Workshops in Creative Computing: Computer Vision Module

Lecture 2 / 3: Image Features

Monday Jan 28, 2012

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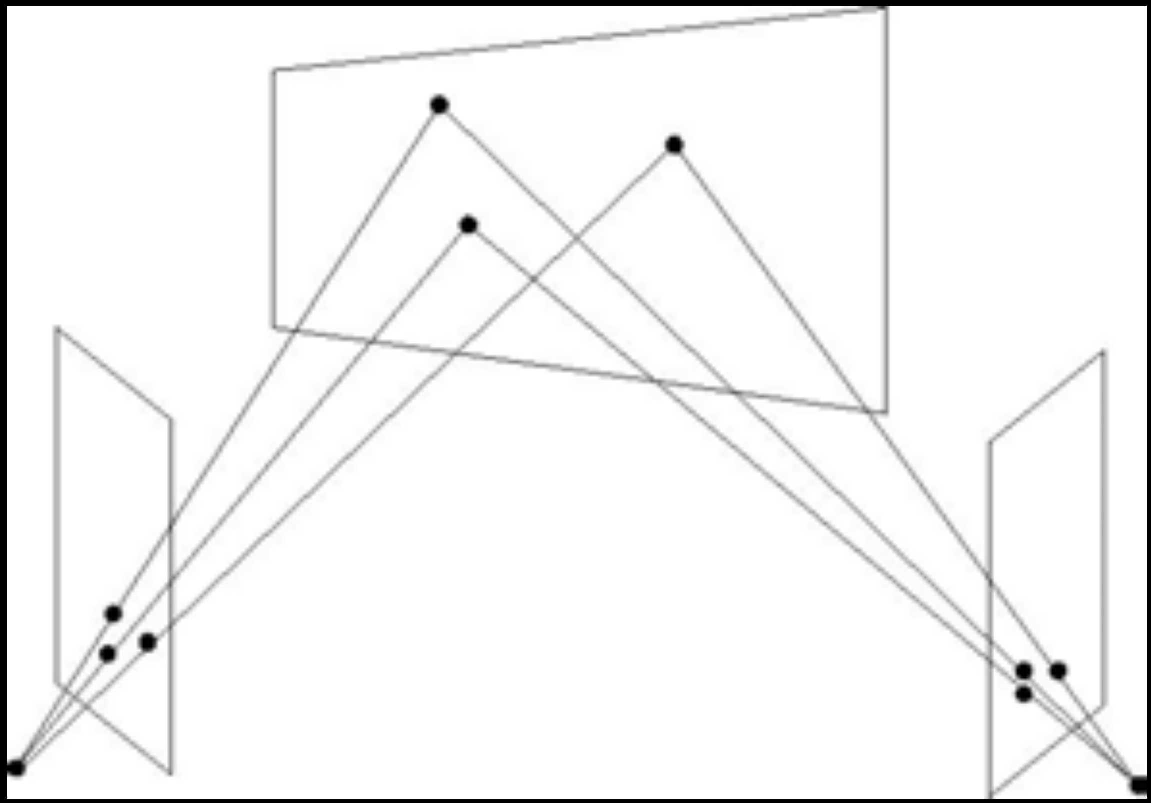
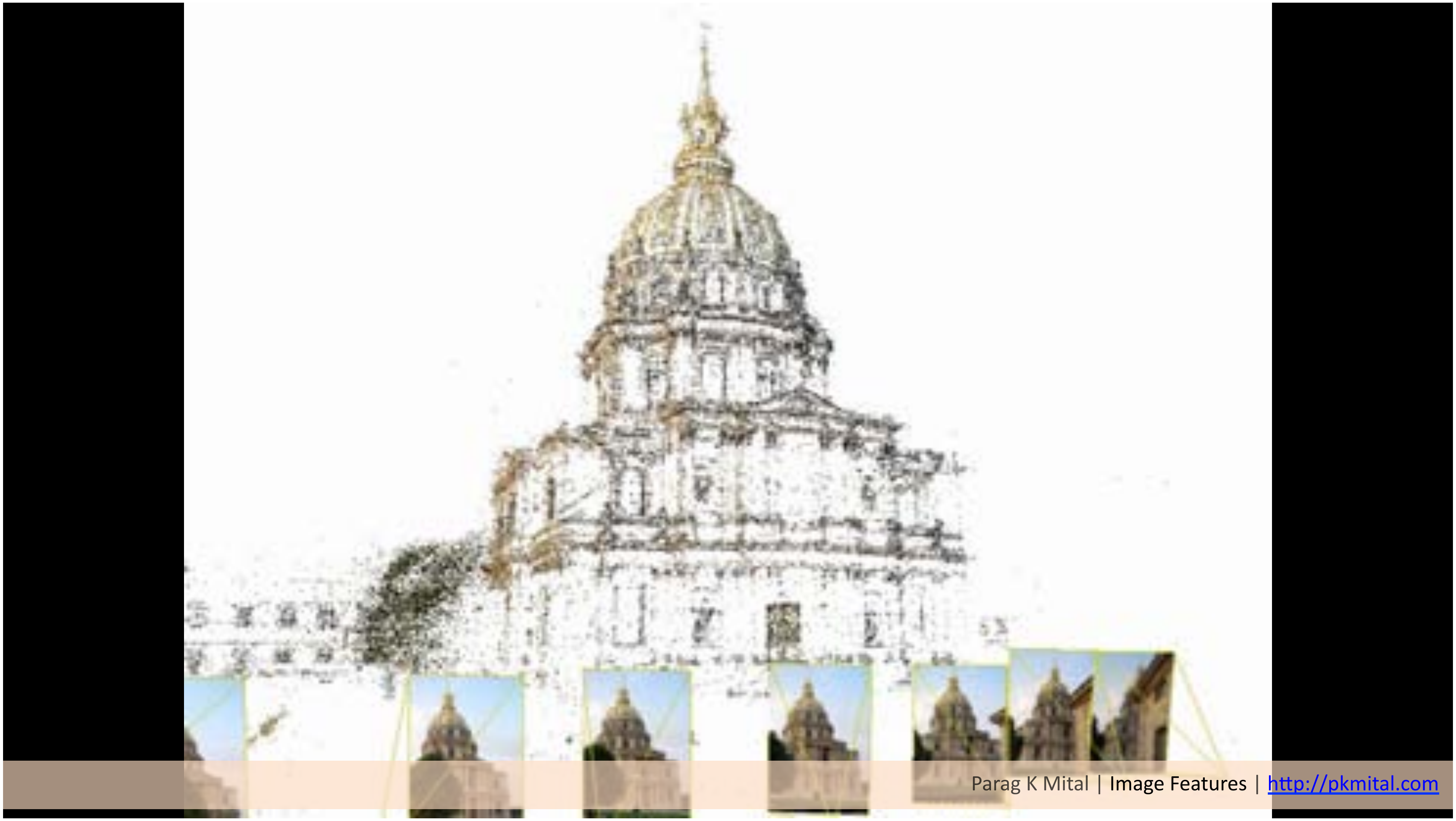
Assignment 1: Still need to solve Computer Vision

