# Mastering Computer Vision with OpenCV in Python

Learn all core basics, do almost coding 50 exercises & completing 12 fun mini projects

**Computer Vision** is a cutting edge field of Computer Science that aims to **enable computers** to **understand** what is **being seen** in an **image**

# The Artificial Intelligence Dream

## Machines that can see and understand the world around them


*Source:* *Terminator 2: Judgement Day*

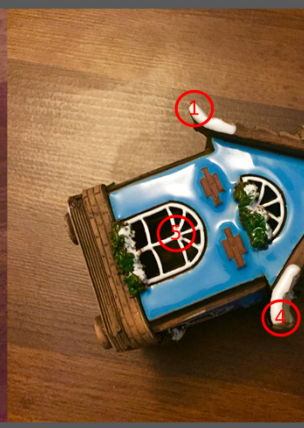
## However, Computer Vision is a Challenging!

# Why is it so hard? So Many Reasons!

## Camera sensor & lens limitations

# Why is it so hard? So Many Reasons!

## Viewpoint variations

# Why is it so hard? So Many Reasons!

## Changing Lighting

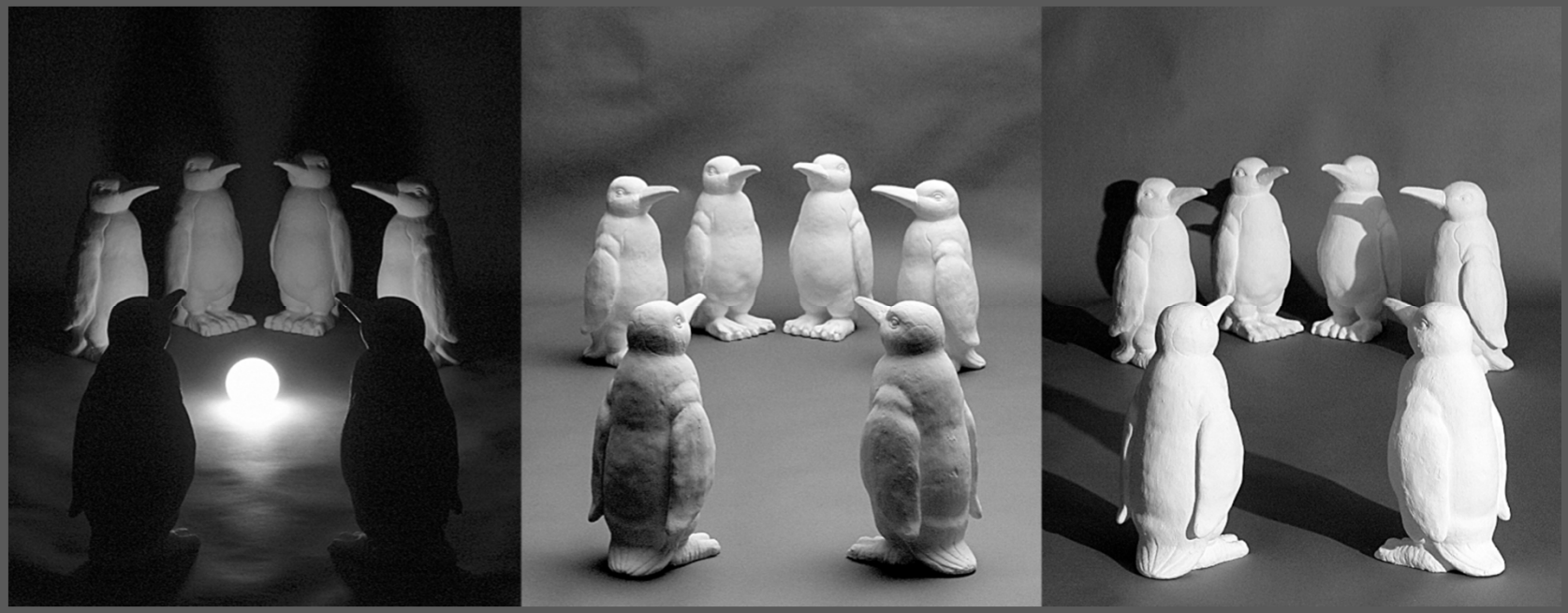


image credit: *J. Koenderink*

# Why is it so hard? So Many Reasons!

## Scaling

# Why is it so hard? So Many Reasons!

## Non-rigid deformations

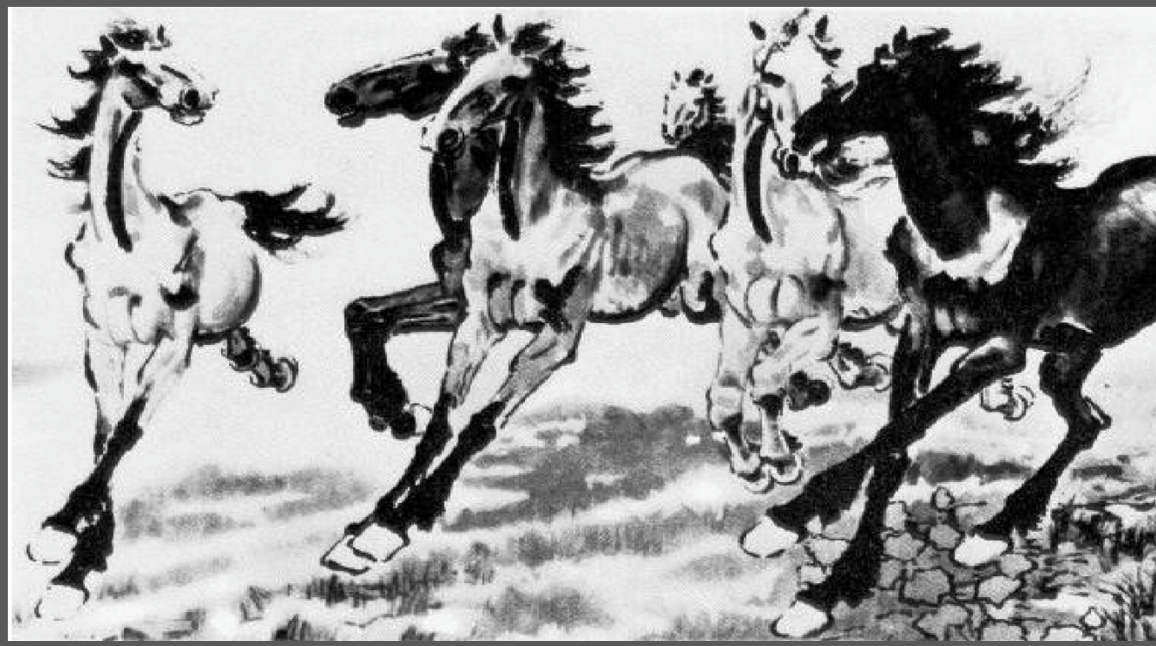


image credit: Xu, Beiho

# Why is it so hard? So Many Reasons!

## Occlusion

image credit: *Magritte, 1957*

# Why is it so hard? So Many Reasons!

## Clutter

# Why is it so hard? So Many Reasons!

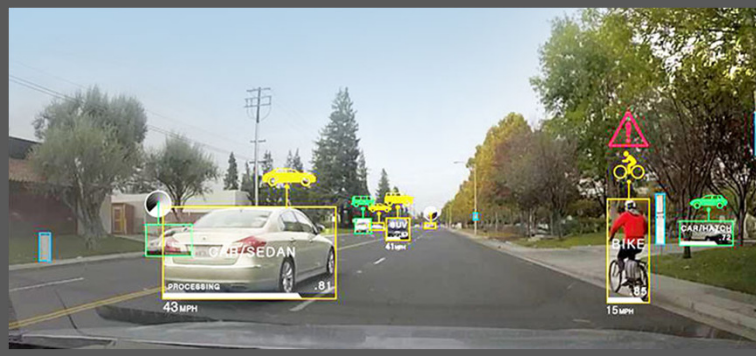
## Object class variations

# Why is it so hard? So Many Reasons!

## Ambiguous Images/Optical Illusions

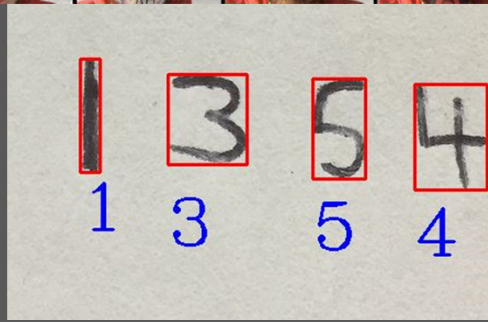
# Despite the difficulty, Computer Vision scientists have had many success stories!

Robotic Navigation – Self Driving Cars
Face Detection & Recognition
Search Engine Image Search
License Plate Reading
Handwriting Recognition
Snapchat & MSQRD Face Filters
Object Recognition
Ball & Player Tracking in Sports
And many more!



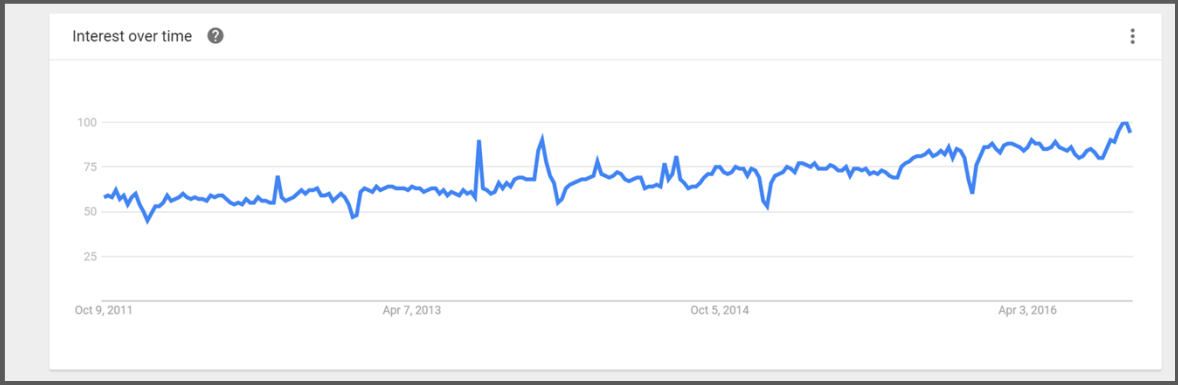






# So why OpenCV in Python?

Python is one of the easiest languages for beginners




It is extremely powerful for data science and machine learning applications

It stores images in numpy arrays which allows us to do some very powerful operations quite easily

# What You'll be Learning!

## Introduction to all key areas of Computer Vision Theory

- Course Introduction & Setup
- Basics of Computer Vision & OpenCV
- Image Manipulations
- Image Segmentation
- Object Detection
- Face, People & Car Detection
- Face Analysis and Filters
- Machine Learning in Computer Vision
- Motion Analysis & Object Tracking
- Bonus - Computational Photography
- Course Summary
  - Become an expert!
  - Explore latest research
  - Startup Ideas

## Coding along with almost 50 exercises

## Develop 12 Fun Mini Projects!

# How this course is taught?

More than half your time will be spent coding

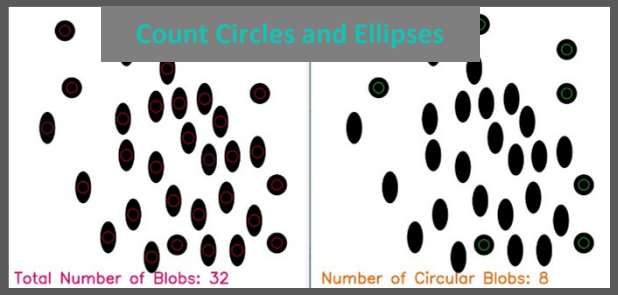
Overview of the theory first then we code

Almost all code is explained line by line

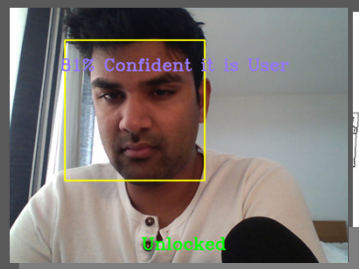
# 12 Amazing Mini Projects

# What are these Mini Projects?

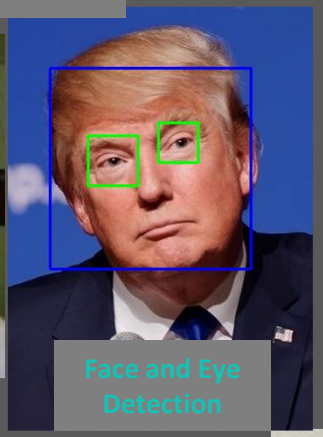
- Making a Live Drawing Sketch of yourself
- Shape Matching
- Counting Circles and Ellipses
- Finding Waldo
- Object Identification
- Face, Pedestrian & Car Detection
- Live Face Swaps - Become Donald Trump or Kim Kardashian (just like MSQRD & Snapchat)
- Face Reader - Detect and count yawns
- Handwritten Digit Recognition
- Facial Recognition
- Ball Tracking
- Photo Restoration

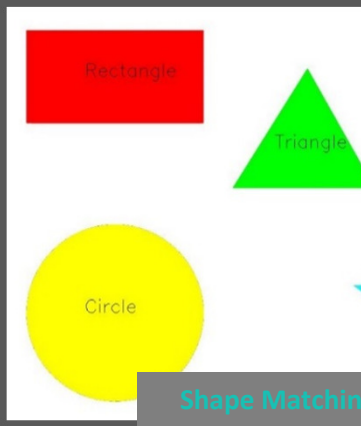




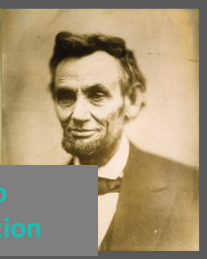




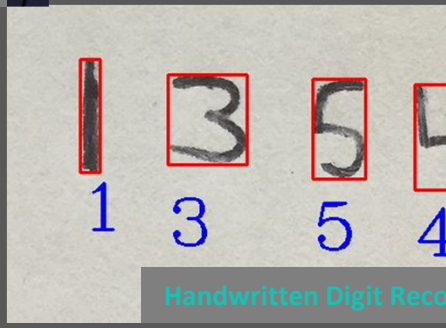








# Requirements?

Basic programming is useful, but not needed I'll walk you through most of the code. Exposure to Numpy would be helpful.

High School Level Math

A Webcam

Python 2.7 or 3.6

- Anaconda Package is preferred but not required. I use Python 2.7, but all code works in 3.6
- I use Python Notebooks which are excellent for teaching

OpenCV 2.14.6 & or 3.4.X

- Ideally we'd like to use the latest version OpenCV 3.4.6, however it is u missing some important functions (SIFT, SURF etc.) that are included in 2.4.16. There are ways around it however, so don't despair.

# Who is this course for?

Beginners interest in Computer Vision

Software developers & engineers looking strengthen their skills for job promo

College/University students looking to get a head start in computer vision projects and research are ideal.

Startup founders who wish to utilize computer vision

Hobbyist who want to build a fun computer vision project. E.g. Raspberry Pi projects.

# Let’s being our exciting journey into The world of Computer Vision using OpenCV in Python!

# Python & OpenCV Windows Installation

TEP 1 – Download & Install Anaconda Python Package

Go to: https://www.anaconda.com/download

Select appropriate version - either Python 2.7 or 3.6

To Test – Go to windows command prompt and type:

- `jupyter notebook`

TEP 2 – Download and Run OpenCV

Go to: https://opencv.org/releases.html

Download either OpenCV 2.4.16 or 3.4.3

- NOTE: A small number of sections in this course require 2.4.16 and some require 3.4.X
- ~~You can download both and switch them easily~~ No longer the case. Choose OpenCV 2.4.16 as most parts of this course are compatible with that version.

NOTE: This works for only Python 2.7 (Python 3.6 on next slide)

# Python & OpenCV Installation

TEP 3

Find your cv2.py file

Your CV2 file should be found here - C:\opencv\build\python\2.7\x64

TEP 4

Copy this cv2.py file and place it in the following directory (main directory will be where your python.exe is located):

- C:\Users\Anaconda2\Lib\site-packages

**And that's it, you're ready to get started!**

# Python 3.6 Installation

## Python & OpenCV Installation

TEP 3

Open command prompt and type:

- pip install opencv-python

**And that’s it, you’re ready to get started!**

# Section 2

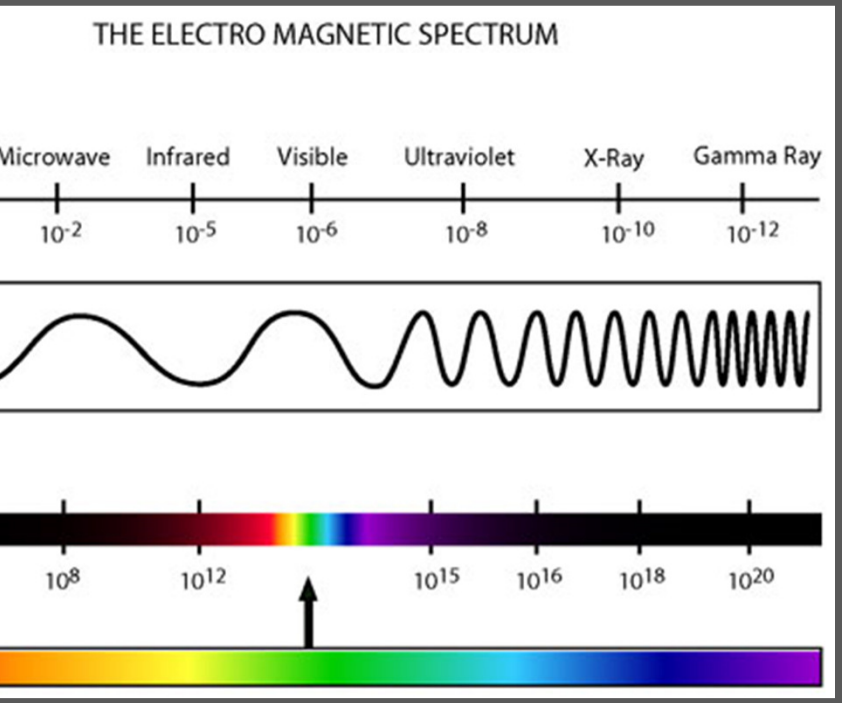
# asics of Computer Vision & OpenC

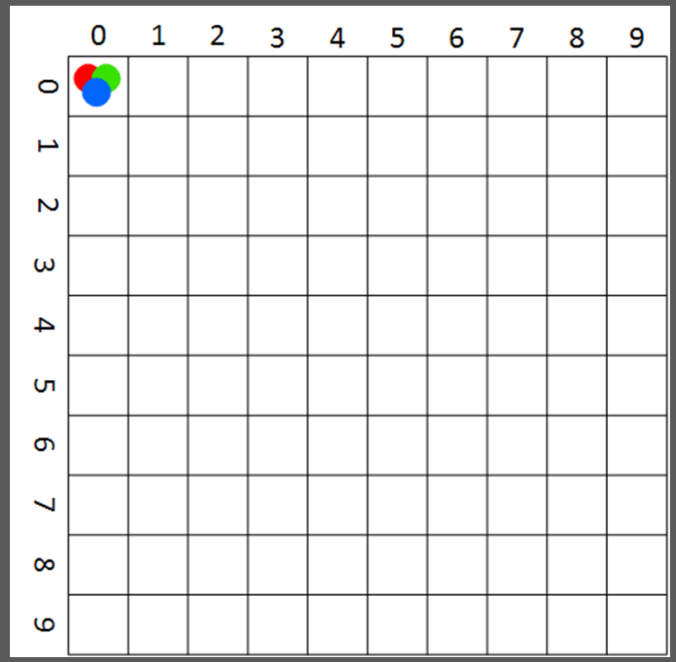
# Basics of Computer Vision & OpenCV

1. What are Images?
2. Image Formation
3. Storing images on computers
4. Getting Started with OpenCV: reading, writing and displaying images
5. Gray scaling
6. Color Spaces
7. Histograms
8. Drawing images

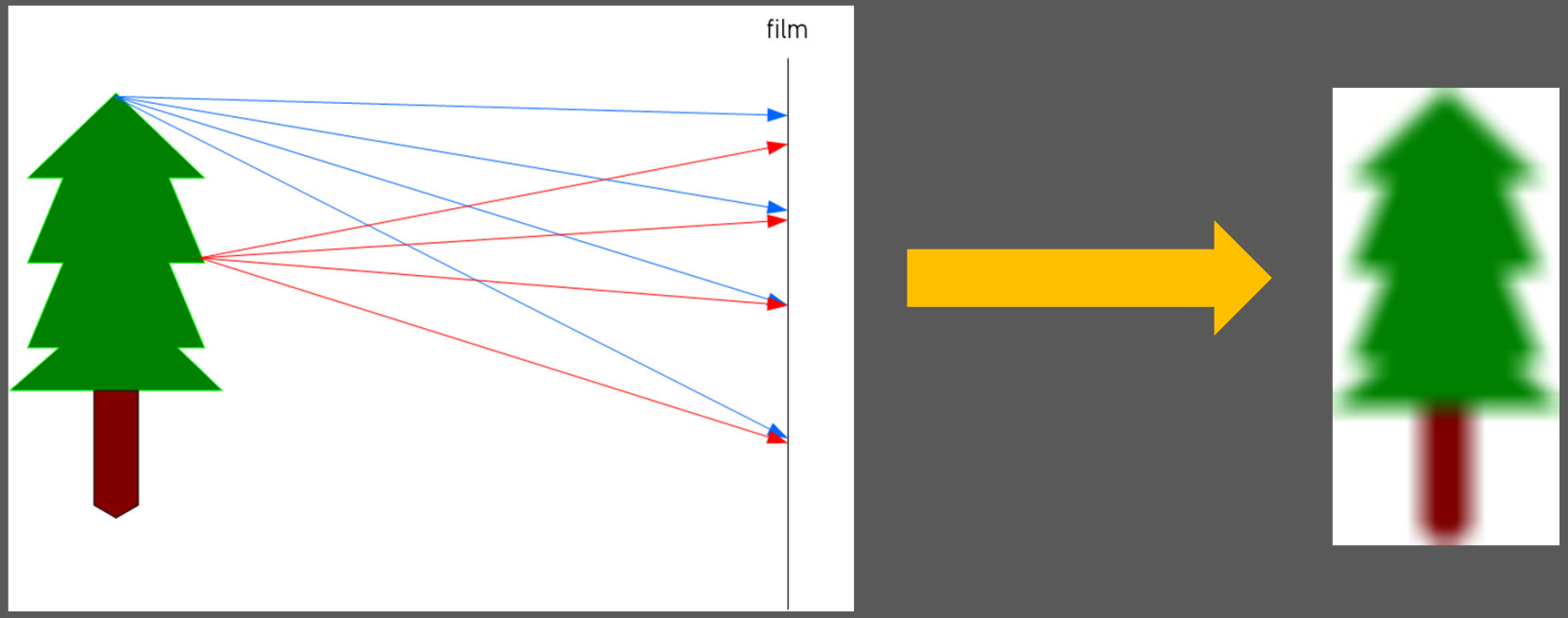
# What are Images?

2-Dimensional representation of the visible light spectrum



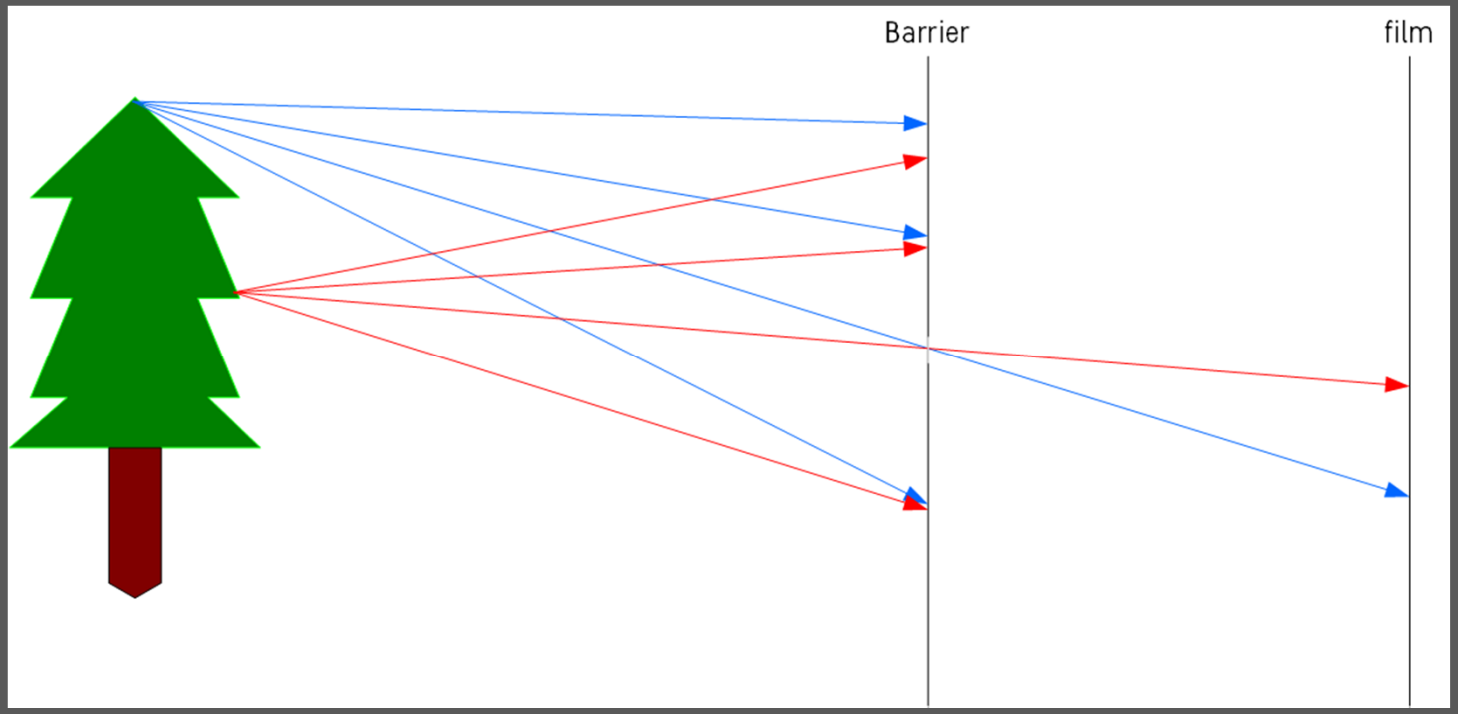




# How are images formed




- When light reflects off an object onto a film, sensor or retina
- In the above example the image here will be blurred

# Image Formation

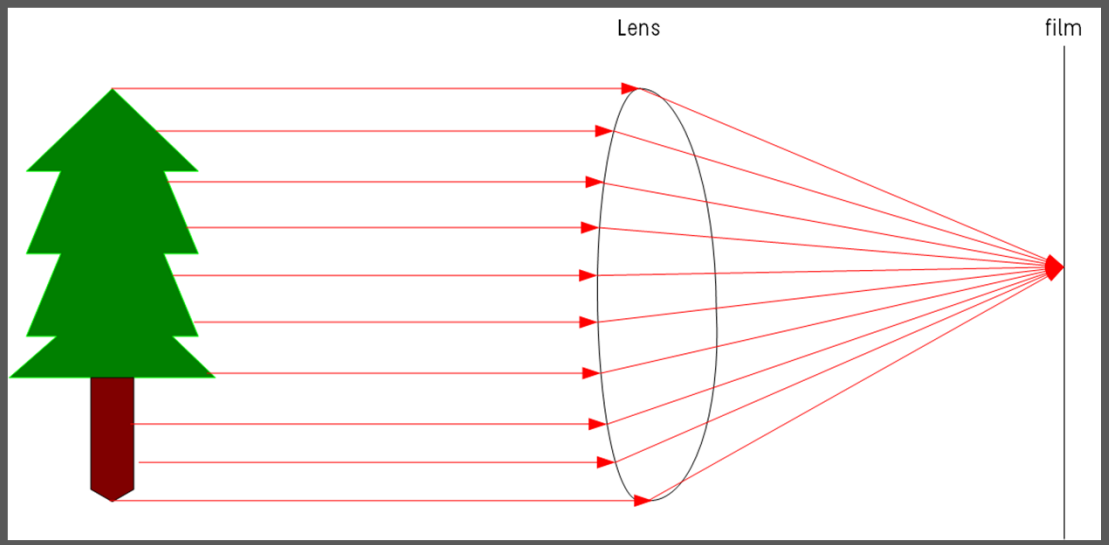



- Using a small opening in the barrier (called aperture), we block off most of the rays of light reducing blurring on the film or sensor
- This is the pinhole camera model

# Controlling Image Formation with a Lens

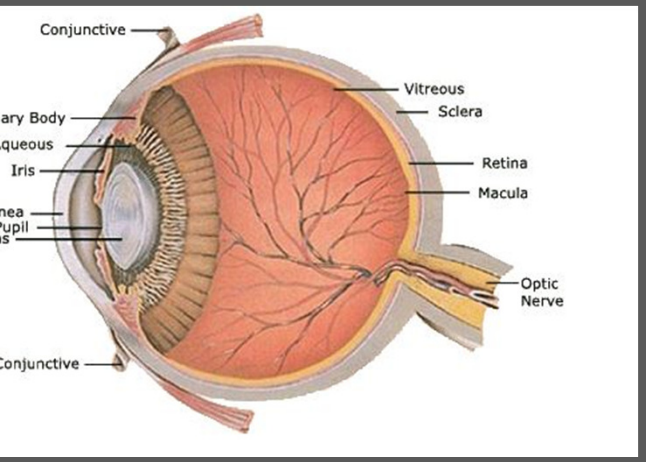
Both our eyes and cameras use an adaptive lens to control many aspects of image formation such as:

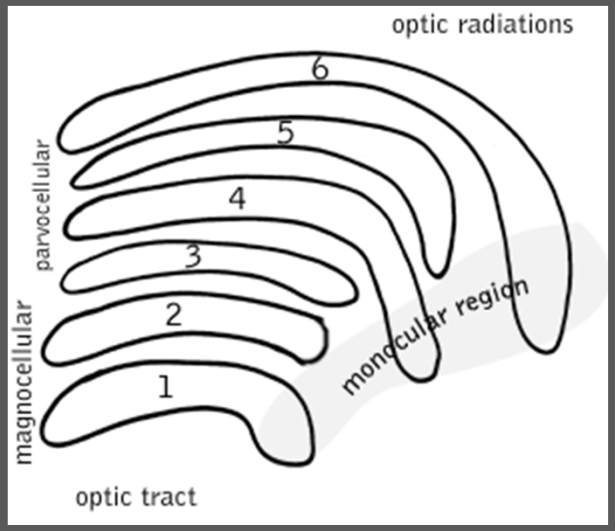
- Aperture Size
  - Controls the amount of light allowed through (f-stops in cameras)
  - Depth of Field (Bokeh)
- Lens width - Adjusts focus distance (near or far)

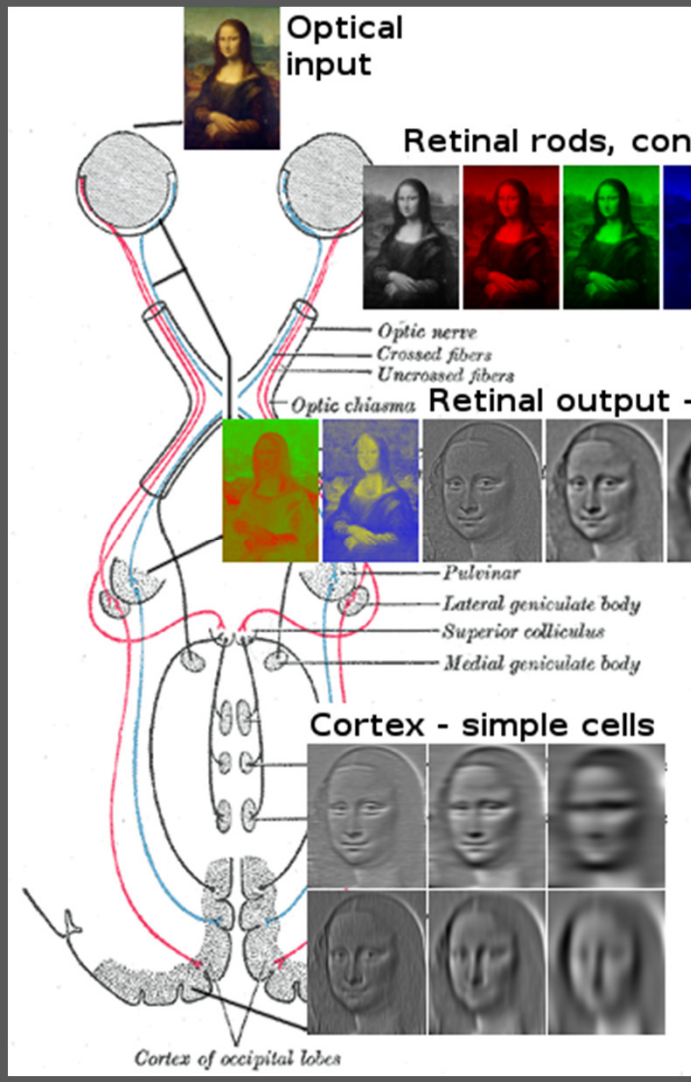


# How Humans See

The human visual system (eye & visual cortex) is incredibly good at image processing



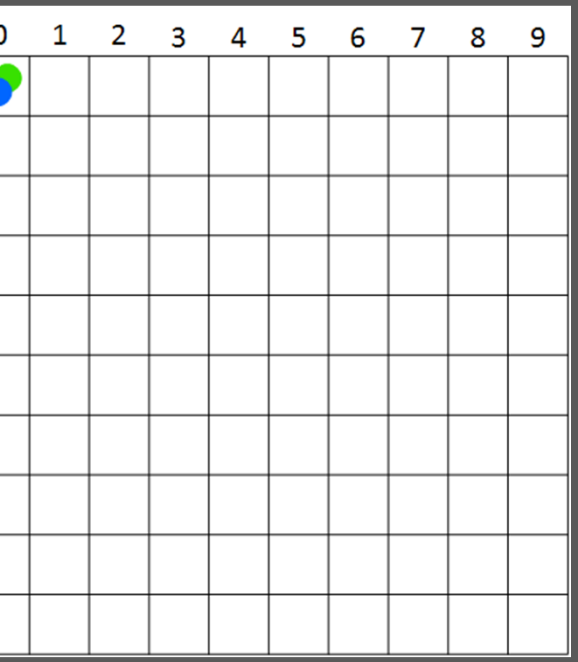




eck out - https://en.wikipedia.org/wiki/Visual_system

# How do Computers store images?

OpenCV uses RBG color space by default.

