Deep Learning for Computer Vision

Ahmed Hosny Abdel-Gawad

Senior AI/CV Engineer

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1.1 From Traditional ConvNets to DL

Semantic gap and CV tasks

The gap between what a computer sees and what we want it to see.

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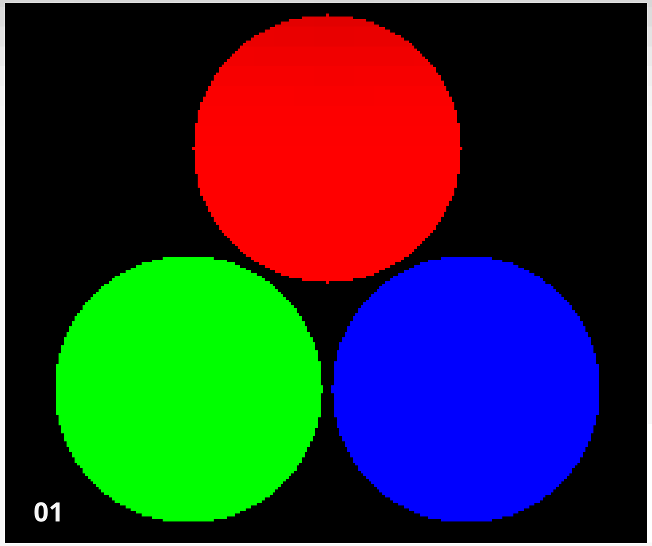
ConvNets and GPU

Why GPUs works perfect with convolution neural networks.

Semantic Gap



01

What Does A Computer See?

Using RGB model to help us understand how a computer looks at an image.

02

What We Want the Computer to see?

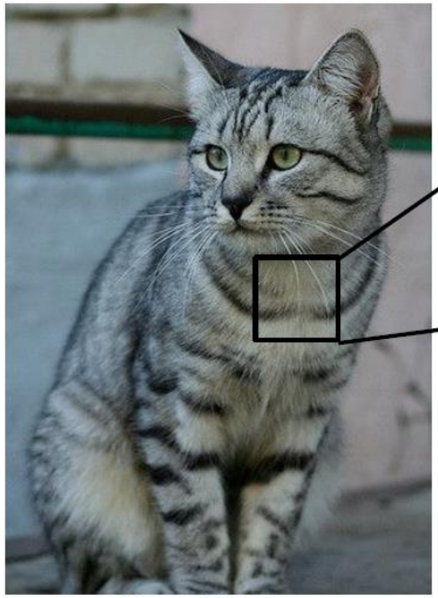
The core computer vision task: Image classification.

03

OpenCV Primer

Introduction to OpenCV.

What Does A Computer See?



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```

What the computer sees

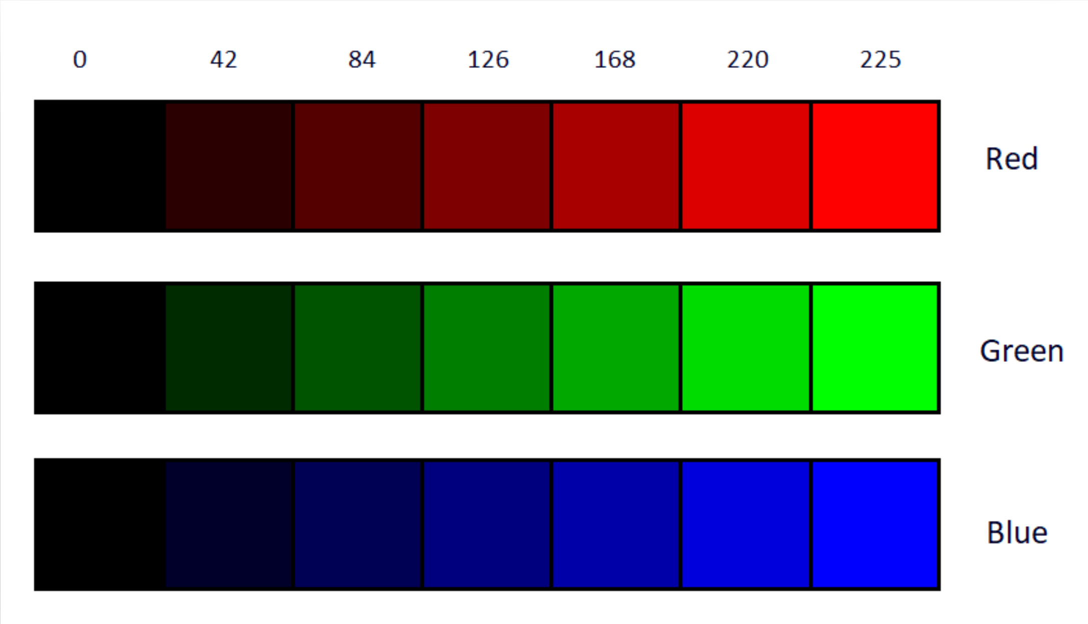
An image is just a big grid of numbers between [0, 255]:

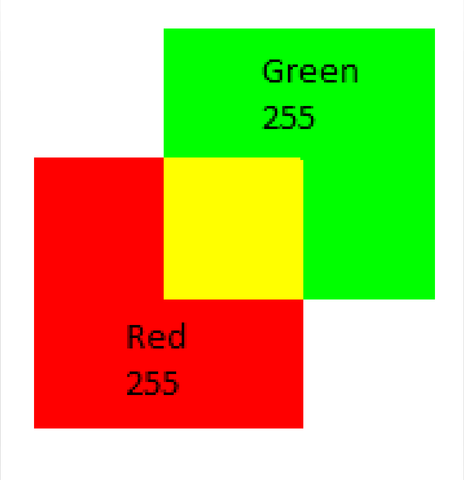
e.g. 800 x 600 x 3
(3 channels RGB)

What Does A Computer See?

Every major color has a range from 0 to 255, we can infer that higher the value, the brighter is the color.

When we combine two colors, say red and green, the resulting color is Yellow. It is represented in the three dimensional space as 255,255,0 (R,G,B).

