DEEP LEARNING FOR COMPUTER VISION

Week2

https://github.com/Tuchsanai/DL-FOR-COMPUTER-VISION-2565_1/tree/main/week2

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Understanding Images

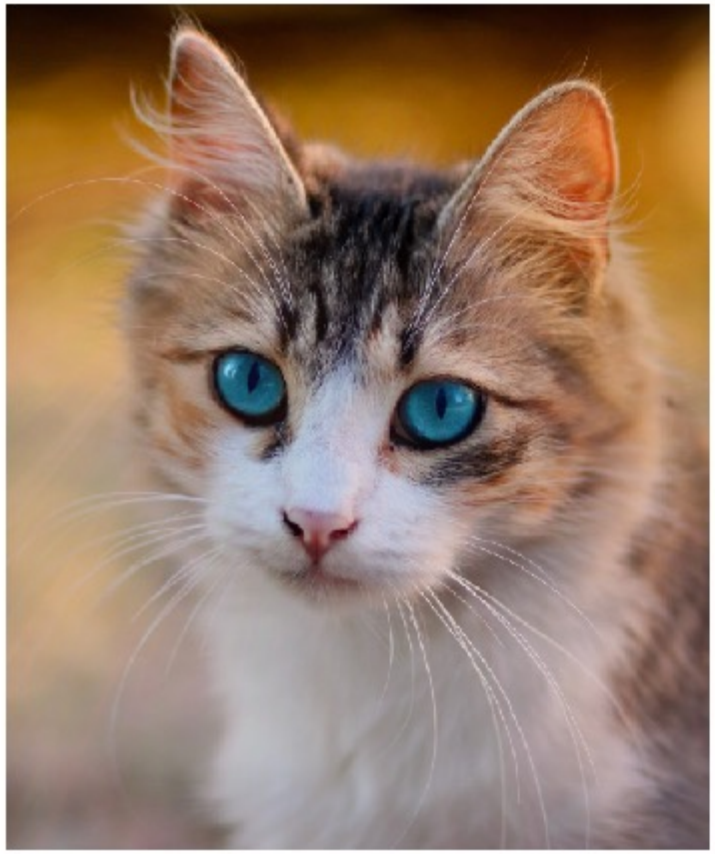
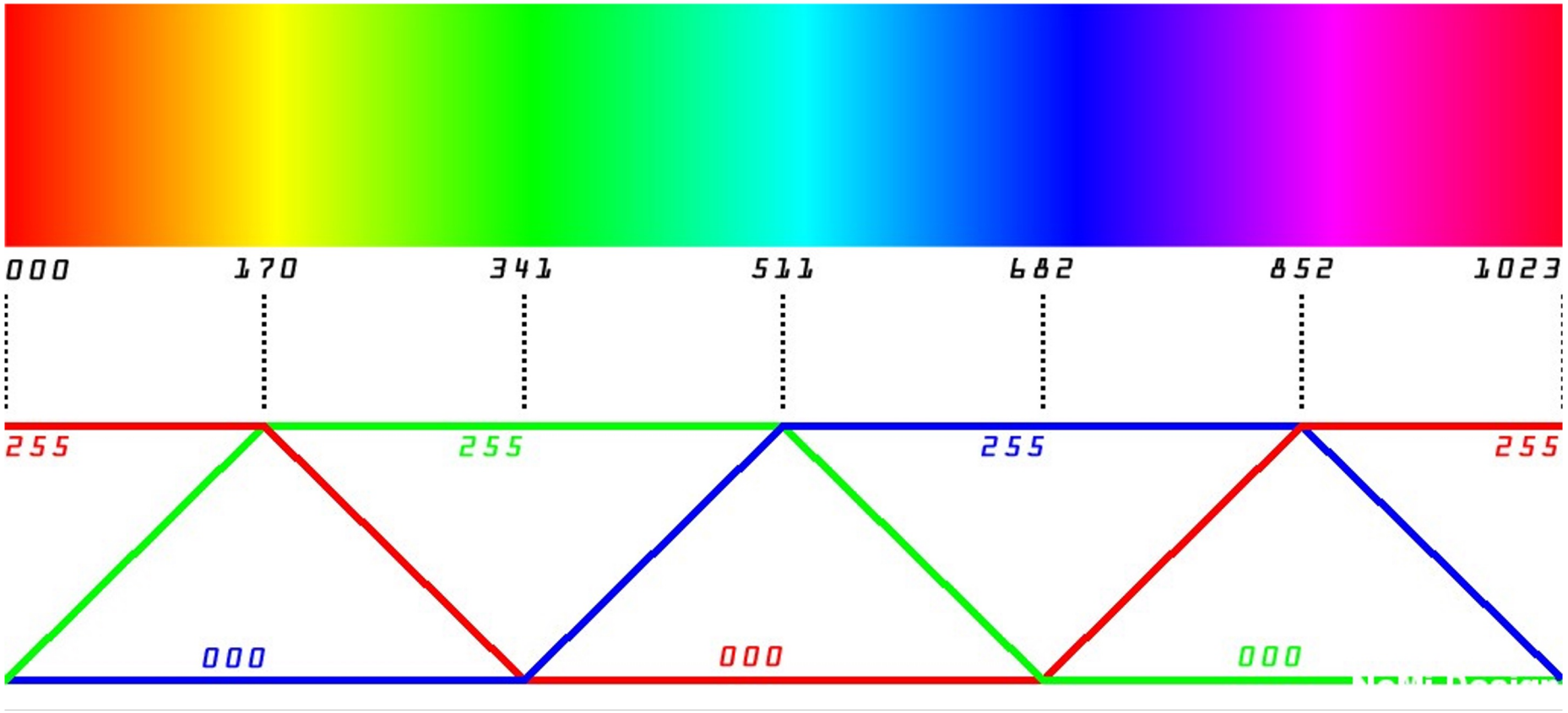
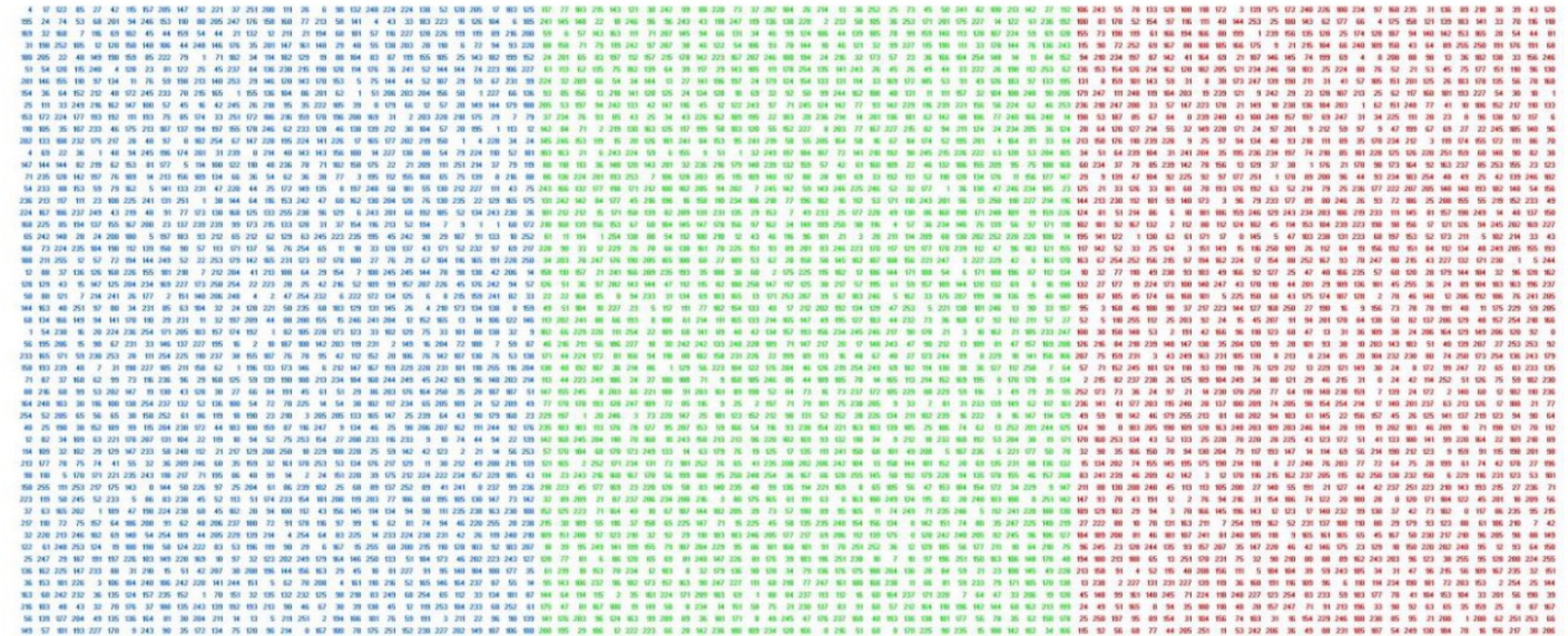


Image Basics



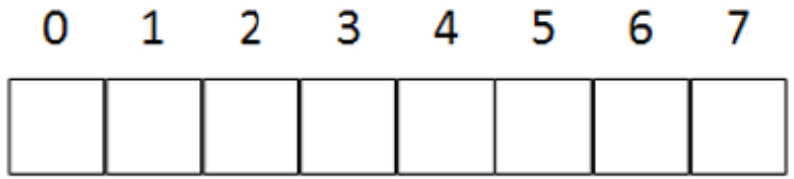
How do Computers ‘see’ Images?