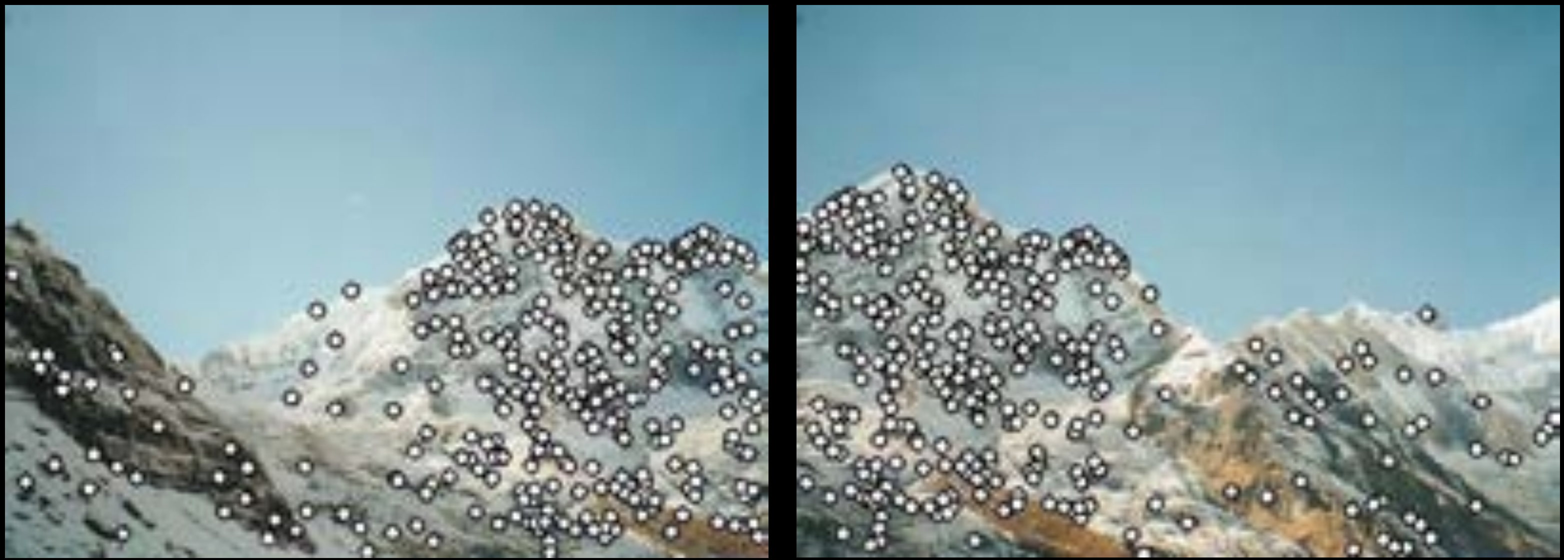
Vision is based on inference

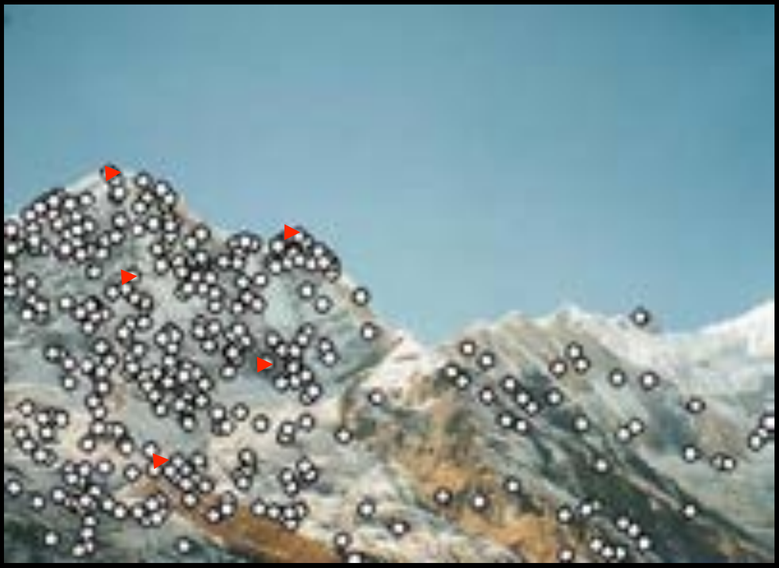
Popular Uses of Feature Detection:

Structure from Motion
Photo-montage
Panorama/Stitching/Mosaicing
Information Retrieval
Object Detection
Scene Detection
Action Detection





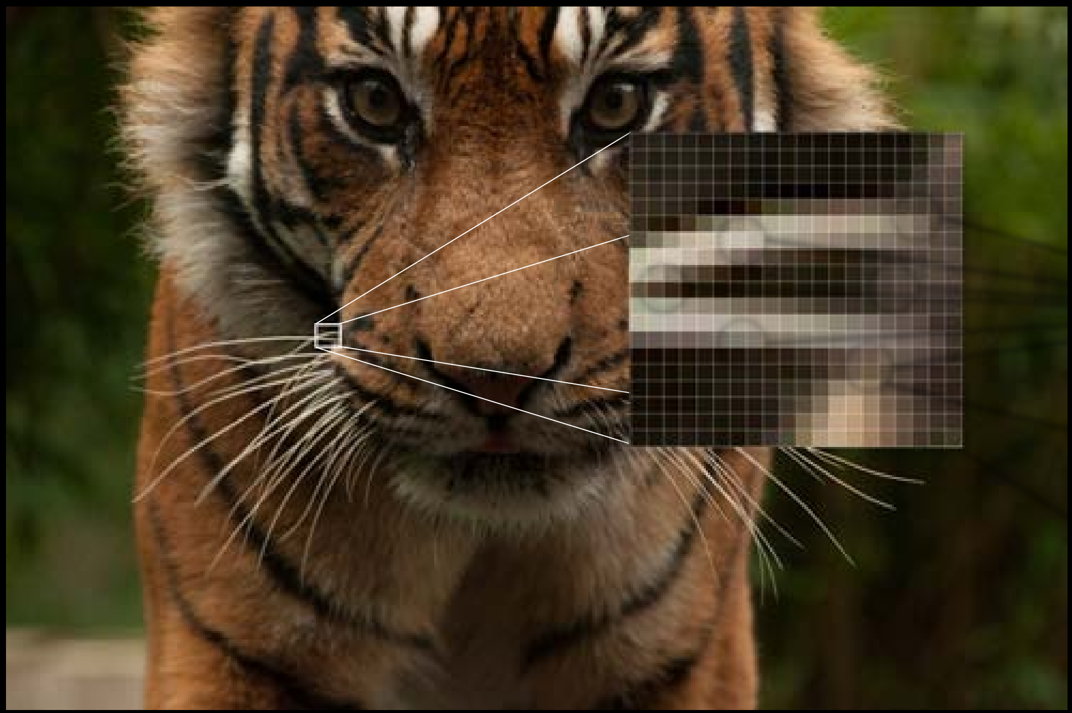




Google Image Search, Google Goggles, etc…

What makes us perceive objects in images?