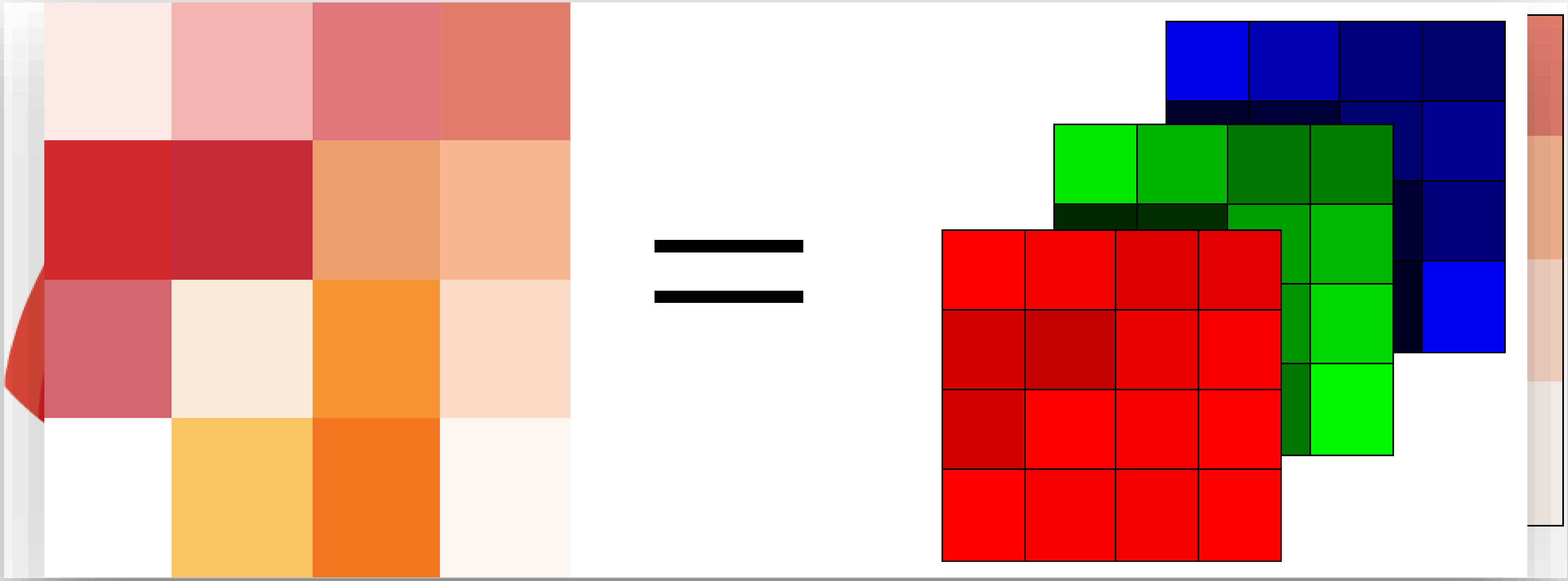




What Does A Computer See?

An image is made up of pixels placed adjacent to one another. These colored pixels are made up of three channels which are placed one behind the another.

The below pixelated image is a combination of the three channels which are placed one behind the other.



Basics of image processing with filtering

When it comes to detecting edges and contours, noise gives a great impact on the accuracy of detection. Therefore removing noises and controlling the intensity of the pixel values can help the model to focus on the general details and get higher accuracy.

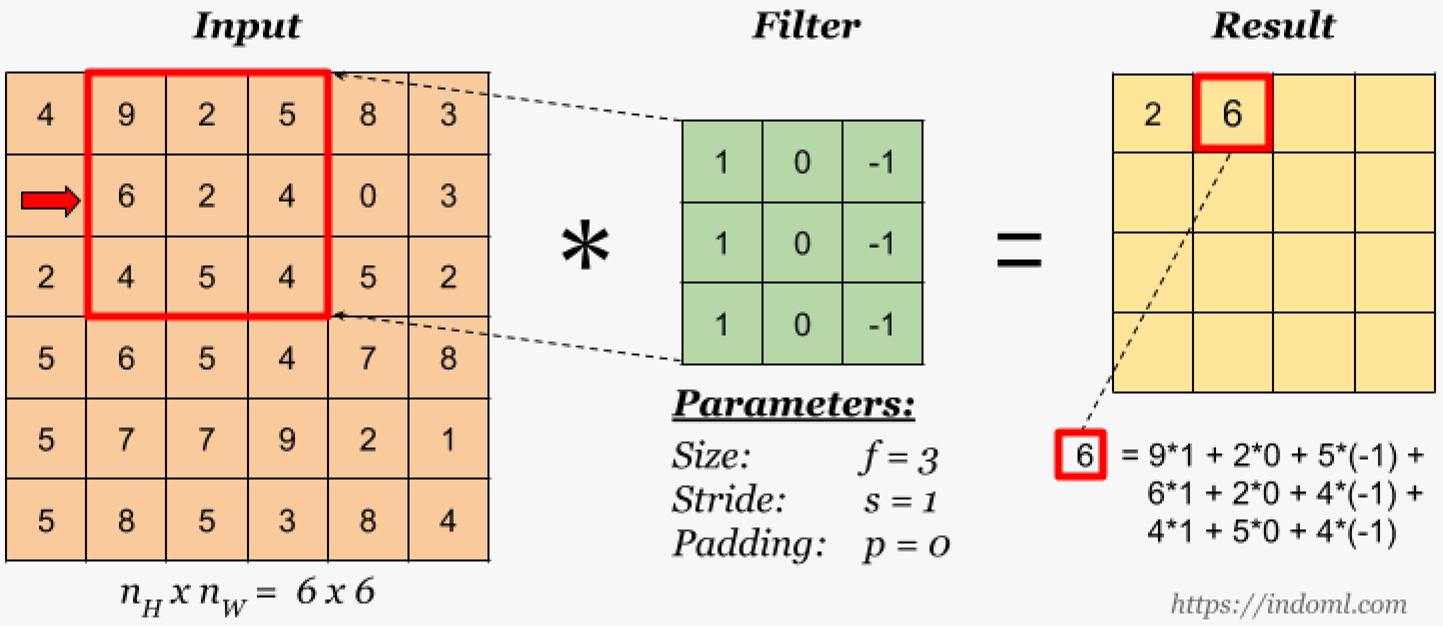
Blurring, thresholding, and morphological transformation are the techniques we use for this purpose.

Blurring

The main goal of blurring is to perform noise reduction.

Four major blurring techniques used in OpenCV: **Averaging blurring**, **Gaussian blurring**, **median blurring** and bilateral filtering.

All four techniques have a common basic principle, which is applying **convolutional operations** to the image with a filter (**kernel**). The values of the applying filters are different between the four blurring methods.



Average **Blurring**

Average blurring is taking the average of all the pixel values under the given kernel area and replace the value at the center. **Then what will it be like if we increase the size of the kernel?**