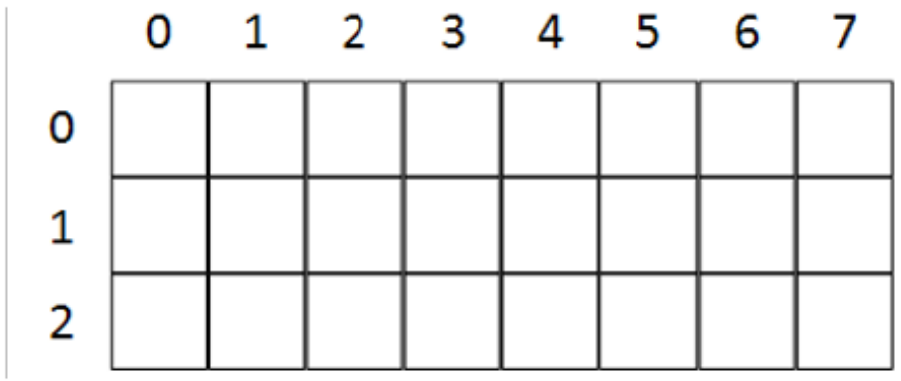
Digital Images Format

Images are stored in Multi-Dimensional Arrays

- A 1-Dimensional array looks like this



- A 2-Dimensional array looks like this



- A **3-Dimensional** array looks like this

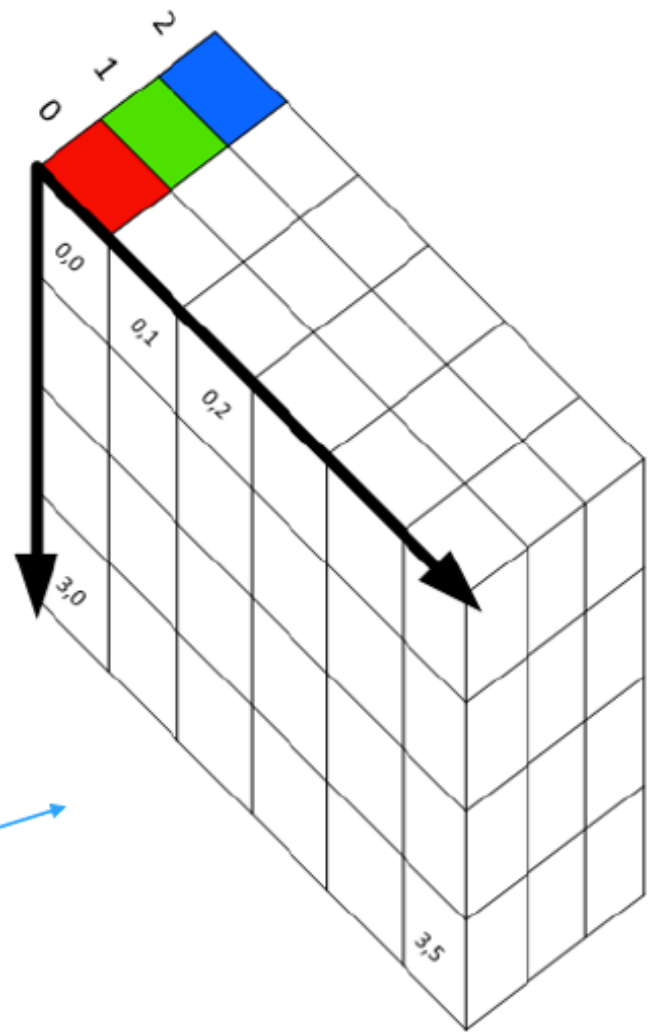


Image File Formats

Raster images

Pixel-based graphics
Resolution dependent
Photos & web graphics

JPG — Web & print photos and quick previews

GIF — Animation & transparency in limited colors

PNG — Transparency with millions of colors

TIFF — High quality print graphics and scans

RAW — Unprocessed data from digital cameras

PSD — Layered Adobe Photoshop design files

Vector images

Curve-based graphics
Resolution independent
Logos, icons, & type

PDF — Print files and web-based documents

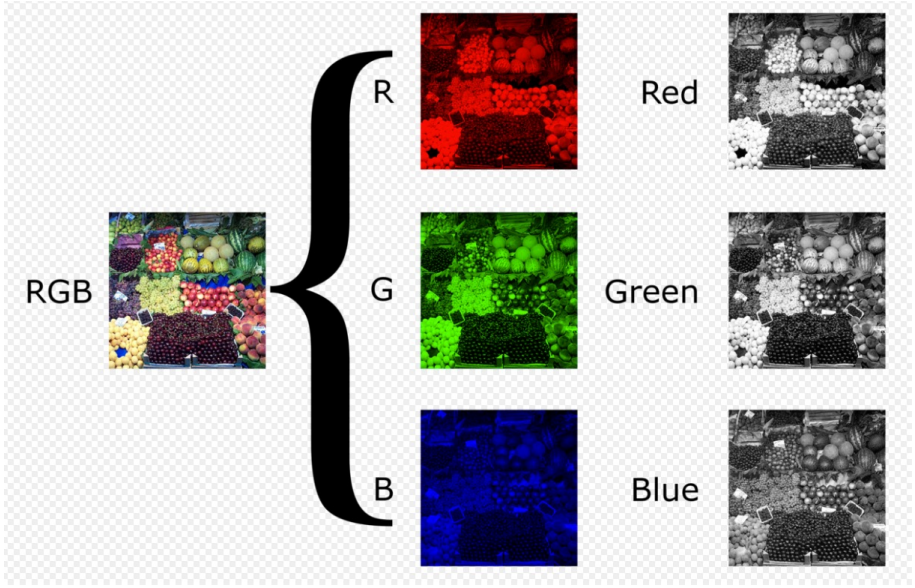
EPS — Individual vector design elements

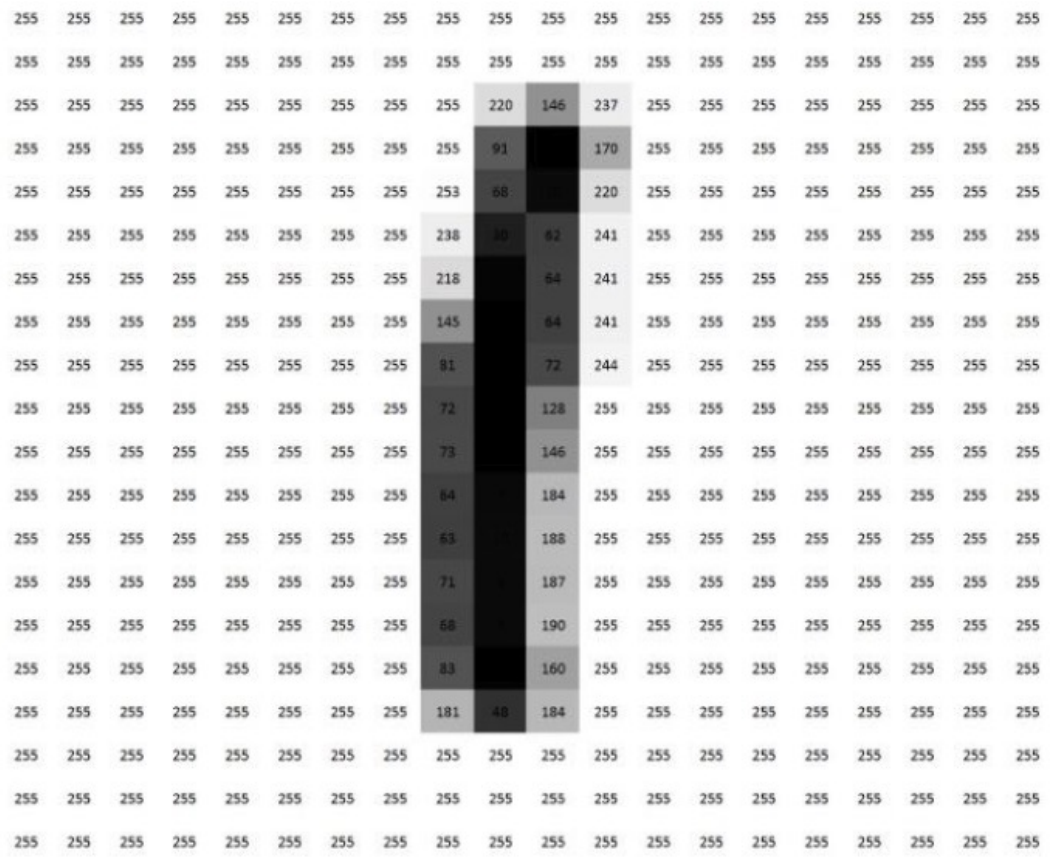
AI — Original Adobe Illustrator design files

SVG — Vector files for web publishing

Grayscale Image

Sometimes referred to as black and white image





Luma coding in video systems [edit]

Main article: luma (video)