Hypothesis: process images bottom-up
– Extract “features”
– Combine features with prior knowledge to classify objects in the image at a high-level



Semantic label =
High-level description
^

Grouping of Features =
Mid-level description

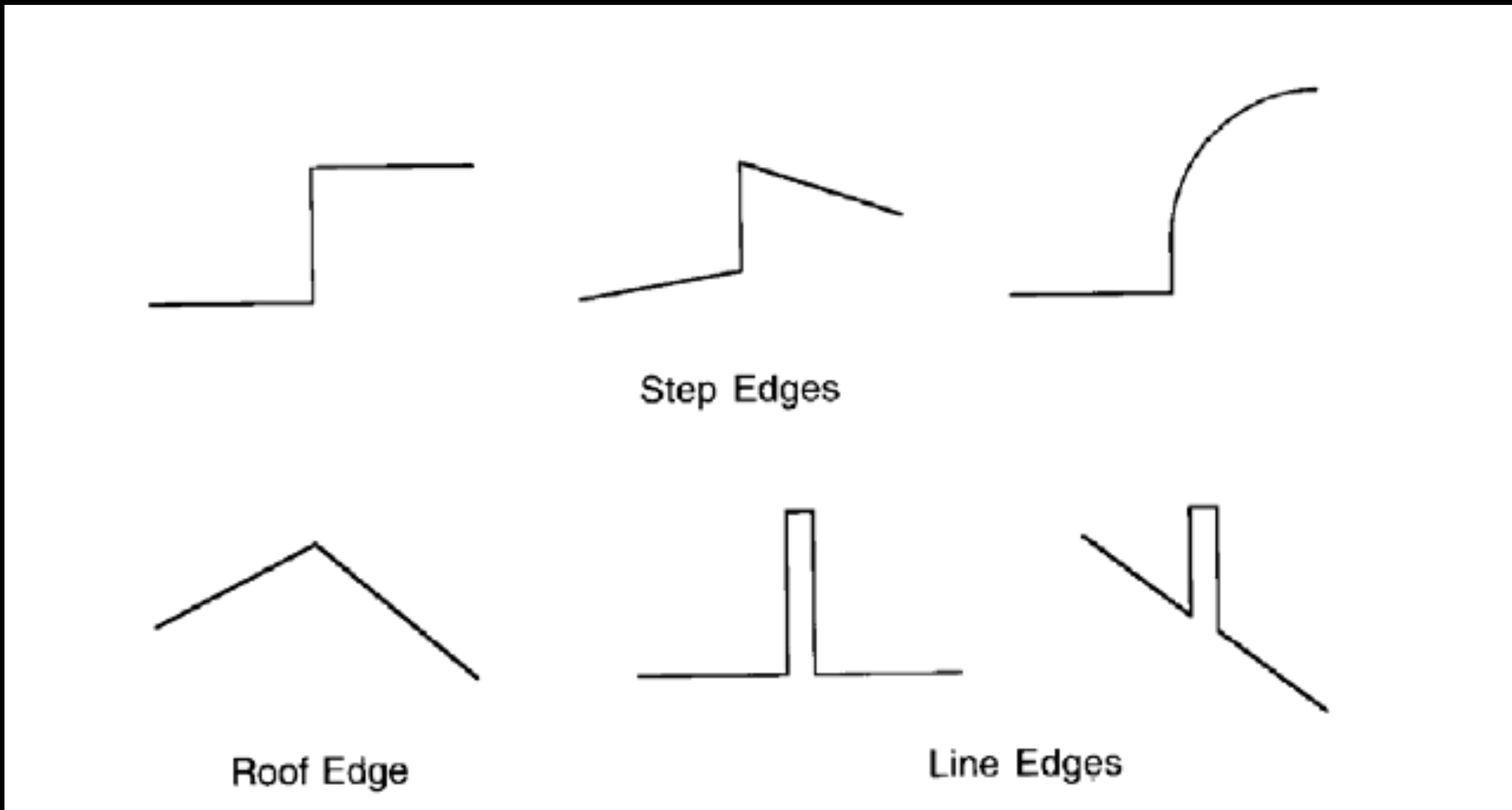
Single feature =
Low-level description

Pixels =
Low-level description

Generic Object Detection Workflow:

1. How do we detect features?
2. How do we describe features?
3. How do we match features?

Pixels	**Luminance; Color-spaces; Depth; Heat**
Edges/Lists	**Sobel; Canny; Hysteresis; Connected Components; Shape Models**
Feature Points	**SIFT; SURF; Harris Corners; HOG; FAST**
Blobs/Regions	**Mean-Shift; MSER; Watershed; Graph-Cuts; Background Subtraction; Appearance Models**
Maps	**Geodesics; Topography; Density**