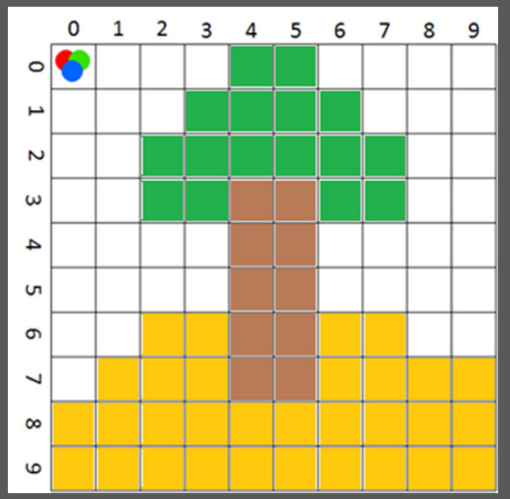



Each pixel coordinate (x, y) contains 3 values ranging for intensities of 0 to 255 (8-bit).

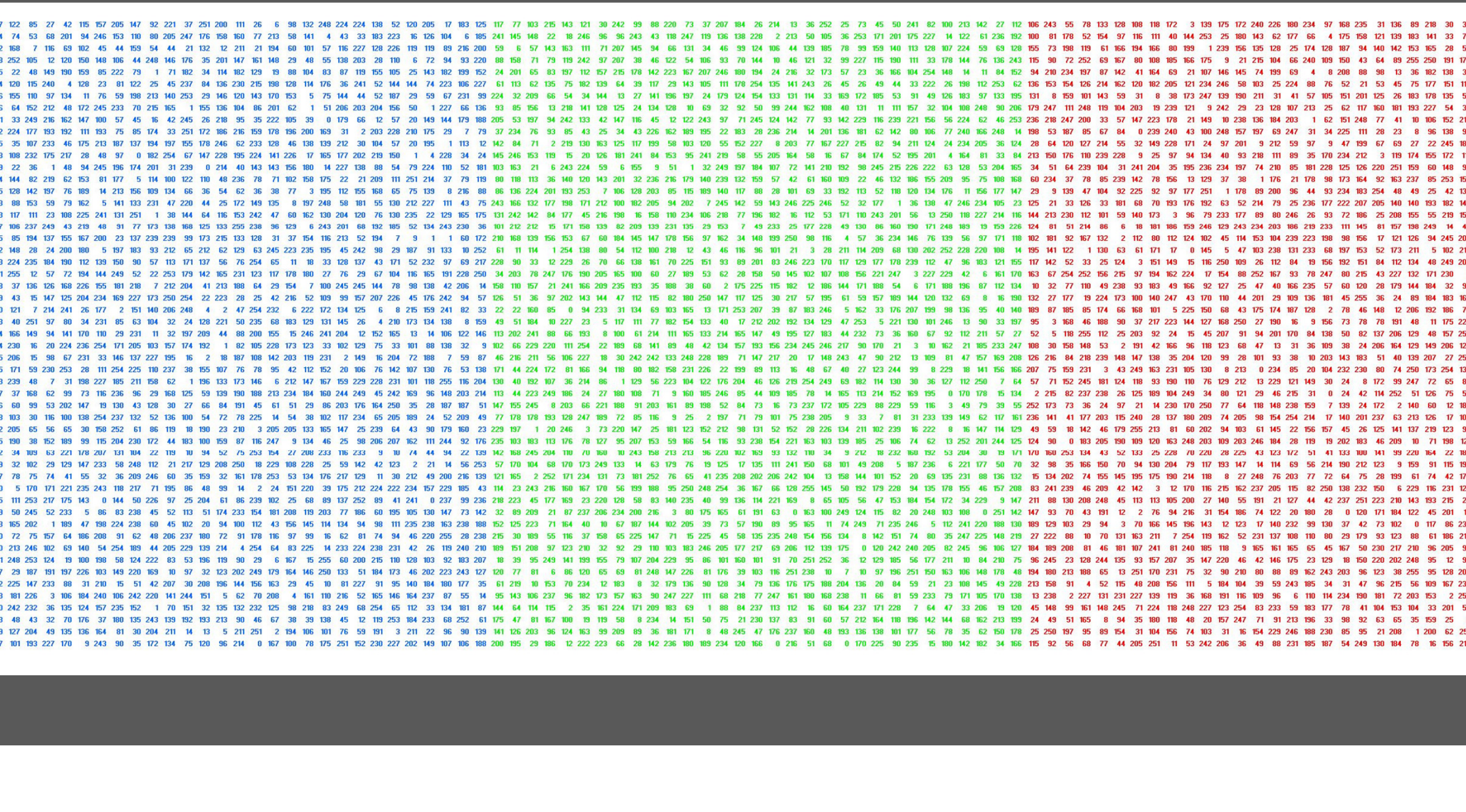
- Red
- Green
- Blue

Mixing different intensities of each color gives us the full color spectrum, example Yellow:

- Red – 255
- Green – 255
- Blue - 0

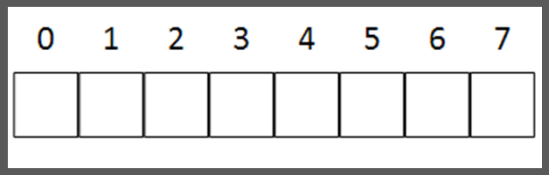



# How does it look when stored on a computer?

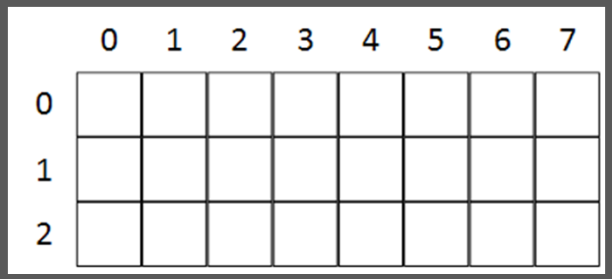


# Images are stored in multi-dimensional arrays

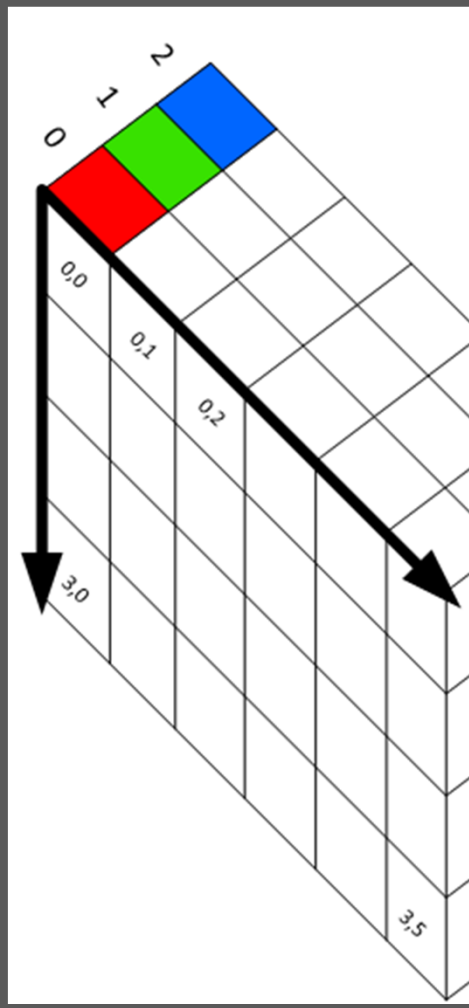
Think of an array as table. A 1-dimensional arrays looks like this:




- A 2-dimensional array looks like this:




3-dimensional array

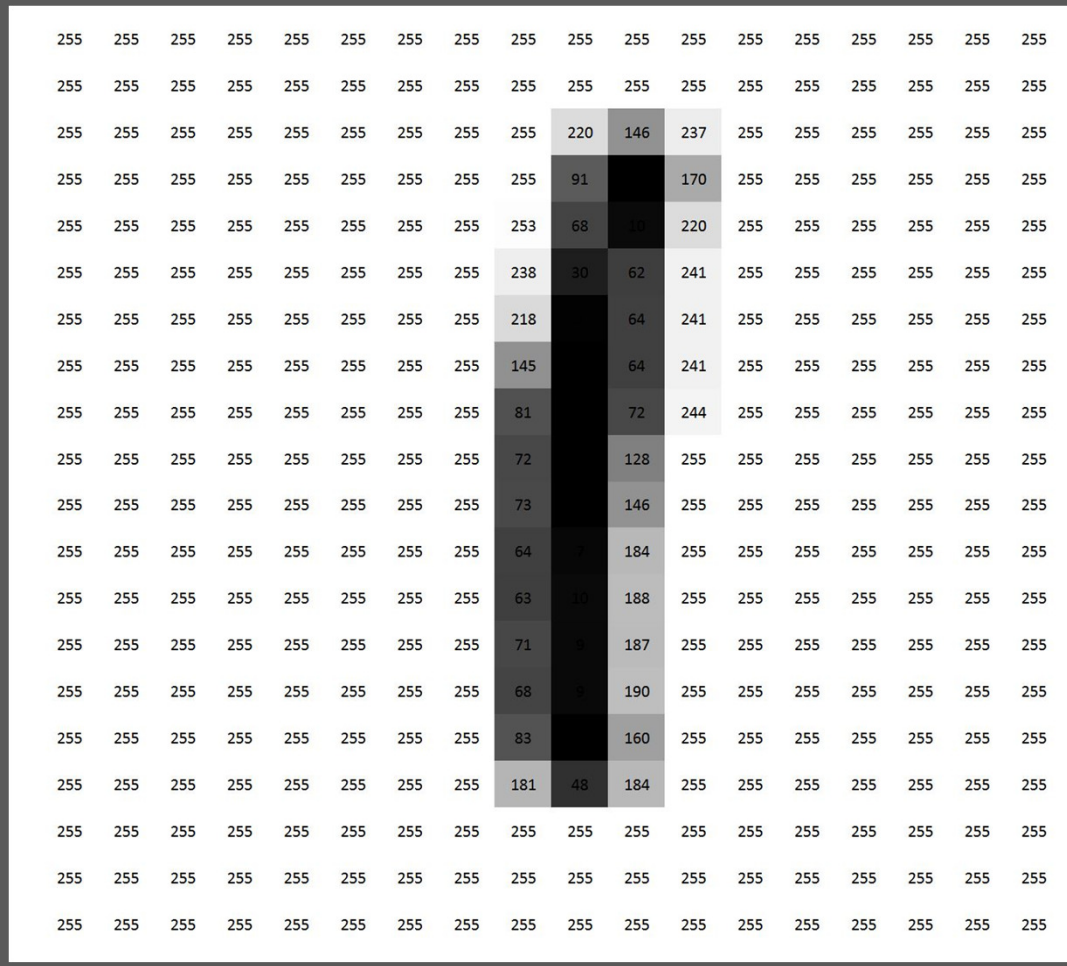


# Black and White or Greyscale

Black and White images are stored in 2-Dimensional arrays

There are two types of B&W images

- Grayscale – Ranges of shades of grey
- Binary – Pixels are either black or white



# What exactly is OpenCV

Officially launched in 1999, OpenCV (Open Source Computer Vision) from an Intel initiative.

OpenCV is written in C++.

First major release 1.0 was in 2006, second in 2009 and third in 2015.

OpenCV 2.4.13 is latest stable release for OpenCV 2.X.

Open 3.X is very similar, and has some benefits and new functions, however, it also removed some of the important algorithms (due to patents) such as SIFT & SURF.

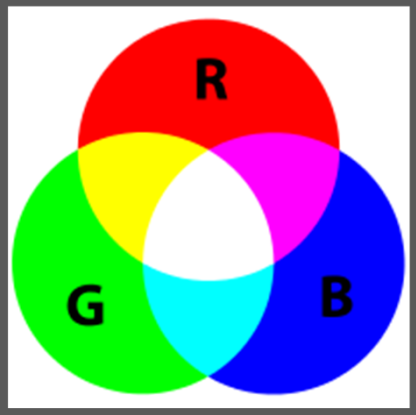
Visit - opencv.org or wikipedia.org/wiki/OpenCV to learn more

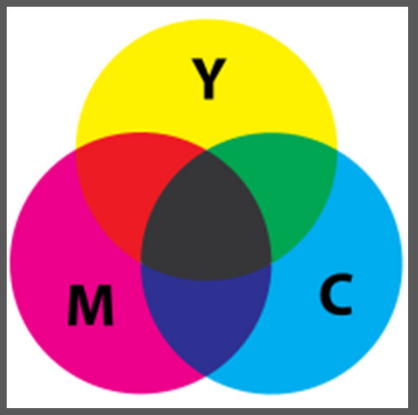
# Let’s now get started with using OpenCV in Python.

# Color Spaces

ver heard of the terms RGB, HSV or CMYK?

hese are color spaces, which is simply a way to represent color.



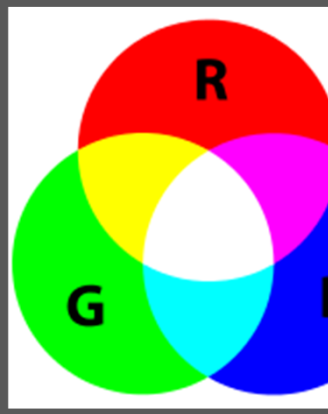



# RGB....wait BGR Color Space

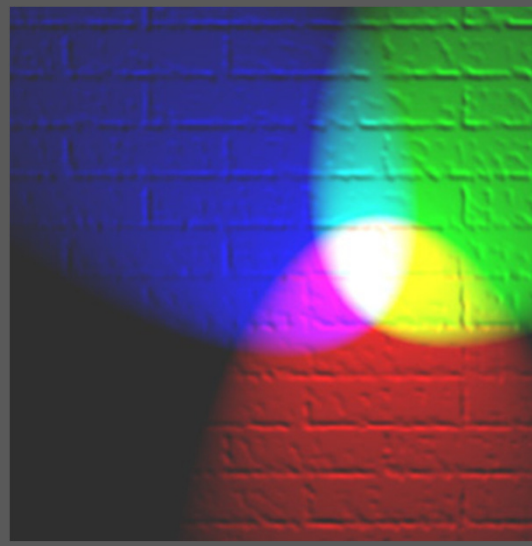
OpenCV's default color space is RGB.

RGB is an additive color model that generates colors by combining blue, green and red and different intensities/brightness. In OpenCV we 8-bit color depths

- Red
- Green
- Blue



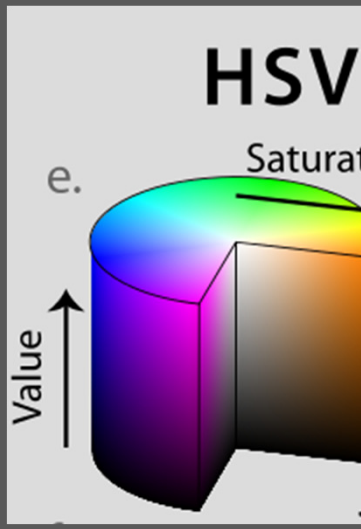

However, OpenCV actually stores color in the BGR format.



COOL FACT - We use BGR order on computers due to how unsigned 32-bit integers are stored in memory, it still ends up being stored as RGB. The integer representing a color e.g. 0x00BBGGRR will be stored as 0xRRGGBB00.

# HSV Color Space

HSV (Hue, Saturation & Value/Brightness) is a color space that attempts to represent colors the way humans perceive it. It stores color information in a cylindrical representation of RGB color points.




Hue – Color Value (0 – 179)
Saturation – Vibrancy of color (0-255)
Value – Brightness or intensity (0-255)

It's useful in computer vision for color segmentation. In RGB, filtering specific colors isn't easy, however, HSV makes it much easier to set color ranges to filter specific colors as we perceive them.

Visit these links to learn more:

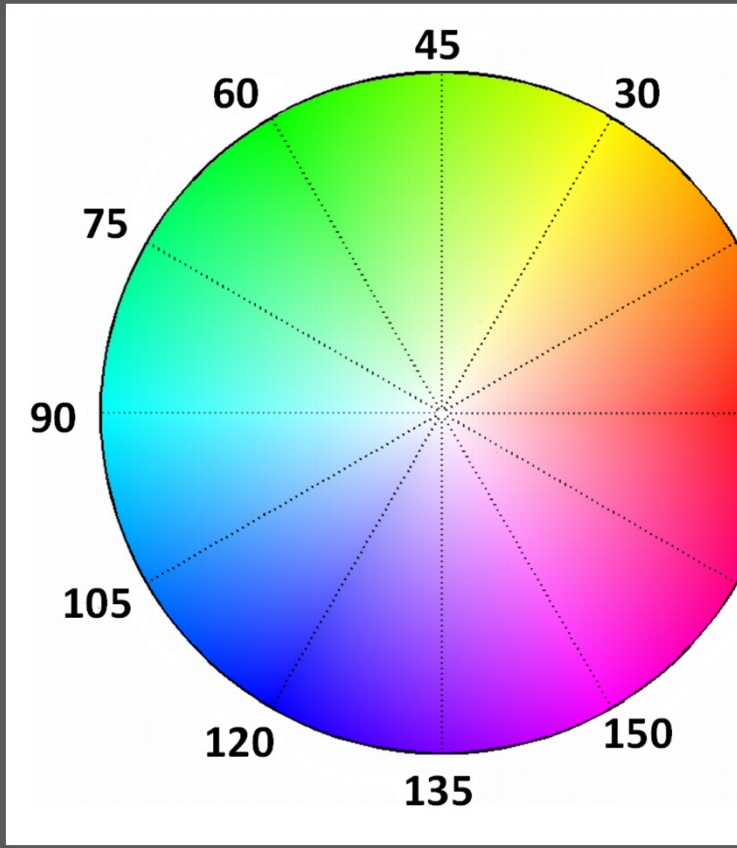
wikipedia.org/wiki/HSL_and_HSV
http://coecsl.ece.illinois.edu/ge423/spring05/group8/FinalProject/HSV_writeup.pdf

# Color Filtering

The Hue (Hue color range, goes from 0 to 180, not 360) and
s mapped differently than standard

Color Range Filters:

- Red – 165 to 15
- Green – 45 to 75
- Blue – 90 to 120



# Section 3

# Image Manipulations

# Image Manipulations

1. Transformations, affine and non affine
2. Translations
3. Rotations
4. Scaling, re-sizing and interpolations
5. Image Pyramids
6. Cropping
7. Arithmetic Operations
8. Bitwise Operations and Masking
9. Convolutions & Blurring
10. Sharpening
11. Thresholding and Binarization
12. Dilation, erosion, opening and closing
13. Edge Detection & Image Gradients
14. Perspective & Affine Transforms
15. Mini Project # 1 – Make a Live Sketch of Yourself!

# Transformations

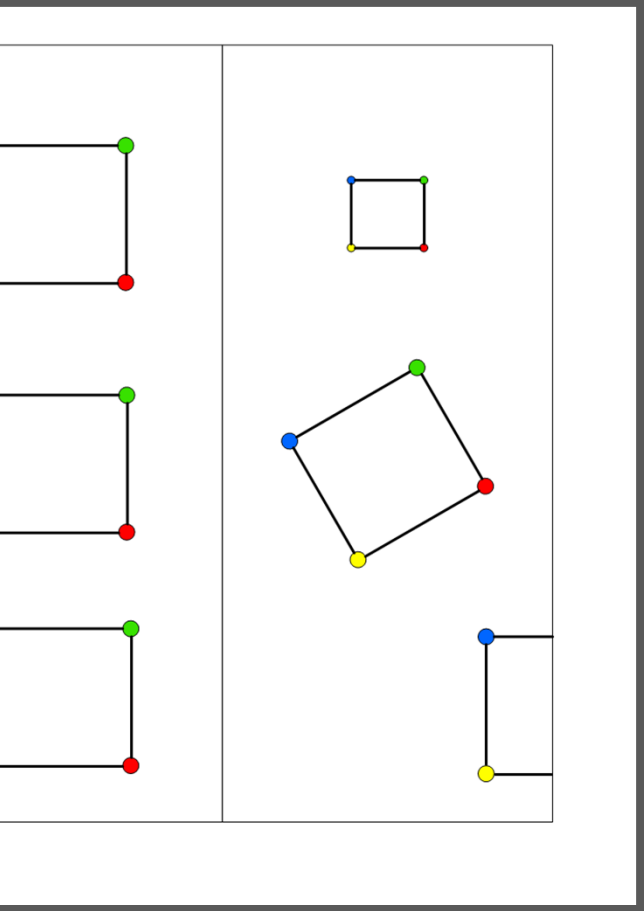
ransformations – are geometric distortions enacted upon an image.

Ve use transformations to correct distortions or perspective issues from
rising from the point of view an image was captured.

ypes:

- Affine
- Non-Affine

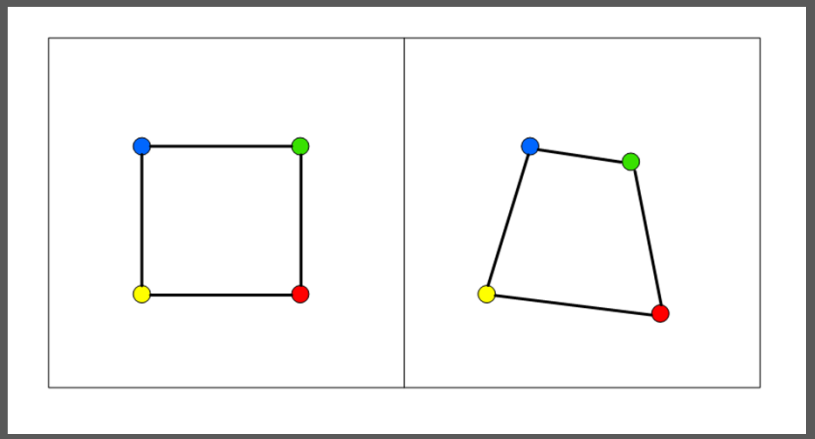
# Affine vs Non Affine Theory



Scaling

Rotation

Translation



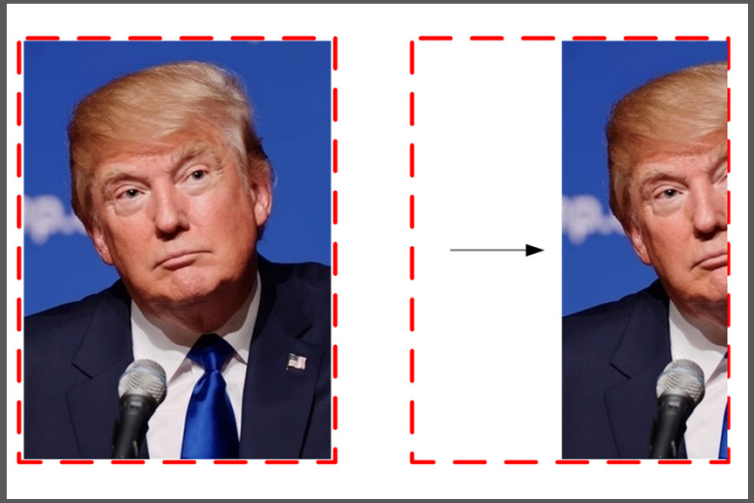
Non-Affine or Projective Trans
also called Hom

The non-affine or projective transformation does not preserve parallelism, length, and angle. It does however preserve collinearity and incidence.

# Translations

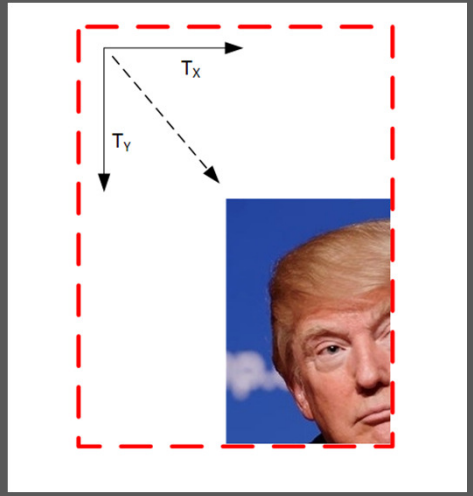
ranslation Matrix

$$= \begin{bmatrix} 1 & 0 & T_x \\ 0 & 1 & T_y \end{bmatrix}$$



$_x$ – Represents the shift along the x-axis (horizontal)
$_y$ - Represents the shift along the y-axis (vertical)

We use the OpenCV function cv2.warpAffine to implement these translations

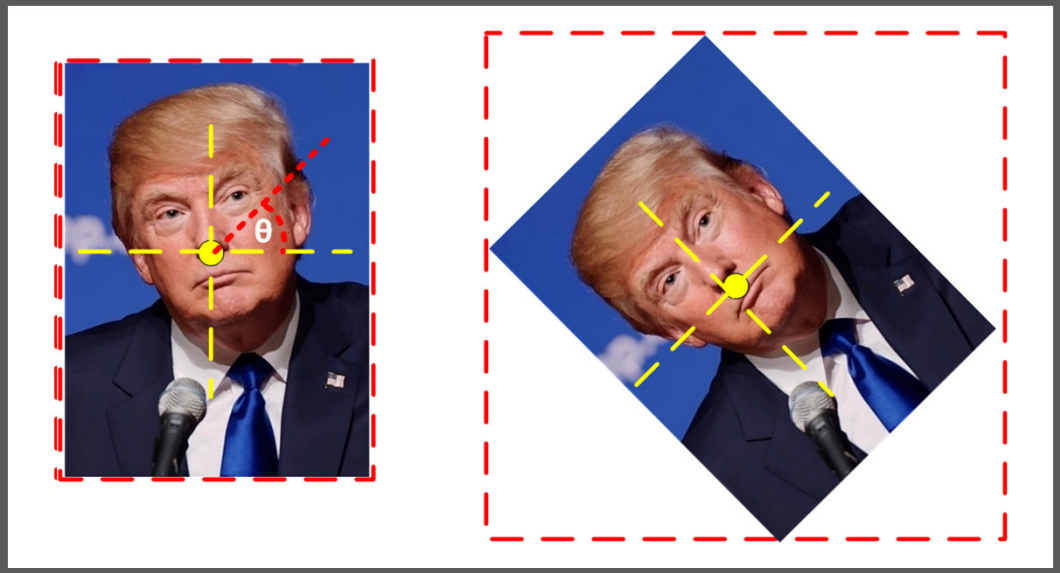


# Rotations

otation Matrix

$$M = \begin{bmatrix} cos\,\theta & -sin\theta \\ sin\theta & cos\theta \end{bmatrix}$$

$\theta$ — the angle of rotation



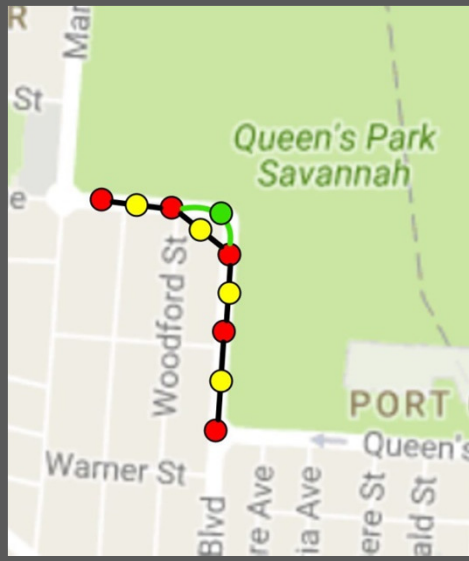

penCV allows you to scale and rotate at the same thing using the function:

```
v2.getRotationMatrix2D(rotation_center_x, rotation_center_y, angle of rotation, scale)
```

# Re-sizing, Scaling and Interpolation

What is interpolation?

Interpolation is a method of constructing new data points within the range of a discrete set of known data points




cv2.INTER_AREA - Good for shrinking or down sampling
cv2.INTER_NEAREST - Fastest
cv2.INTER_LINEAR - Good for zooming or up sampling (default)
cv2.INTER_CUBIC - Better
cv2.INTER_LANCZOS4 - Best

Good comparison of interpolation methods:
http://tanbakuchi.com/posts/comparison-of-openv-interpolation-algorithms/

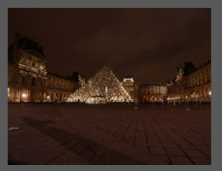
# Image Pyramids

yramiding image refers to either upscaling (enlarging) and downscaling (shrinking images).

's simply a different way of re-sizing that allows us to easily and quickly scale images. Scaling do
educes the height and width of the new image by half.