For images in color spaces such as Y'UV and its relatives, which are used in standard color TV and video systems such as PAL, SECAM, and NTSC, a nonlinear luma component (Y') is calculated directly from gamma-compressed primary intensities as a weighted sum, which, although not a perfect representation of the colorimetric luminance, can be calculated more quickly without the gamma expansion and compression used in photometric/colorimetric calculations. In the Y'UV and Y'IQ models used by PAL and NTSC, the rec601 luma (Y') component is computed as

$$Y' = 0.299R' + 0.587G' + 0.114B'$$

where we use the prime to distinguish these nonlinear values from the sRGB nonlinear values (discussed above) which use a somewhat different gamma compression formula, and from the linear RGB components. The ITU-R BT.709 standard used for HDTV developed by the ATSC uses different color coefficients, computing the luma component as

$$Y' = 0.2126R' + 0.7152G' + 0.0722B'.$$

Although these are numerically the same coefficients used in sRGB above, the effect is different because here they are being applied directly to gamma-compressed values rather than to the linearized values. The ITU-R BT.2100 standard for HDR television uses yet different coefficients, computing the luma component as

$$Y' = 0.2627R' + 0.6780G' + 0.0593B'.$$

Images & Kernel Convolutions

Images & Kernel Convolutions

247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247
247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247
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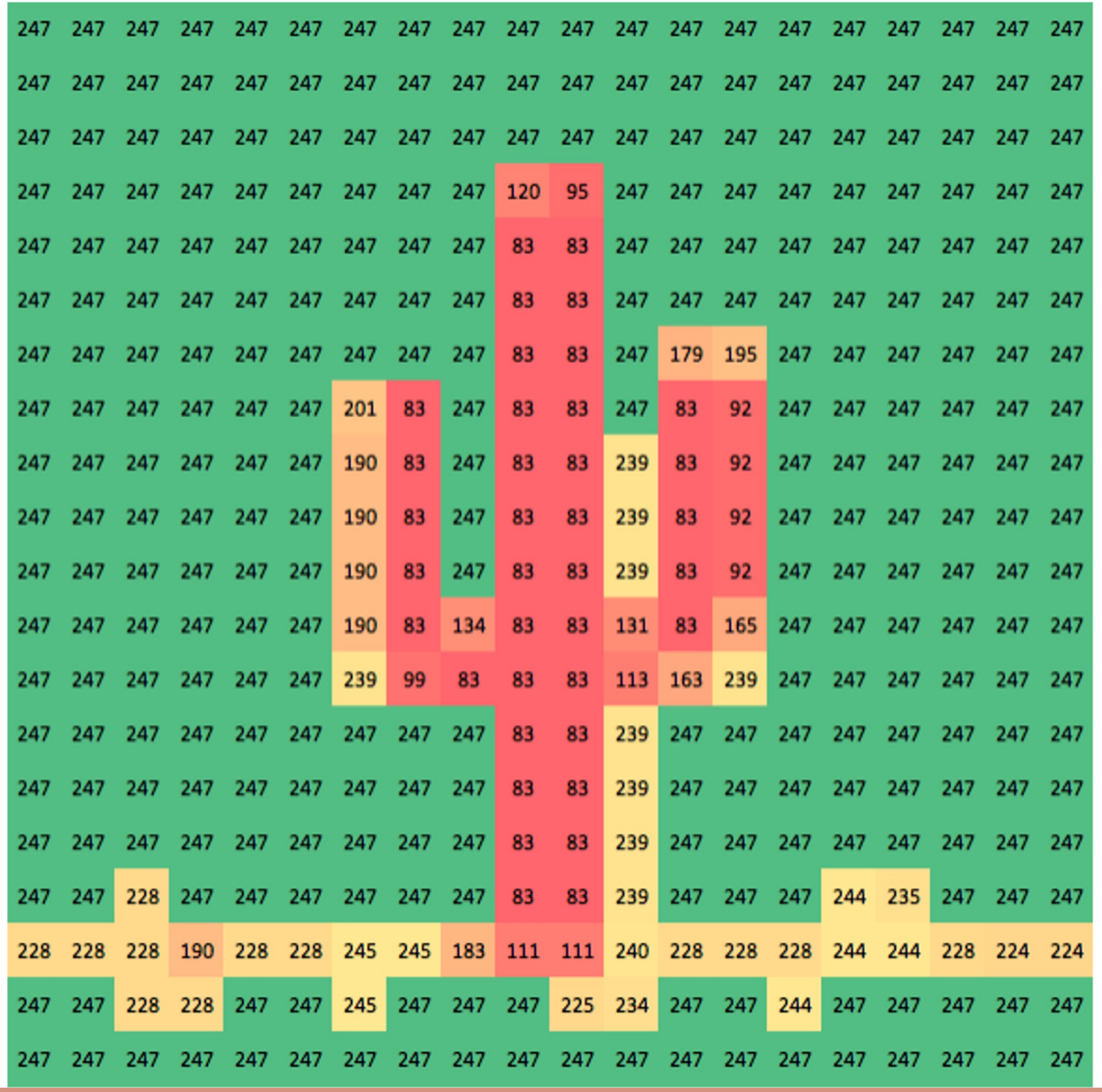
Images & Kernel Convolutions