Step Edges
Roof Edge
Line Edges

Edges are where change occurs

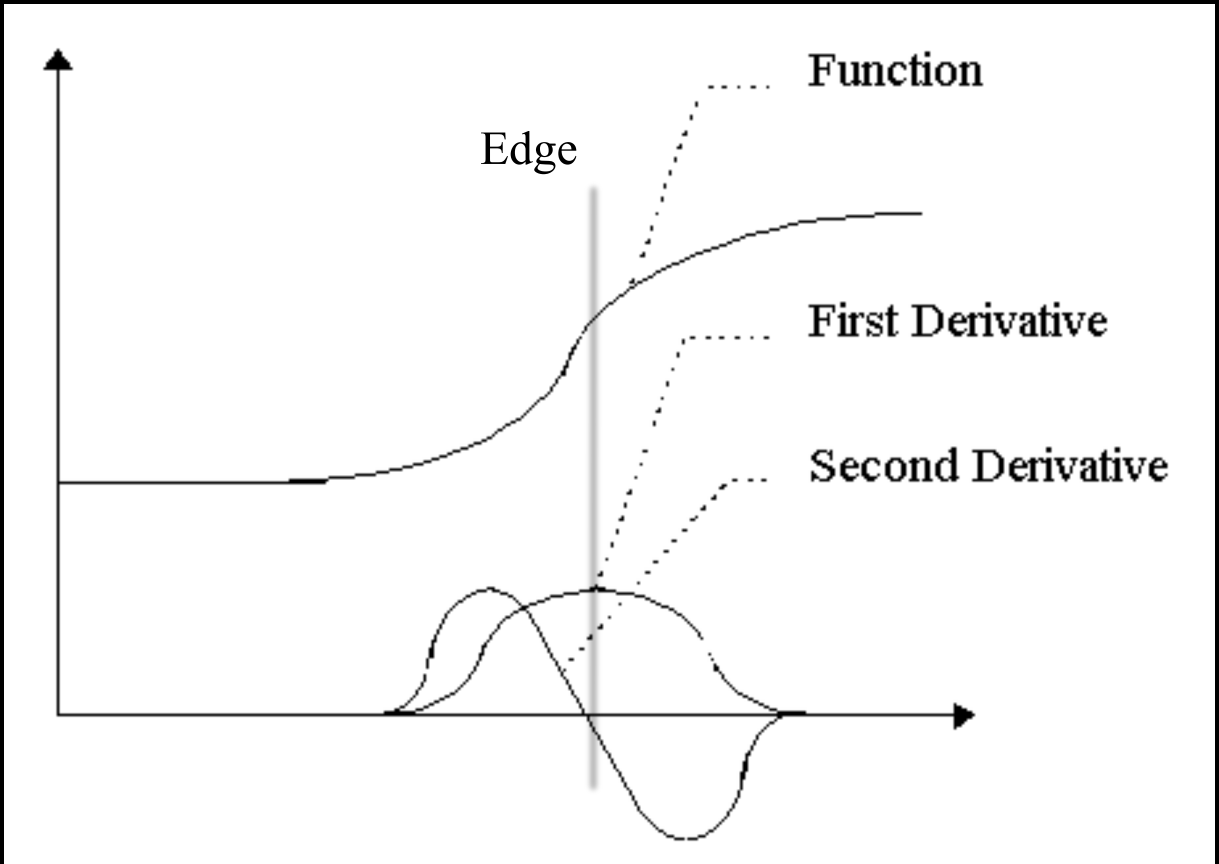
Images can be thought of as functions:

Pixel at location `x`:

`P(x)`

Then we can create a function `f`, which describes the intensity of pixel `x`:

`f(x)`


Function
Edge
First Derivative
Second Derivative

Derivative

$$\frac{df}{dx} = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$$

Gradient

$$\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$$

Images are Discrete Functions

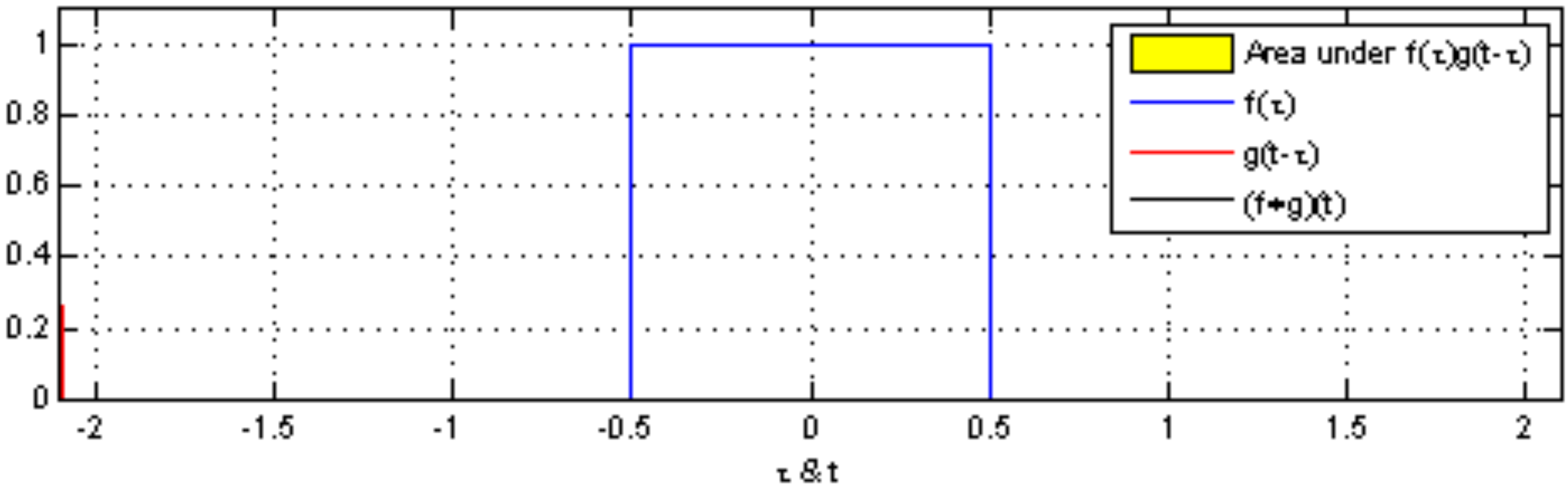
$$\frac{\partial f}{\partial x}[x, y] \approx f[x+1, y] - f[x, y]$$

