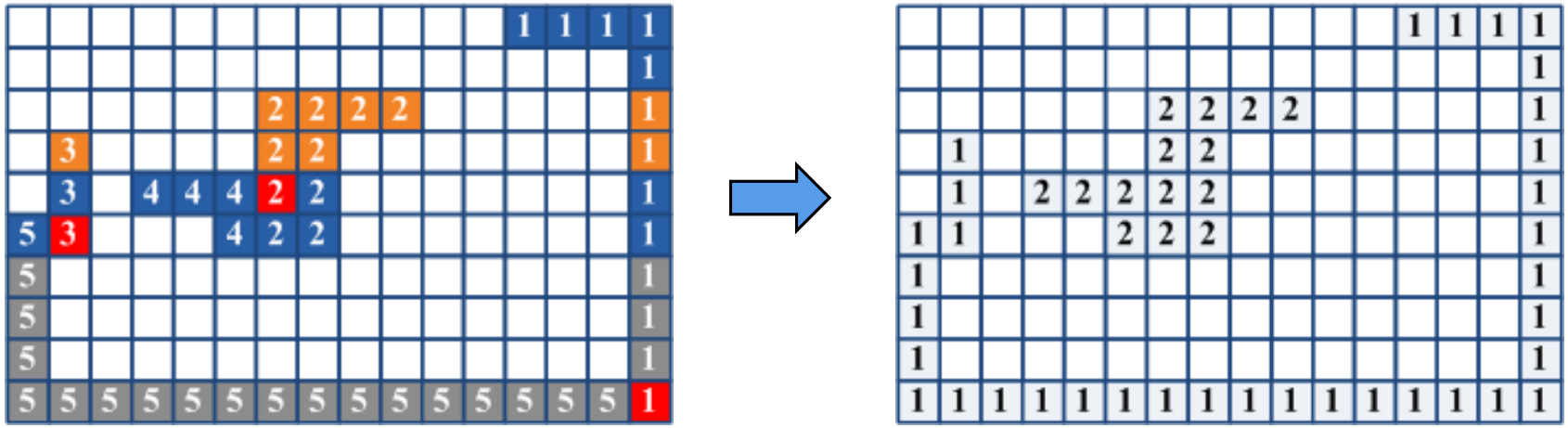
{3=5}

{1=5}

Algorithm 2: Classic Algorithm

- Example:
  - Resolve Function

{2=4} {3=5} {1=5} ⇨ {2=4} {1=3=5}



- Computational Efficiency
- Need a lot of space to store equivalence

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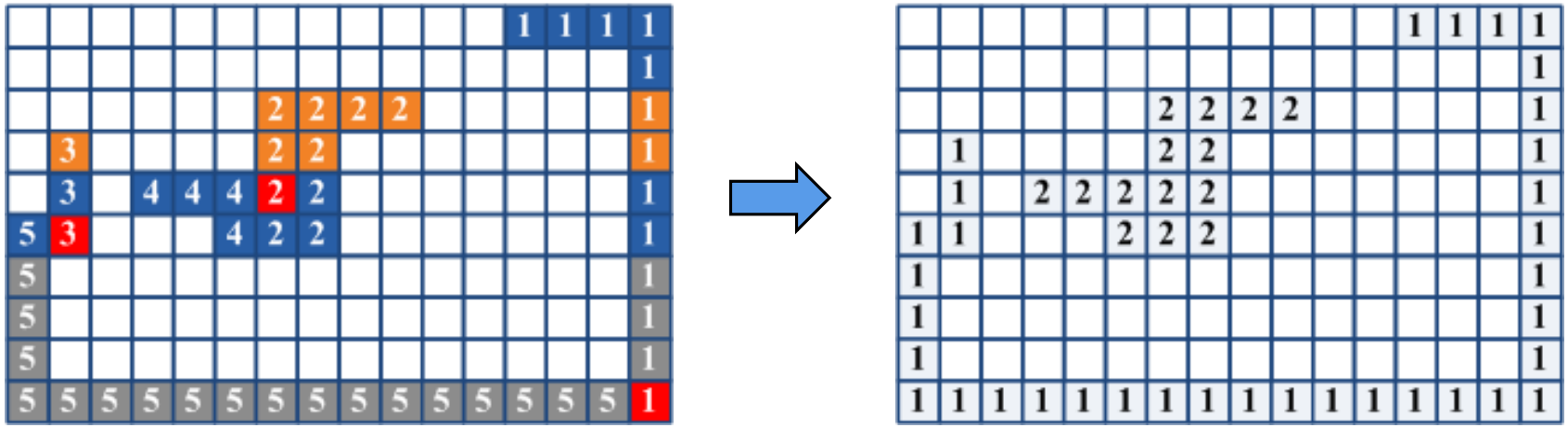
{2=4} {3=5} {1=5} ⇨ {2=4} {1=3=5}



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