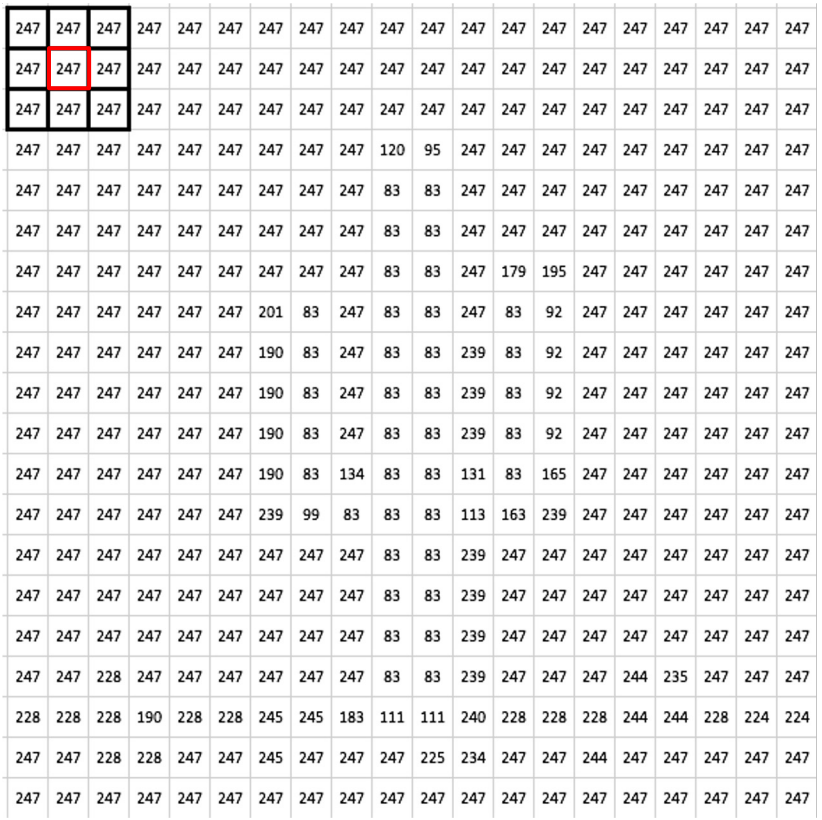
Kernel Convolutions

Kernel is an MxN matrix

3x3 Kernel Example

1	1	1
1	1	1
1	1	1

Kernel Convolutions



Window

247	247	247
247	247	247
247	247	247

x

Kernel

1	1	1
1	1	1
1	1	1

Sum = 9

=

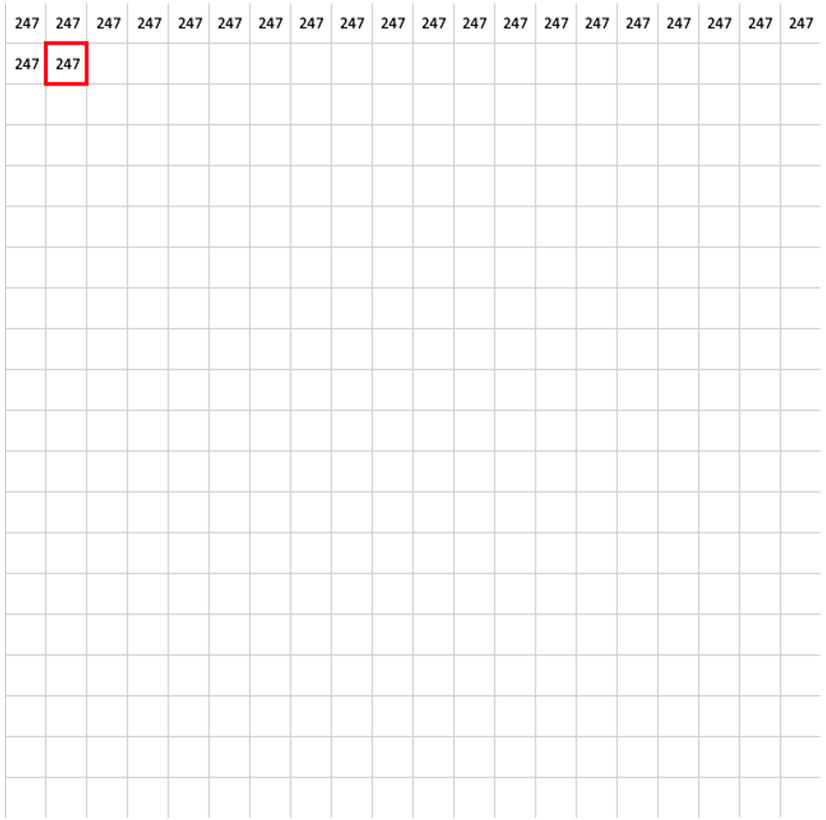
Multiplied

247	247	247
247	247	247
247	247	247

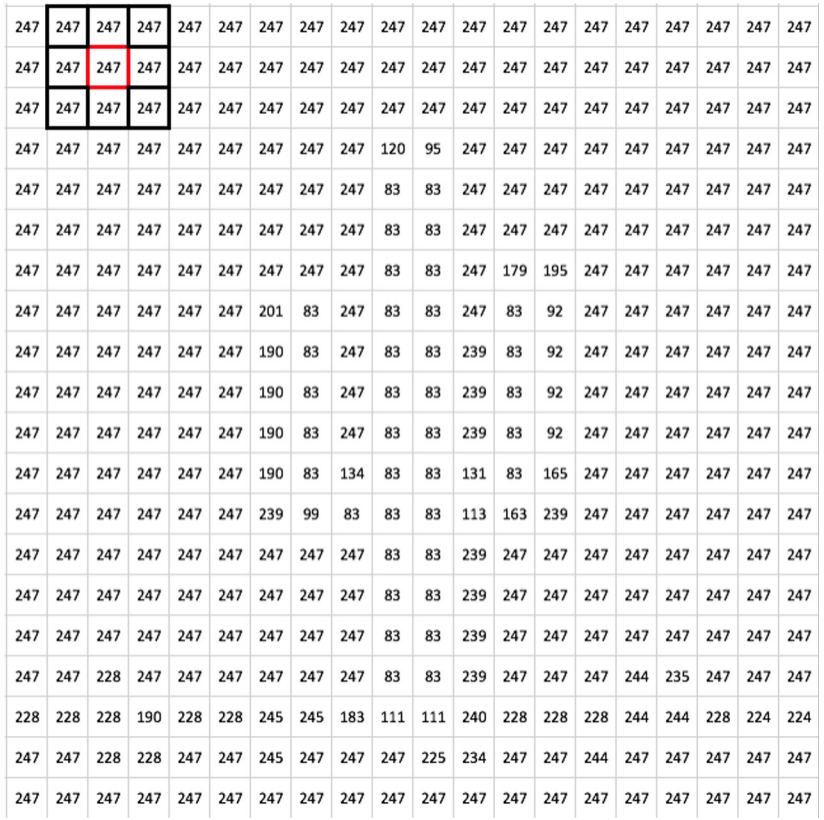
Sum = 2223

New Pixel Value

2223 / 9 = **247**



Kernel Convolutions



Window

247	247	247
247	247	247
247	247	247

x

Kernel

1	1	1
1	1	1
1	1	1

Sum = 9

=

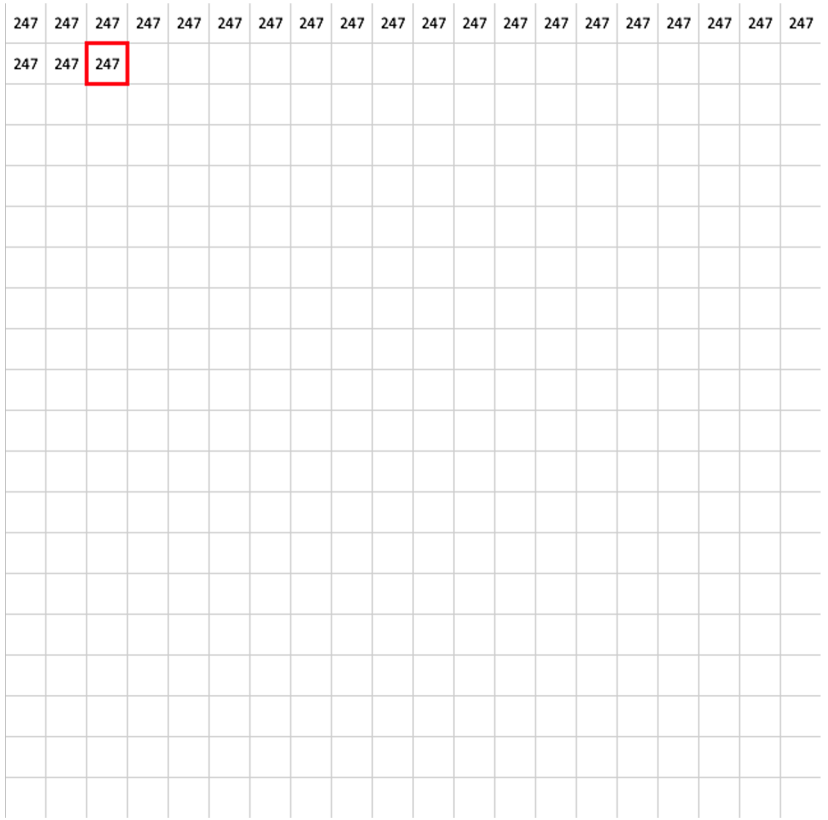
Multiplied

247	247	247
247	247	247
247	247	247

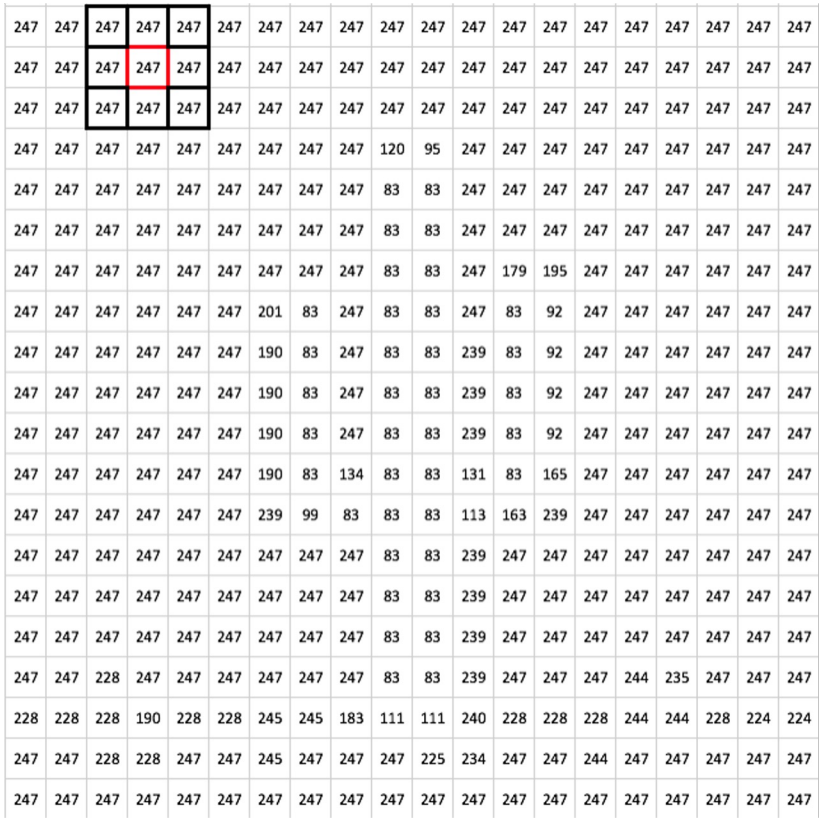
Sum = 2223

New Pixel Value

2223 / 9 = **247**



Kernel Convolutions



Window

247	247	247
247	247	247
247	247	247

x

Kernel

1	1	1
1	1	1
1	1	1

Sum = 9

=

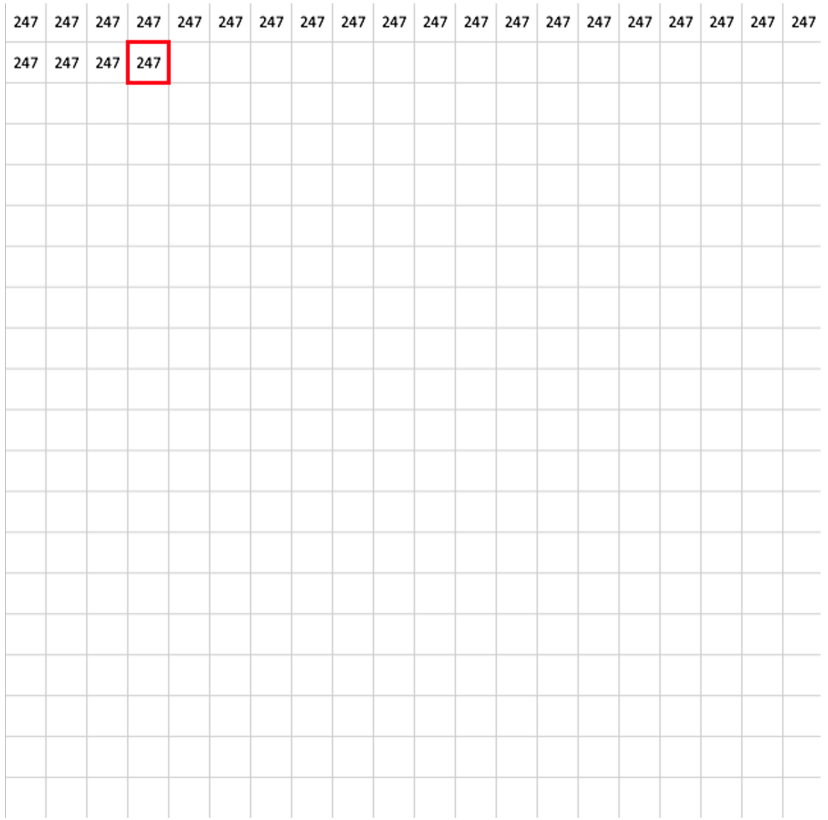
Multiplied

247	247	247
247	247	247
247	247	247

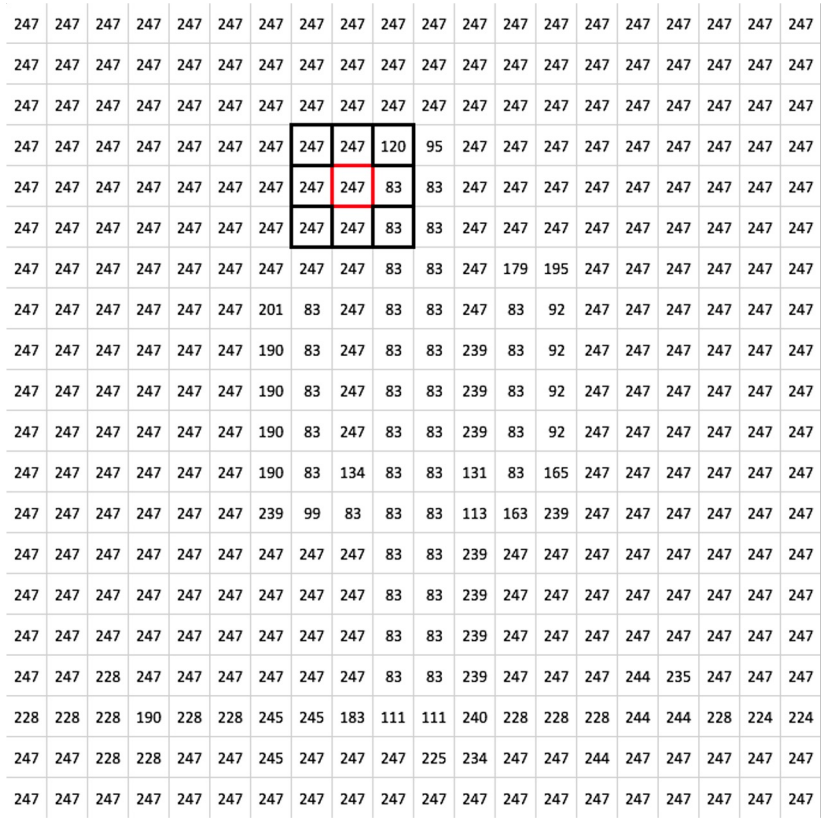
Sum = 2223

New Pixel Value

2223 / 9 = **247**



Kernel Convolutions



Window

247	247	120
247	247	83
247	247	83

x

Kernel

1	1	1
1	1	1
1	1	1

Sum = 9

=

Multiplied

247	247	120
247	247	83
247	247	83

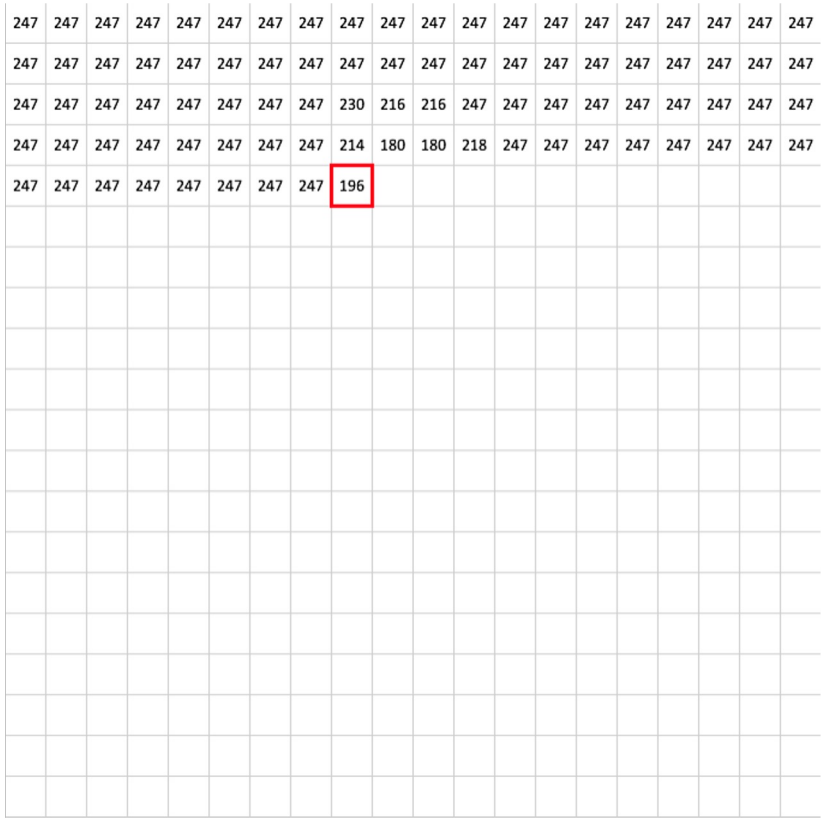
Sum = 1768

New Pixel Value

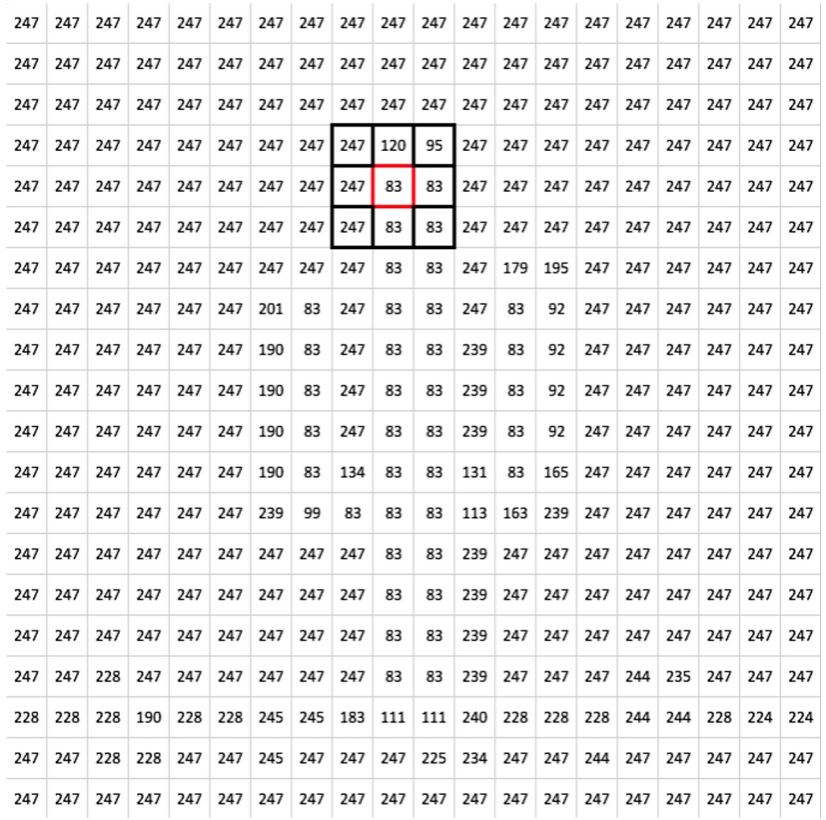
1768 / 9 =

196.4

196



Kernel Convolutions



Window

247	120	95
247	83	83
247	83	83