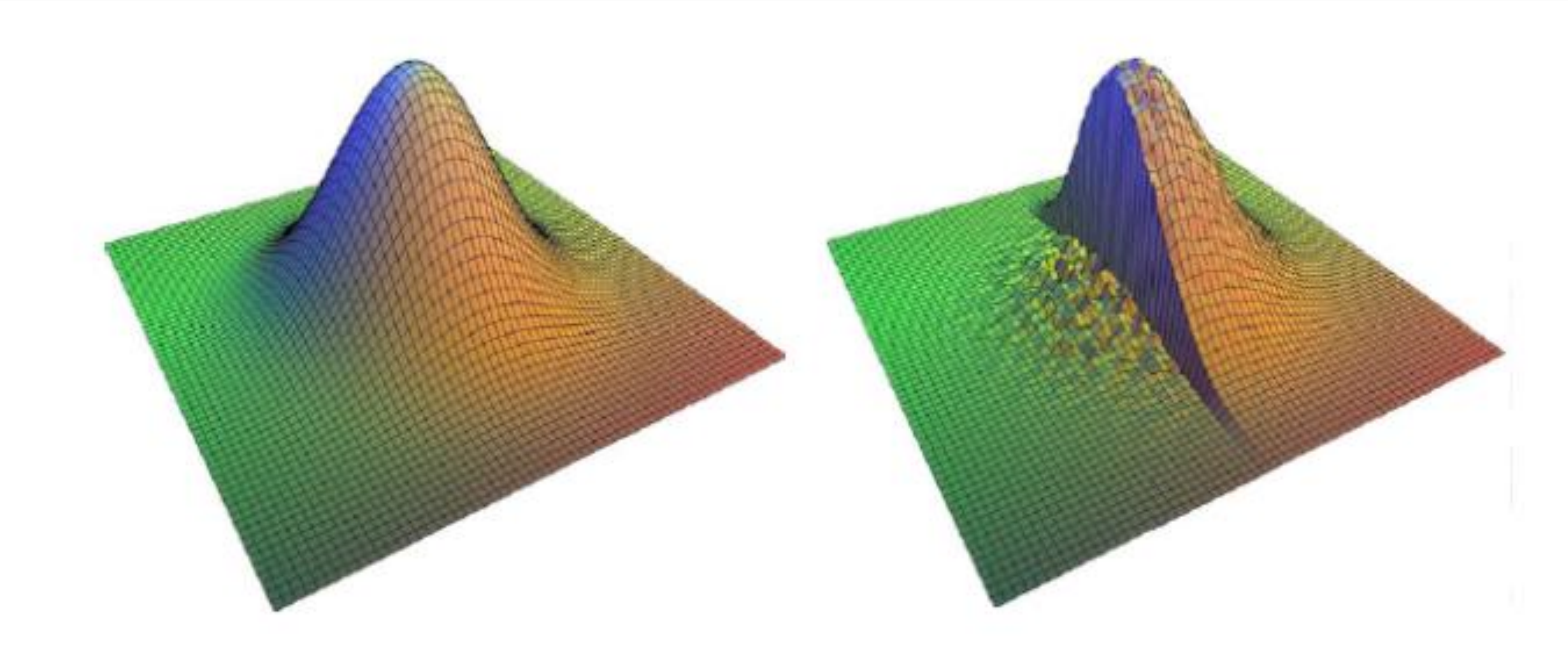
$$\frac{1}{25}\begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix} \rightarrow$$

156	124	112	150	130	142
128	180	130	144	145	140
111	150	110	200	142	128
101	130	170	250	133	120
121	150	200	170	119	150
130	150	150	135	200	150

Gaussian/Bilateral Blurring

Gaussian blurring is nothing but using the kernel whose values have a Gaussian distribution. The values are generated by a Gaussian function so it requires a sigma value for its parameter.

Bilateral ... olving
noises bu ... s. It
uses Gau ... count.
Therefor

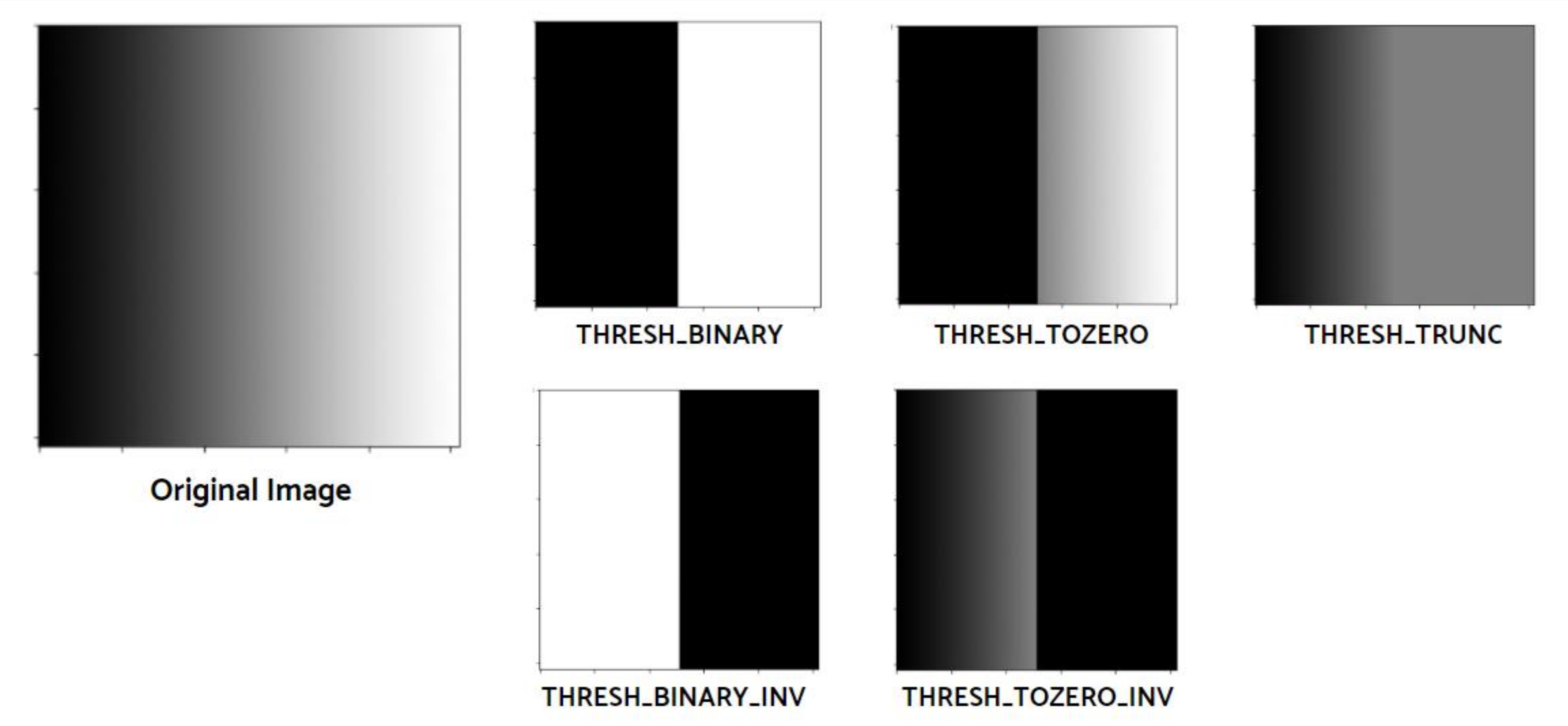


The shape of a Gaussian filter (on the left) and a Bilateral filter (on the right)

Thresholding

Thresholding transforms images into binary images.