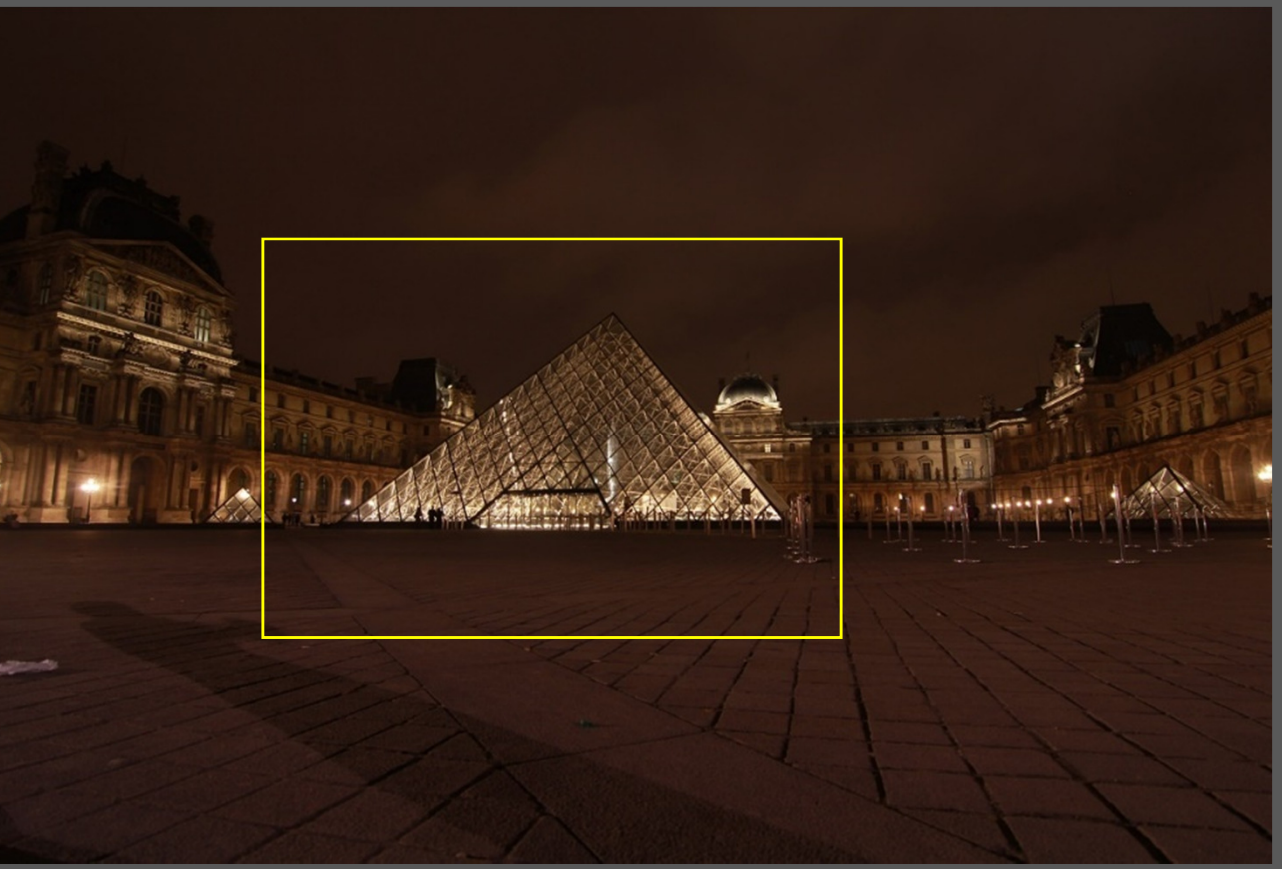
his comes in useful when making object detectors that scales images each time it looks for an o






# Cropping Images

Cropping images refers to extracting a segment a of that image.

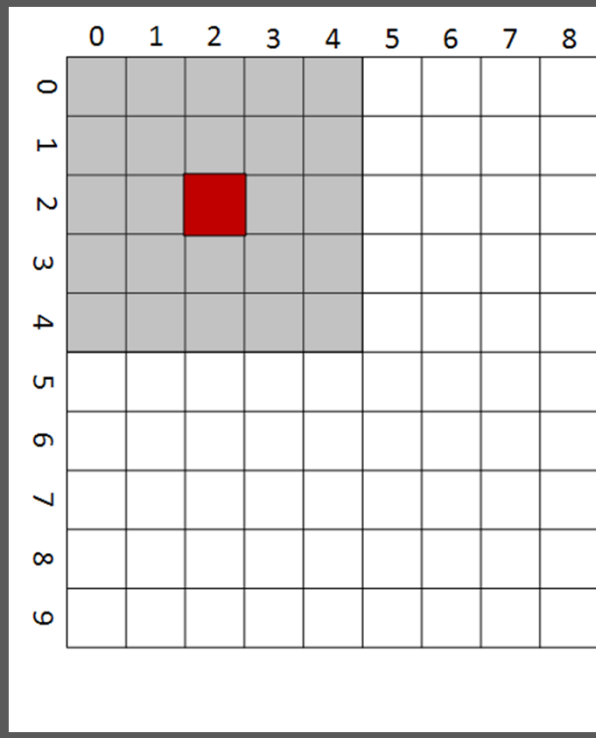


# Convolutions & Blurring

A Convolution is a mathematical operation performed on two functions producing a third function which is typically a modified version of one of the original functions.

$$Output\ Image = Image \otimes Function_{Kernel\ Size}$$

In Computer Vision we use kernel's to specify the size over which we run our manipulating function over our image.




5 x 5 Kernel over our imag

# Blurring

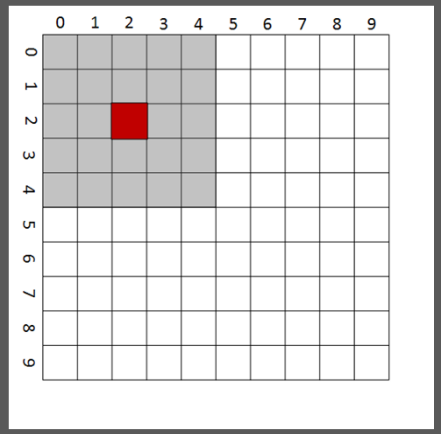
lurring is an operation where we average the pixels within a region
kernel).

$$Kernel\_ = \frac{1}{25}\begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix}$$

he above is a 5 x 5 kernel.

Ve multiply by 1/25 to normalize i.e. sum to 1,
otherwise we'd be increasing intensity.

```
cv2.filter2D(image, -1, kernel)
```




5 x 5 Kernel over our image

# Other Types of Blurring

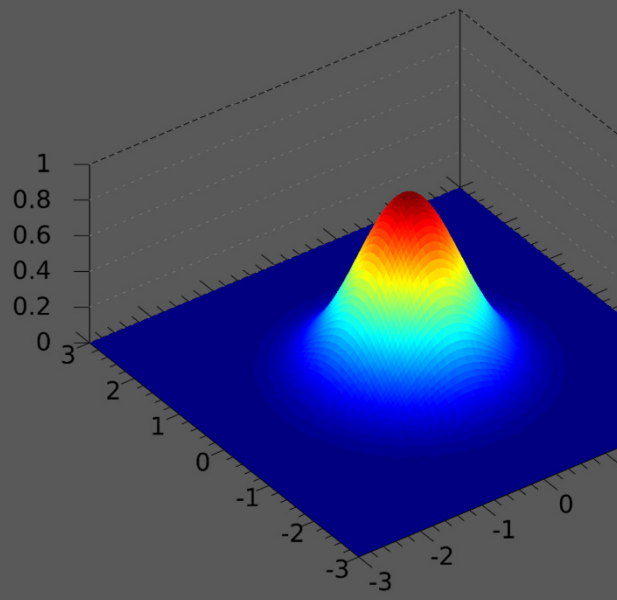
cv2.blur – Averages values over a specified window

cv2.GaussianBlur – Similar, but uses a Gaussian window (more emphasis or weighting on points around the center)

cv2.medianBlur – Uses median of all elements in the window

cv2.bilateralFilter – Blur while keeping edges sharp (slower). It also takes a Gaussian filter in space, but one more Gaussian filter which is a function of pixel difference. The pixel difference function makes sure only those pixels with similar intensity to central pixel is considered for blurring. So it preserves the edges since pixels at edges will have large intensity variation.

$$\frac{1}{273}\begin{bmatrix} 1 & 4 & 7 & 4 \\ 4 & 16 & 26 & 16 \\ 7 & 26 & 41 & 26 \\ 4 & 16 & 26 & 16 \\ 1 & 4 & 7 & 4 \end{bmatrix}$$

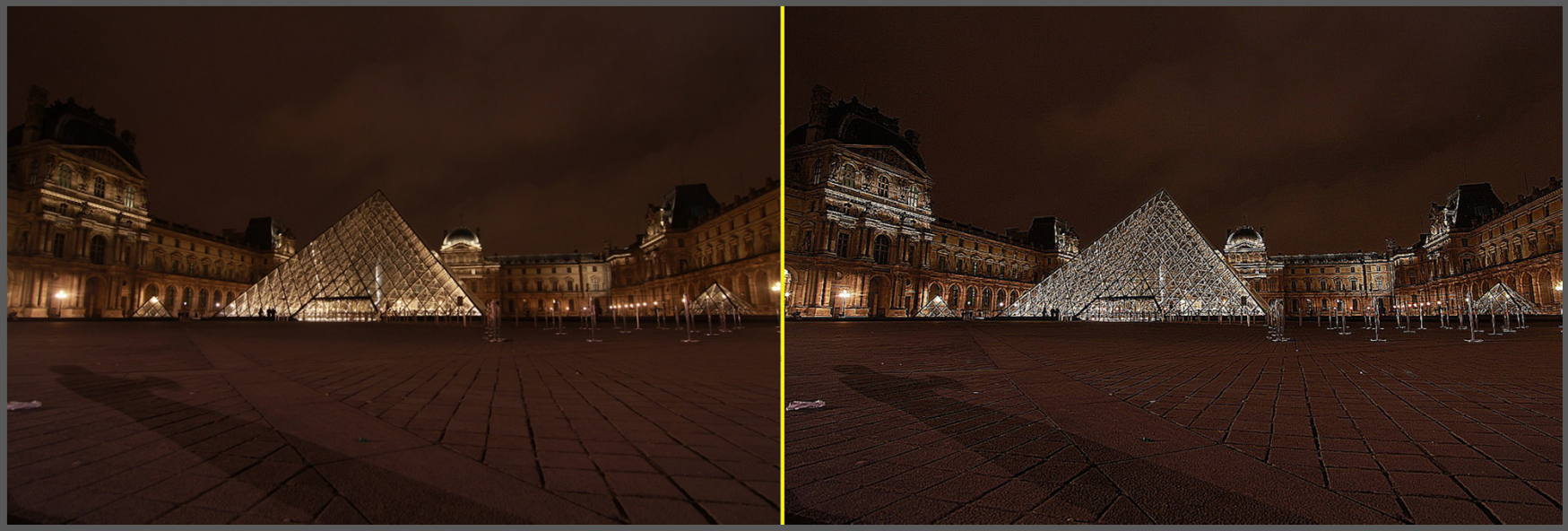


# Sharpening

harpening is the opposite of blurring, it strengthens or emphasizing edges in an image

$$Kernel\_ = \begin{bmatrix} -1 & -1 & -1 \\ -1 & 9 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

Our kernel matrix sums to one, so there is no need to normalize (i.e. multiply by a factor to retain the same brightness of the original)



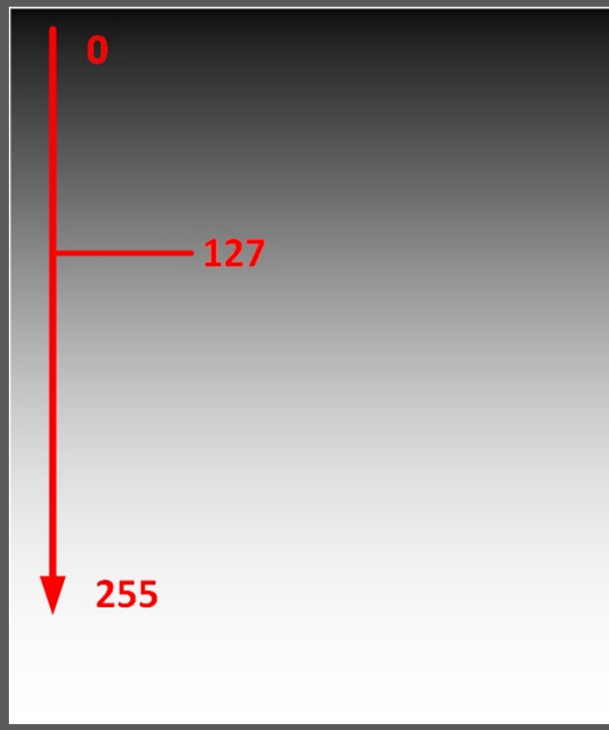
# Thresholding, Binarization & Adaptive Thresholding

hresholding is act of converting an image to a binary form.

```
v2.threshold(image, Threshold Value, Max Value, Threshold Type)
```

hreshold Types:

- cv2.THRESH_BINARY – Most common
- cv2.THRESH_BINARY_INV – Most common
- cv2.THRESH_TRUNC
- cv2.THRESH_TOZERO
- cv2.THRESH_TOZERO_INV




NOTE: Image need to be converted to greyscale before thresholding.

# Adaptive Thresholding

Simple threshold methods require us to provide the threshold value.

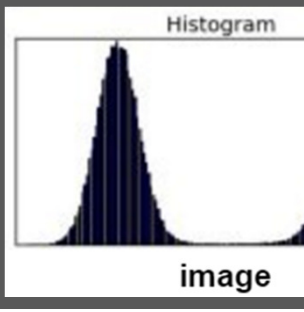
Adaptive threshold methods take that uncertainty away

```
v2.aptiveThreshold(image, Max Value, Adaptive type, Threshold Type, Block size, Constant that i
ubtracted from mean)
```

OTE: Block sizes need to be odd numbers!

daptive Threshold Types:

ADAPTIVE_THRESH_MEAN_C – based on mean of the neighborhood of pixels
ADAPTIVE_THRESH_GAUSSIAN_C – weighted sum of neighborhood pixels under the Gaussian window
THRESH_OTSU (uses cv2.threshold function) – Clever algorithm assumes there are two peaks in the gray scale histogram of the image and then tries to find an optimal value to separate these two peaks  to find T.

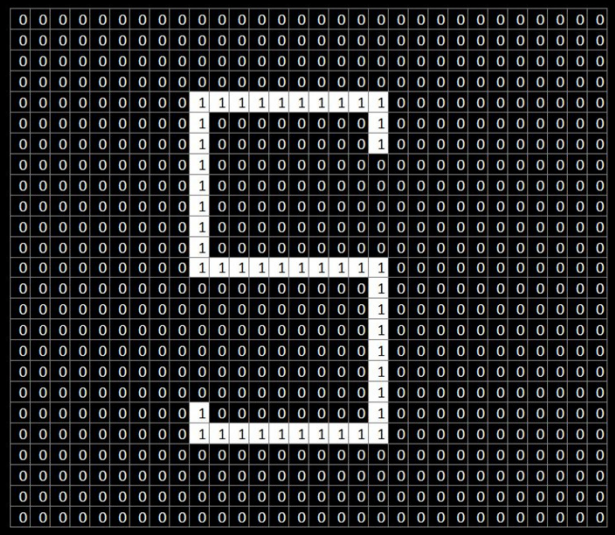


# Dilation and Erosion

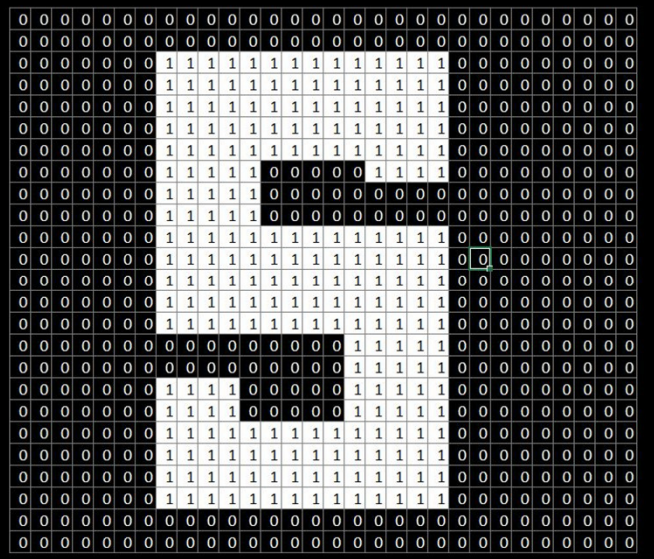
hese are operations in the field of mathematical morphology:

ilation – Adds pixels to the boundaries of objects in an image
rosion – Removes pixels at the boundaries of objects in an image
pening - Erosion followed by dilation
losing - Dilation followed by erosion

Erosion



Dilation



# Confusion with Dilation and Erosion

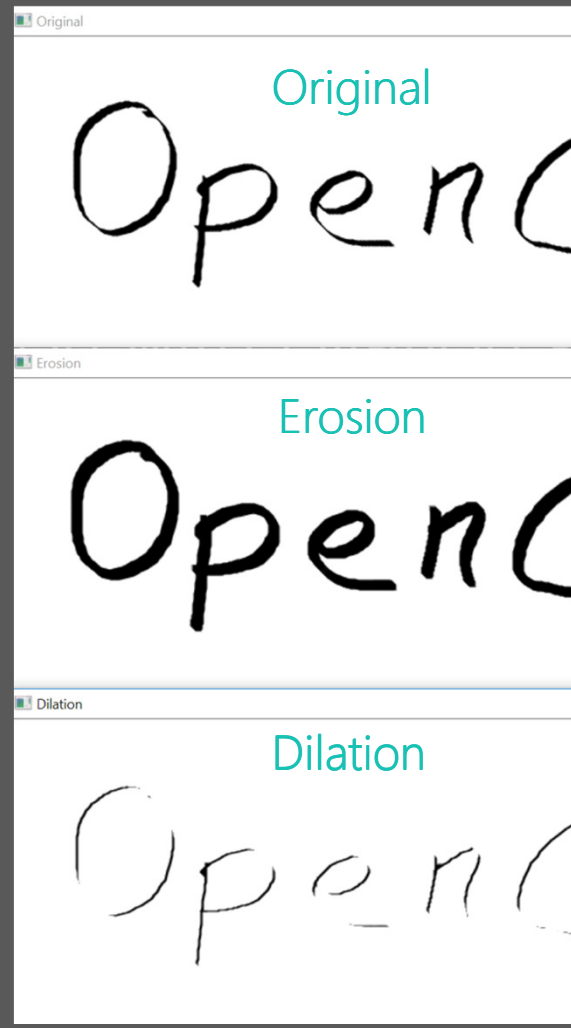
Common StackOverflow question:

*"Why is dilation and erosion doing the reverse of what I expect?*

Remember:

Dilation – Adds pixels to the boundaries of objects in an image

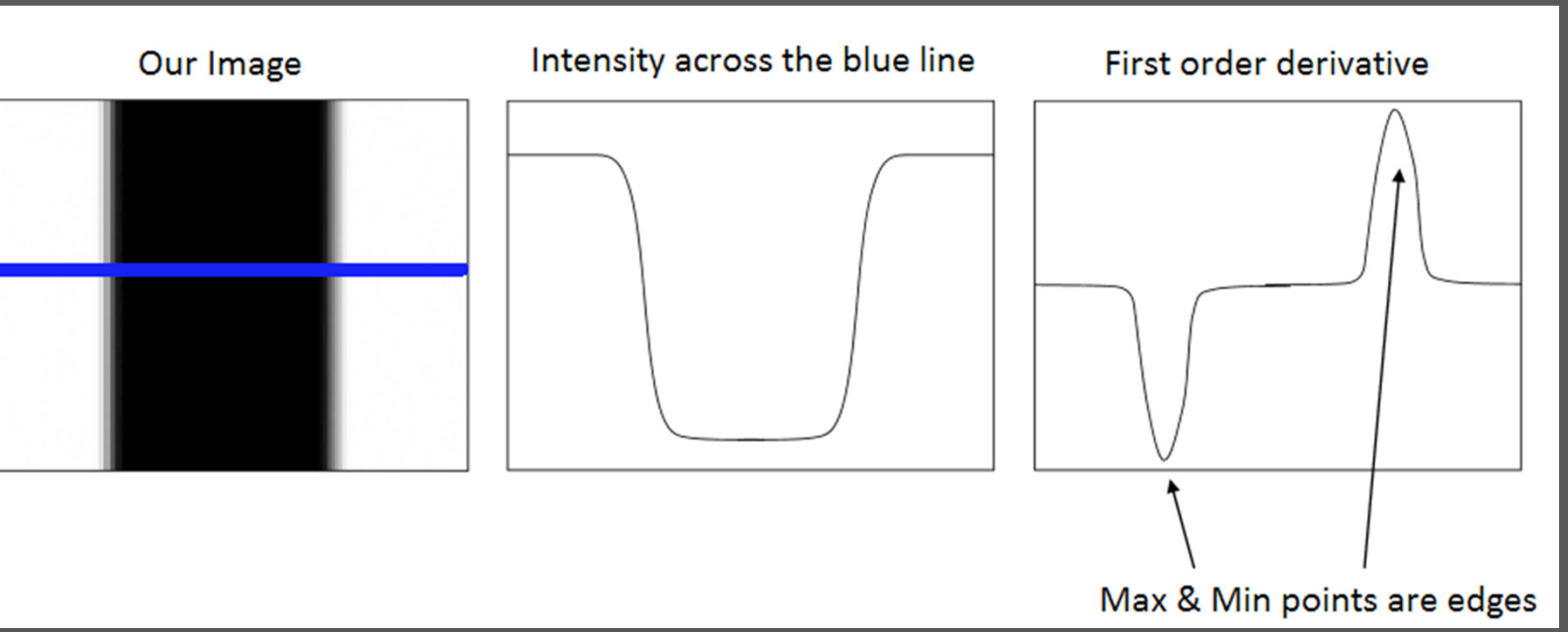
Erosion – Removes pixels at the boundaries of objects in an image



# Edge Detection & Image Gradients

dge Detection is a very important area in Computer Vision, especially when dealing with conto
you'll learn this later soon).

dges can be defined as sudden changes (discontinuities) in an image and they can encode just
nuch information as pixels.




# Edge Detection Algorithms

here are three main types of Edge Detection:

- Sobel – to emphasize vertical or horizontal edges
- Laplacian – Gets all orientations
- Canny – Optimal due to low error rate, well defined edges and accurate detection.

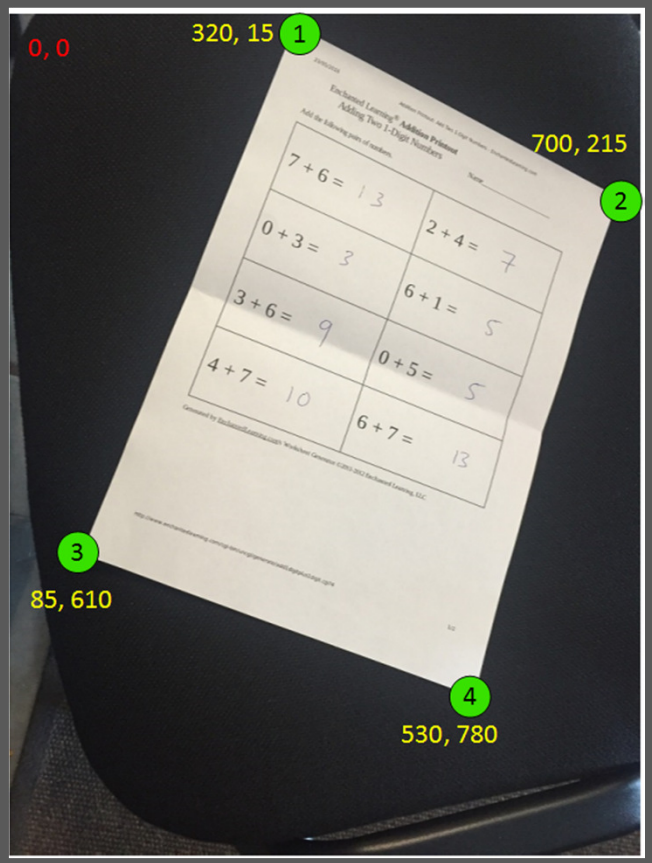
anny Edge Detection Algorithm (developed by John F. Canny in 1986)

1. Applies Gaussian blurring
2. Finds intensity gradient of the image
3. Applied non-maximum suppression (i.e. removes pixels that are not edges)
4. Hysteresis – Applies thresholds (i.e. if pixel is within the upper and lower thresholds, it is considered an edge)

rn more here – https://en.wikipedia.org/wiki/Canny_edge_detector
nparison of Edge Detection Techniques - http://www.ijcsi.org/papers/IJCSI-9-5-1-269-276.pdf

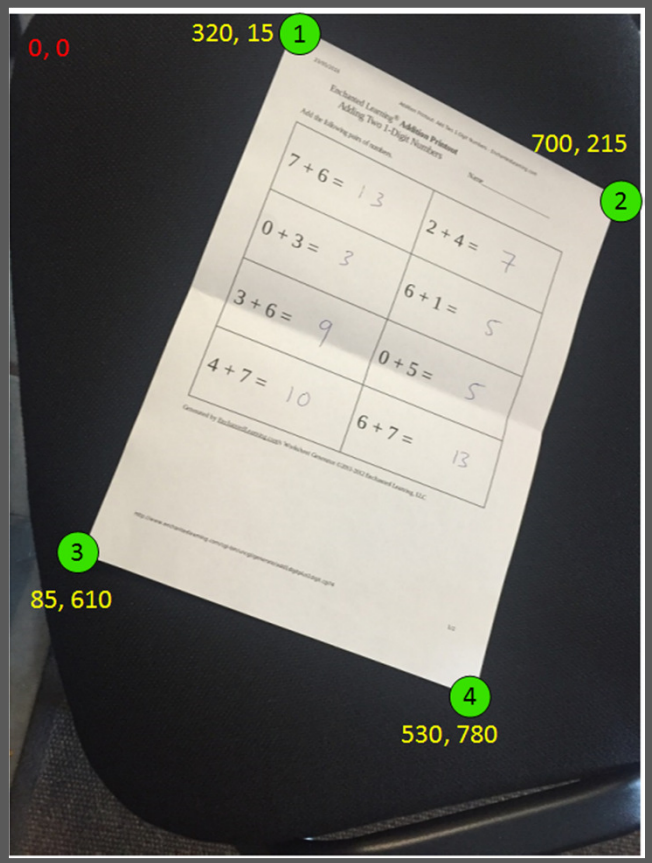
# Obtaining the Perspective of Non-Affine Transforms

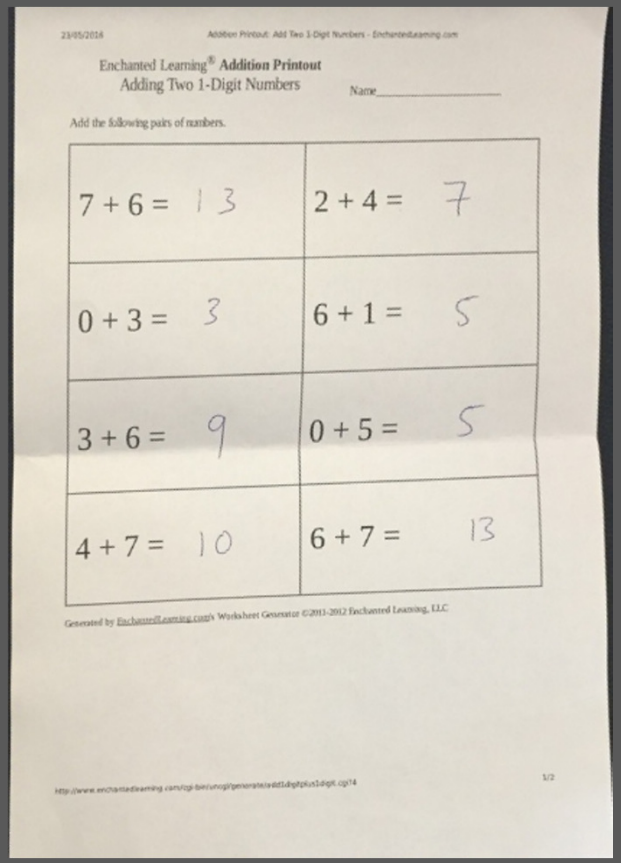
What if we had a mapping of points between images?



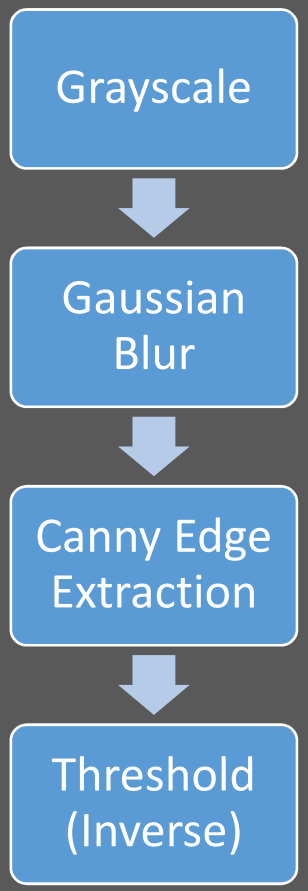
# Obtaining the Perspective of Affine Transforms

What if we had a mapping of points between images?



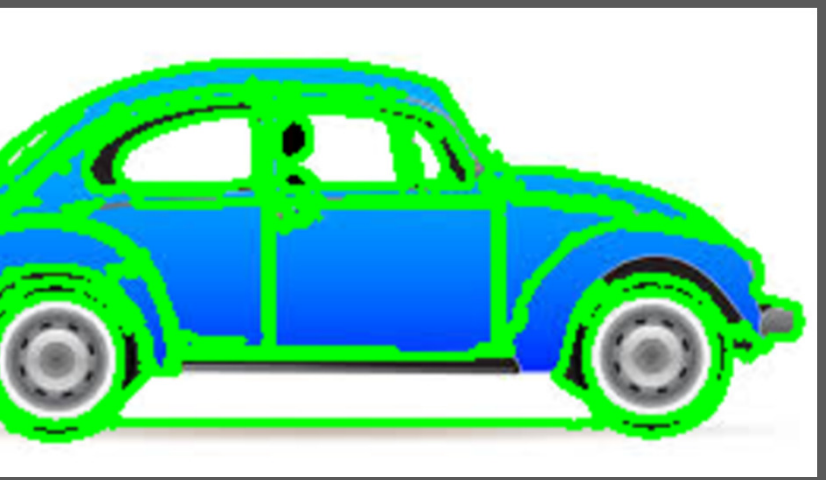
# Mini Project # 1 – Live Sketch Using Webcam

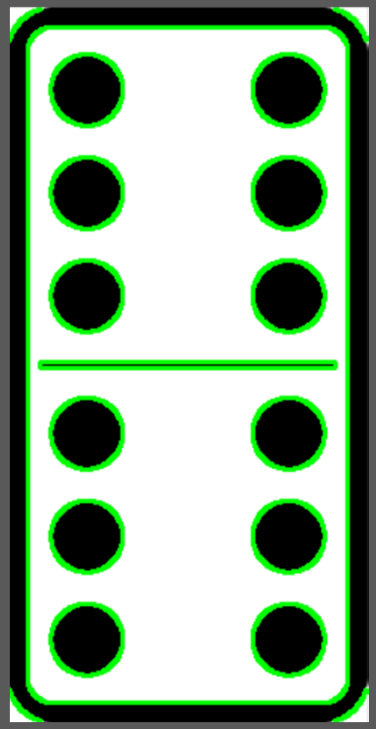


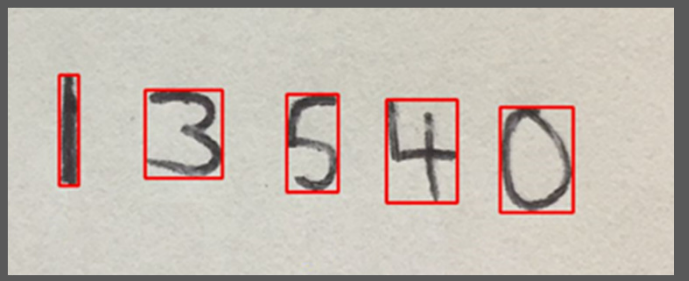

# Section 4

# Image Segmentation

# Segmentation - Partitioning images into different regions





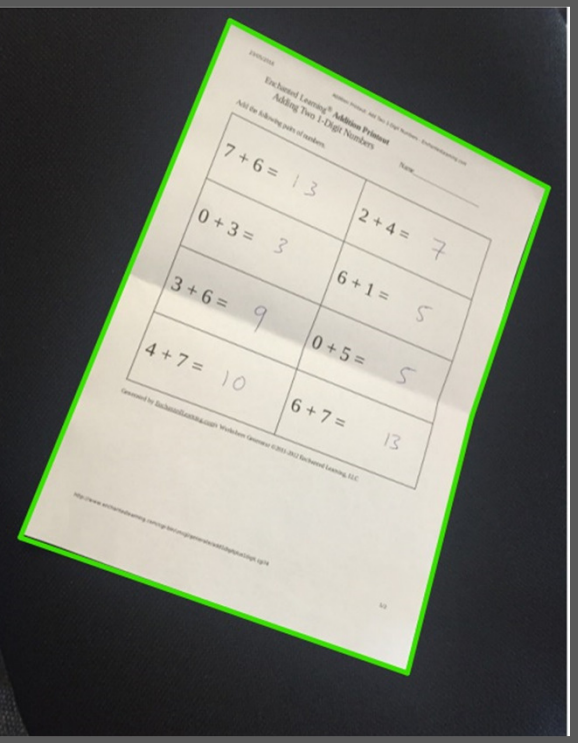



# Image Segmentation

1. Understanding contours
2. Sorting contours by size or left to right
3. Approximating contours & finding their convex hull
4. Matching Contour Shapes
5. Mini Project # 2 – Identifying Shapes
6. Line Detection
7. Circle Detection
8. Blob Detection
9. Mini Project # 3 – Counting Circles and Ellipses

# Contours

Contours are continuous lines or curves that bound or cover the full boundary of an object in an image.