Sobel: Convolution Operators

$$\frac{1}{8}\begin{array}{|c|c|c|}\hline -1 & 0 & 1 \\ \hline -2 & 0 & 2 \\ \hline -1 & 0 & 1 \\ \hline \end{array} \qquad \frac{1}{8}\begin{array}{|c|c|c|}\hline 1 & 2 & 1 \\ \hline 0 & 0 & 0 \\ \hline -1 & -2 & -1 \\ \hline \end{array}$$

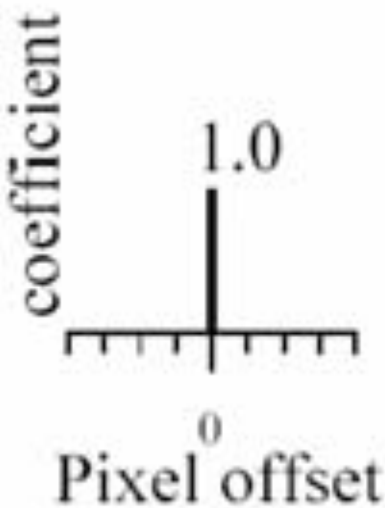
$$s_x \qquad\qquad\qquad s_y$$

What the **** is Convolution



What the **** is Convolution

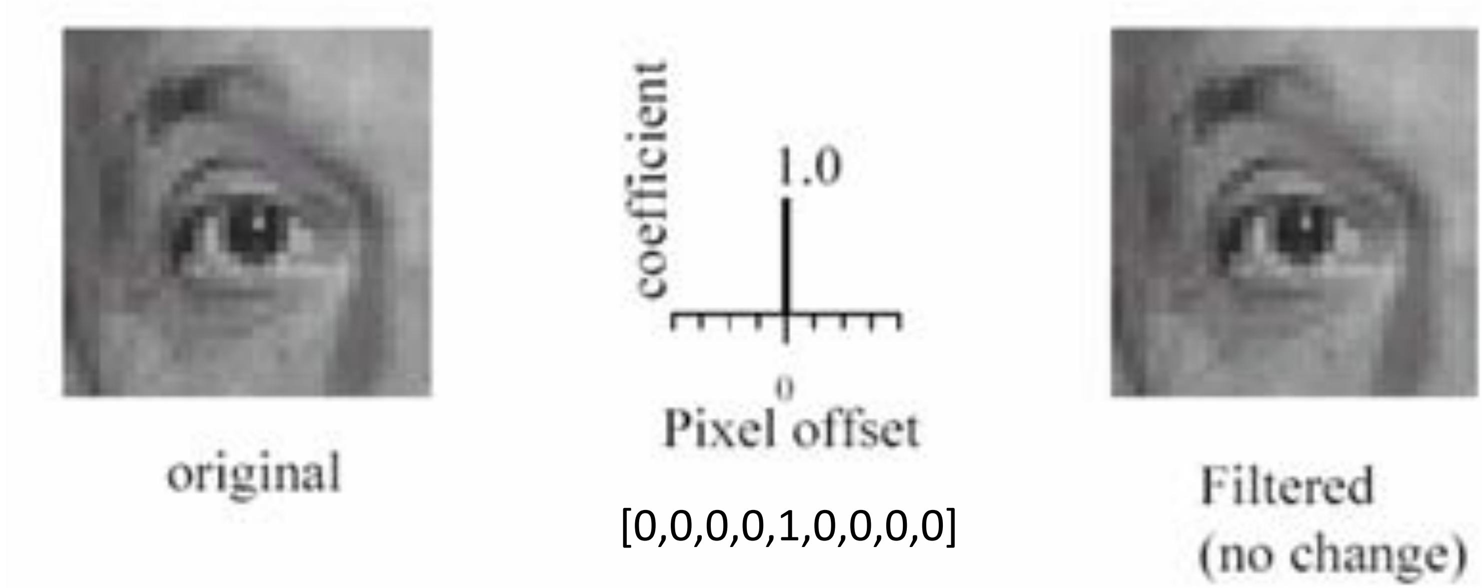
original



[0,0,0,0,1,0,0,0,0]

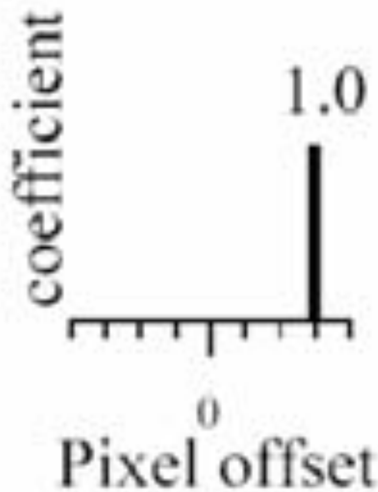
?