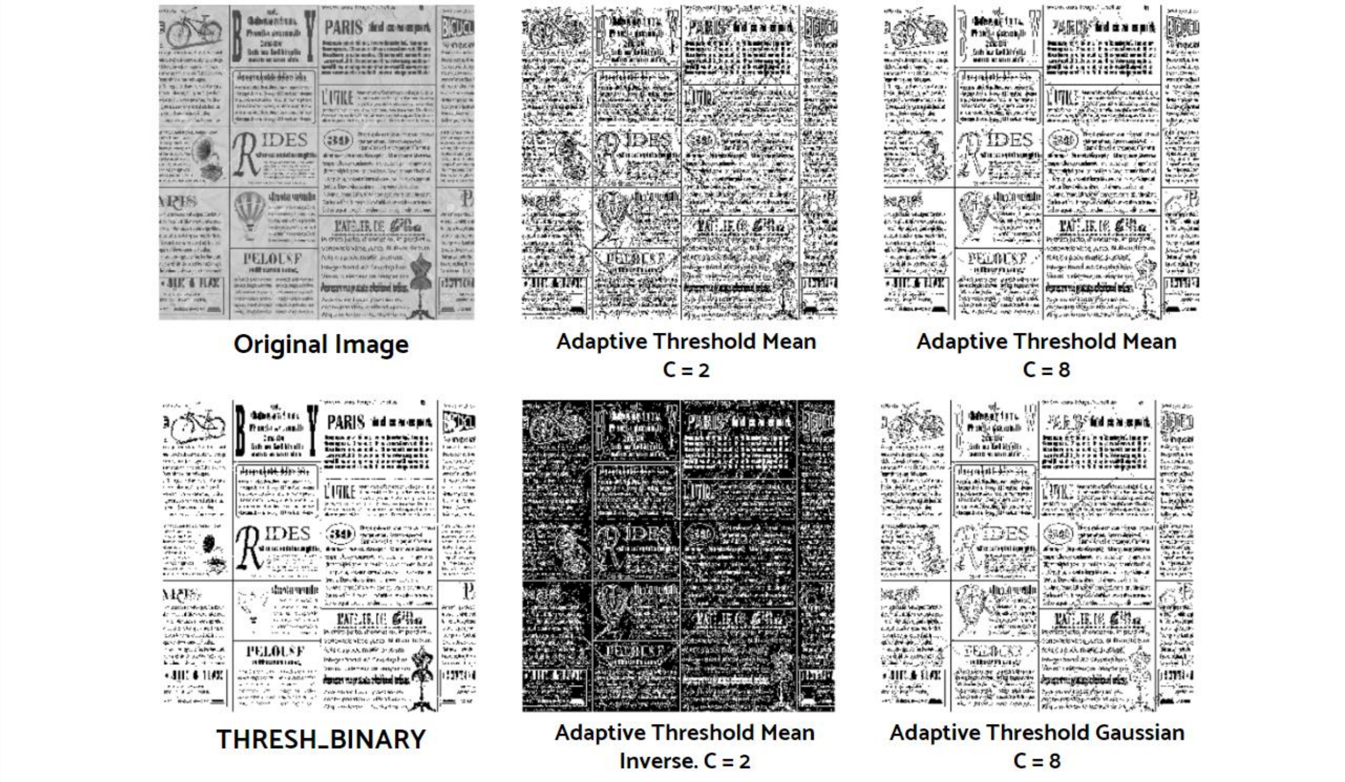
We need to set the threshold value and max values and then we convert the pixel values accordingly. There are five different types of thresholding: Binary, the inverse of Binary, Threshold to zero, the inverse of Threshold to Zero, and Threshold truncation. link



Adaptive Thresholding

What if we have a picture with various amount of lighting in different areas?

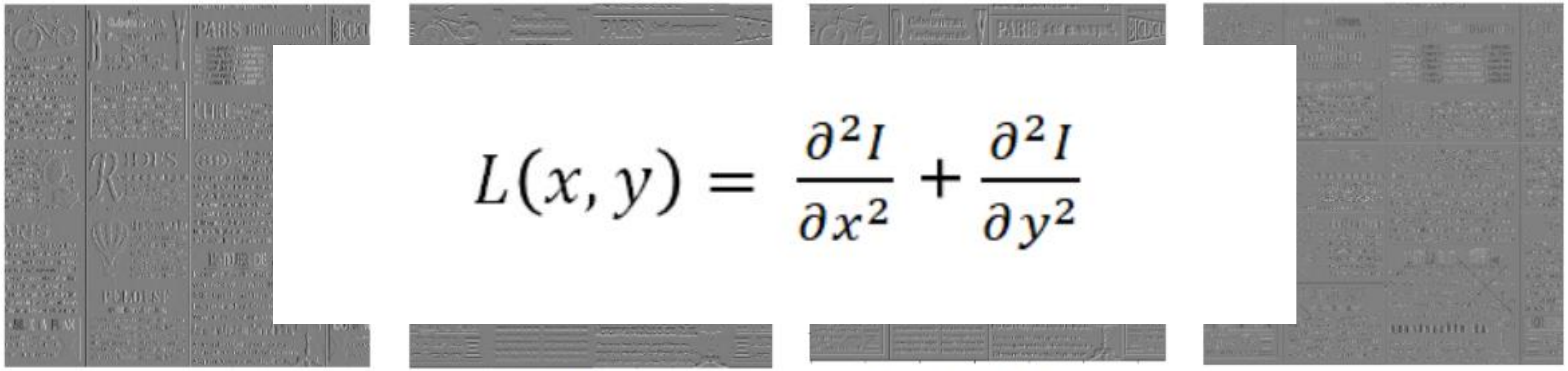
In this case, applying one value to the whole image would be a bad choice. A better approach would be using different thresholds for each part of the image. **Adaptive thresholding**, which serves this issue. By calculating the threshold within the neighborhood area of the image, we can achieve a better result from images with varying illumination.



Gradient

In mathematics, the gradient geometrically represents the slope of the graph of a function with multi-variables.

The image gradient represents directional changes in the intensity or color mode and we can use this concept for locating edges.



$$L(x, y) = \frac{\partial^2 I}{\partial x^2} + \frac{\partial^2 I}{\partial y^2}$$

Sobel X | Sobel Y | Sobel X + Sobel Y | Laplacian

Morphological transformations

It's also possible to manipulate the figures of images by filtering, which is called as **morphological transformation**.

Erosion is the technique for shrinking figures and it's usually processed in a grayscale. The shape of filters can be a **rectangle**, an **ellipse**, and a **cross** shape. By applying a filter we remove any 0 values under the given area.