x

Kernel

1	1	1
1	1	1
1	1	1

Sum = 9

=

Multiplied

247	120	95
247	83	83
247	83	83

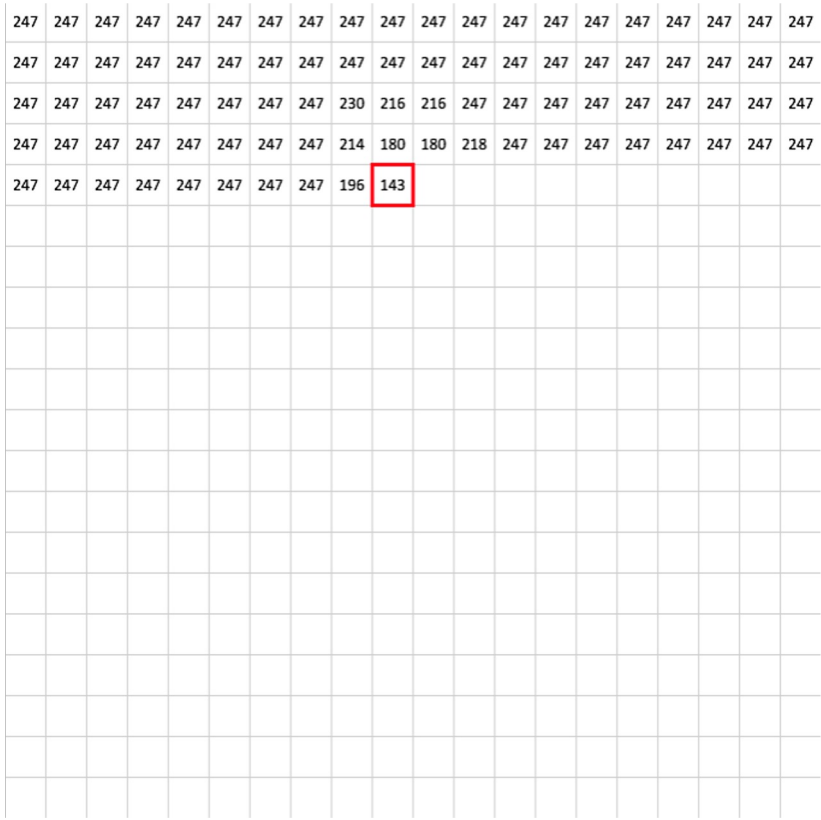
Sum = 1288

New Pixel Value

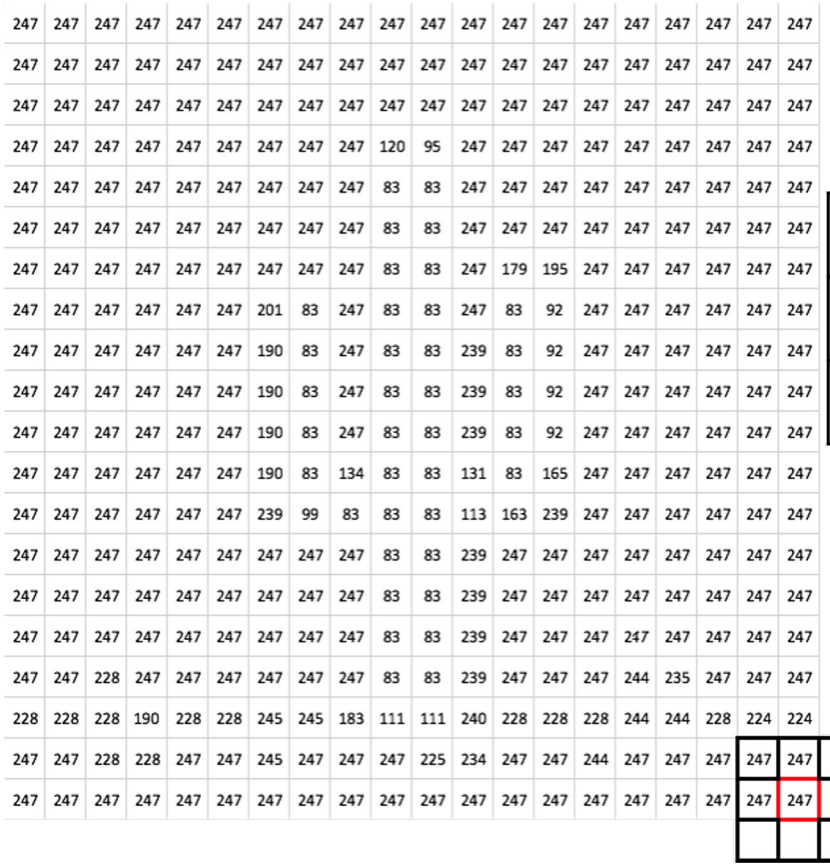
1288 / 9 =

143.1

143



Kernel Convolutions



Window

247	247	
247	247	

x

Kernel

1	1	
1	1	

Sum = 4

=

Multiplied

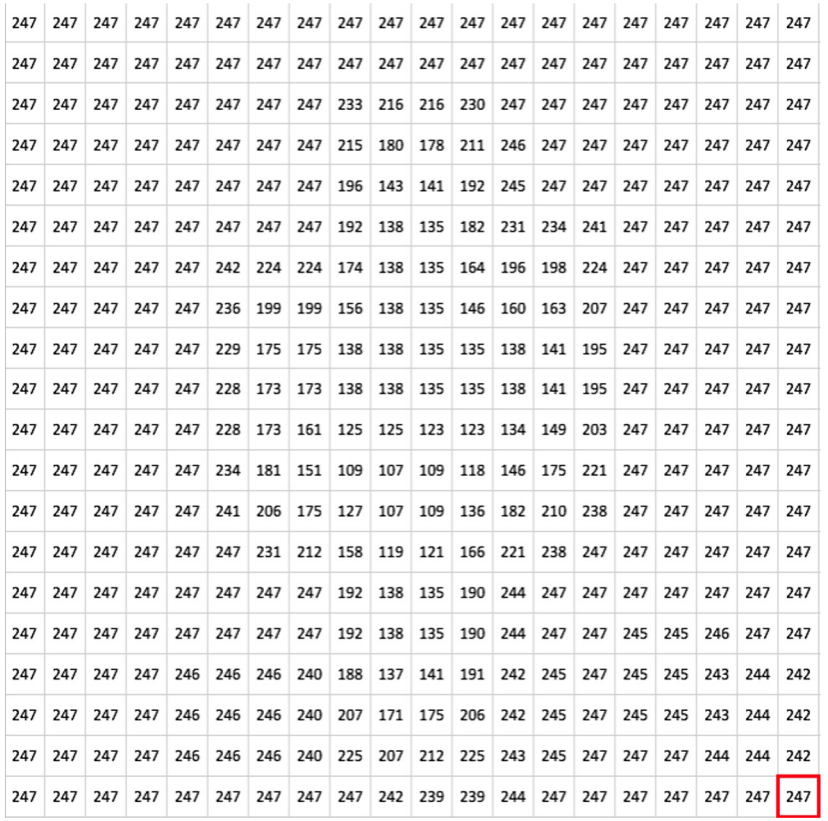
247	247	
247	247	

Sum = 988

New Pixel Value

998 / 4 = 247

247



Kernel Convolutions

247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247
247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247
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247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247

Kernel

1	1	1
1	1	1
1	1	1

247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247
247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247
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Kernel Convolutions

Mean Blur

247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247
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247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247

Kernel

1	1	1
1	1	1
1	1	1

247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247	247
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247	247	247	247	247	236	199	199	156	138	135	146	160	163	207	247	247	247	247	247
247	247	247	247	247	229	175	175	138	138	135	135	138	141	195	247	247	247	247	247