Contours are very important in:

- Object Detection
- Shape Analysis

# Contours

OpenCV stores Contours in a list of lists.

| Contour 1 | Contour 2 | Contour 3 |
|---|---|---|
| (11,28) | (-105,250) | (-733,163) |
| (12,28) | (-105,251) | (-734,164) |
| (13,28) | (-105,252) | (-735,165) |
| (13,28) | (-105,252) | (-736,166) |
| . | . | . |
| . | . | . |
| . | . | . |
| . | . | . |
| . | . | . |
| . | . | . |
| . | . | . |
| . | . | . |

# Contours in OpenCV

`cv2.findContours(image, Retrieval Mode, Approximation Method)`

- Returns -> contours, hierarchy
- Contours are stored as a numpy array of (x,y) points that form the contour
- Hierarchy describes the child-parent relationships between contours (i.e. contours within contours)

Retrieval Mode:

- cv2.CHAIN_APPROX_NONE – Stores all the points along the line (inefficient!)
- cv2.CHAIN_APPROX_SIMPLE – Stores the end points of each line

NOTE: Differences between OpenCV 2.4 and OpenCV 3.X:

cv2.findContours – returns 3 arguments in OpenCV3, which is the modified image with contours overlaid

# Drawing Contours

```
v2.drawContours(image, contours, specific contour, color,
hickness)
```

- The 'contours' parameter is the output from findContours
- Specific contour relates to which contour you wish to draw e.g. Contour[0], Contour[1].
- If you wish to draw all contours, use '-1'

# Hierarchy in Contours

Hierarchy Types (the first two are the most useful)

- cv2.RETR_LIST – Retrieves all contours
- cv2.RETR_EXTERNAL - Retrieves external or outer contours only
- cv2.RETR_COMP - Retrieves all in a 2-level hierarchy
- cv2.RETR_TREE - Retrieves all in full hierarchy

Hierarchy is stored in the following format: [Next, Previous, First Child, Parent]

NOTE - Contour Hierarchy is a quite lengthy to explain, if you're interested read here:

http://opencv-python-tutroals.readthedocs.io/en/latest/py_tutorials/py_imgproc/py_contours/py_contours_hierarchy/py_contours_hierarchy.html

# Sorting Contours

Sorting contours is quite useful when doing image processing.

Sorting by Area can assist in Object Recognition (using contour area)

- Eliminate small contours that may be noise
- Extract the largest contour

Sorting by spatial position (using the contour centroid)

- Sort characters left to right
- Process images in specific order

# Contour Moments

Moments are a set of scalers that are an aggregate of set of vectors

Used in Mechanics and Statistics quite frequently and has now been adopted in Computer Vision

Without getting to heavy into the mathematics behind it think of it as a measure of image intensities

An image with pixel intensities *I(x,y), moments are given by:*

$$M_{ij} = \sum_x \sum_y I(x,y)$$

# Approximating Contours

Approximating contours is useful when correcting slight distortions your contour.

We can use approxPolyDP to achieve this:

```
v2.approxPolyDP(contour, Approximation Accuracy, Closed)
```

- Contour – is the individual contour we wish to approximate
- Approximation Accuracy – Important parameter is determining the accuracy of the approximation. Small values give precise approximations, large values give more generic approximation. A good rule of thumb is less than 5% of the contour perimeter
- Closed – a Boolean value that states whether the approximate contour should be open or closed

# Using OpenCV's matchShapes function

**`cv2.matchShapes(contour template, contour, method, method paramete`**

- Output – match value (lower values means a closer match)

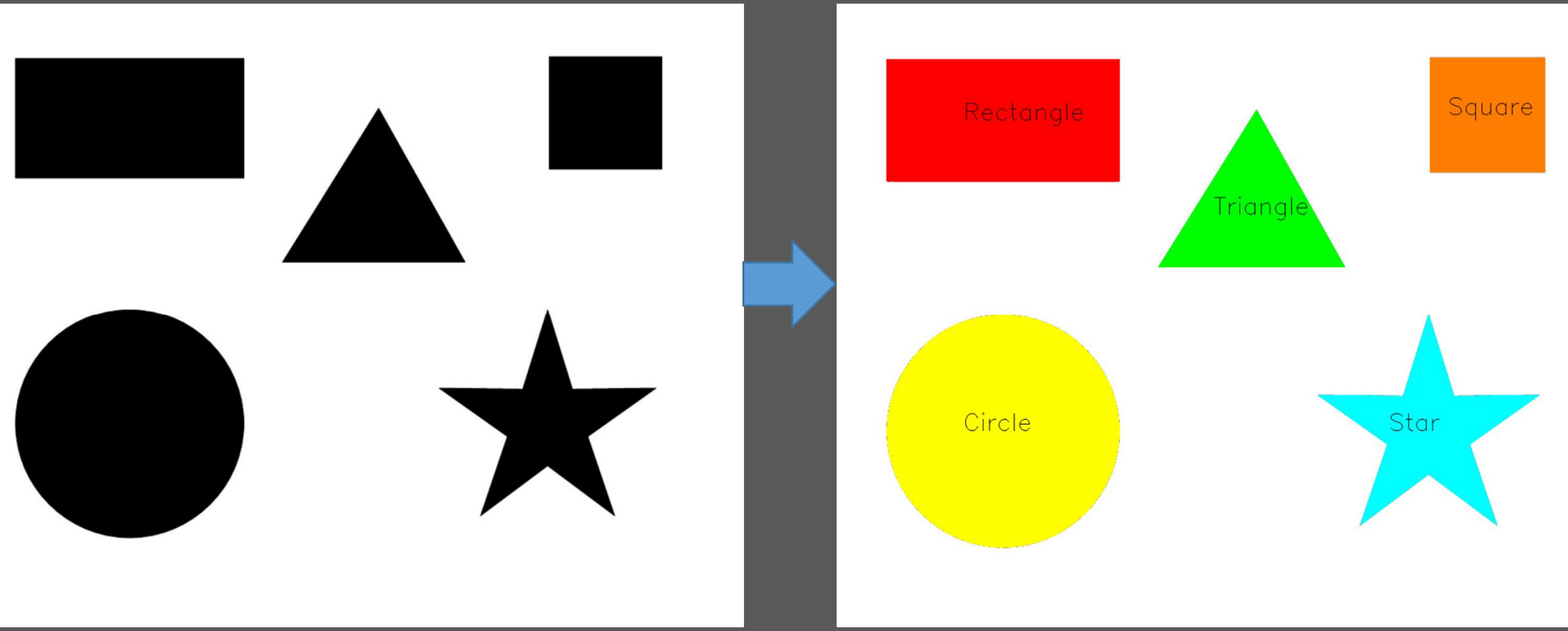
Contour Template – This is our reference contour that we're trying to find in the new image

Contour – The individual contour we are checking against

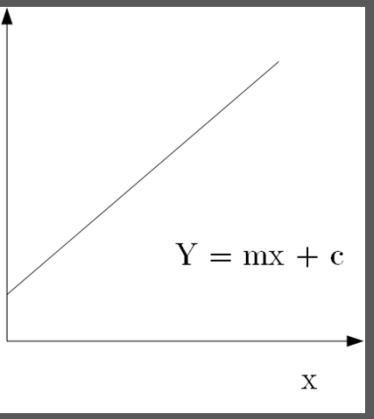
Method – Type of contour matching (1, 2, 3)

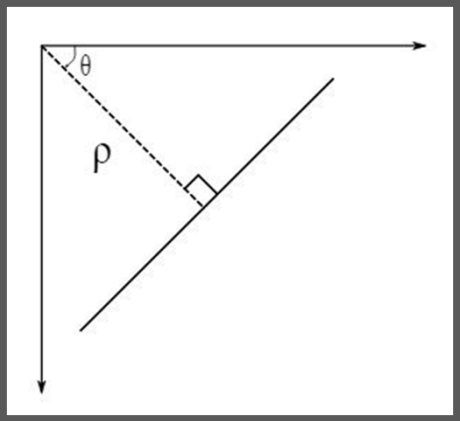
Method Parameter – leave alone as 0.0 (not fully utilized in python OpenCV)

# Mini Project # 2 – Shape Matching



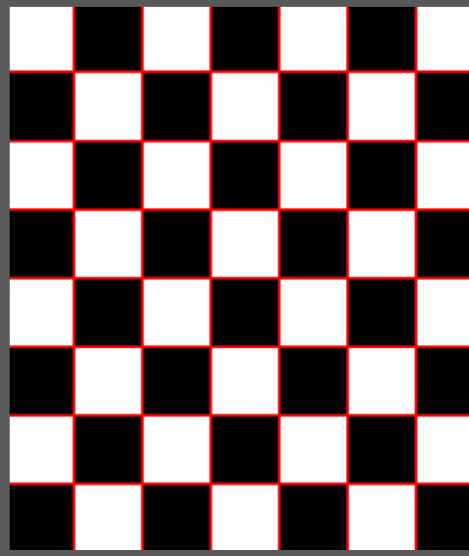
# Line Detection – Hough Lines & Probabilistic Hough Lines




$$\rho = xcos\theta + ysin\theta$$

$\rho$ is the perpendicular distance from origin
$\theta$ is the angle formed by the normal of this line to the orig
(measured in radians)



`v2.HoughLines(binarized image, ρ accuracy, θ accuracy, threshold)`

Threshold here is the minimum vote for it to be considered a line

robabilistic Hough Lines (http://cmp.felk.cvut.cz/~matas/papers/matas-bmvc98.pdf)

Idea is that it takes only a random subset of points sufficient enough for line detection

Also returns the start and end points of the line unlike the previous function

`v2.HoughLinesP(binarized image, ρ accuracy, θ accuracy, threshold, minimum line length, max line gap)`

# Circle Detection

```
cv2.HoughCircles(image, method, dp, MinDist, param1, param2, minRadius, MaxRadius)
```

Method - currently only cv2.HOUGH_GRADIENT available

dp - Inverse ratio of accumulator resolution

MinDist - the minimum distance between the center of detected circles

param1 - Gradient value used in the edge detection

param2 - Accumulator threshold for the HOUGH_GRADIENT method,

- Lower allows more circles to be detected (false positives)

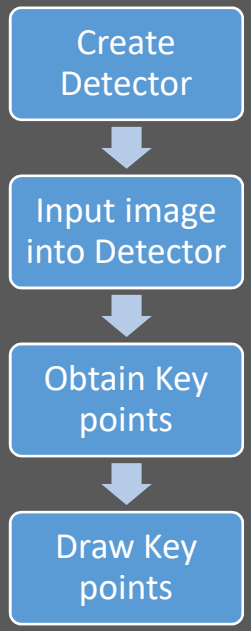
minRadius - limits the smallest circle to this size (via radius)

MaxRadius - similarly sets the limit for the largest circles

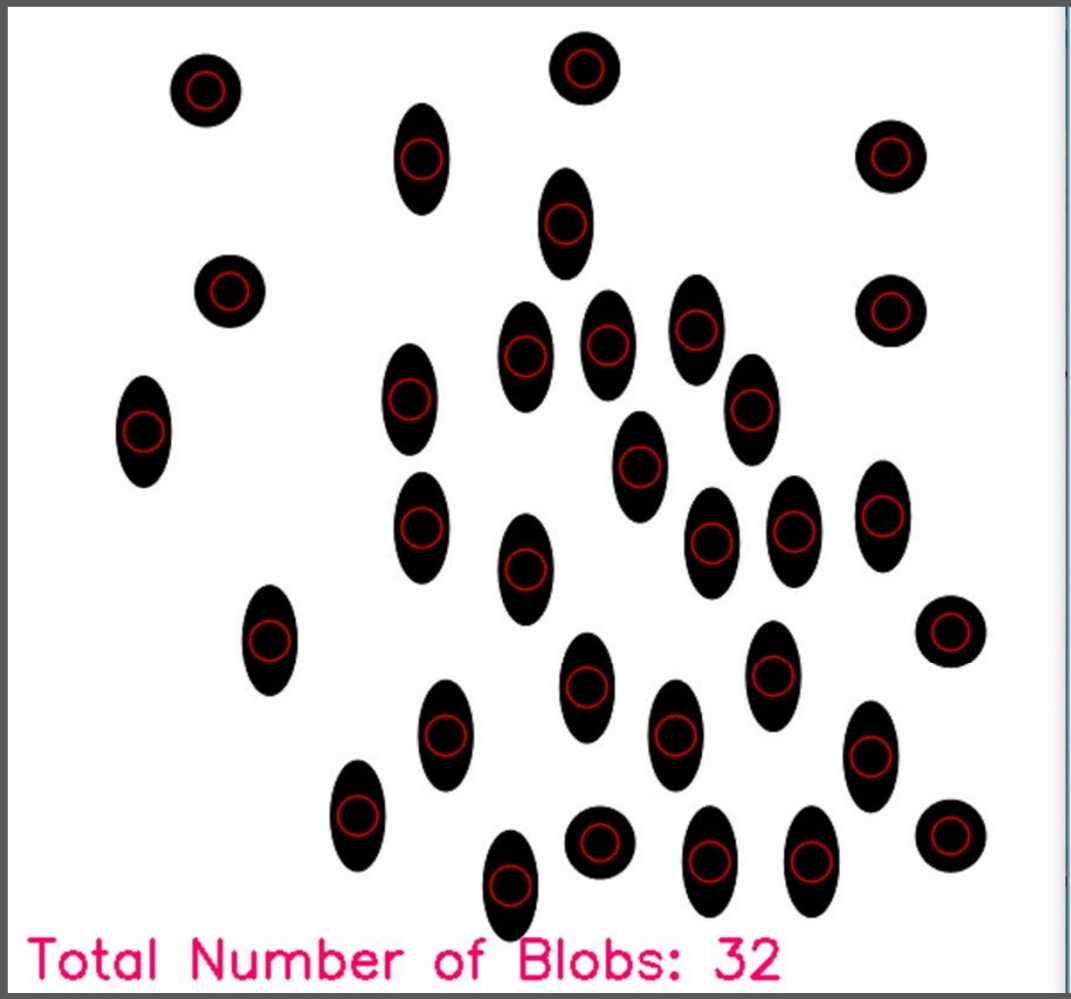
# Blob Detection

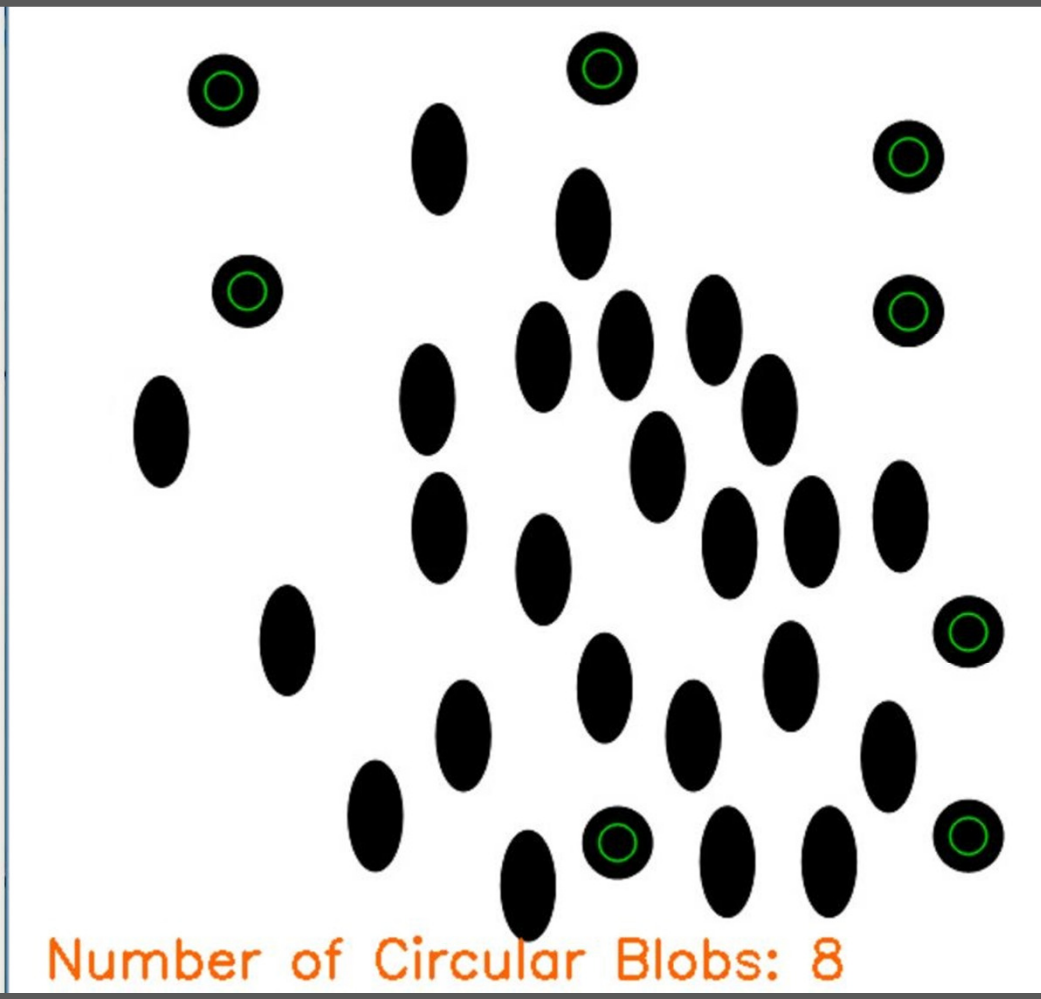
Blobs can be described as groups of connected pixels that all share a common property.

How to use OpenCV's simpleBlobDetector?




# Mini Project # 3 – Counting Circles and Ellipses



# Blob Filtering – Shape & Size

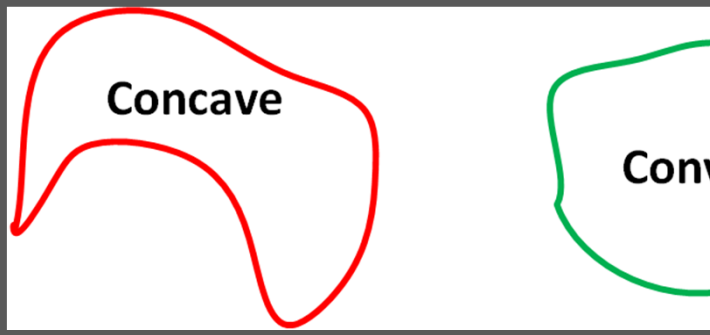
`v2.SimpleBlobDetector_Params()`

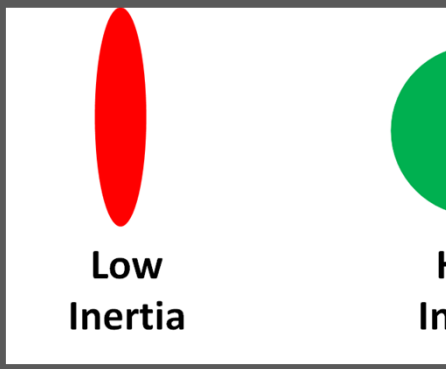
ea
params.filterByArea = True/False
params.minArea = pixels
params.maxArea = pixels

cularity
params.filterByCircularity = True/False
params.minCircularity = 1 being perfect circle, 0 the opposite

nvexity – Area of blob / Area of Convex Hull
params.filterByConvexity = True/False
params.minConvexity = 0 to 1

rtia – Measure of ellipticalness (low being more elliptical, high being more circular)
params.filterByInertia = True/False
params.minInertiaRatio = 0.01



# Section 5

# Object Detection

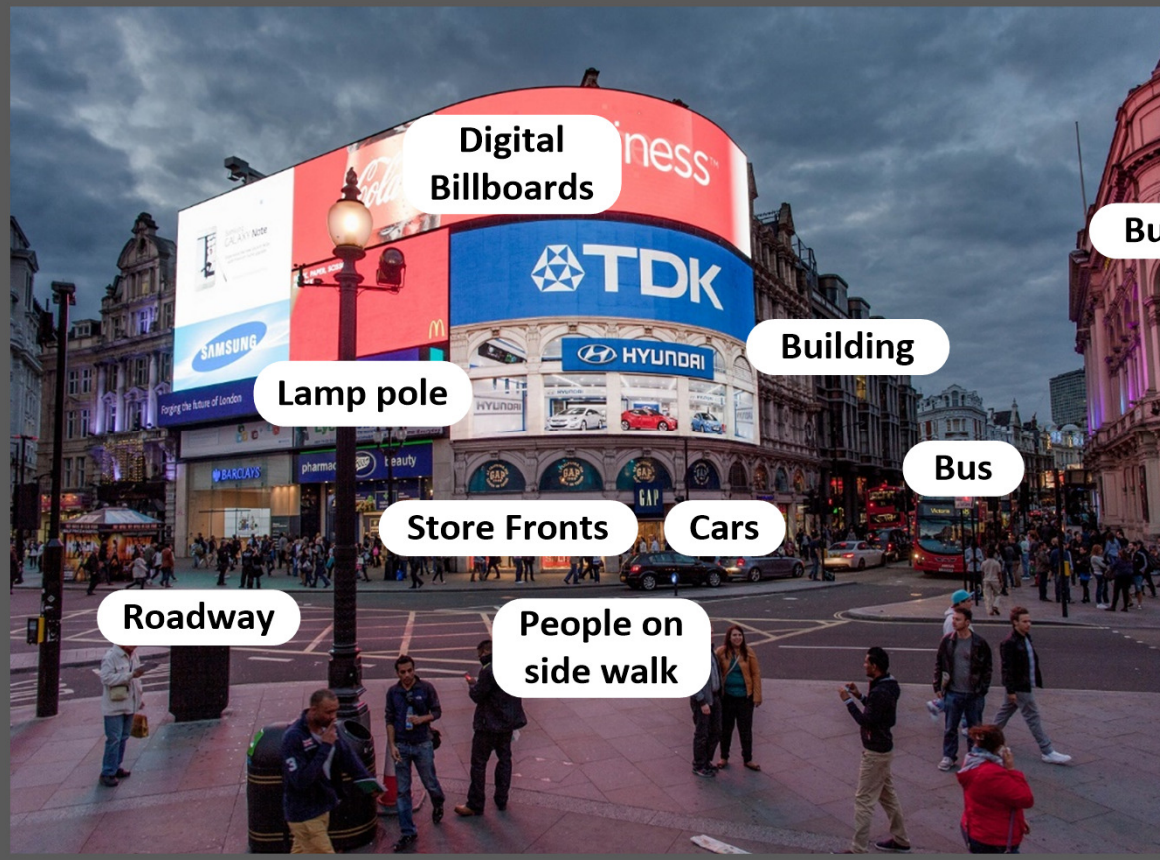
# Object Detection

1. Object Detection using Template Matching
2. Mini Project – Finding Waldo
3. Feature Description Theory
4. Finding Corners
5. SIFT, SURF, FAST, BREIF & ORB
6. Mini Project – Object Detection using Features
7. Histogram of Gradients (HoG) as a Descriptor

# Object Detection

y do we need detect objects in image?

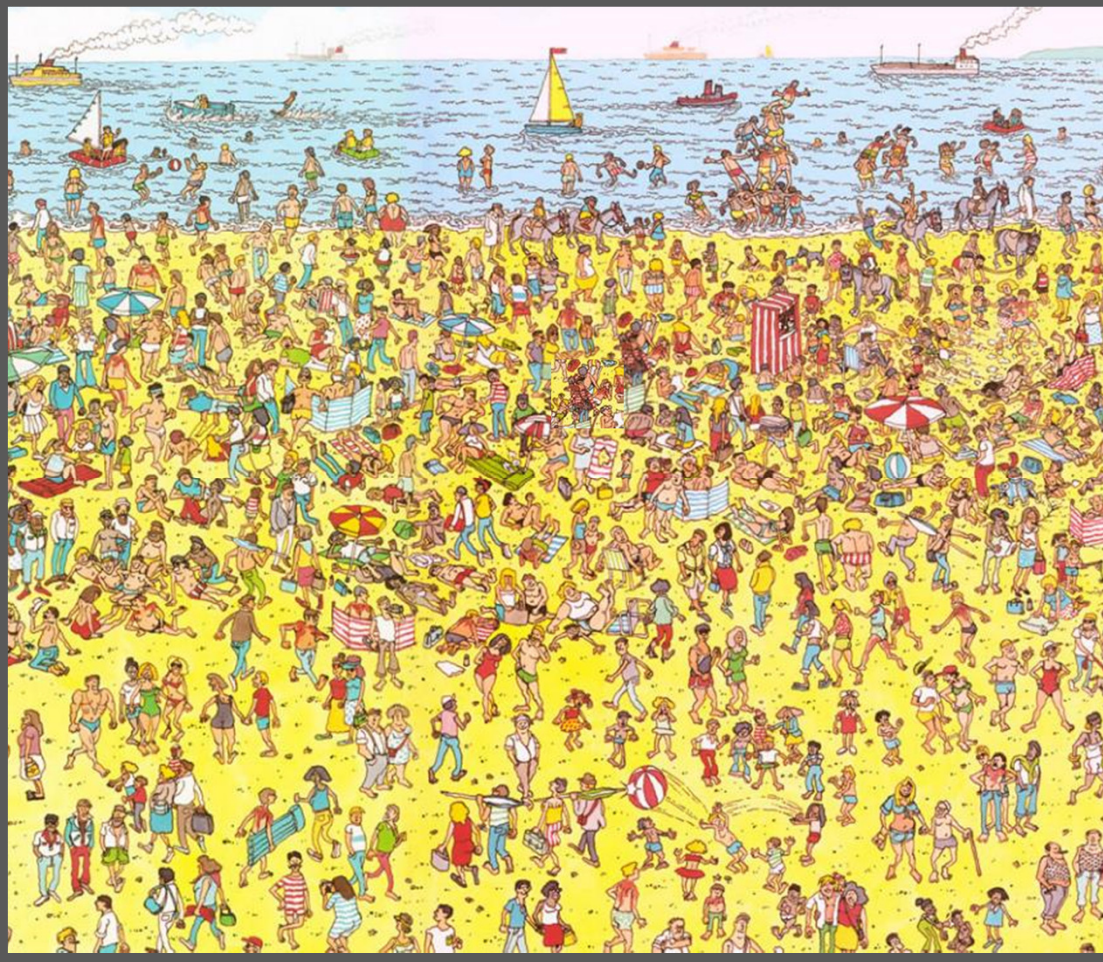
- beling Scenes
- obot Navigation
- elf Driving Cars
- ody Recognition (Microsoft Kinect)
- sease & Cancer Detection
- cial Recognition
- andwriting Recognition
- entifying objects in satellite images
- c.



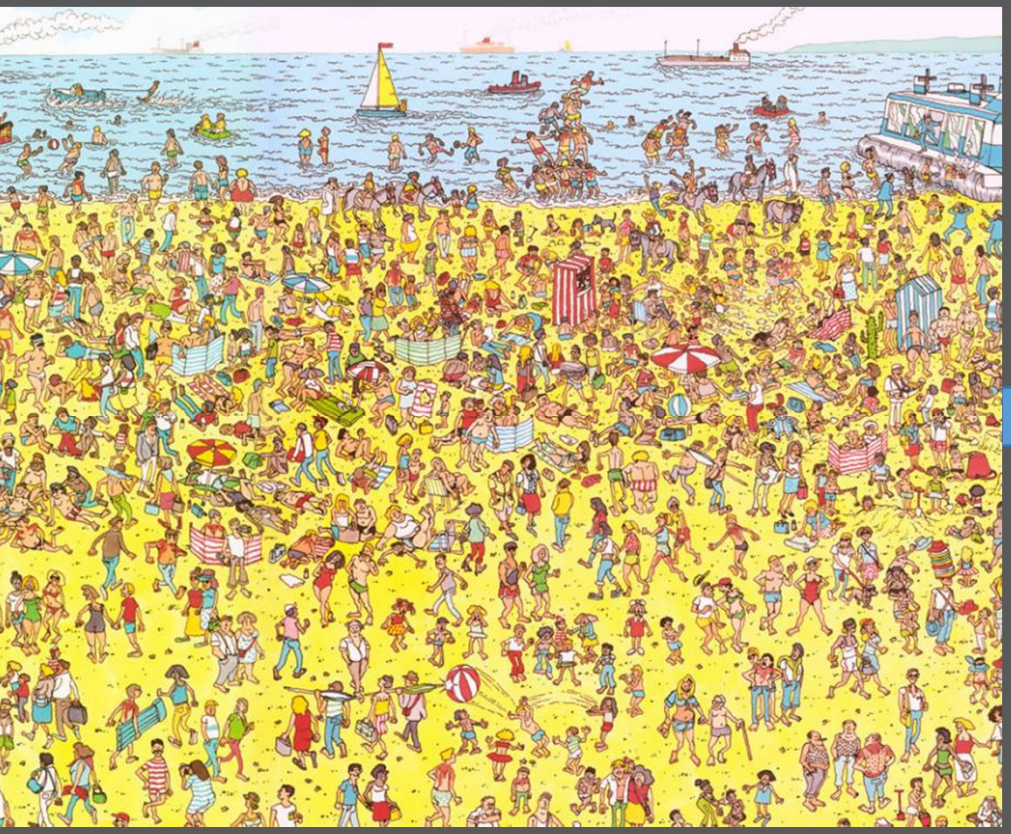
# Object Detection vs Recognition

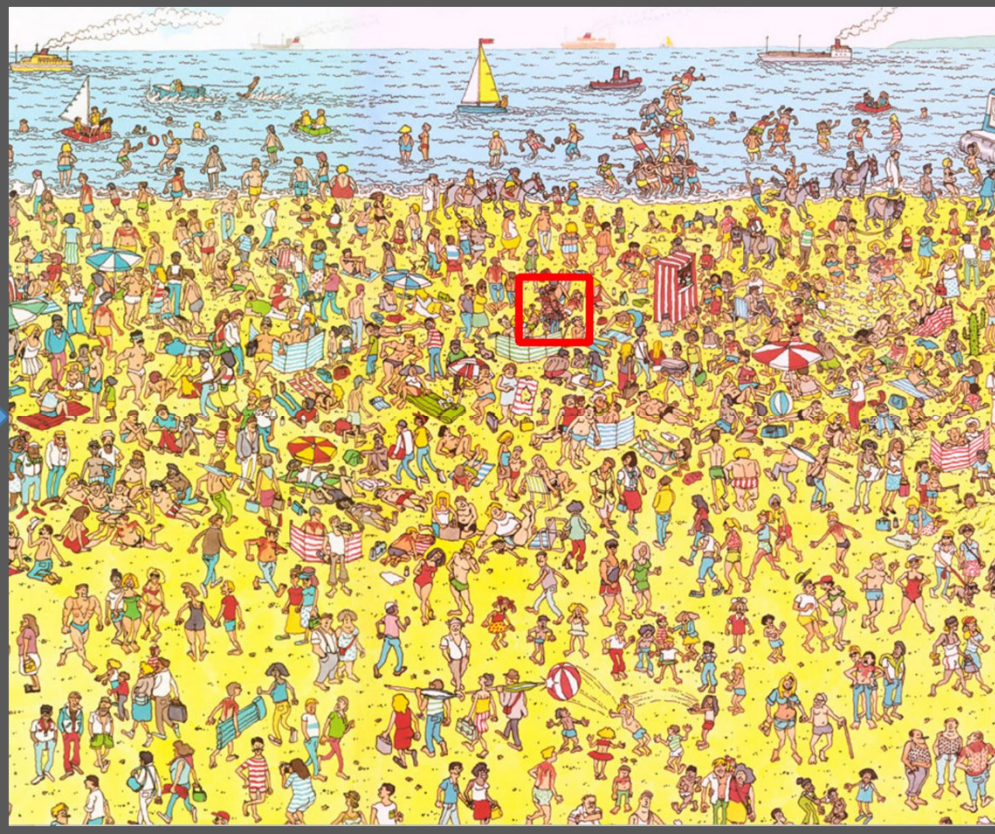

# Template Matching

What if we slide a template image across a source image until the a match is found.