What the **** is Convolution



[0,0,0,0,1,0,0,0,0]

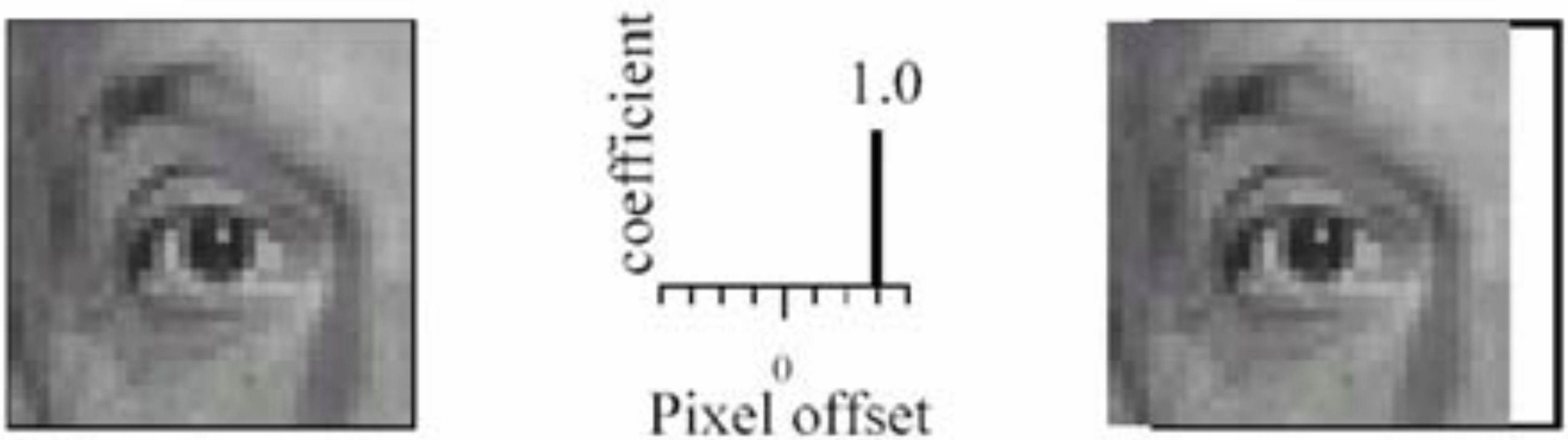
What the **** is Convolution



[0,0,0,0,0,0,0,1,0]

?

What the **** is Convolution

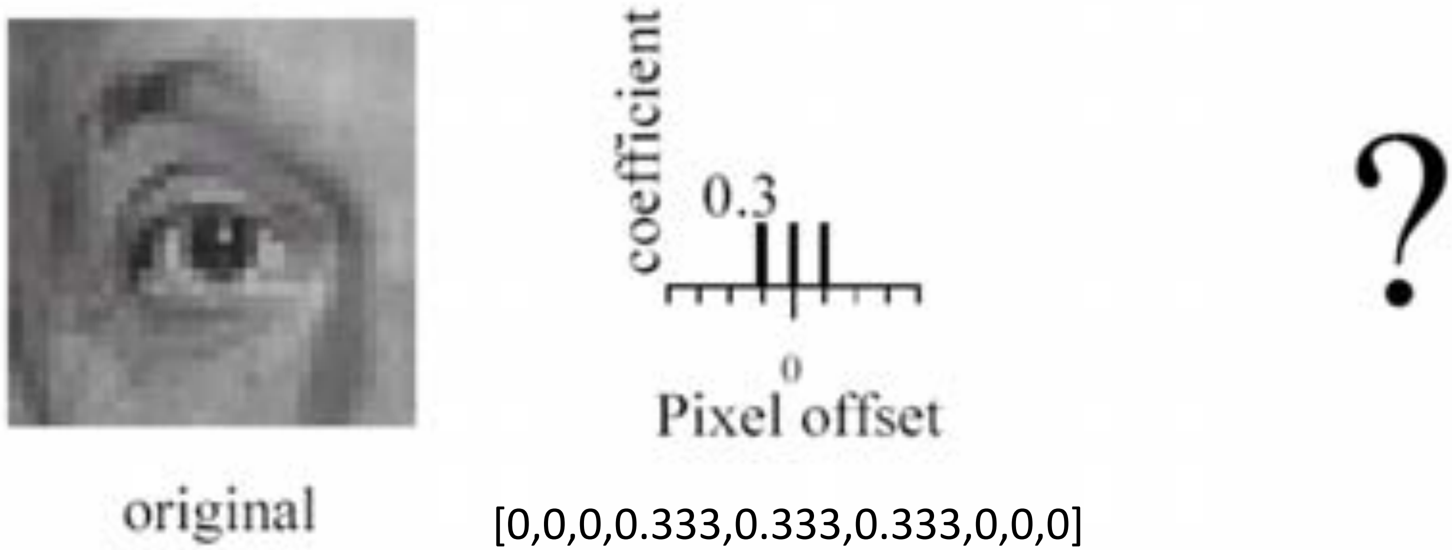


original

[0,0,0,0,0,0,0,1,0]