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

Erosion →

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

Morphological transformations

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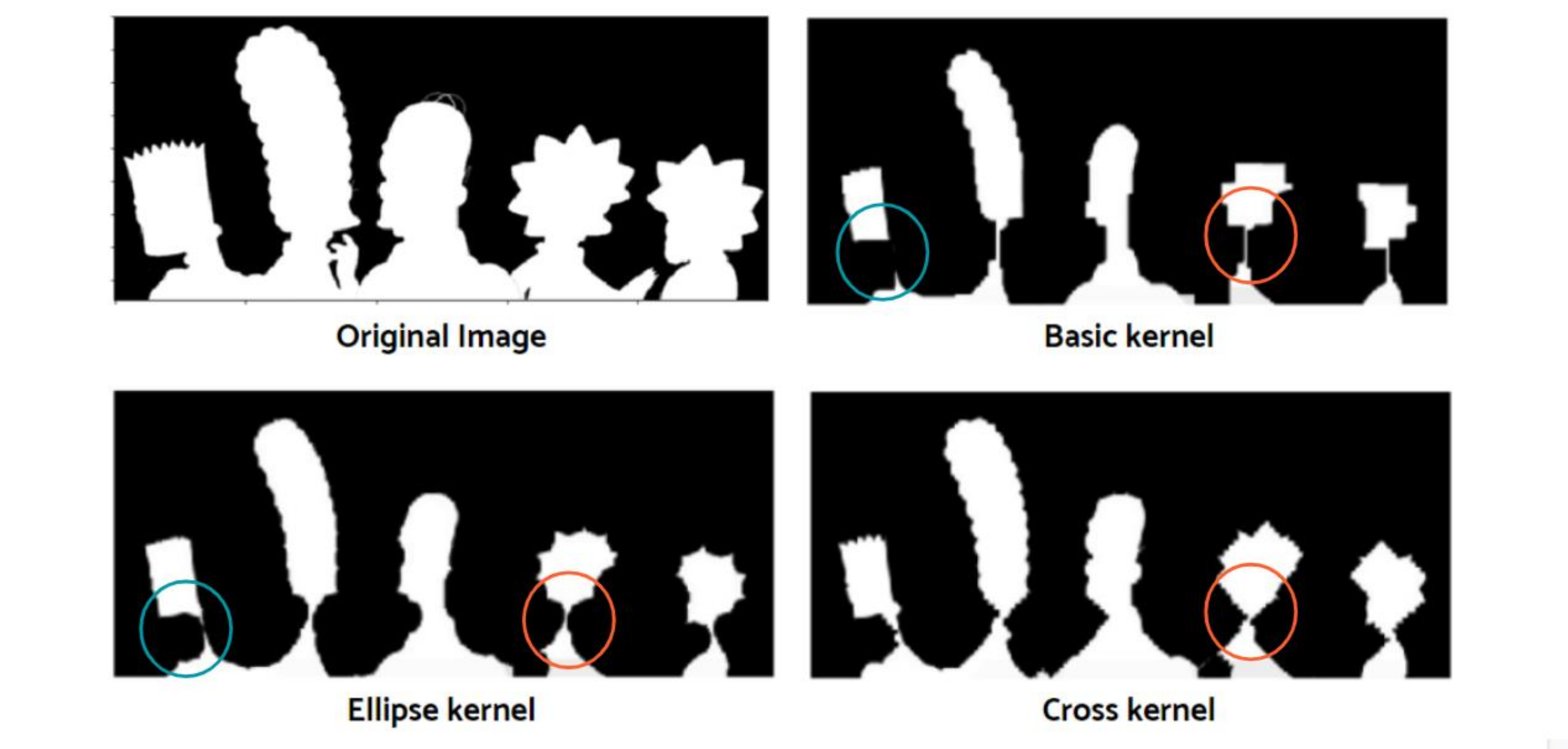


Morphological transformations

It’s also possible to manipulate the figures of images by filtering, which is called as **morphological transformation**.

Dilation is the opposite to erosion. It is making objects expand and the operation will be also opposite to that of erosion.

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

$\xrightarrow{\textbf{Dilation}}$

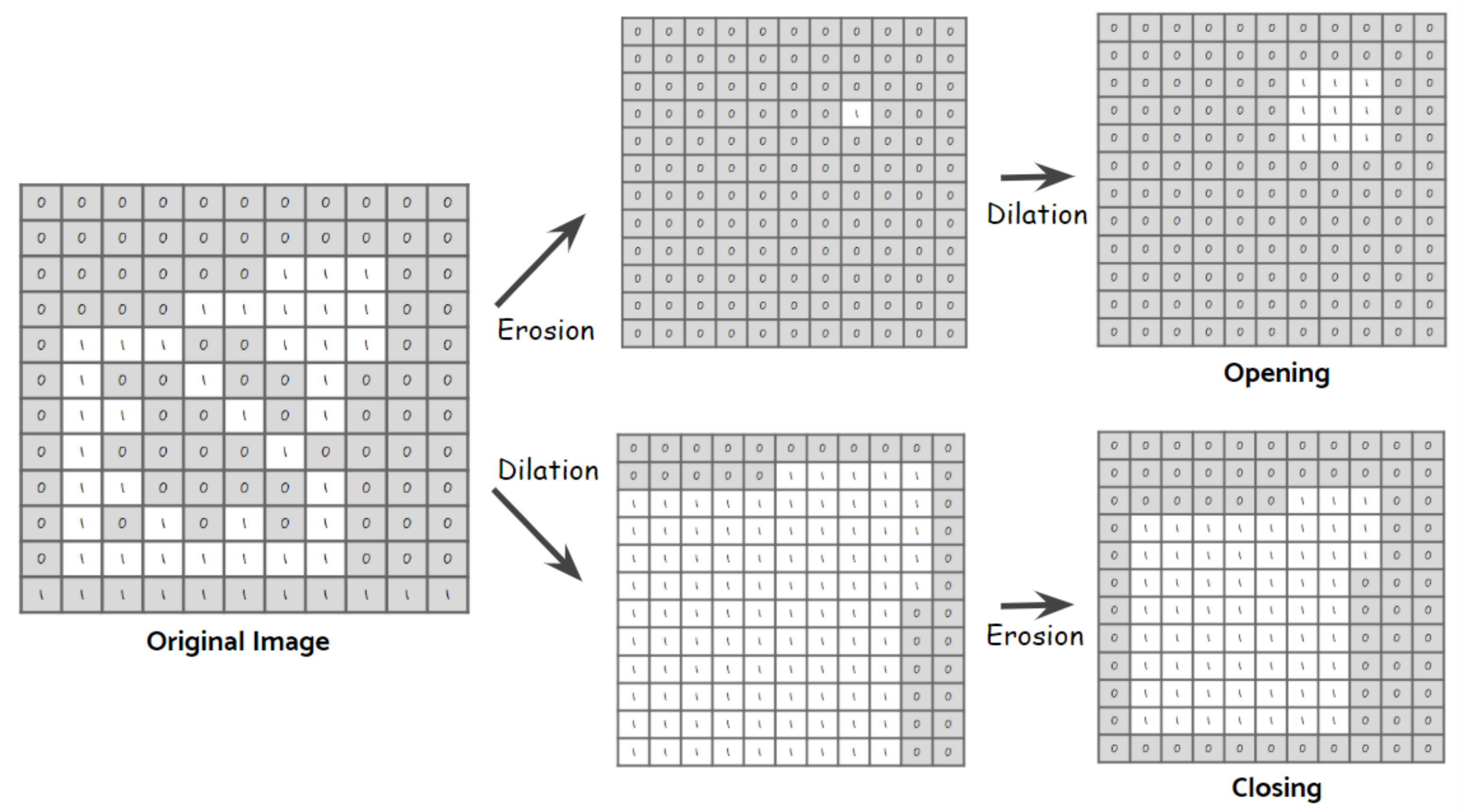
0	0	0	0	0	0	0
0	1	1	1	1	1	0
1	1	1	1	1	1	0
1	1	1	1	1	1	0
1	1	1	1	1	1	0
1	1	1	1	1	1	0
1	1	1	1	1	1	0

Morphological transformations

Dilation is the opposite to erosion. It is making objects expand and the operation will be also opposite to that of erosion.

Morphological transformations

Opening and **closing** operation is the mixed version of erosion and dilation. Opening performs erosion first and then dilation is performed on the result from the erosion while closing performs dilation first and the erosion.