# Mini Project # 4 – Finding Waldo





# This method isn't very resilient

Rotation renders this method ineffective

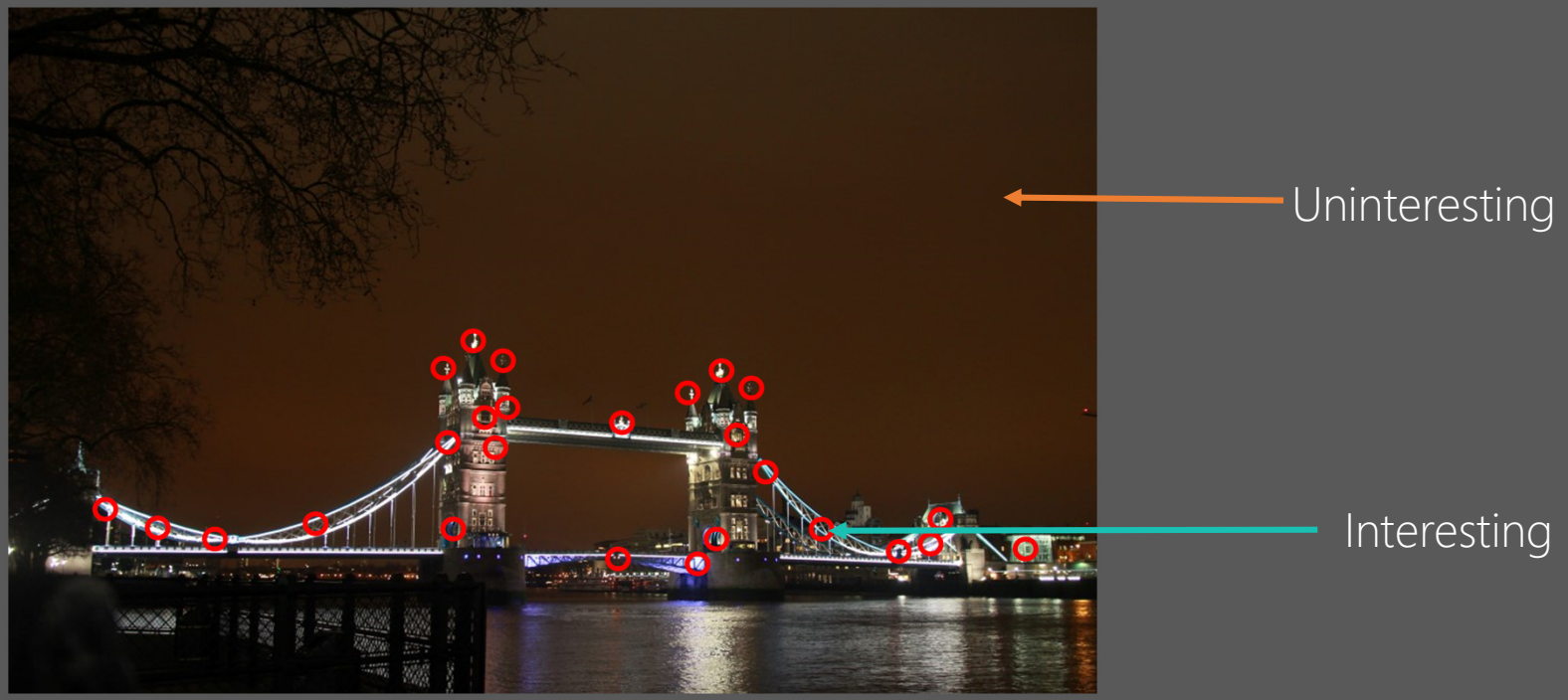
Size (known as scaling) affects this as well

Photometric changes (e.g. brightness, contrast, hue etc.)

Distortions from view point changes (Affine)

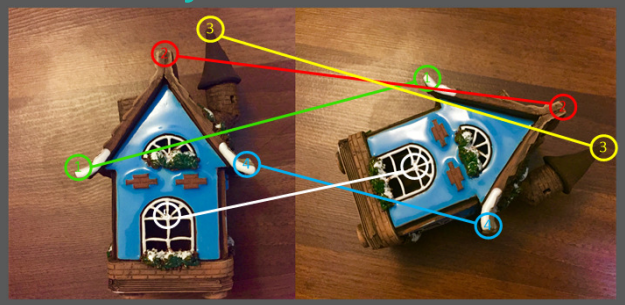
# mage Features

Image Features are interesting areas an image that are somewhat unique to that specific image. The are also popularly called key point features or interest points.



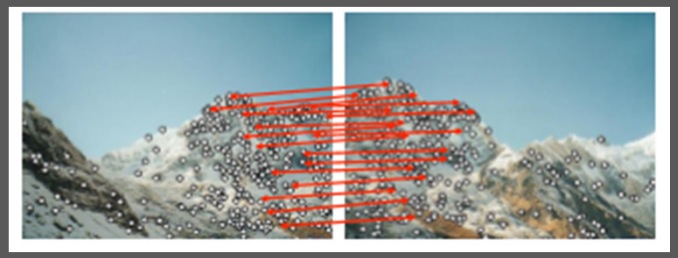
# Why is this important?

Features are important as they can be used to analyze, describe and match images.



They are used in:

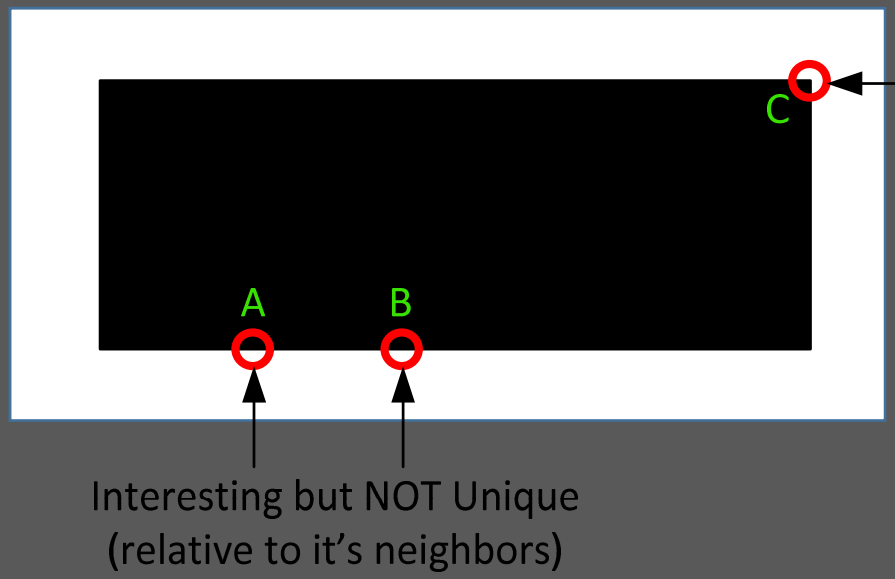
- Image Alignment – e.g. Panorama Stitching (finding corresponding matches so we can stitch images together)
- 3D Reconstruction
- Robot Navigation
- Object Recognition
- Motion Tracking
- And more!



# What Defines Interesting?

Interesting areas carry a lot of distinct and unique information at that point.

- High change of intensity
- Corners or edges
- And more!




Be careful that noise can appear "informative" when it is not!

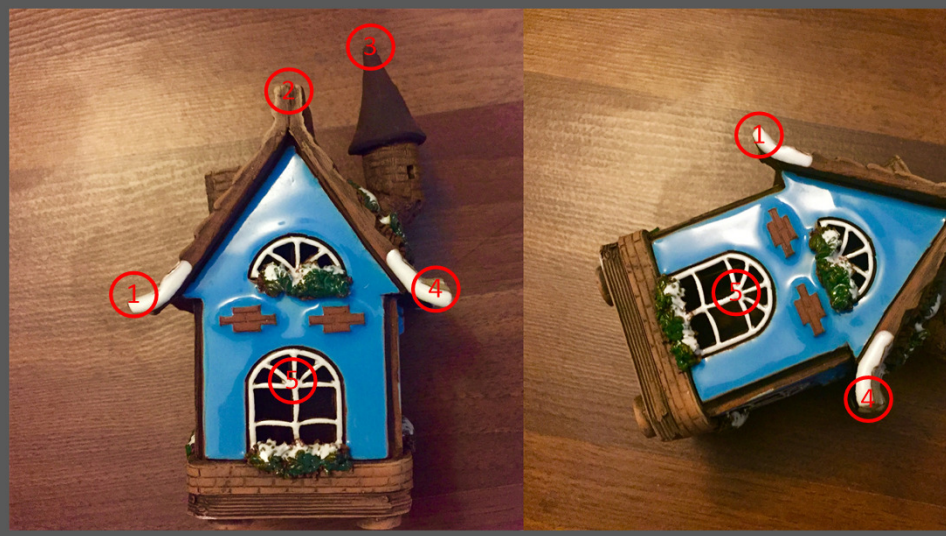
# Characteristics of Good or Interesting Features

eatable – they can be found in multiple
ures of the same scene

nctive – Each feature is somewhat unique
different to other features of the same scene

npactness/Efficiency – Significantly less
ures than pixels in the image

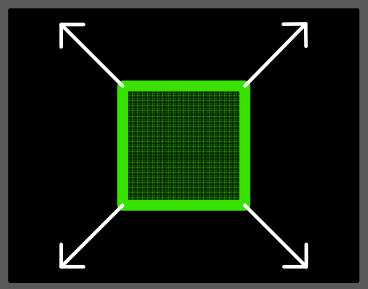
ality – Feature occupies a small area of the
ge and is robust to clutter and occlusion



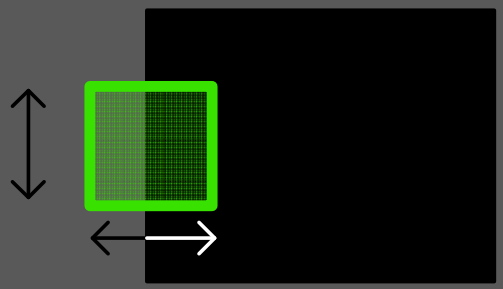
# Corners as Features

Corners are identified when shifting a window in any direction over that point gives a large change in intensity.

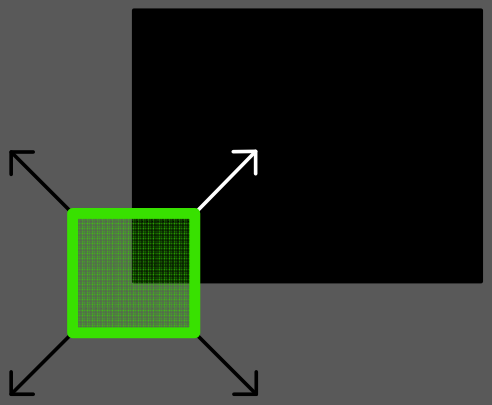
**Flat** – No change in any direction



**Edge** – Change in one direction



**Corner** – Change in all directions



# Corner Detection Methods – `Harris Corners`

Harris Corner Detection is an algorithm developed in 1998 for corner detection (http://www.bmva.org/bmvc/1988/avc-88-023.pdf) and works fairly well.

- `cv2.cornerHarris (input image, block size, ksize, k)`
  - Input image - should be grayscale and float32 type.
  - blockSize - the size of neighborhood considered for corner detection
  - ksize - aperture parameter of Sobel derivative used.
  - k - harris detector free parameter in the equation
  - Output – array of corner locations (x,y)

It was improved in 1994 by improving the scoring function when determining corners locations.

- `cv2.goodFeaturesToTrack`

# Corner Detection Methods – 'good Features To Track'

It was improved in 1994 by improving the scoring function when determining corners locations

- `cv2.goodFeaturesToTrack (input image, maxCorners, qualityLevel, minDistance)`

Input Image - 8-bit or floating-point 32-bit, single-channel image.

maxCorners – Maximum number of corners to return. If there are more corners than are found the strongest of them is returned.

qualityLevel – Parameter characterizing the minimal accepted quality of image corners. The parameter value is multiplied by the best corner quality measure (smallest eigenvalue). The corners with the quality measure less than the product are rejected. For example, if the best corner has the quality measure = 1500, and the qualityLevel=0.01 , then all the corners with the quality measure less than 15 are rejected.

minDistance – Minimum possible Euclidean distance between the returned corners.

# Problems with corners as features

Corner matching in images is tolerant of:

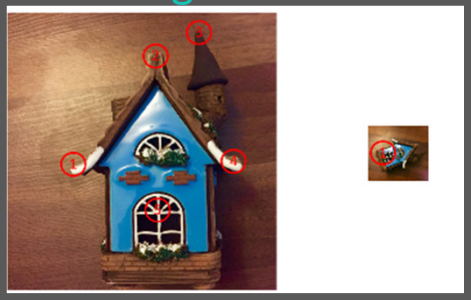
- Rotations
- Translations (i.e. shifts in image)
- Slight photometric changes e.g. brightness or affine intensity

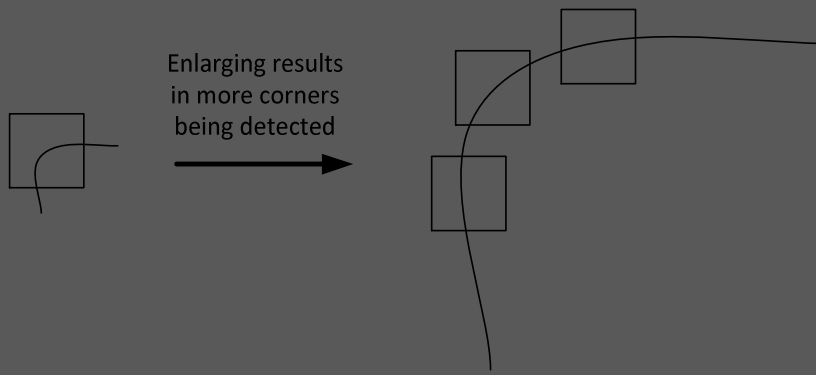
However, it is intolerant of:

- Large changes in intensity or photometric changes)
- Scaling (i.e. enlarging or shrinking)

Intensity Issues

Scaling Issues



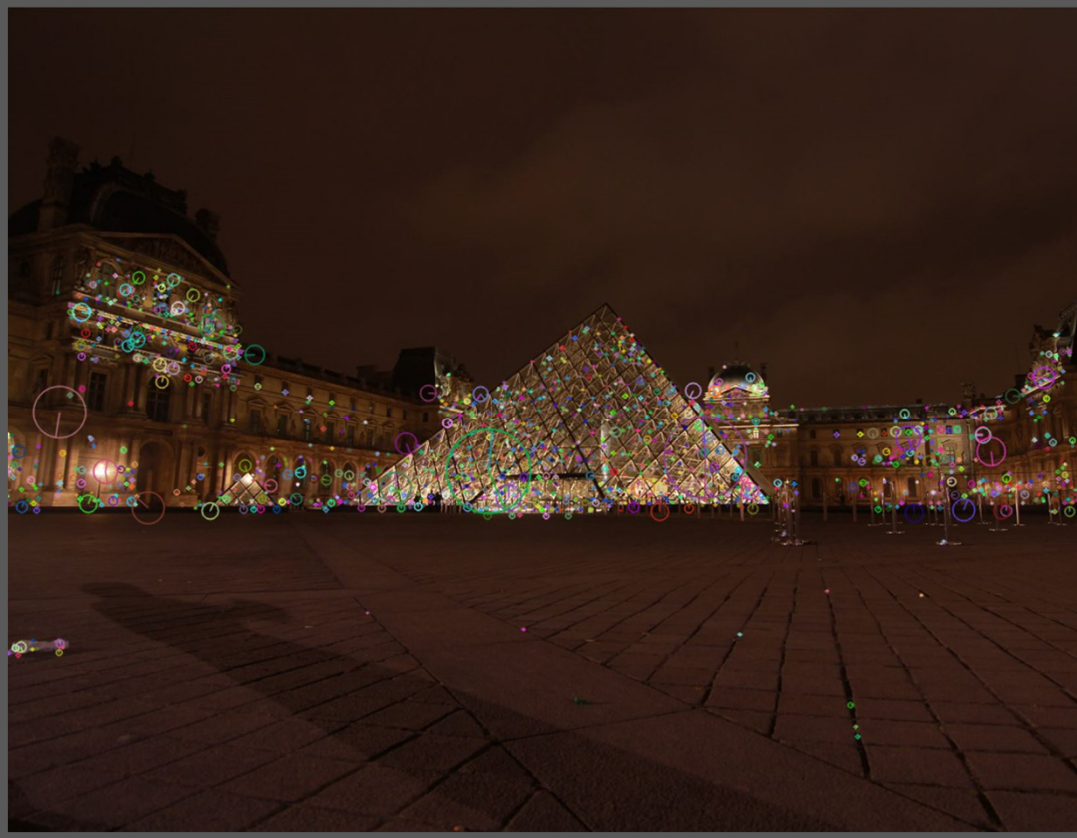


# ntroducing SIFT (Scale Invariant Feature Transform)

Needed tolerance to scaling *(known as scale invariance)*

SIFT is widely used (although patented) in computer vision as it very successfully dealt with the scale invariance issue

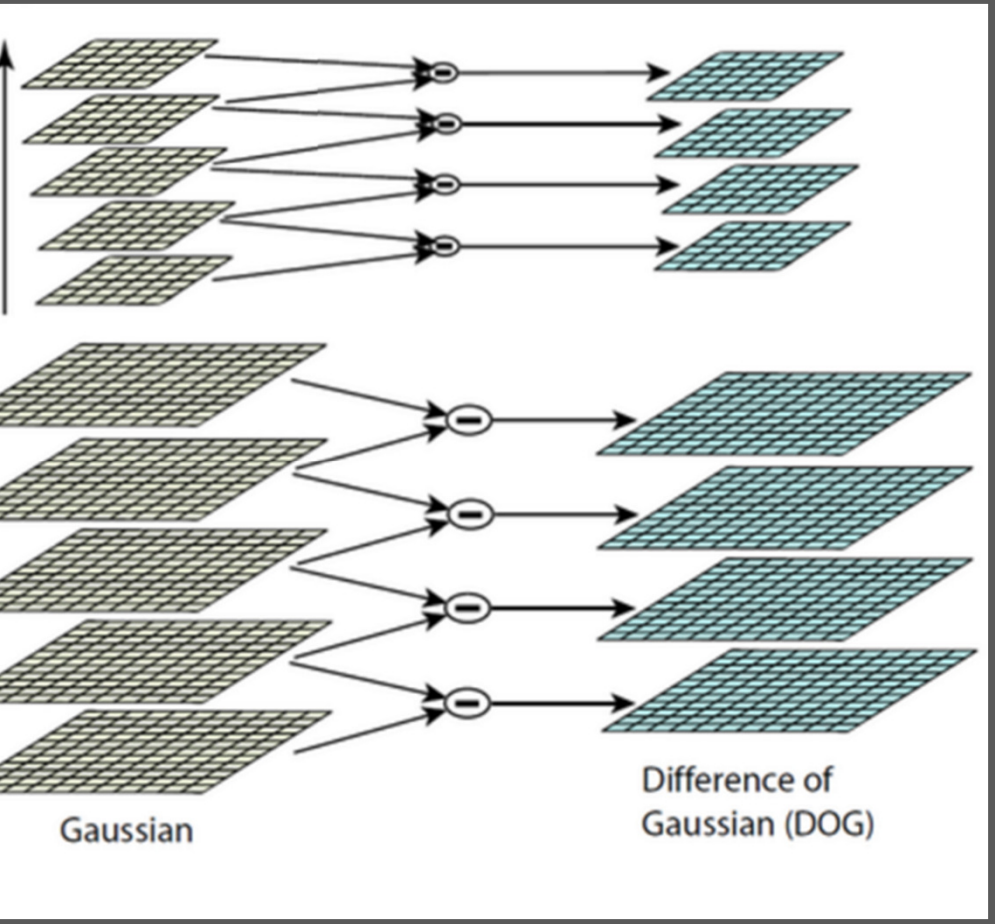
Patented and no longer freely available with OpenCV 3.0+

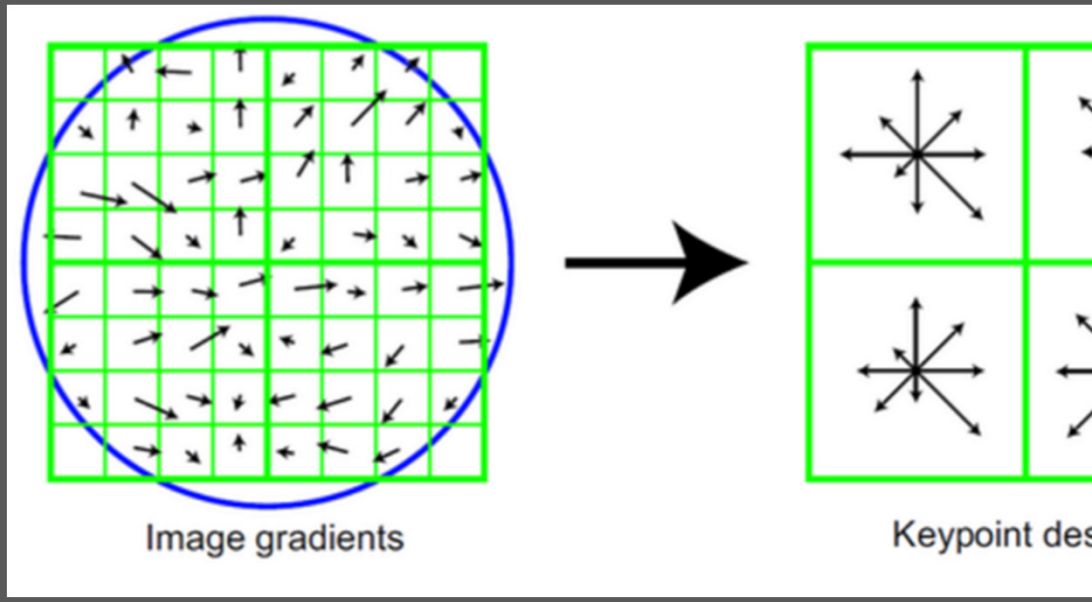


# SIFT in a nutshell

1. We firstly detect interesting key points in an image using the Difference of Gaussian method. These are areas of the image where variation exceeds a certain threshold and are better than edge descriptors.
2. We then create vector descriptor for these interesting areas. Scale invariance is achieved via the following process:
   i. Interest points are scanned at several different scales
   ii. The scale at which we meet a specific stability criteria, is then selected and is encoded by the vector descriptor. Therefore, regardless of the initial size, the more stable scale is found which allows us to be scale invariant.
3. Rotation invariance is achieved by obtaining the Orientation Assignment of the key point using image gradient magnitudes. Once we know the 2D direction, we can normalize this direction.
4. The full paper on SIFT can be read here:
   - http://www.cs.ubc.ca/~lowe/papers/ijcv04.pdf
5. An excellent tutorial on SIFT also available here
   - http://opencv-python-tutroals.readthedocs.io/en/latest/py_tutorials/py_feature2d/py_sift_intro/py_sift_intro.html

# SIFT (Scale Invariant Feature Transform)



# Speeded Up Robust Features (SURF)

- SIFT is quite effective buy computationally expensive
- SURF was developed to improve the speed of a scale invariant feature detecto
- Instead of using the Difference of Gaussian approach, SURF uses Hessian matri approximation to detect interesting points and use the sum of Haar wavelet responses for orientation assignment.

# Alternatives to SIFT and SURF

## Features from Accelerated Segment Test (FAST)

- Key point detection only (no descriptor, we can use SIFT or SURF to computer that)
- Used in real time applications

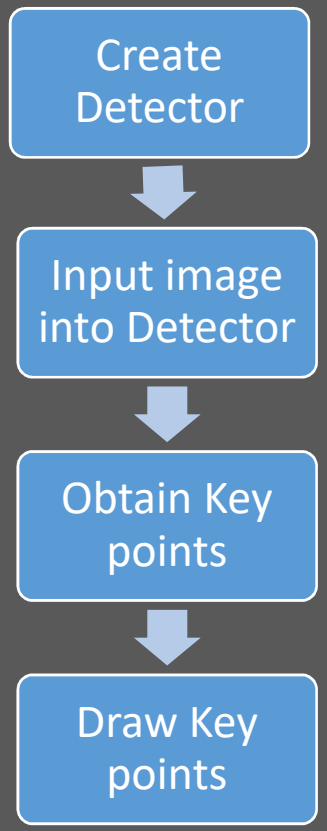
## Binary Robust Independent Elementary Features (BRIEF)

- Computers descriptors quickly (instead of using SIFT or SURF)
- Fast

## Oriented FAST and Rotated BRIEF (ORB) – Developed out of OpenCV Labs (no patented so free to use!)

- Combines both Fast and Brief
- http://www.willowgarage.com/sites/default/files/orb_final.pdf

# Using SIFT, SURF, FAST, BRIEF & ORB in OpenCV



# Mini Project # 5 – Object Detection

# Histogram of Oriented Gradients (HOGs)

HOGs are a feature descriptor that has been widely and successfully used for object detection.

It represents objects as a single feature vector as opposed to a set of feature vectors where each represents a segment of the image.

It's computed by sliding window detector over an image, where a HOG descriptor is a computed for each position. Like SIFT the scale of the image is adjusted (pyramiding).

HOGs are often used with SVM (support vector machine) classifiers. Each HOG descriptor that is computed is fed to a SVM classifier to determine if the object was found or not).

reat Paper by Dalal & Triggs on using HOGs for Human Detection:

- https://lear.inrialpes.fr/people/triggs/pubs/Dalal-cvpr05.pdf

# Histogram of Gradients (HOGs) Step by Step

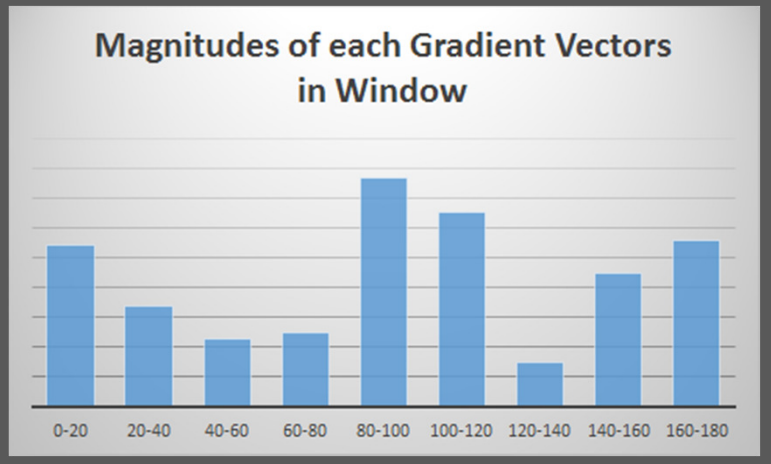
1. Using an 8 x 8 pixel detection window or cell (in green), we compute the gradient vector or edge orientations at each pixel.

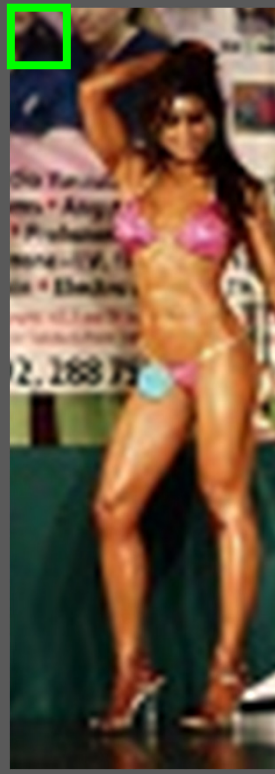
2. This generates 64 (8 x 8) gradient vectors which are then represented as a histogram.

3. Each cell is then split into angular bins, where each bin corresponds to a gradient direction (e.g. x, y). In the Dalal and Triggs paper, they used 9 bins 0-180° (20° each bin).

4. This effectively reduces 64 vectors to just 9 values.

5. As it stores gradients magnitudes, it's relatively immune to deformations.



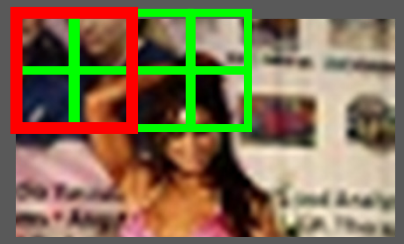



64 x 128

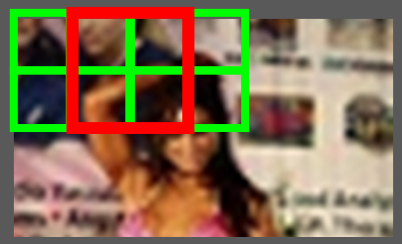
# Histogram of Gradients (HoG) Step by Step

. We then Normalize the gradients to ensure invariance to illumination changes i.e. Brightness and Contrast. E.g. in the images on the right, if we divide the vectors by the gradient magnitudes we get 0.707 for all, this is normalization.

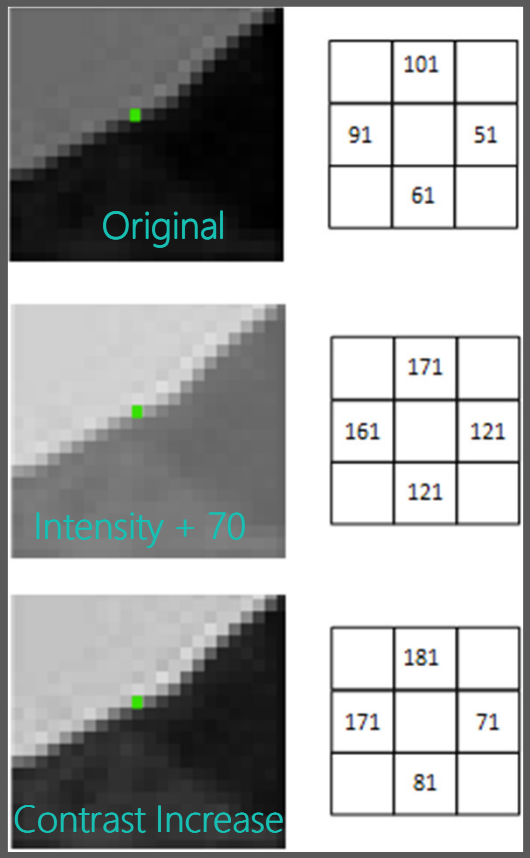
. Instead of individual window cell normalization, a method called Block Normalization is used. This takes into account neighboring blocks so we normalize taking into consideration larger segments of the image.