247	247	247	247	247	228	173	173	138	138	135	135	138	141	195	247	247	247	247	247
247	247	247	247	247	228	173	161	125	125	123	123	134	149	203	247	247	247	247	247
247	247	247	247	247	234	181	151	109	107	109	118	146	175	221	247	247	247	247	247
247	247	247	247	247	241	206	175	127	107	109	136	182	210	238	247	247	247	247	247
247	247	247	247	247	247	231	212	158	119	121	166	221	238	247	247	247	247	247	247
247	247	247	247	247	247	247	247	192	138	135	190	244	247	247	247	247	247	247	247
247	247	247	247	247	247	247	247	192	138	135	190	244	247	247	245	245	246	247	247
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247	247	247	247	246	246	246	240	207	171	175	206	242	245	247	245	245	243	244	242
247	247	247	247	246	246	246	240	225	207	212	225	243	245	247	247	247	244	244	242
247	247	247	247	247	247	247	247	247	242	239	239	244	247	247	247	247	247	247	247

Kernel Convolutions

Blur

Kernel

1	1	1
1	1	1
1	1	1

Kernel Convolutions

Sharpen

Kernel

0	-1	0
-1	5	-1
0	-1	0

Kernel Convolutions

Edge Highlight Kernel

0	1	0
1	-4	1
0	1	0

Kernel Convolutions

Emboss

Kernel

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

Kernel Convolutions

Horizontal "Derivative"

Kernel

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

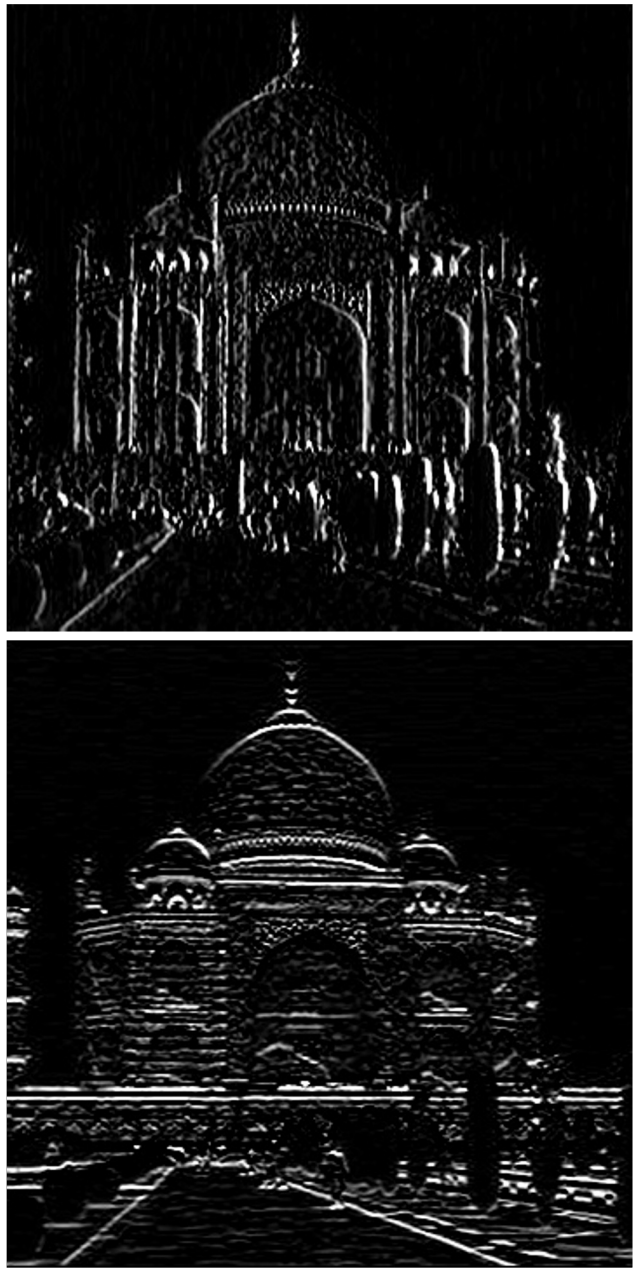
Kernel Convolutions

Vertical “Derivative”