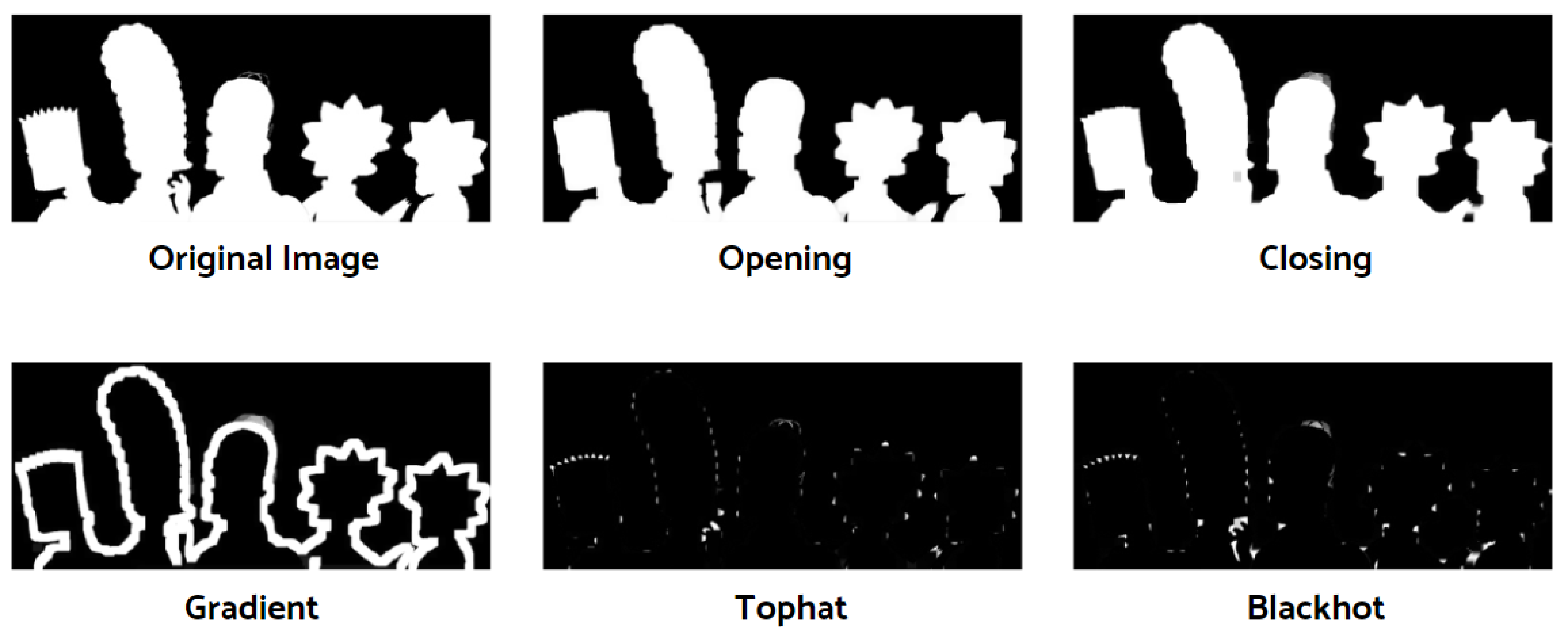


Subpatterns

Contour

Morphological transformations

Top hat filter is the subtracted area from opening to the original image while **black hat filter** is that from closing.



More...

A core task in CV:
Image Classification

Image Classification

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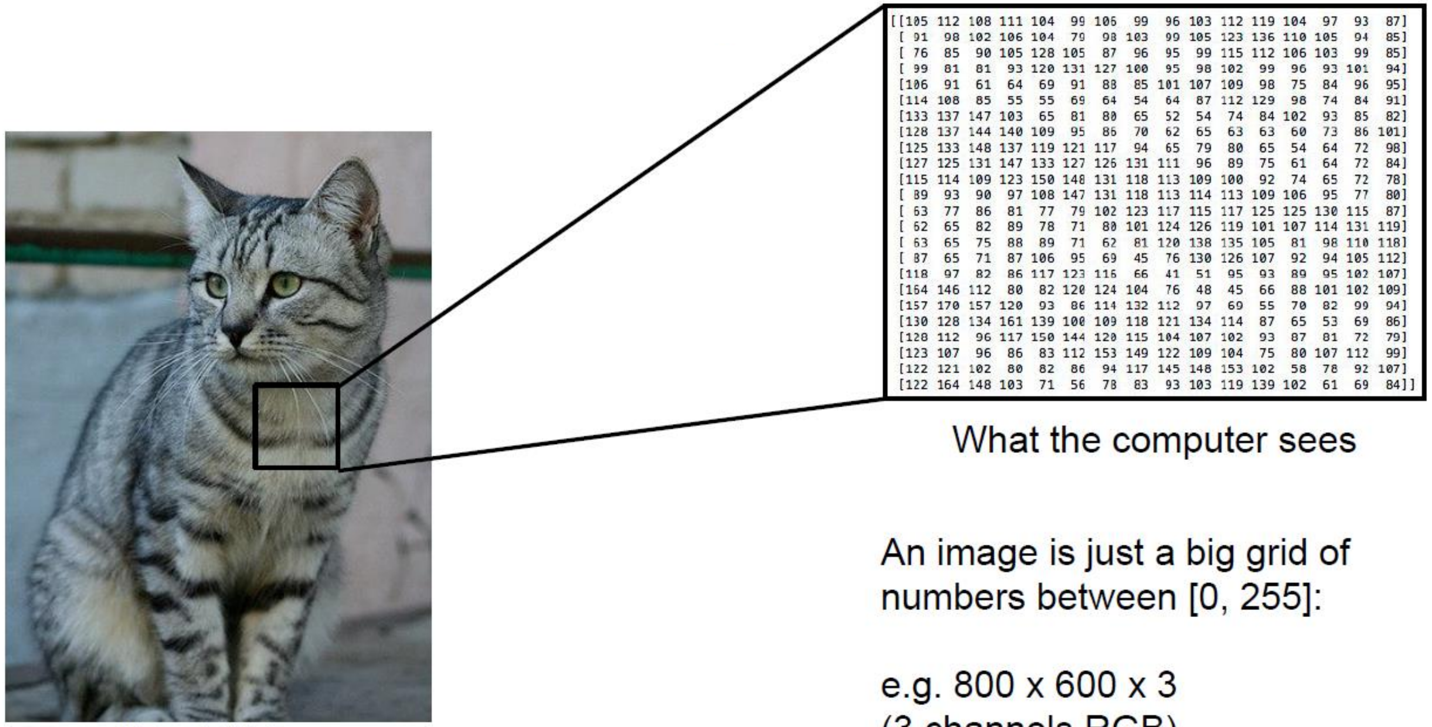
(assume given set of discrete labels)
{dog, cat, truck, plane, ...}