Block 1



Block 2



# Section 6

# Face, People & Car Detection

# Face, People & Car Detection

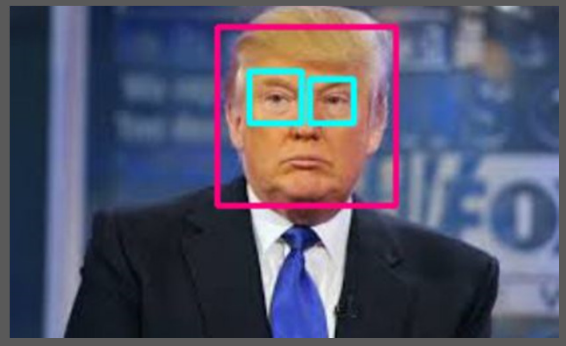
1. Understanding HAAR Cascade Classifiers
2. Face & Eye Detection
3. Mini Project # 6 - Car Detection & Pedestrian (Body) Detection

# HAAR Cascade Classifiers

As we saw in the previous section, we can extract features from an image and use those features to classify objects.

## What are HAAR Cascade Classifiers?

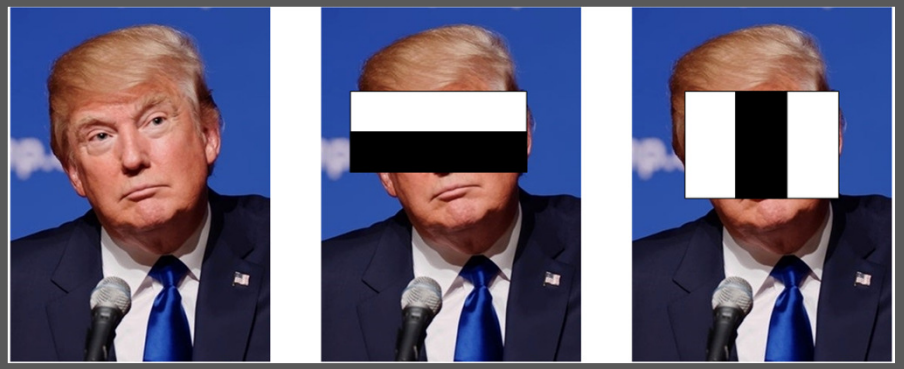
An object detection method that inputs Haar features into a series of classifiers (cascade) to identify objects in an image. They are trained to identify one type of object, however, we can use several of them in parallel e.g. detecting eyes and faces together.

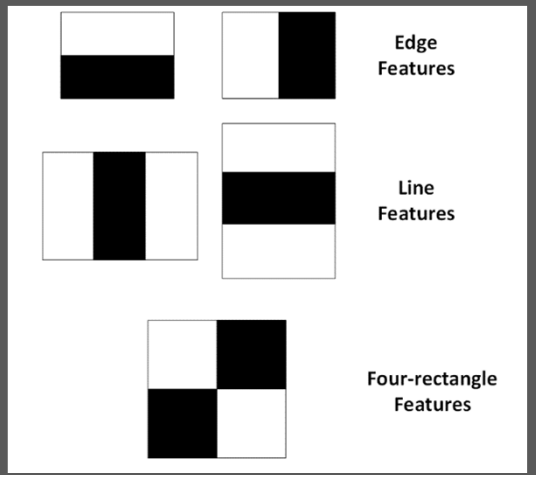


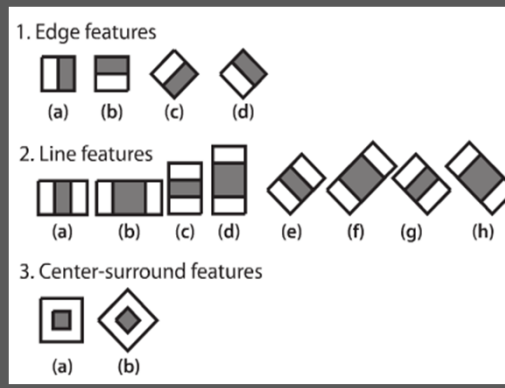
# HAAR Classifiers Explained

HAAR Classifiers are trained using lots of positive images (i.e. images with the object present) and negative images (i.e. images without the object present).


We then extract features using sliding windows of rectangular blocks. These features are single valued and are calculated by subtracting the sum of pixel intensities under the white rectangles from the black rectangles. However, this is a ridiculous number of calculations, even for a base window of 24 x 24 pixels (180,000 features generated). So the researchers devised a method called Integral Images that computed this with four array references.

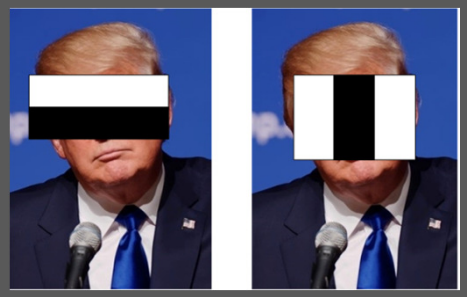




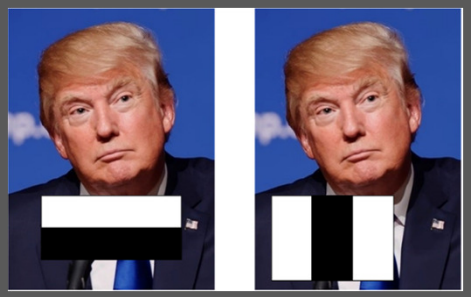



# HAAR Classifiers Explained

- However, they still had 180,000 features and the majority of them added no real value.



**Relevant**



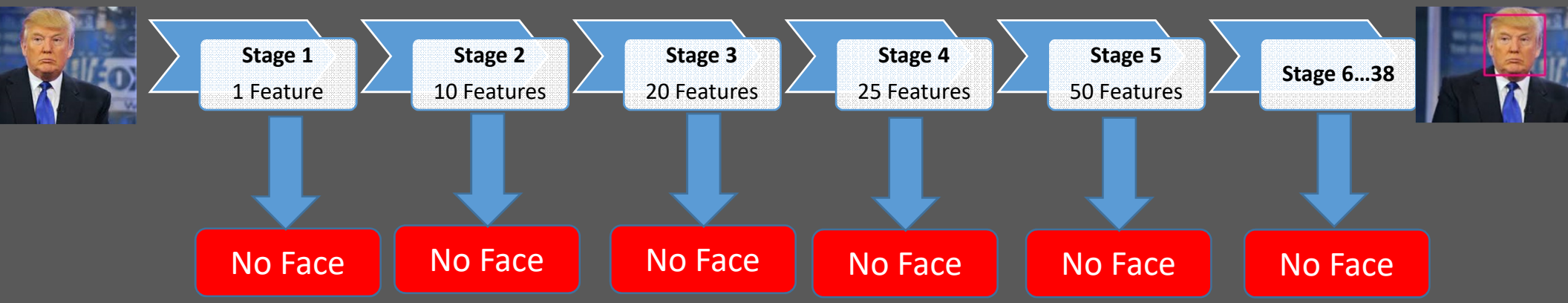
**Irrelevant**

- Boosting was then used to determine the most informative features, with Freund & Schapire's AdaBoost the algorithm of choice due to its ease of implementation. Boosting is the process by which we use weak classifiers to build strong classifiers, simply by assigning heavier weighted penalties on incorrect classifications. Reducing the 180,000 features to 6000, which is still quite a bit features.

# HAAR Classifiers Explained

- Think about this intuitively, if of those 6000 features, some will be more informative than others. What if we used the most informative features to first check whether the region can potentially have a face (false positives will be no big deal). Doing so eliminates the need for calculating all 6000 features at once.

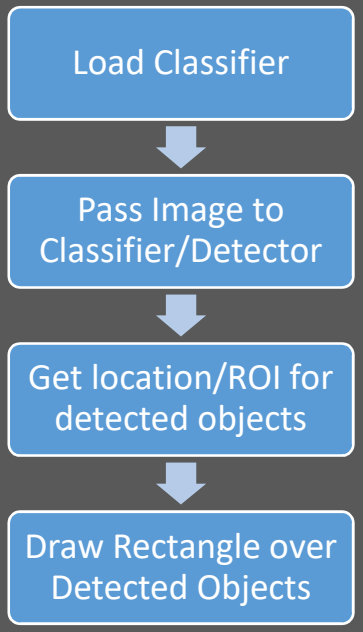
- This concept is called the Cascade of Classifiers - for face detection, the Viola Jones method used 38 stages.

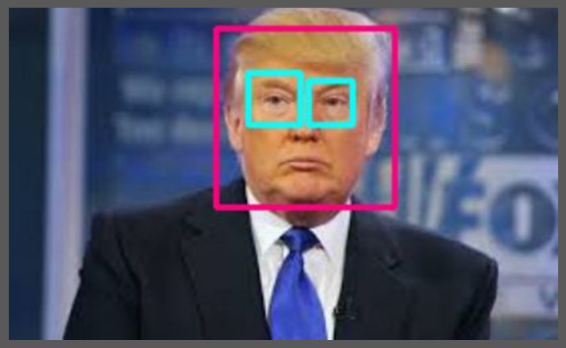


# Face & Eye Detection

1. We use some pre-trained classifiers that have been provided by OpenCV
   - Stored as .XML files
2. These pre-trained classifiers can be found here:
   - https://github.com/opencv/opencv/tree/master/data/haarcascades

Cascade Classifiers Flow



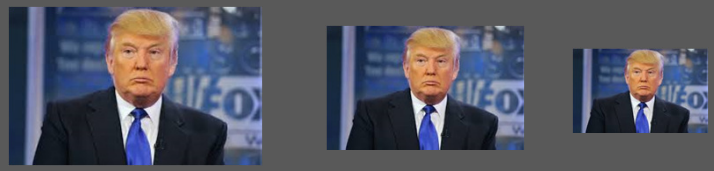



# Parameters for detectMultiScale

```
yourClassifier.detectMultiScale(input image, Scale Factor , Min Neighbors)
```

### Scale Factor

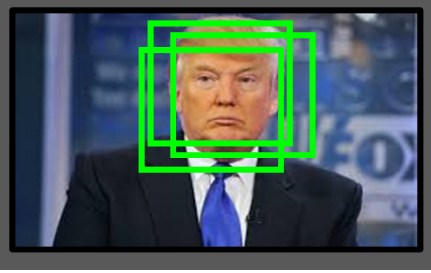
Specifies how much we reduce the image size each time we scale. E.g. in face detection we typically use 1.3. This means we reduce the image by 30% each time it's scaled. Smaller values, like 1.05 will take longer to compute, but will increase the rate of detection.



### Min Neighbors

Specifies the number of neighbors each potential window should have in order to consider it a positive detection. Typically set between 3-6.

- It acts as sensitivity setting, low values will sometimes detect multiples faces over a single face. High values will ensure less false positives, but you may miss some faces.



# List of OpenCV Pre-Trained Cascade Classifiers

ound Here - https://github.com/opencv/opencv/tree/master/data/haarcascades

| | |
|---|---|
| haarcascade_eye.xml | some attempts to tune the performance |
| haarcascade_eye_tree_eyeglasses.xml | some attempts to tune the performance |
| haarcascade_frontalcatface.xml | Removing whitespace to appease doc builder |
| haarcascade_frontalcatface_extende... | Removing whitespace to appease doc builder |
| haarcascade_frontalface_alt.xml | some attempts to tune the performance |
| haarcascade_frontalface_alt2.xml | some attempts to tune the performance |
| haarcascade_frontalface_alt_tree.xml | some attempts to tune the performance |
| haarcascade_frontalface_default.xml | some attempts to tune the performance |
| haarcascade_fullbody.xml | fixing wrong model sizes |
| haarcascade_lefteye_2splits.xml | some attempts to tune the performance |
| haarcascade_licence_plate_rus_16sta... | Added Haar cascade for russian cars licence plate detection, 16 stage... |
| haarcascade_lowerbody.xml | fixing wrong model sizes |
| haarcascade_profileface.xml | some attempts to tune the performance |
| haarcascade_righteye_2splits.xml | some attempts to tune the performance |
| haarcascade_russian_plate_number.... | Create haarcascade_russian_plate_number.xml |
| haarcascade_smile.xml | fixing wrong model sizes |
| haarcascade_upperbody.xml | fixing wrong model sizes |

# Mini Project # 6- Car and Pedestrian Detection

# Section 7

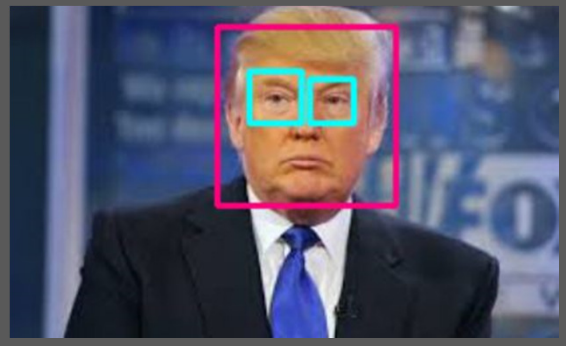
# Face Analysis & Filters

# HAAR Cascade Classifiers

As we saw in the previous section, we can extract features from an image and use those features to classify objects.

## What are HAAR Cascade Classifiers?

An object detection method that inputs Haar features into a series of classifiers (cascade) to identify objects in an image. They are trained to identify one type of object, however, we can use several of them in parallel e.g. detecting eyes and faces together.



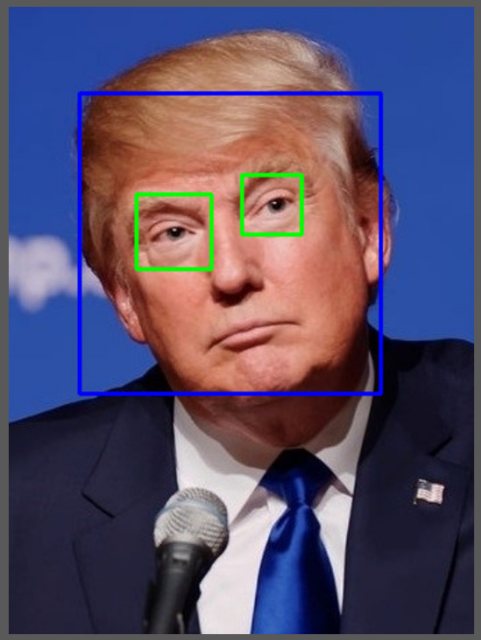
# Face Analysis & Filters

3. Finding Facial Landmarks using Dlib
4. Merging faces
5. Mini Project # 7 – Live Face Swaps – Become Donald Trump or Kim Kardashian
6. Mini Project # 8 – Face Reader, detect and count Yawns!

# Why is Advanced Face Morphing Hard?

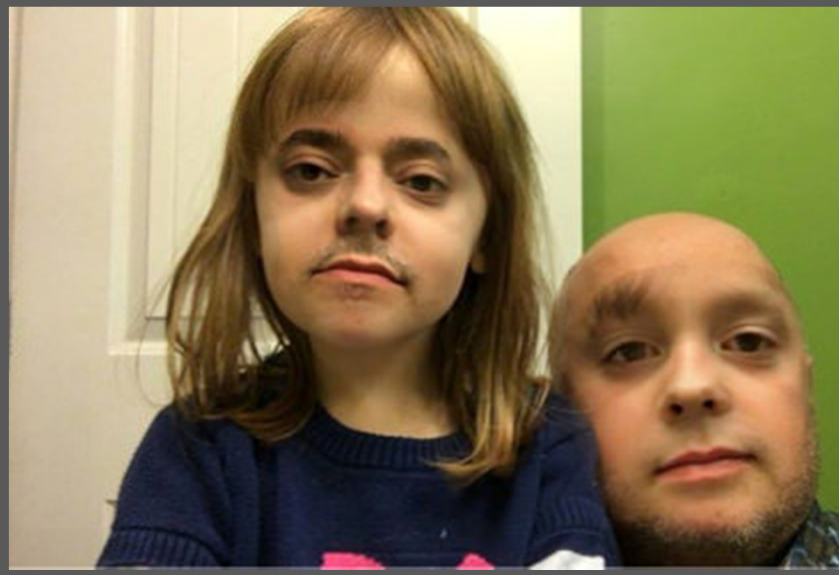
Previously we saw that HAAR Cascade Classifiers provide excellent results in Face Detection

However, we can’t simply cut someone's face out of one picture and place it onto another and expect realistic results



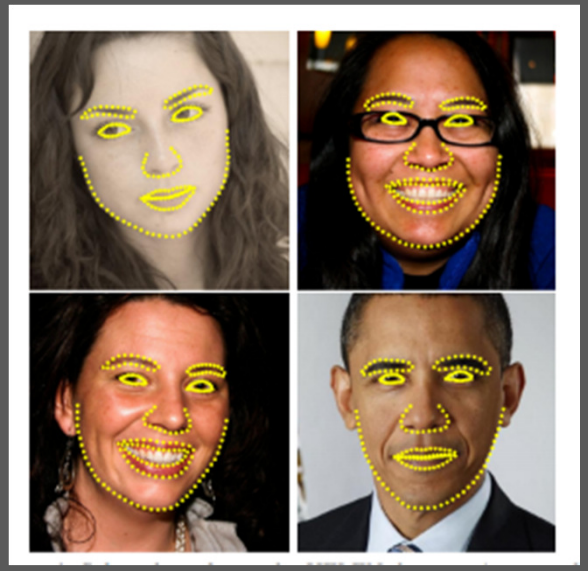
ace morphing isn’t simply cutting and sticking a face on another image!

# However, the latest Apps like MSQRD and Snapchat are doing this well! How?

# Researchers are getting better at detecting facial landmarks

In 2014, Swedish Computer Vision researchers Kazemi and Sullivan, created the One Millisecond Face Alignment with Ensemble of Regression Trees.



They developed a method to quickly determine facial landmarks in almost real-time! This was a major milestone in Face Swaps!

# Better Morphing Methods Produce Much Better (and scarier!) Results




# Better Morphing Methods Produce Much Better (and scarier!) Results

# What was so hard about that?

1. Identifying Facial Features
2. Warping the image to fit the new and different facial expression
3. Color Matching
4. Creating seamless borders on the edges of the new swapped face

It is hard, but we can now do it relatively easy in Python using dlib and OpenCV

# Finding Facial Landmarks Using DLIB

DLIB is a fantastic Machine Learning C++ library that be utilized in python to quickly identify facial landmarks.

Let's take a look and test it out!

# Setting up DLIB in Python

Download and Install Dlib

- https://sourceforge.net/projects/dclib/
- Extract files in C:/dlib
- Use command prompt to Cd to folder and run *"python setup.py install"*

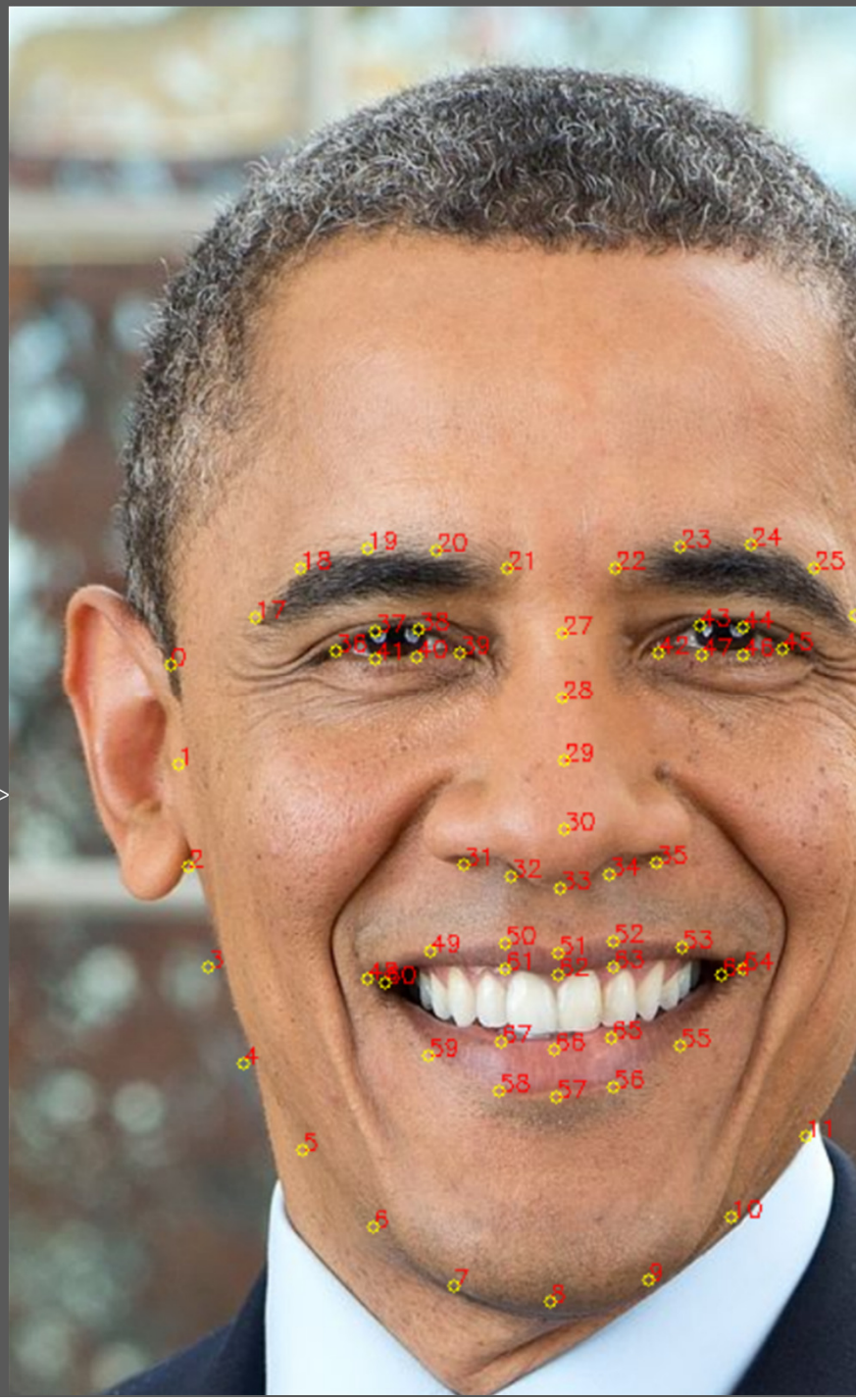
Download the pre-trained model here

- http://dlib.net/files/shape_predictor_68_face_landmarks.dat.bz2
- Place this file in your default ipython notebook folder

Run a simple example to show facial landmarks on face ---------->

Facial Landmarks Number Order

- MOUTH_POINTS = 48 to 61
- RIGHT_BROW_POINTS = 17 to 21
- LEFT_BROW_POINTS = 22 to 27
- RIGHT_EYE_POINTS = 36 to 42
- LEFT_EYE_POINTS = 42 to 48
- NOSE_POINTS = 27 to 35
- JAW_POINTS = 0 to 17

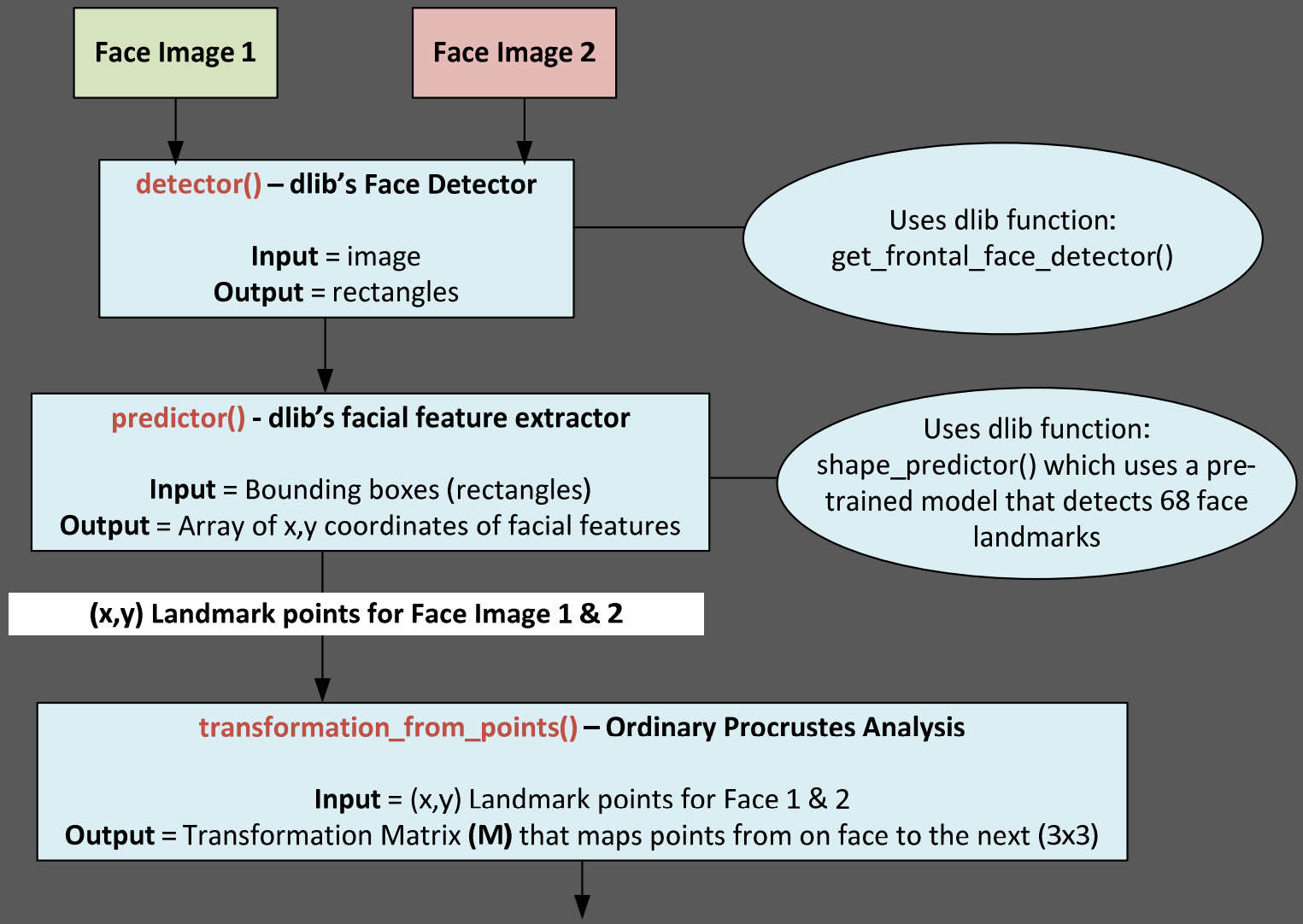


# Making Our Own Face Swapping App

This involves some complicated math and advanced computer vision techniques

We will not go through the code in detail, however we will attempt to understand at a high level, what each function does and the steps we need to take to create our swapped face.

# First Half of our Face Swapper



# Continued..


get_face_mask() – Generates a mask for an image and a landmark matrix
Input = Image 2 and its Facial Landmarks (x,y)
Output = An image mask outlining which parts of image 2 will be overlaid on image 1
warp_im() – Maps one image onto another image using Transformation Matrix (M)
Input = Image 1, Transformation Matrix (M) & Image 2's shape/matrix dimensions
Output = Image 1 with Image 2's face overlaid over it (warped_mask)
Generate a Combined Masks by taking an element-wise maximum
Input = Image 1 and is Facial Landmarks (x,y) & the warped_mask
Output = A combined mask which ensures the features from image 1 are covered up and the images for image 2 are visible
correct_colours() – Attempts to match skin tone and lighting between 2 images
Input = Images 1 & warped_im2 (reverse of warped_mark) and facial landmarks of image 1
Output = Color Corrected Warped image 2
Apply Mask to produce final image
Input = Color Corrected Warped image 2, the Combined Mask and the Original Image 1
Output = Final Face Swapped Image

Let’s do a quick run through of the code and have some fun!

t's sort of impressive for still images, but
can we turn this into a live face swapper?

YES!

Let’s now edit the code to turn this into our own
version the popular and $35M app MSQRD!

# Mini Project # 7 – Live Face Swapping


# Mini Project # 8 – Yawn Detector and Counter

# Section 8

# achine Learning in Computer Visio

# Machine Learning

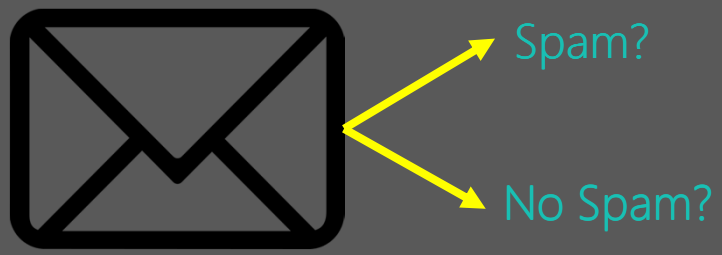
1. Overview of Machine Learning in Computer Vision and KNNs
2. Mini Project # 9 – Handwritten Digit Recognition
3. Mini Project # 10 – Face Recognition, Unlock Your Computer With Your Face!

# What is Machine Learning?

achine Learning gives computers the ability to make predictions or learn from d

amples:

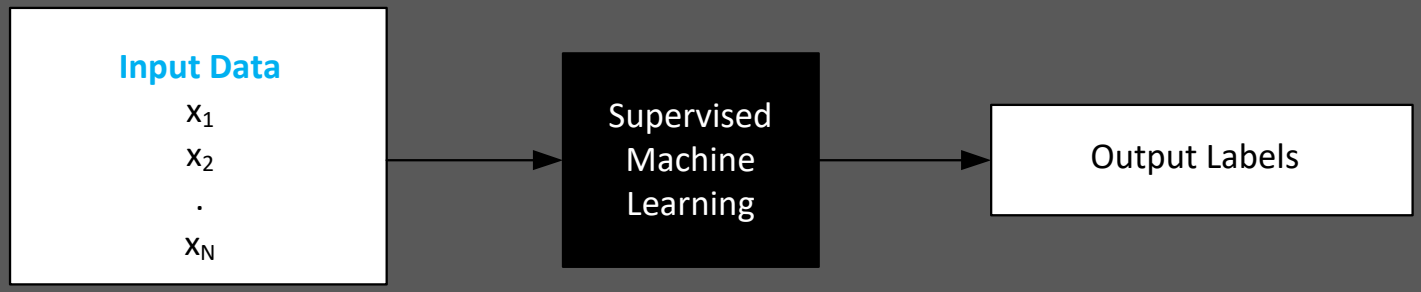
1. Using today's news articles to predict tomorrows stock price
2. Using words in a Tweet to predict the sentiment express (e.g. anger, sadnes joy, political views)
3. Predicting illnesses based on medical data
4. Using your past shopping data to predict future purchases'
5. And the most popular example, filtering email spam.