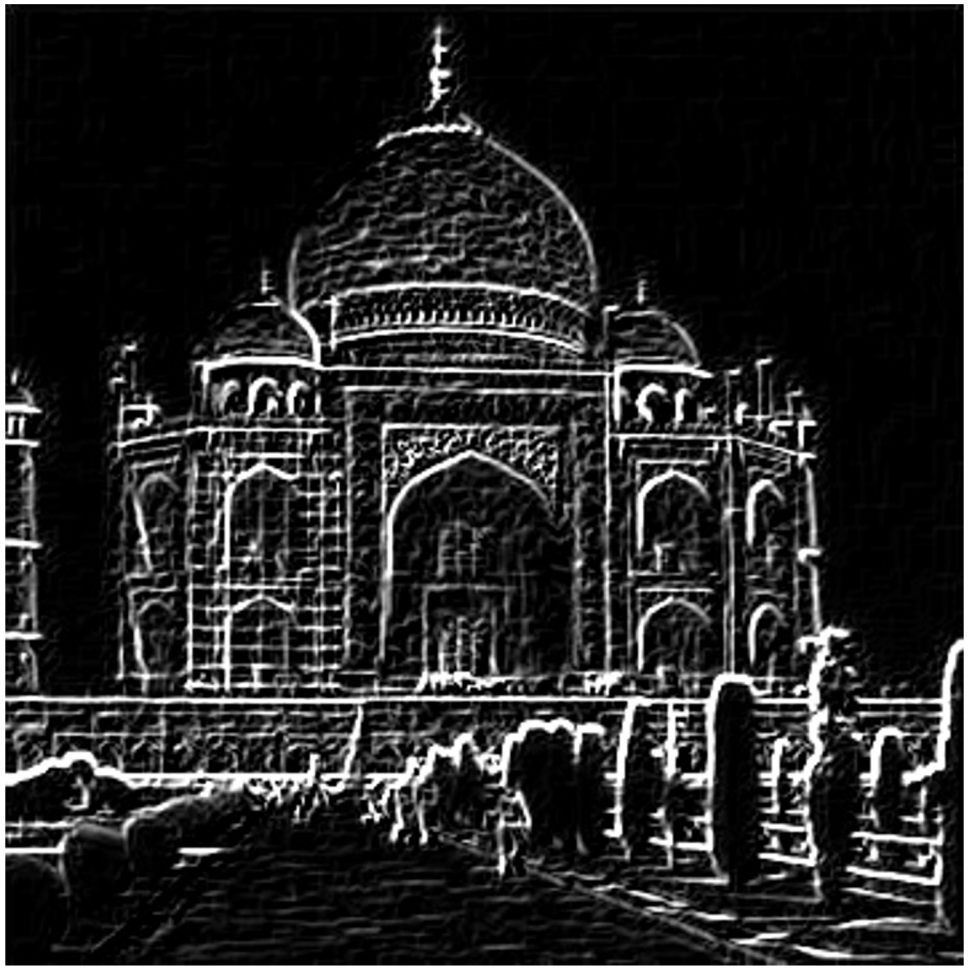
Kernel

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

Kernel Convolutions

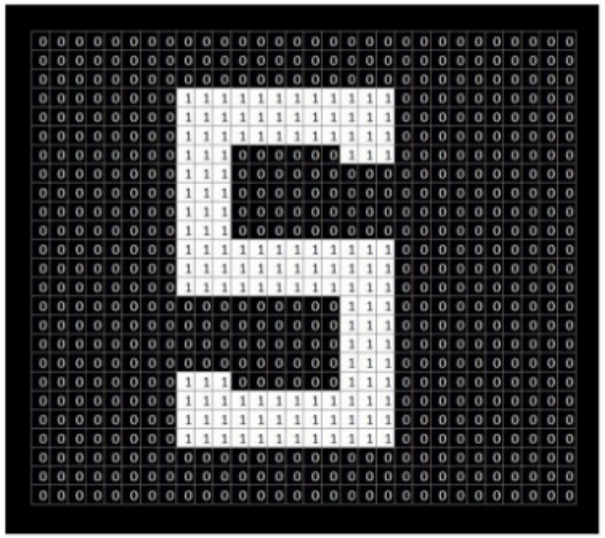


Overlay them to get **Sobel Operator**

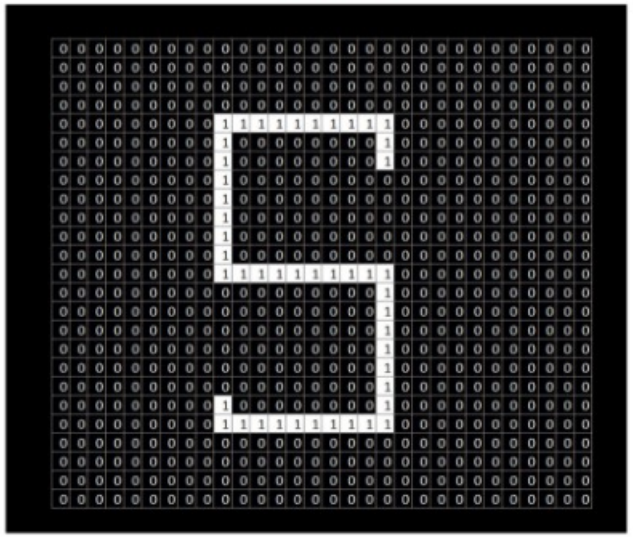


- **Dilation** – Adds pixels to the boundaries of objects in an image
- **Erosion** – Removes pixels at the boundaries of objects in an image
- **Opening** - Erosion followed by dilation
- **Closing** - Dilation followed by erosion

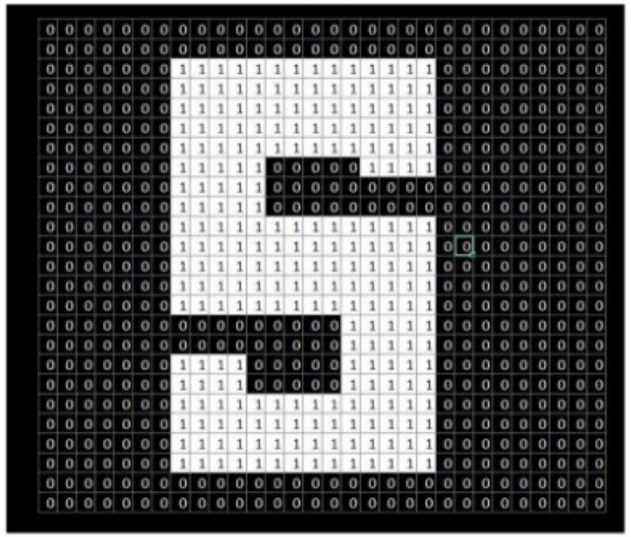
Original



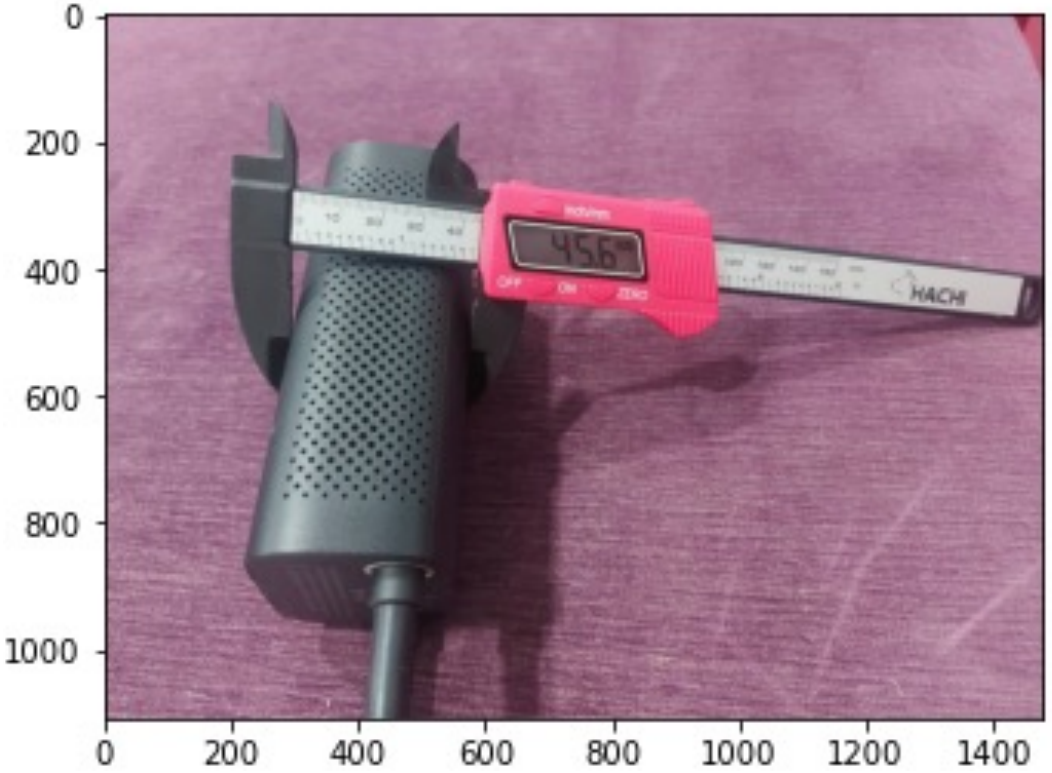
Erosion



Dilation



Home Works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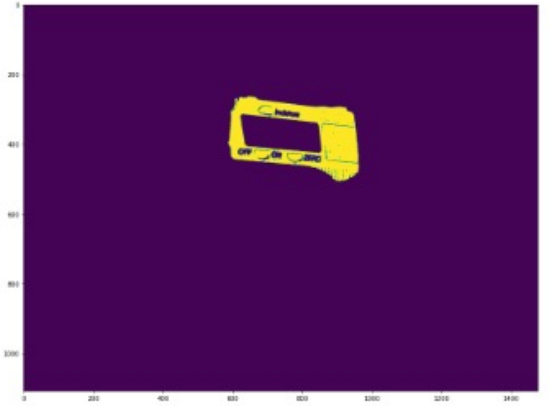
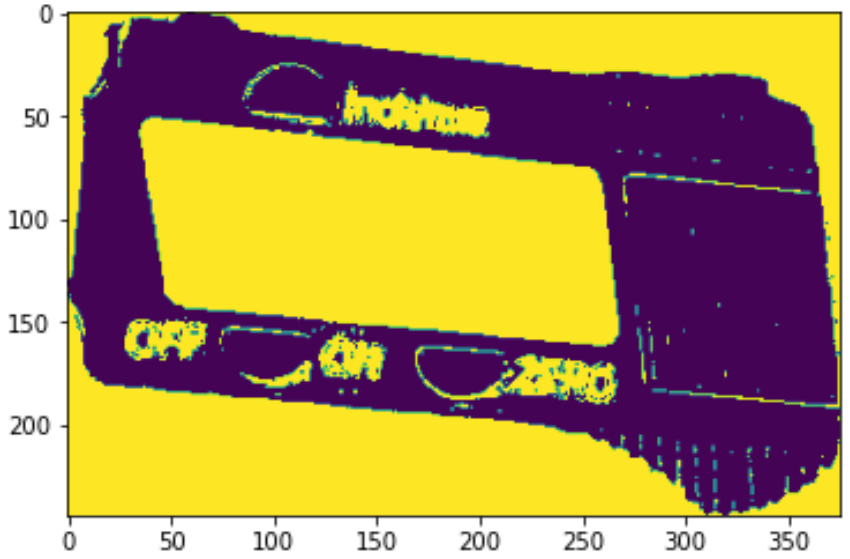
400
600
800
1000
1200
1400
456
HACHI