→ cat

The Problem: Semantic Gap



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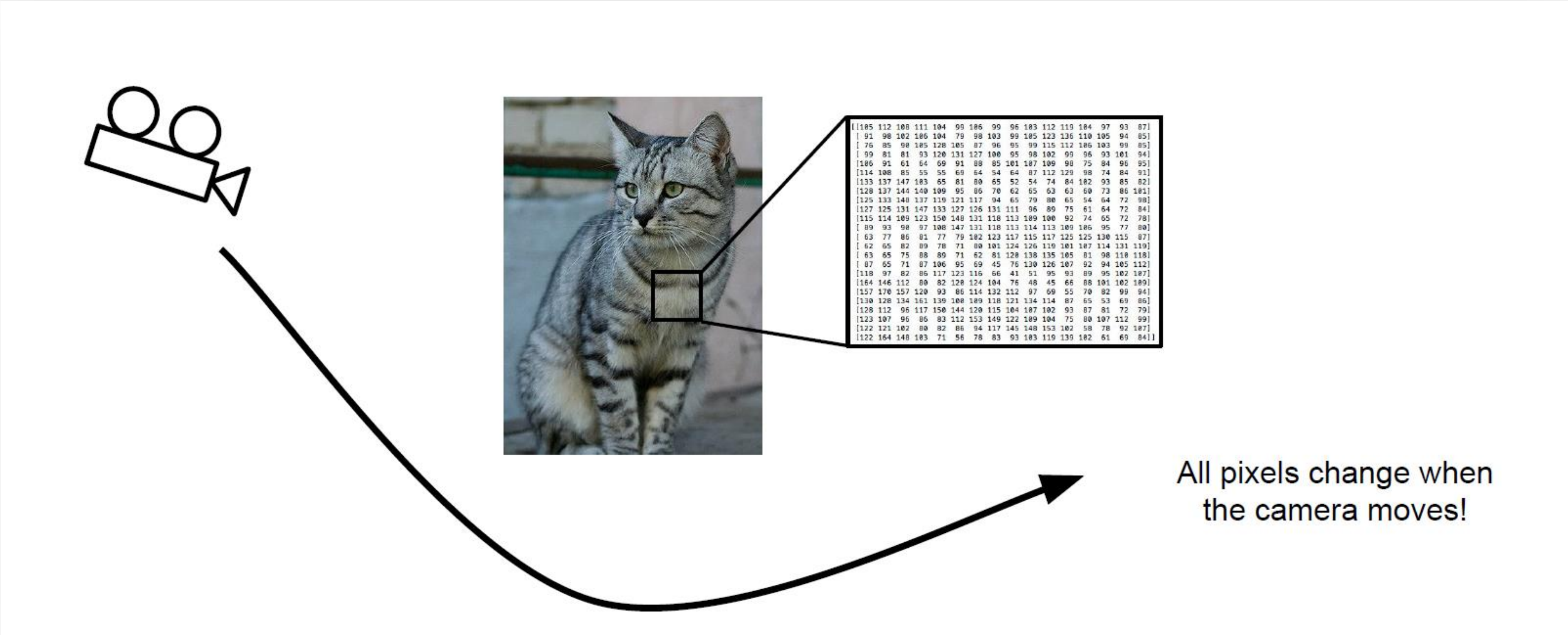
What the computer sees

An image is just a big grid of numbers between [0, 255]:

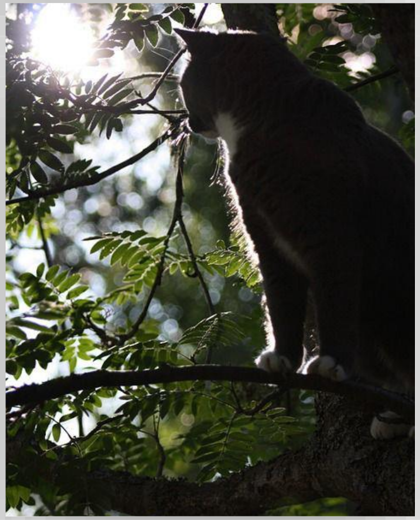
e.g. 800 x 600 x 3
(3 channels RGB)

Challenges: Viewpoint variation



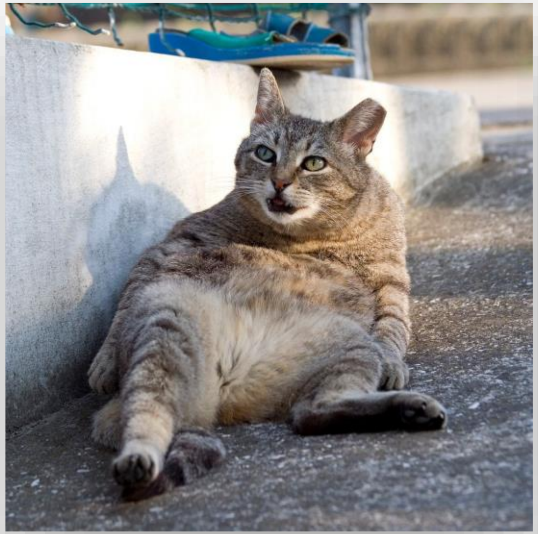
Challenges: Illumination

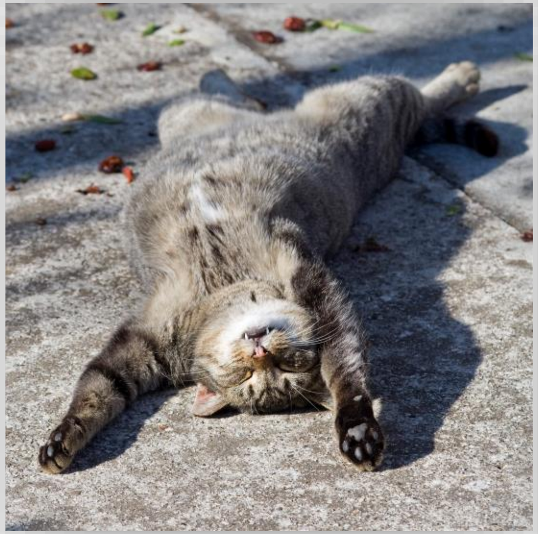


We need the computer to classify all of them as cats!

Challenges: Deformation






Again, we need the computer to classify all of them as cats!