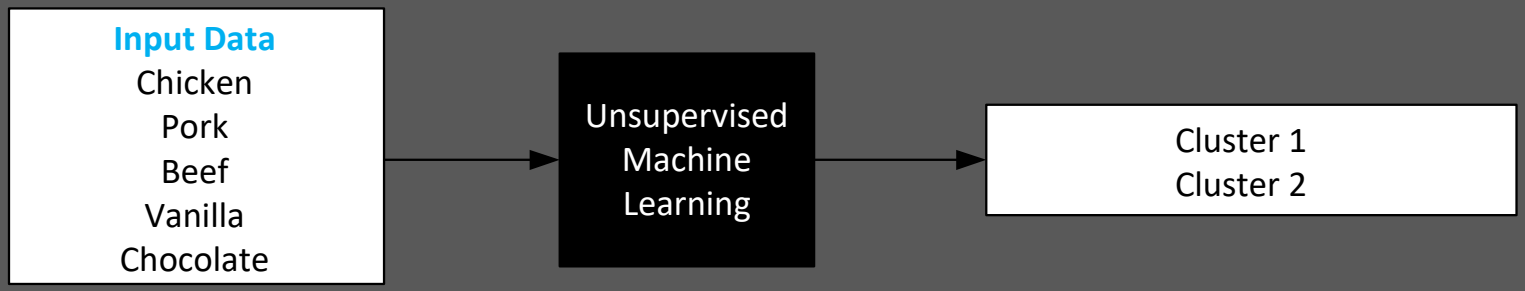
# Two main types of Machine Learning

## upervised & Unsupervised Learning

upervised Learning – We feed an algorithm some ground truth examples. It then ormulates a model mapping inputs to outputs (Training Process). We then use this model o predict the outputs of new inputs.



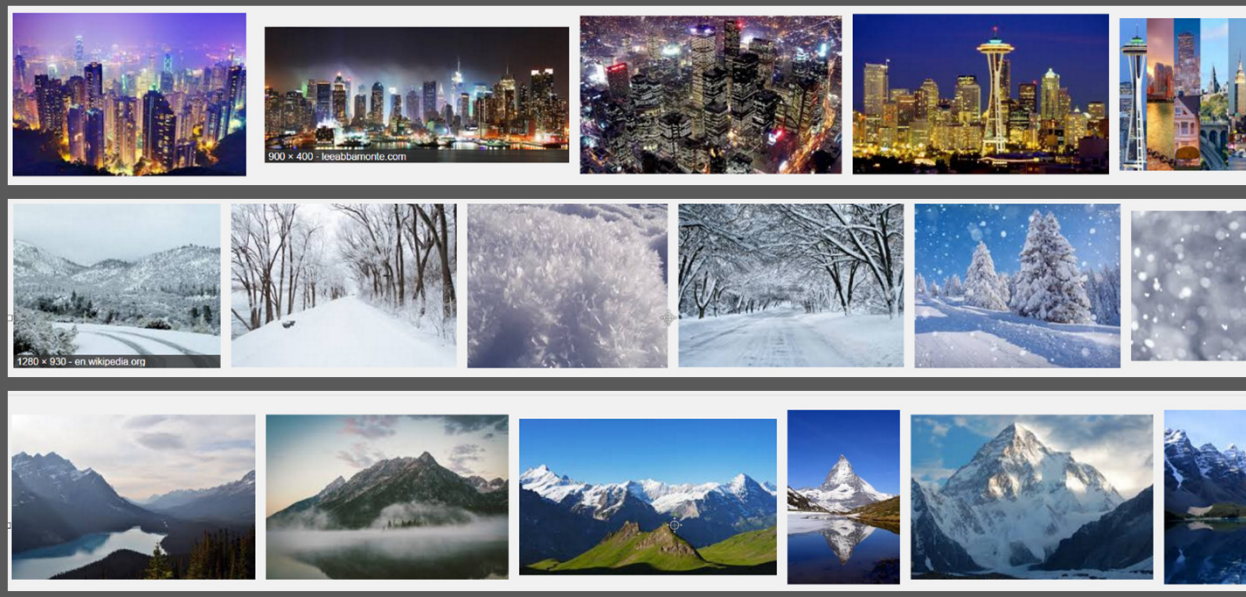

nsupervised Learning – We similarly try to predict the output from input data, however no round truth examples are given. Think clustering!



# Examples - Supervised & Unsupervised Learning

upervised Learning

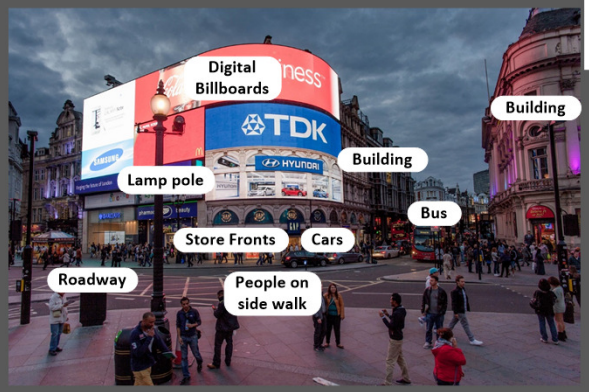
Unsupervised Learning



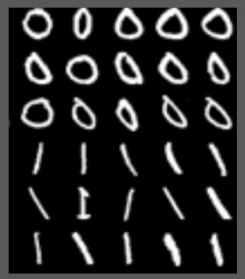
# Machine Learning in Computer Vision

## What is it good for?

- Predicting if a face is in image (Face Detection)
- Recognizing Faces in Images (Mini Project # 10)
- Classifying the type of car in an image
- Road Sign Detection
- License Plate Reading
- Signature Verification
- Finger Print Reading
- Xbox Kinect
- Object Recognition
- Robotic Navigation
- Understanding Handwriting (Mini Project # 9)





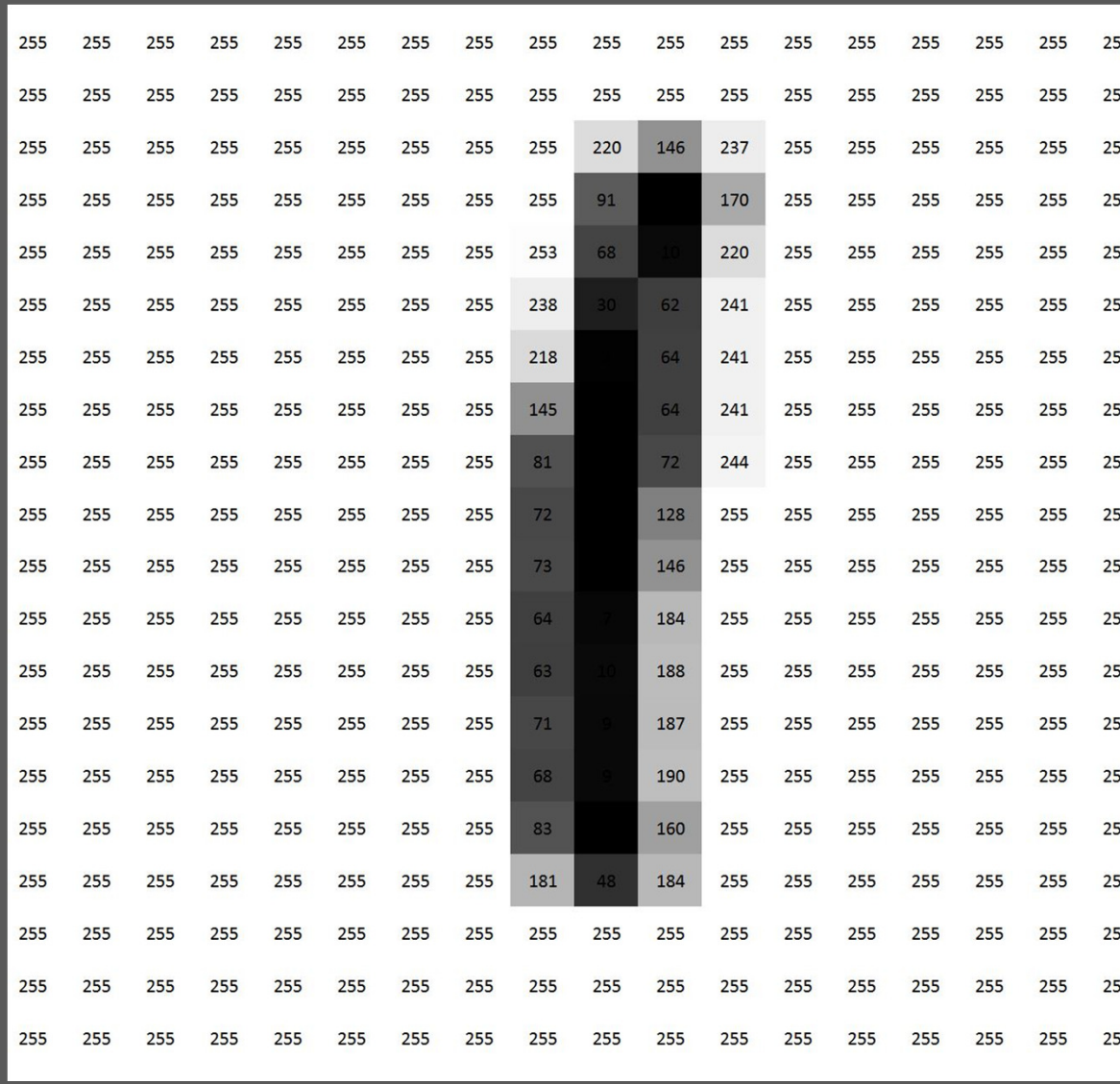
# How is typically used?

Looking at raw pixel intensities or colors

Key point Descriptors

Histograms of Image Gradients (HOGS)

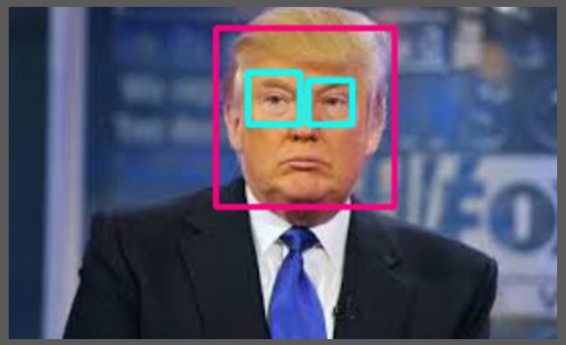
Pixel statistics (such as dimensions, mean, variance and many more)



# Common Machine Learning Algorithms used in Computer Vision

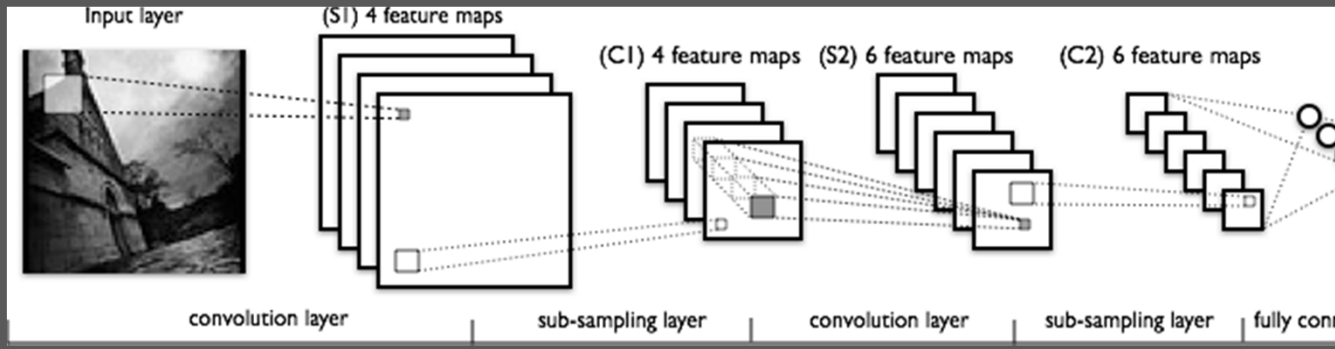
## Traditional ML Algorithms

- KNN
- SVMs
- Haar Cascade Classifiers



## Neural Networks

- Convolutional Neural Networks (CNN) – are able to beat humans in object recognition tasks
  - Café
  - TensorFlow
  - Theano & Keras
- Deep Belief Networks

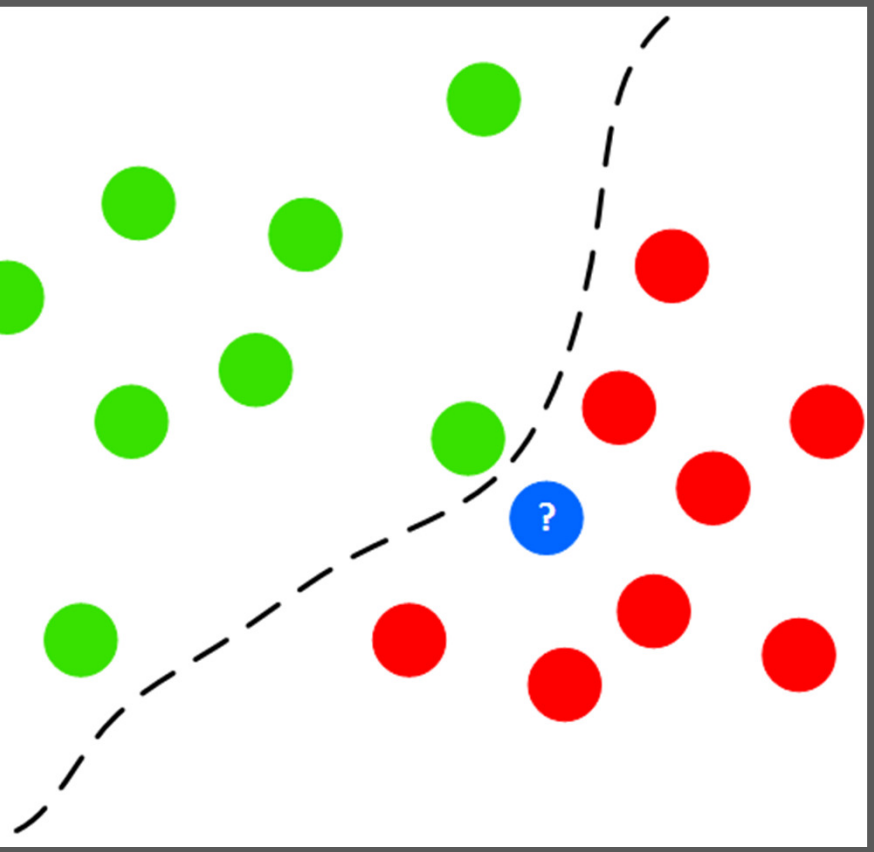


# K-Nearest Neighbors Algorithm

KNN is a simple machine learning classifier that classifiers a new input based on the closest examples in the feature space.

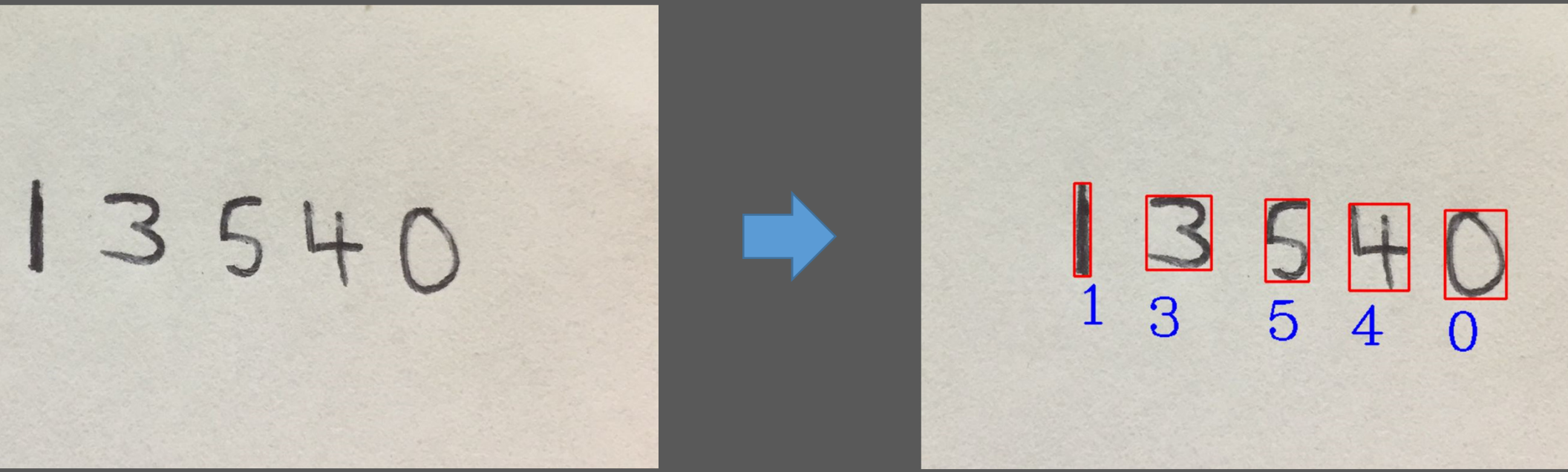
It's based on the weighted Euclidean distance of the k-nearest neighbors.

# K-Nearest Neighbors Algorithm




- The new blue dot is closest to a green dot
- However, it's obvious that the blue dot belongs to the red class
- Let's look at the blue dot's 3 nearest neighbors:
  - 1 Green
  - 2 Red
- Using this logic, the blue should be in the red class now.
- What if k was even, or we had 3 class categories?
- To avoid ties in the above scenario, we use the Euclidean distance function:
  - $distance = \sum_{i=1}^{N}(a_i - b_i)^2$
- Each neighbor is assigned a distance weight which is used to determine it's class e.g.
  - d(blue, green) = 2
  - d(blue, red1) = 3
  - d(blue, red2) = 3
- Overall Distance from Red = 3/2 = 1.5
- Overall Distance from Green = 2

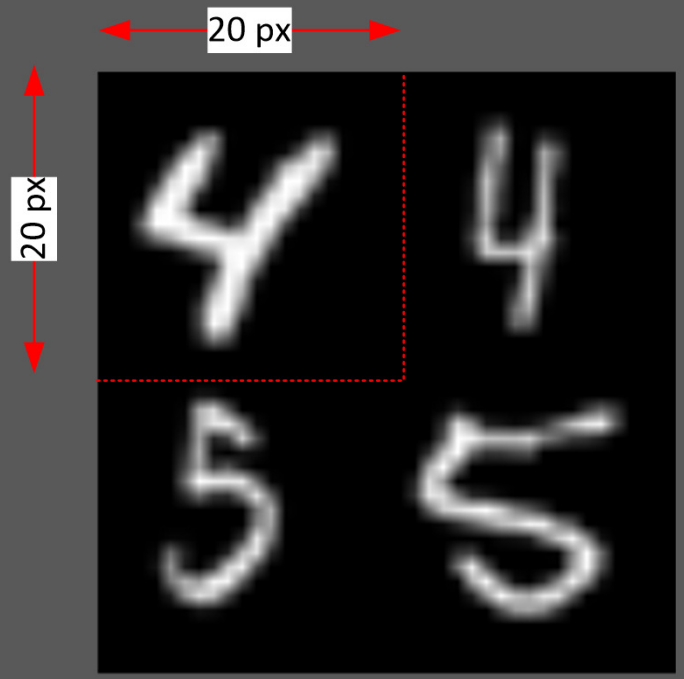
# Mini Project # 9 – Handwritten Digits Classification

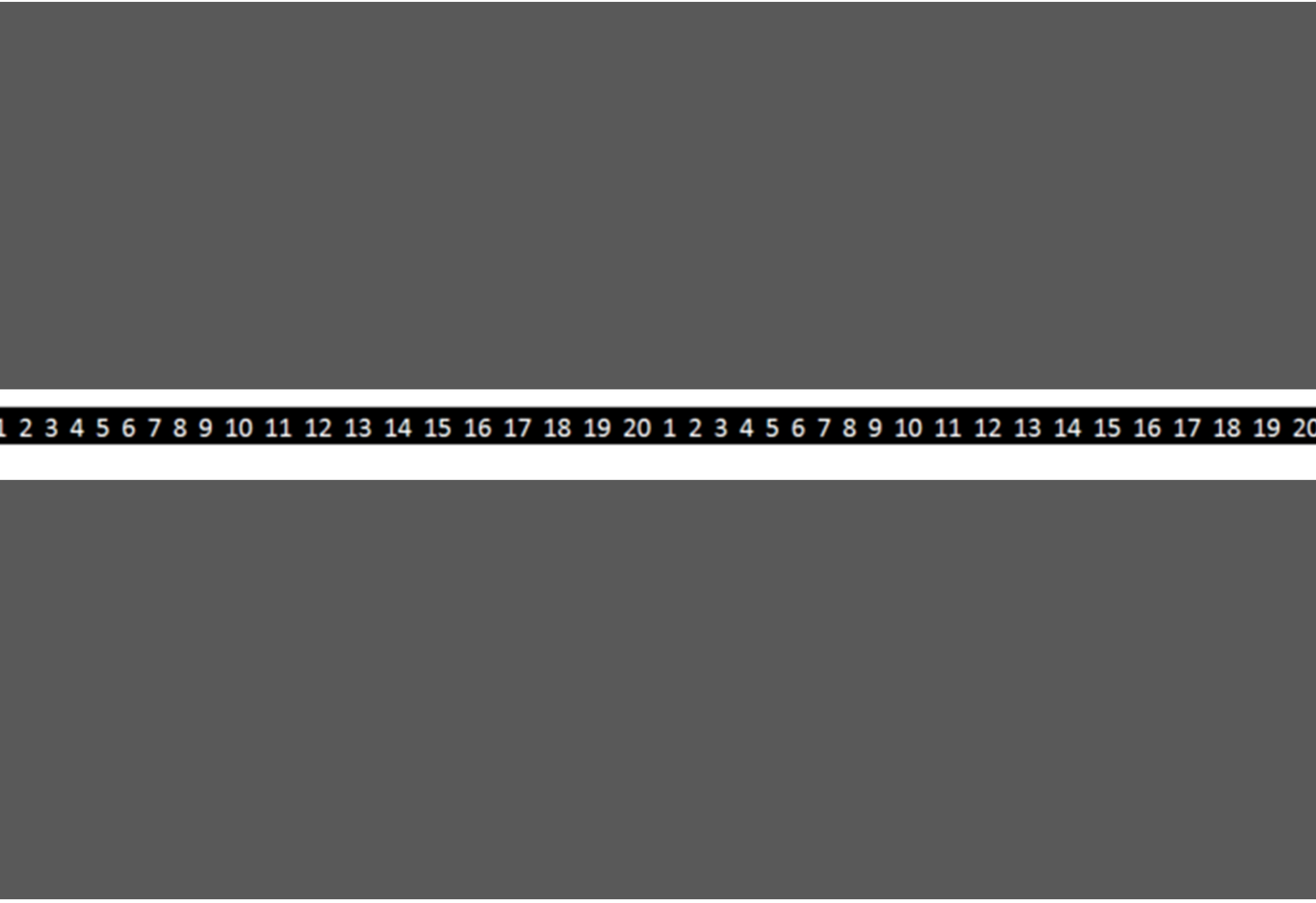


50 x 100 Images, 500 samples of each number

# About the Digits Data Set

- The digits.png image contains 500 samples of each numeral (0-9)
- Total of 5000 samples of data
- Each individual character has dimensions: 20 x 20 pixels
- Is grayscale with black backgrounds




1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20

# Preparing our Dataset

How we prepare the data?

- 500 samples of each digit with 5 rows of 100 samples
- Each character is a grayscale 20 x 20 pixels
- We use numpy to arrange the data in this format:
  - 50 x 100 x 20 x 20
- We then split the training dataset into 2 segments and flatten our 20x20 array.
  - Training Set - 70% of the data
  - Test Set - 30% of the data - we use a test set to evaluate our model
  - Each dataset is then flattened, meaning we turn the 20 x 20 pixel array into a flat 1 x 400. Each row of 20 pixels is simply appended into one long column.
- We then assign labels to both training & test datasets (i.e. 0,1,2,3,4,5,6,7,9)

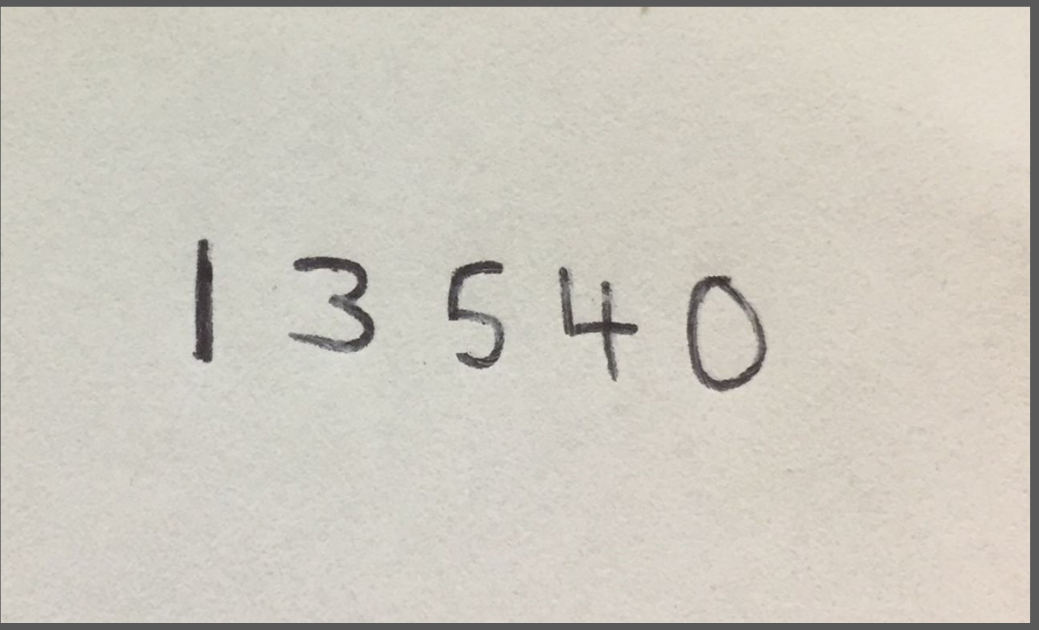
# Using OpenCV's KNN

Using OpenCV's KNN functions are very simple

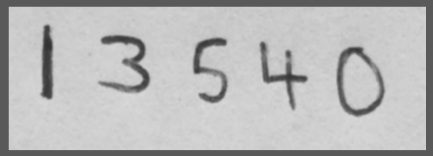
1. Initialize our KNN Classifier
   - `knn = cv2.KNearest()`
2. Train Model using the training dataset and correct labels
   - `knn.train(train, train_labels)`
3. Evaluate Model with the test dataset
   - `ret, result, neighbors, distance = knn.find_nearest(test, k)`
     - ret – true or false Boolean indicating if operation was successful
     - Result – Accuracy i.e. (number correctly classified) / total number of inputs
     - Neighbors – the class of the nearest k neighbors
     - Distance – Euclidean distance from each point neighbor

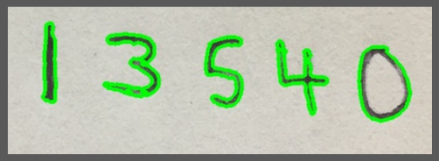
# Testing Our Classifier

- So we got an accuracy of 93.47%
- How do we test this on a new image

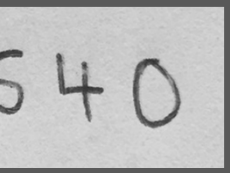


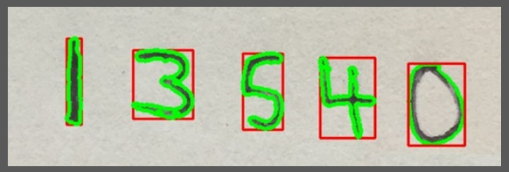
# Processing a New Image

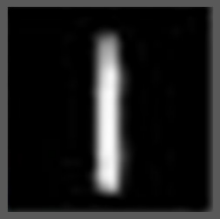




Gaussian Blur → Canny Edges → Extract Contours → Get Bounding Rectangle → Filter Contours → Crop Bounding Rectangle of blurred image → Binarize and then make into a 20x20 Square → Convert to 1 x 400 array





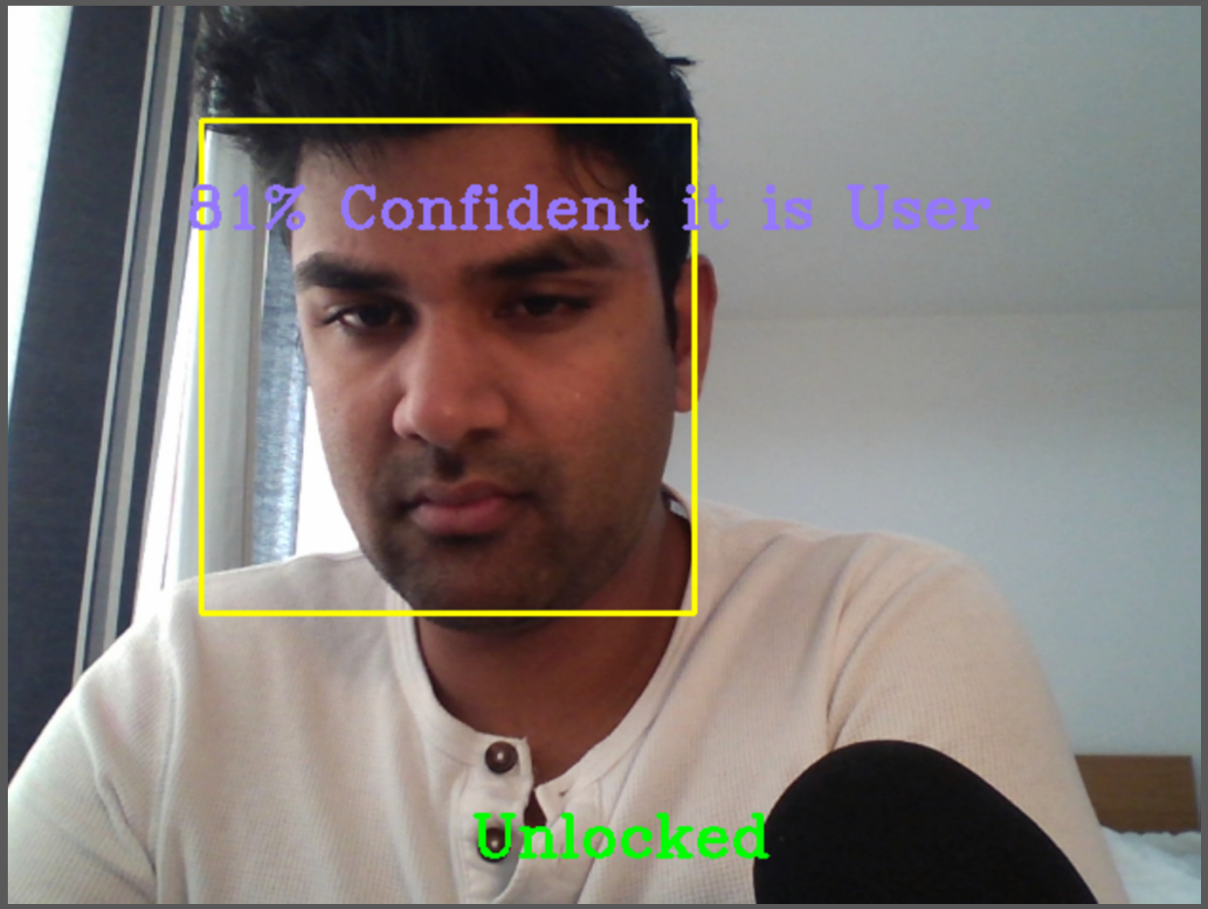


# Can we Improve this?

- Get larger Dataset (MNIST is a excellent with 6000 examples per class)
- Add perturbations in data to account for variances (neat way of expanding training dataset)
- Use different classifiers, Neural Networks are excellent at getting 99%+ accuracy

Check out the current accuracy levels achieved in classifying the MNIST dataset: http://yann.lecun.com/exdb/mnist/

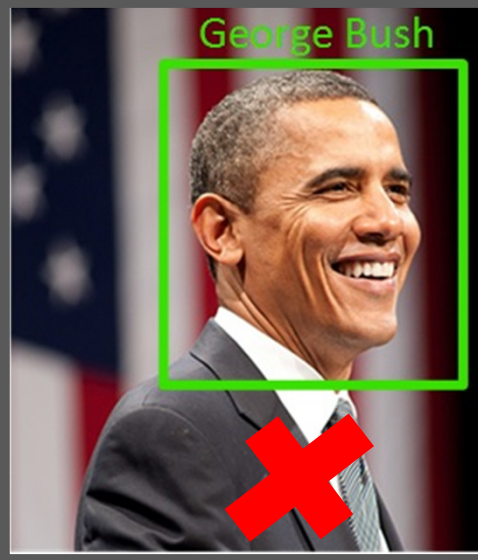
# Mini Project # 10 – Facial Recognition



# Facial Recognition

Facial Recognition is a task that human abilities are absolutely brilliant, and even some animals, dogs, crows, sheep can do it.