456
HACHI

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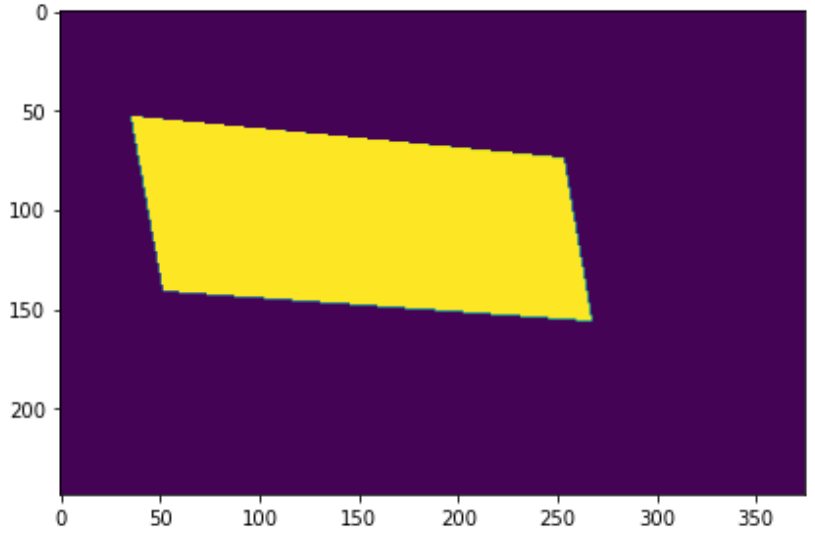
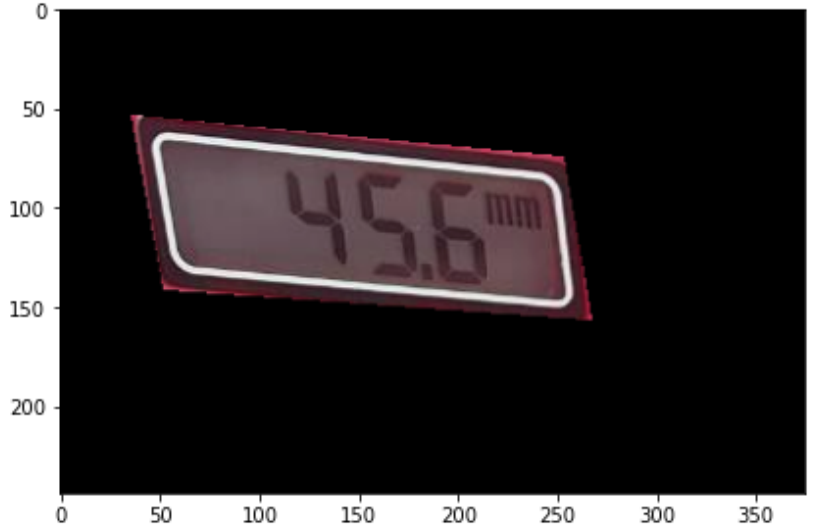
150
200
0
50
100
150
200
250
300
350






```
import easyocr
reader = easyocr.Reader(['en'])
```

```
bounds = reader.readtext(img5)
bounds
```

```
[([[48, 0], [166, 0], [166, 62], [48, 62]], '4561', 0.29313910007476807)]
```

```
bounds[0][1]
```

```
'4561'
```

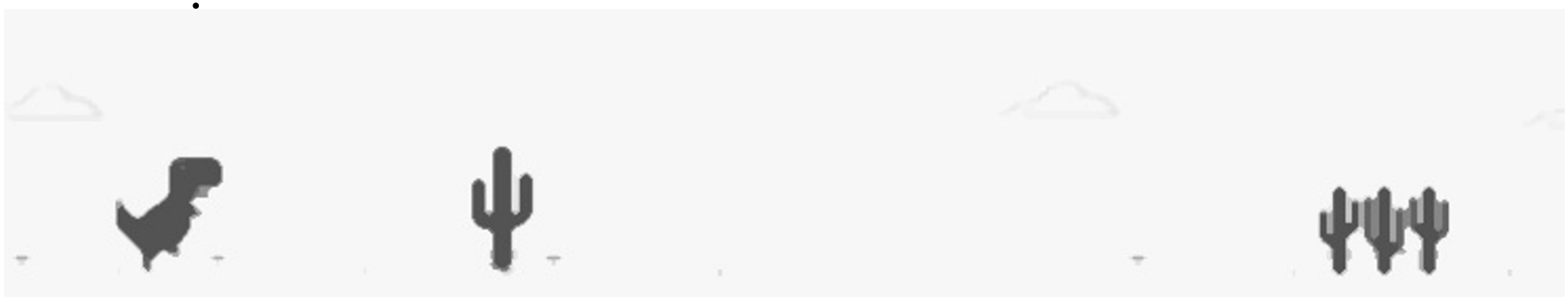
T-Rex Runner — The Plan

Step 1: Take a screenshot from

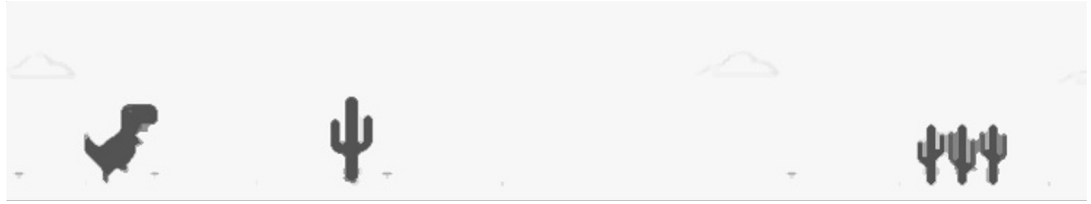
1.

T-Rex Runner — The Plan

Step 2: (preprocessing): Blur the image to get rid of



1. 

2. 

T-Rex Runner — The Plan

Step 3 (preprocessing): Threshold the image.

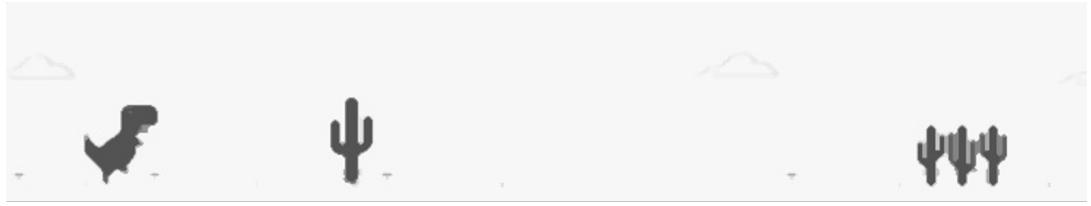
1. 
2. 
3. 

T-Rex Runner — The Plan

Step 4: Detect Contours using the thresholded

1.

2.



3.

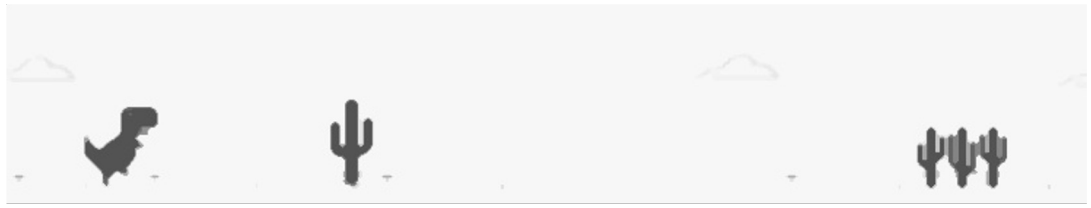
4.

T-Rex Runner — The Plan

Step 5: Filter contours by area and get bounding rectangle info

1.

2.



3.

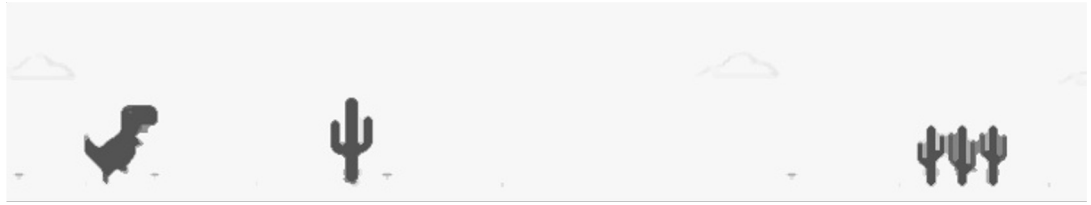
4.

5.

T-Rex Runner — The Plan

Step 6: Check if a detected object is close

1. 

2. 

3. 

4. 

5. 

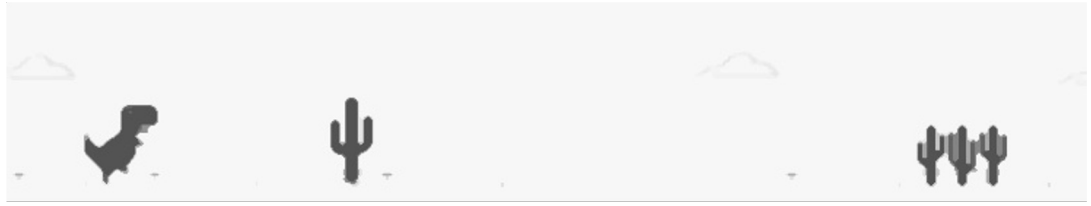
5. 

T-Rex Runner — The Plan

Step 6: If it's too close,

1.

2.



3.

4.

5.

5.

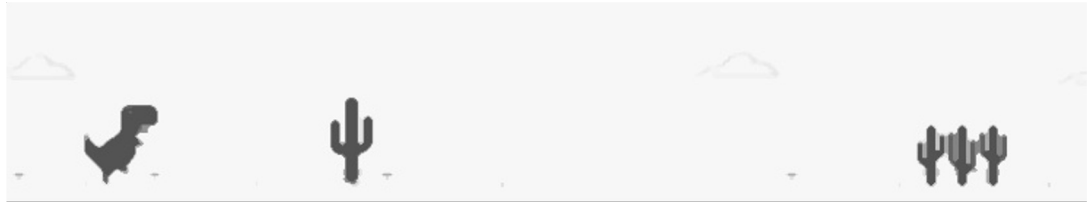
T-Rex Runner

Let’s learn the bits.

(demo and walkthroughs)

1.

2.



3.

4.

5.

5.