Challenges: Occlusion

Challenges: Background Clutter

Challenges: Intraclass variation

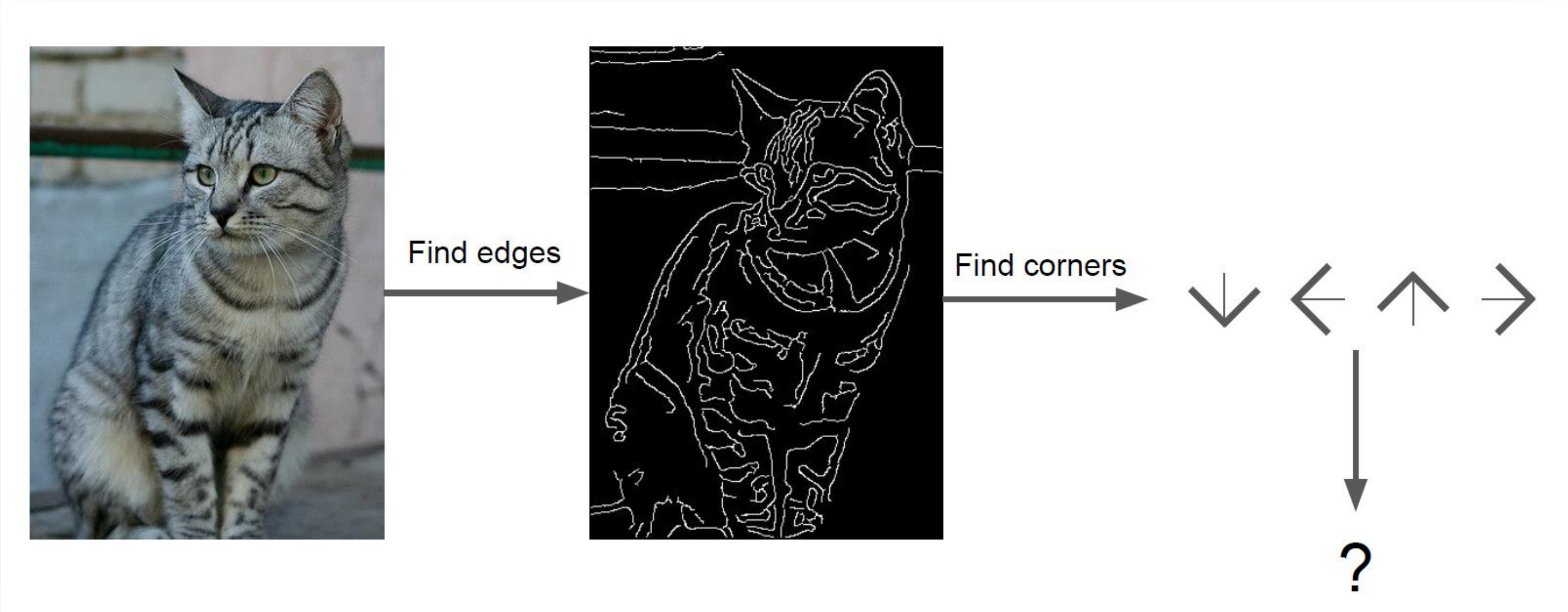
An Image Classifier

```
def classify_image(image):
  # Some magic?
  return class_label
```

Unlike e.g. sorting a list of numbers,

No obvious way to hard-code the algorithm for recognizing a cat, or other classes.

Attempts: Traditional CV

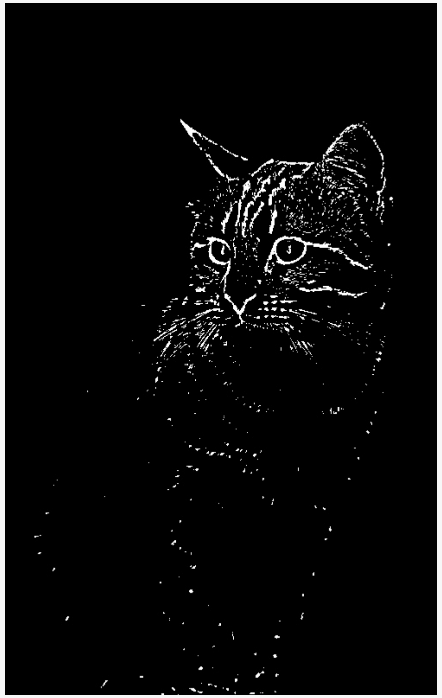


Layers of features

Pixels

Gray Pixels

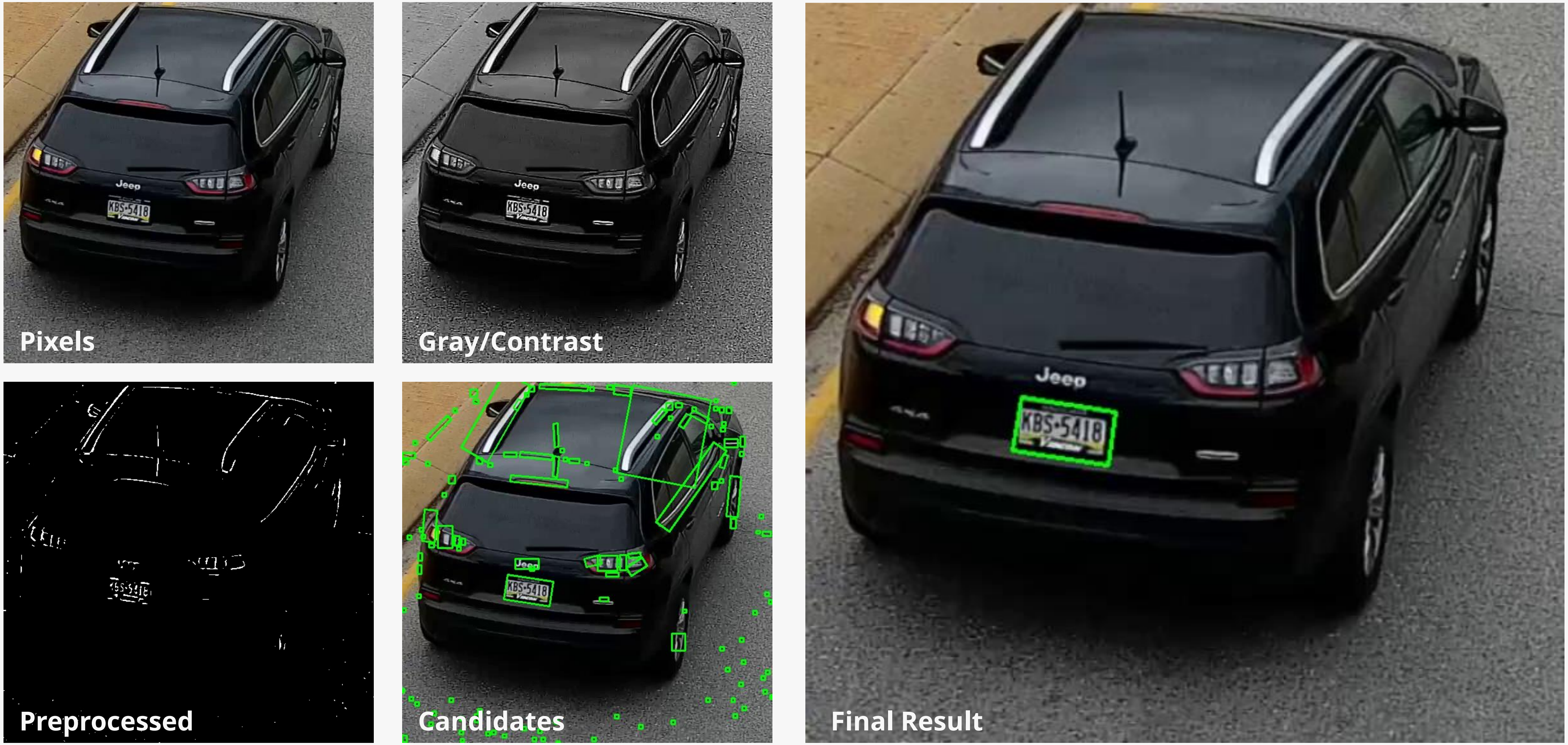
Threshold Pixels



Edges/Dilation

Contours

Traditional LPD



Thank You!