## General overview of facial recognition systems steps:




1. Obtain faces & normalize images (face alignment etc.)
   - Build a dataset of face images
2. Detect and record features of face
   - General global features
   - Geometric features such as spatial relations of eyes, nose, mouth etc.
   - PCA or LDA representations
   - Local feature extraction
3. Use features to then classify face or return a confidence/probability value

# Facial Recognition with OpenCV

OpenCV comes with 3 facial recognition libraries, all of which operate similarly where they take our dataset of labelled faces, and compute features to represent the images. Their classifiers then utilize these features to classify.

1. Eigenfaces - createEigenFaceRecognizer()
2. Fisherfaces - createFisherFaceRecognizer()
3. Local Binary Patterns Histograms - createLBPHFaceRecognizer()

Learn more here - http://docs.opencv.org/2.4/modules/contrib/doc/facerec/facerec_tutorial.html

# Facial Recognition with OpenCV

1. Eigenfaces - Uses Principle Component Analysis to reduce the dimensionality of the face. However, this neglects the class label into account and can represent variance from changes in illumination.

2. Fisherfaces – Solves this by using LDA (Linear Discriminant Analysis) that is a class-specific projection, which means it attempts to minimize variance within a class, while maximizing variance between classes.

3. Local Binary Patterns Histograms - Uses local feature extraction while persevering spatial relationships. It divides faces into cells and then compares each cell to face being classified. It then produces a histogram showing the matching values of an area.

# Mini Project # 10 – Face Recognition

eate our Training Data

ord 100 Images of your using the HAAR Cascade Face Detector

nalize by gray scaling and izing to 200 x 200 pixels

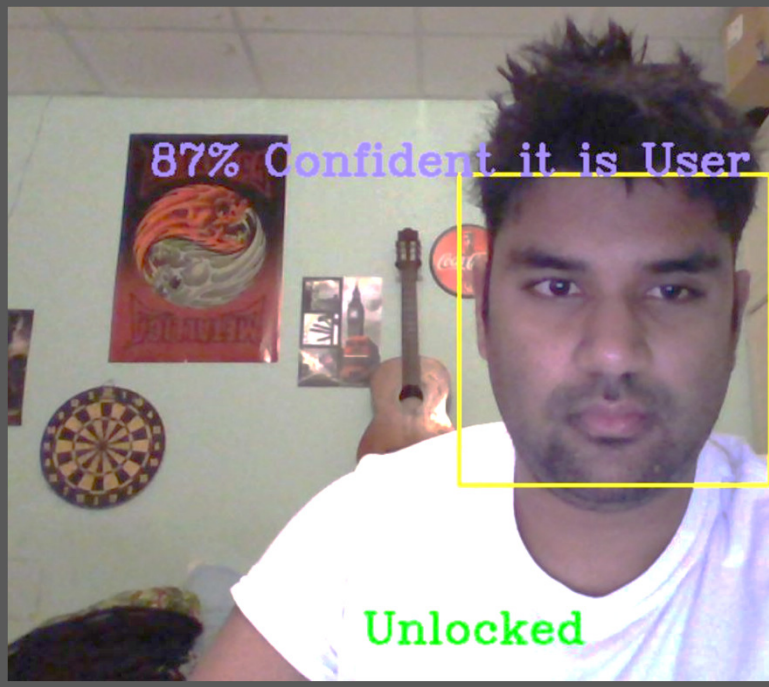
ate an array of labels for ded images (will you only yourself in this example)

Classify New Face

Extract Face from Webcam using the HAAR Cascade Face Detector

Normalize by gray scaling and re-sizing to 200 x 200 pixels

Pass face to our model predictor to get label and confidence value



# Section 9

# otion Analysis and Object Trackin

# Motion Analysis and Object Tracking

1. Filtering by Color
2. Background Subtraction
3. Meanshift
4. Camshift
5. Optical Flow
6. Mini Project # 11 – Ball Tracking

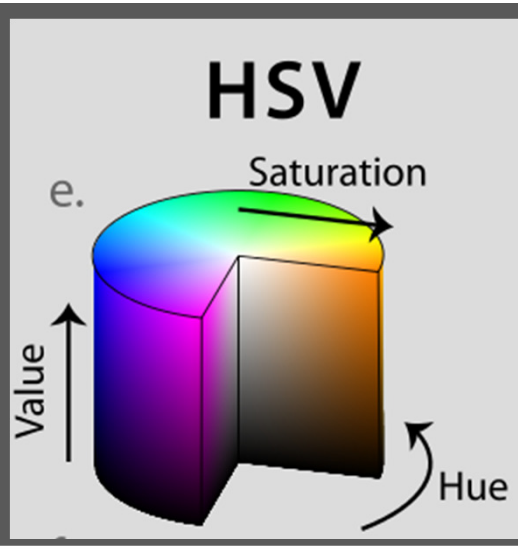
# Color Filtering

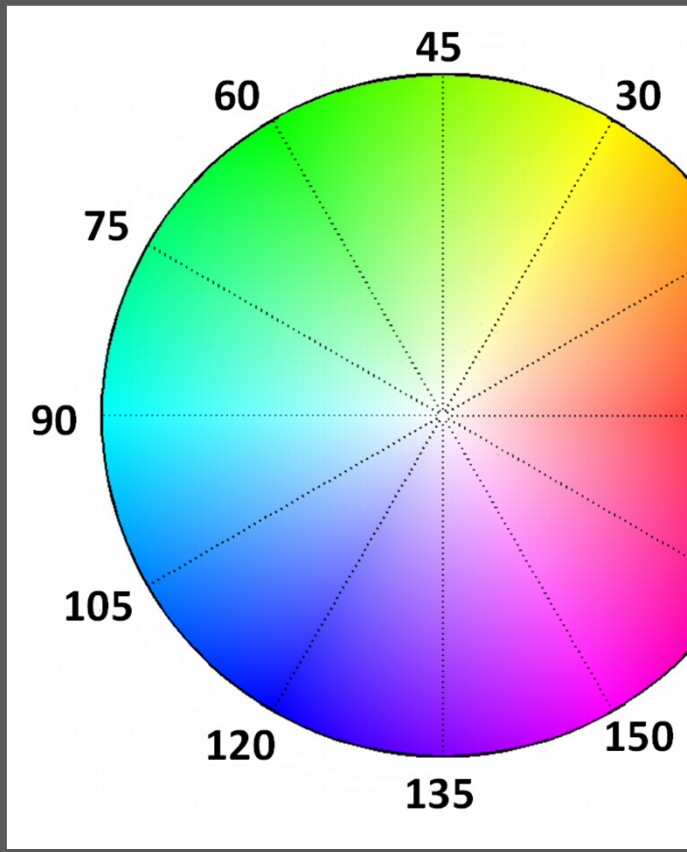
## Filter by Hue

- Hue color range, goes from 0 to 180
- Color Range Filters:
  - Red – 165 to 15
  - Green – 45 to 75
  - Blue – 90 to 120

## Filter by Saturation & Value/Brightness

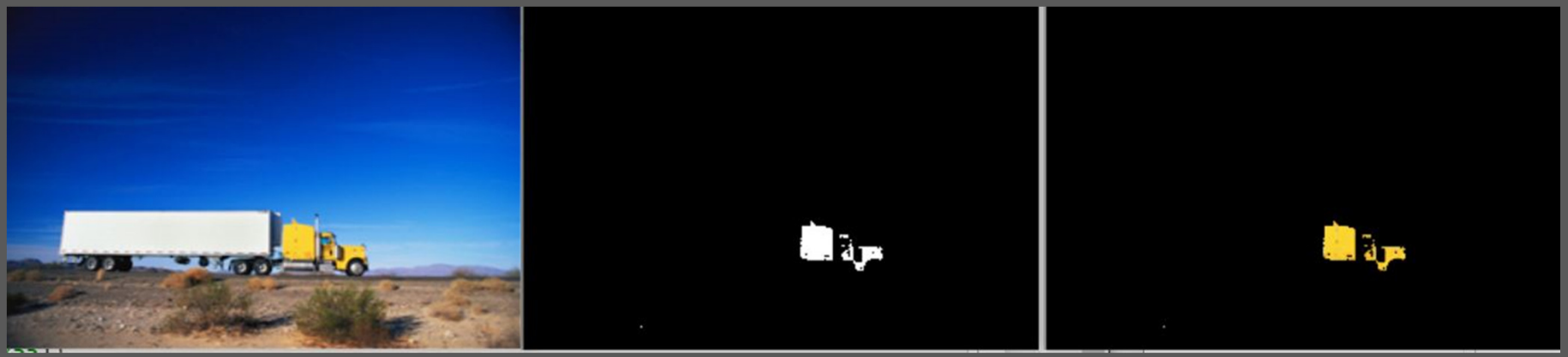
- Typically we set the filter range from 50 to 255 for both saturation and value as this captures the actual colors
- 0 to 60 in Saturation is close to white
- 0 to 60 in Value is close to black



# Implementing a Color Filter

1. Define upper and lower range of color filter.
2. Create a binary (thresholded) mask showing only the desired colors in white
   - `mask = cv2.inRange(hsv_img, lower_color_range, upper_color_range)`
3. Perform a `bitwise_and` operation on the original image and the mask.



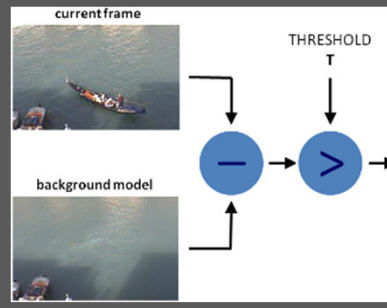
# Background Subtraction

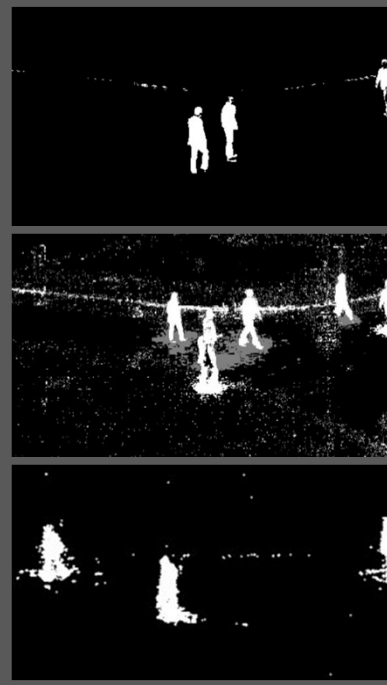
is is a very useful computer vision technique which allows us to separate egrounds from the backgrounds in a video stream.

ese algorithms essentially learn about the frame in view (video stream) and e able to accurate "learn" and identify the foreground mask. What results is a nary segmentation of the image which highlights regions of non-stationary jects.

ere are a several Background subtraction algorithms in OpenCV specifically r video analysis:

- BackgroundSubtractorMOG - Gaussian Mixture-based background/foreground Segmentation Algorithm.
- BackgroundSubtractorMOG2 – Another Gaussian Mixture-based background subtraction method, however with better adaptability to illumination changes and with better ability to detect shadows!
- Geometric Multigrid (GMG) - This method combines statistical background image estimation and per-pixel Bayesian segmentation

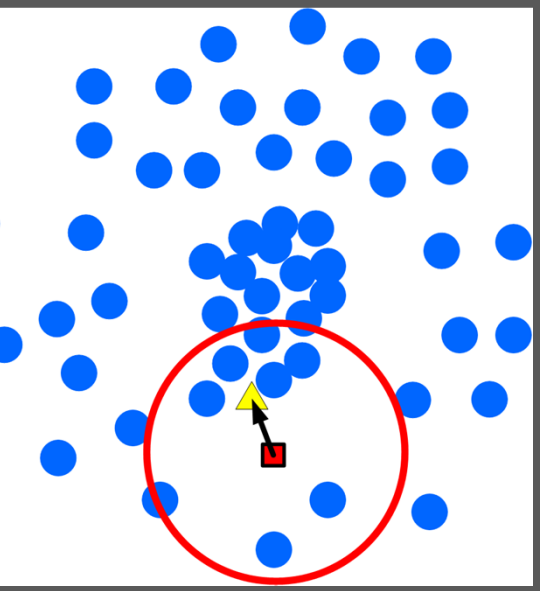


# Meanshift – An Object Tracking Algorithm

ts premise is simple, it tracks objects by finding the maximum density of a discrete sample of points and then recalculates it at the next frame. This effectively, moves our observation window n the direction the object has moved.

n OpenCV we typically use the histogram back projected image and initial target location.



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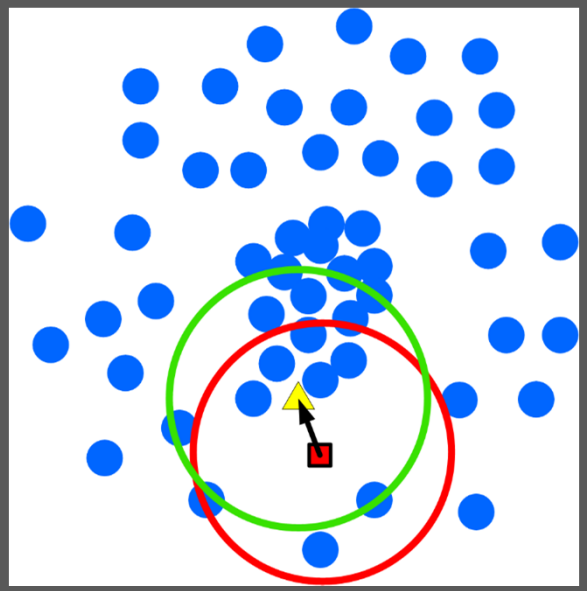
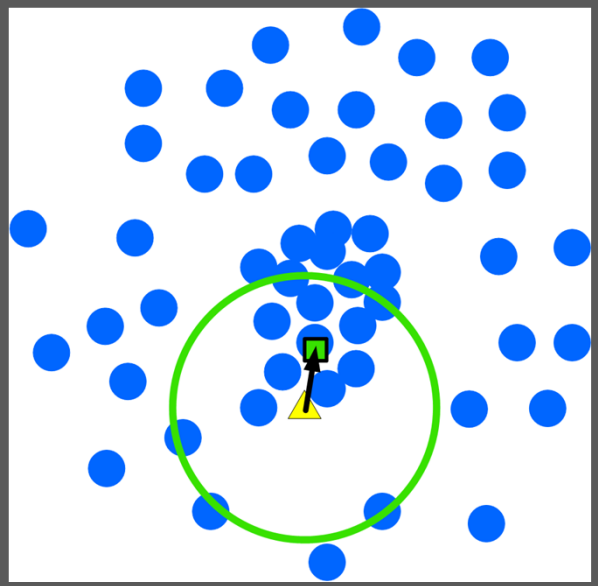


2



3

# Camshift – An Object Tracking Algorithm

Camshift is very similar to Meanshift, however you may have noted the window in Meanshift is o fixed size. That is problematic since movement in images can be small or large. If the window i oo large, you can miss the object when tracking.

Camshift (Continuously Adaptive Meanshift) uses an adaptive window size that changes both siz nd orientation (i.e. rotates). We'll simply it's steps here:

1. Applies Meanshift till it converges
2. Calculates the size of the window
3. Calculates the orientation by using the best fitting ellipse

# When and how to use Meanshift or Camshift?

If you have some prior knowledge of the object being tracked (e.g. size wrt to camera point of view) then Meanshift would work well.

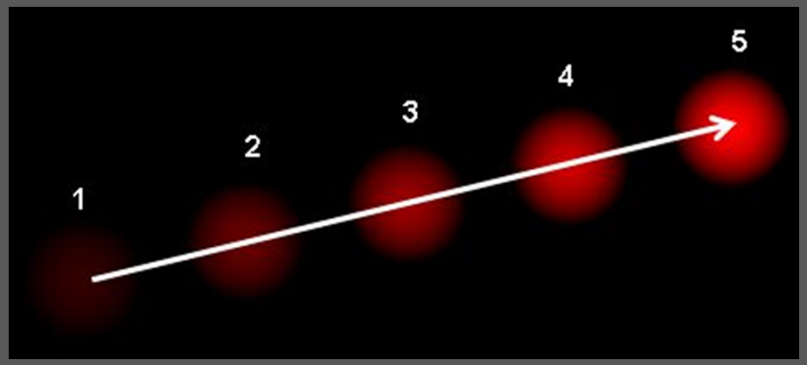
Employ Camshift when the object being track is changing shape wrt to the camera perspective. Generally more versatile, but also more sensitive.

ip: Beware of the starting location of the window, you can get stuck in a local
inima!

# Optical Flow

Seeks to get the pattern of apparent motion of objects in an image between two consecutive frames.

Shows the distribution of the apparent velocities of objects in an image.



# Optical Flow Implementations in OpenCV

OpenCV has two implementations of Optical Flow.

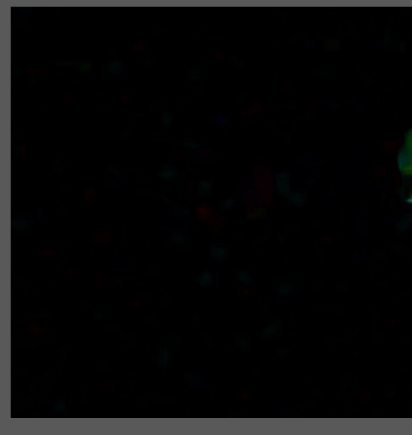
Lucas-Kanade Differential Method – Tracks some keypoints in the video, good for corner-like features (tracking cars from drones)

- http://www.cse.psu.edu/~rtc12/CSE486/lecture30.pdf
- https://www.cs.cmu.edu/afs/cs/academic/class/15385-s12/www/lec_slides/Baker&Matthews.pdf

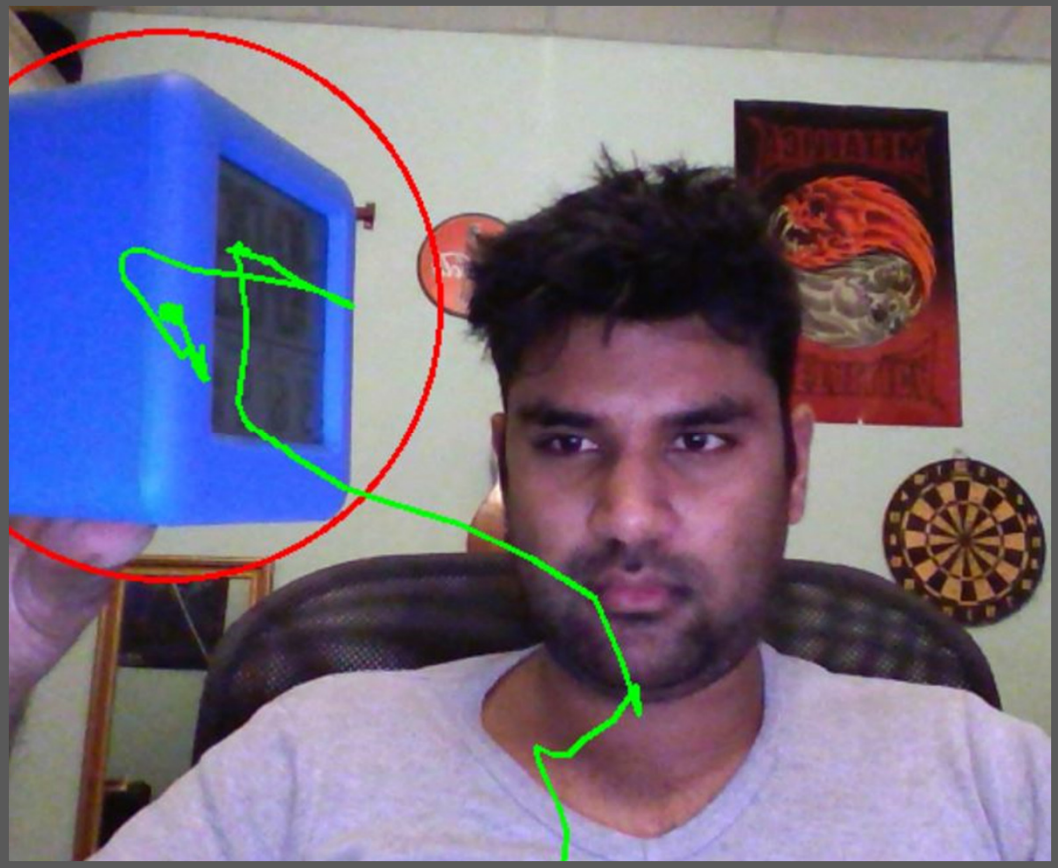
Dense Optical Flow – Slower, but computes the optical flow for all points in a frame, unlike Lucas-Kanad which uses corner features (sparse dataset). Colors are used to reflect movement with Hue being direction and value (brightness/intensity) being speed.

cas-Kanade Method

Dense Optical



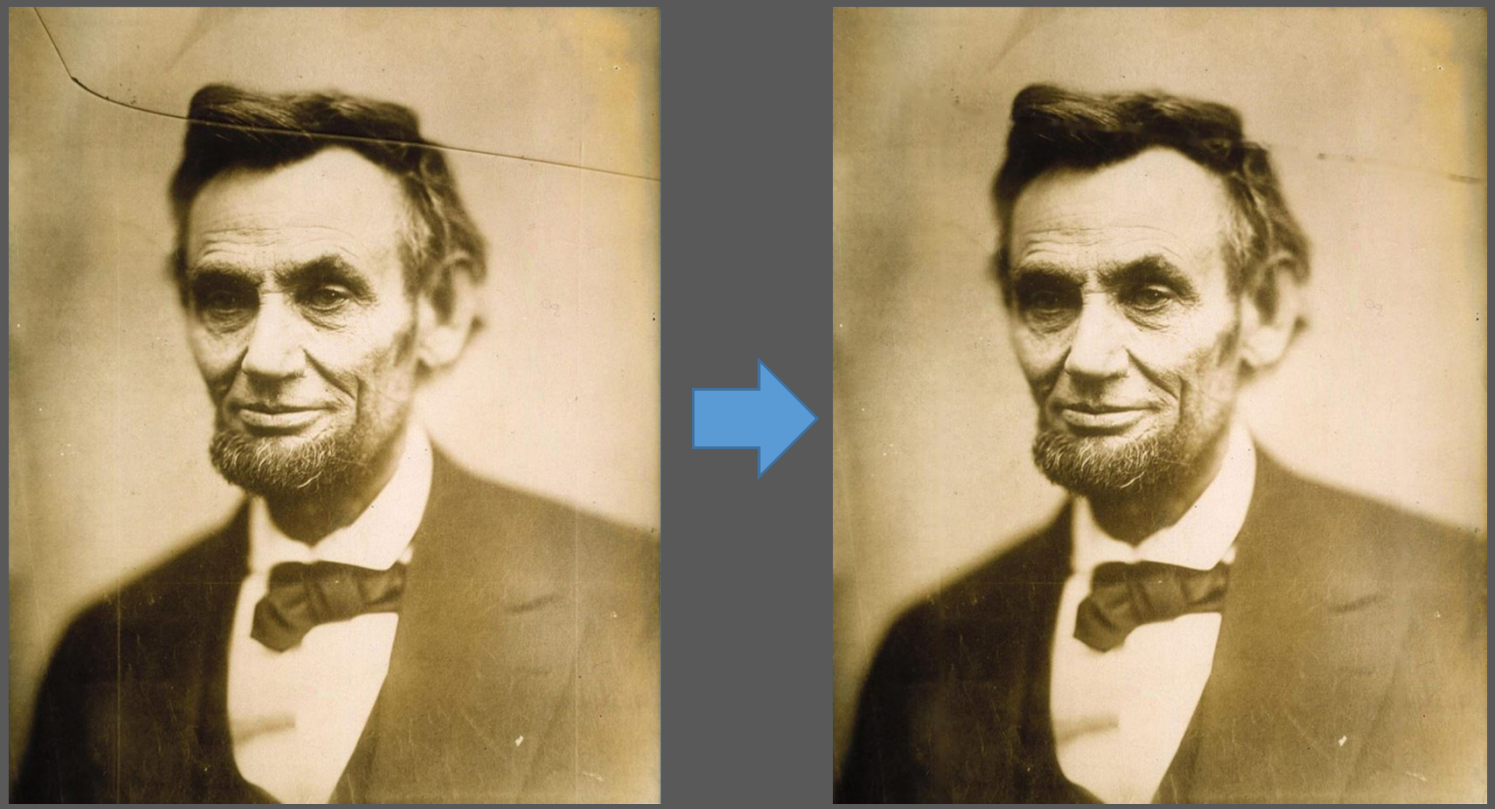
# Mini Project # 11 – Object Tracking



# Computational Photography

1. What is Computational Photography
2. Noise Reduction
3. Mini Project # 11 – Photo Restoration (remove strokes, scratches, bends in old photos)

# Mini Project # 12 – Photo-restoration



# What is Computational Photography?

These are digital image processing techniques used on images produced by cameras.

They seek to enhance images via computational processing rather than use expensive optical processes (cost more and are bulky).

Used significantly in all cameras, especially smartphones:

- Noise Reduction
- High Dynamic Range
- Image stabilization
- Panoramas
- Inpainting (removal of small noises, strokes etc.)

# Noise Reduction

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They seek to enhance images via computational processing rather than use expensive optical processes (cost more and are bulky).

Used significantly in all cameras, especially smartphones:

- Noise Reduction
- High Dynamic Range
- Inpainting (removal of small noises, strokes etc.)
- Image stabilization
- Panoramas

# Advanced Topics

Other Computer Vision Python Libraries & Tools

- PIL
- imutilties
- skImage
- Matlab Labview

. OCR (Tesseract) & OMR

- QR Code & Barcode Reading

. Other Advanced Algorithms

- Watershed
- Connected Components

3D Reconstruction

Augmented Reality

Bag of Words Model

. SVM & HOGs

. Deep Learning & Convolutional Neural Networks (TensorFlow, theano, lasagna, café)

. C++ vs Python OpenCV

. OpenCV 3.1 vs 2.4

. Mobile Apps Computer Visions

# Section 10

# Course Wrap Up

# Course Wrap Up

1. Where do you go from here?
2. Computer Vision Research Areas & Startup Ideas and Mobile Computer Vision

# Consolidating What You've Learnt

Familiarity with Python and Numpy

Computer Vision:

- Image Manipulation and Segmentation
- Object Recognition Methods
- Machine Learning in Computer Vision
- Facial Feature Analysis and Recognition
- Motion Analysis and Object Tracking

# Becoming an Expert


1. Create your own project

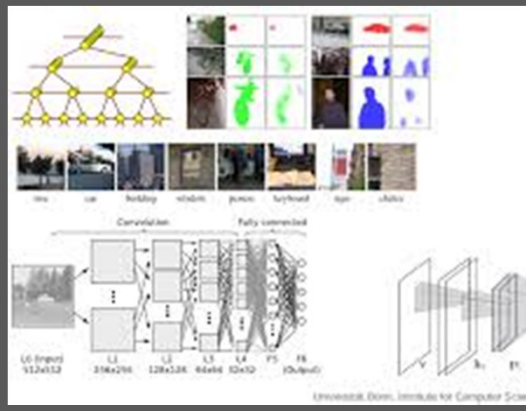
2. Read and implement research papers
   - See my document titled "ResearchPapersandURLS.pdf"

3. Explore Computer Vision Blogs
   - pyimagesearch.com (Outstanding!)
   - learnopencv.com (Outstanding!)
   - aishack.in (lots of projects)
   - opencv.org/category/news

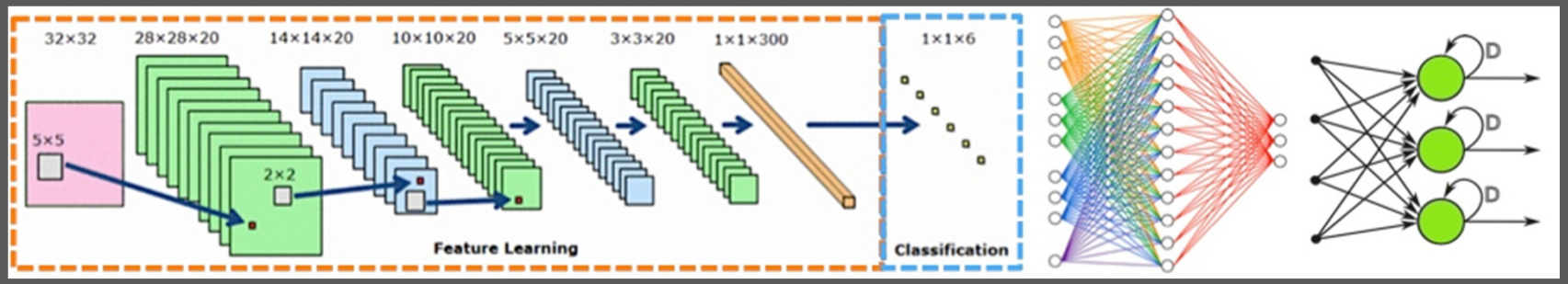
# Current State of Computer Vision?

Object Recognition - Deep Belief and Convolution Neural Networks are changing everything!

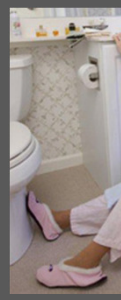
Where to learn more?



Stanford CS231 class - cs231n.github.io
Café - caffe.berkeleyvision.org/tutorial
Deep Learning Tutorial - ufldl.stanford.edu/tutorial
Deep Learning Tutorial - deeplearning.net/reading-list/tutorials
Deep Learning Tutorial - www.deeplearningbook.org
Tensor Flow - www.tensorflow.org/versions/r0.11/tutorials/index.html

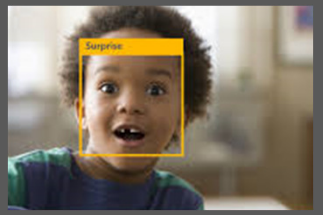


# 12 Awesome Startup Ideas



Fall Detection for elderly people
Searching for missing people using drones (e.g. Hikers)
Using drones for people counting and/or tailing
Using CCTV footage for Smart surveillance systems (e.g. detect when children are unsupervised near a swimming pools or balconies)
Identifying the state of crops (e.g. checking for diseases)
Understanding medical images (x-rays, MRI scans etc.)
Identify swimmers who may be in trouble
Identify counterfeit money or products

Novelty apps (e.g. upload a photo of chess or checkers being played and it then gives you the next best move)
Take a picture of a product and it brings reviews or prices of that item online
Identifying calories and macros from a picture of food
Analyze faces to detect emotions and wellbeing
Want More? - cs229.stanford.edu/projects2015.html#vision




# OpenCV in Mobile Apps & Web APIs?

API - Create a RESTful API using DJANGO or FLASK to bundle you OpenCV code

- PROS
  - Can be accessed on any mobile phone app or on a PC/MAC
  - Can be updated remotely (cloud based)
  - Powerful as processing is off loaded
- CONS
  - Requires internet connection to transfer images
  - Will need to pay API cloud hosting
  - Can't do real time video based apps

Native Mobile – Use OpenCV natively (using wrappers for iOS and Android)

- PROS
  - Can do real time video based apps
  - No need to pay for cloud based storage
- CONS
  - Can't do heavy processing on mobile device
  - More difficult than using OpenCV in python

iOS - http://docs.opencv.org/2.4/doc/tutorials/introduction/ios_install/ios_install.html
Android - http://blog.codeonion.com/2015/11/17/learning-the-packages-of-opencv-sdk-for-android/