shifted

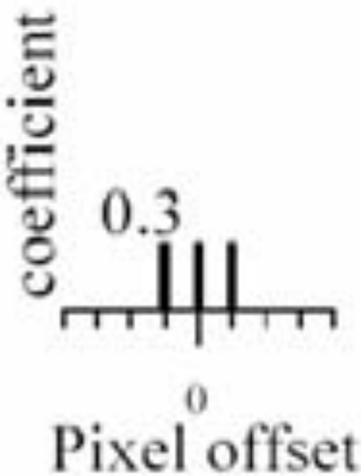
What the **** is Convolution



[0,0,0,0.333,0.333,0.333,0,0,0]

What the **** is Convolution

original



[0,0,0,0.333,0.333,0.333,0,0,0]

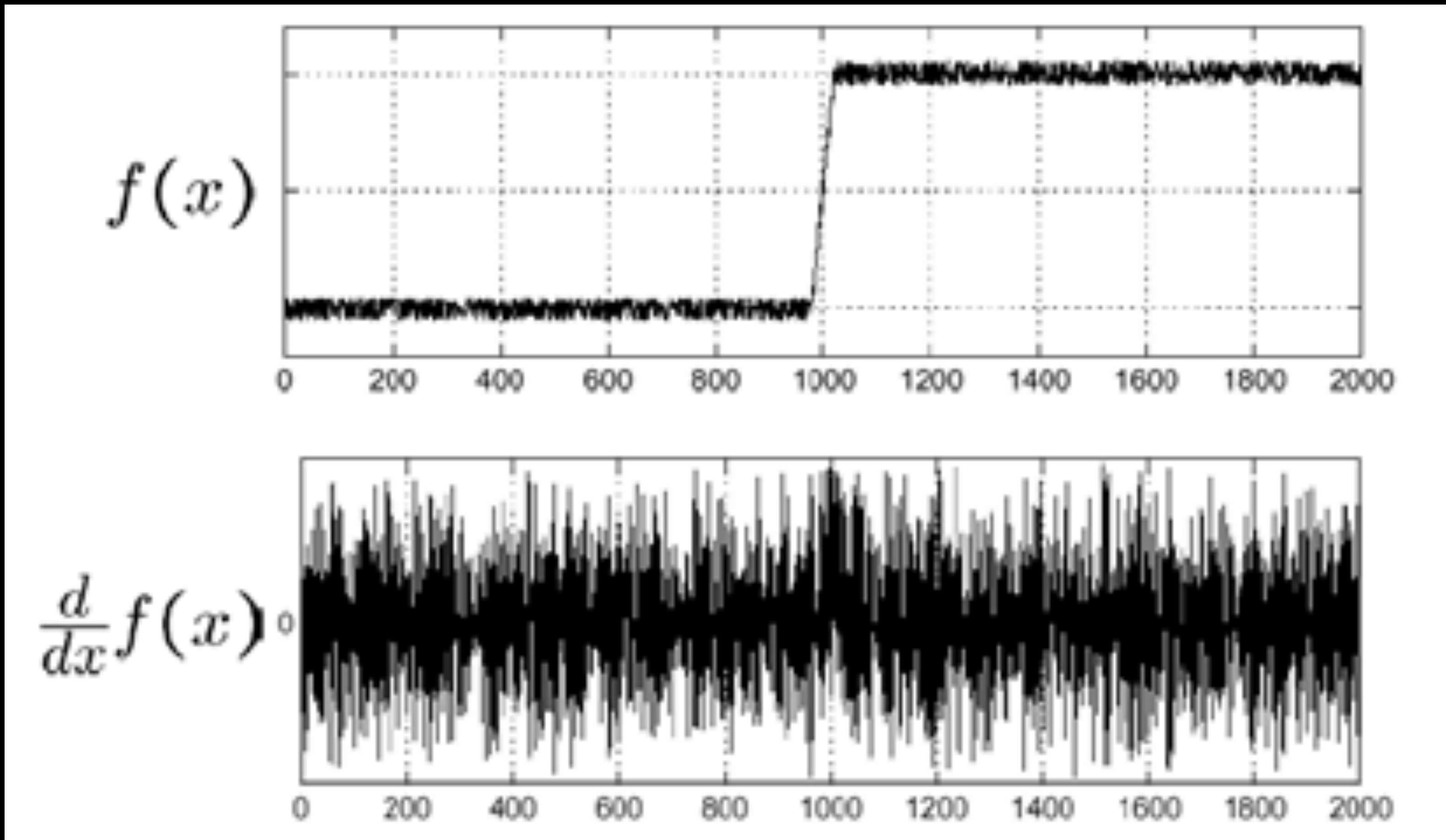
Blurred (filter applied in both dimensions).

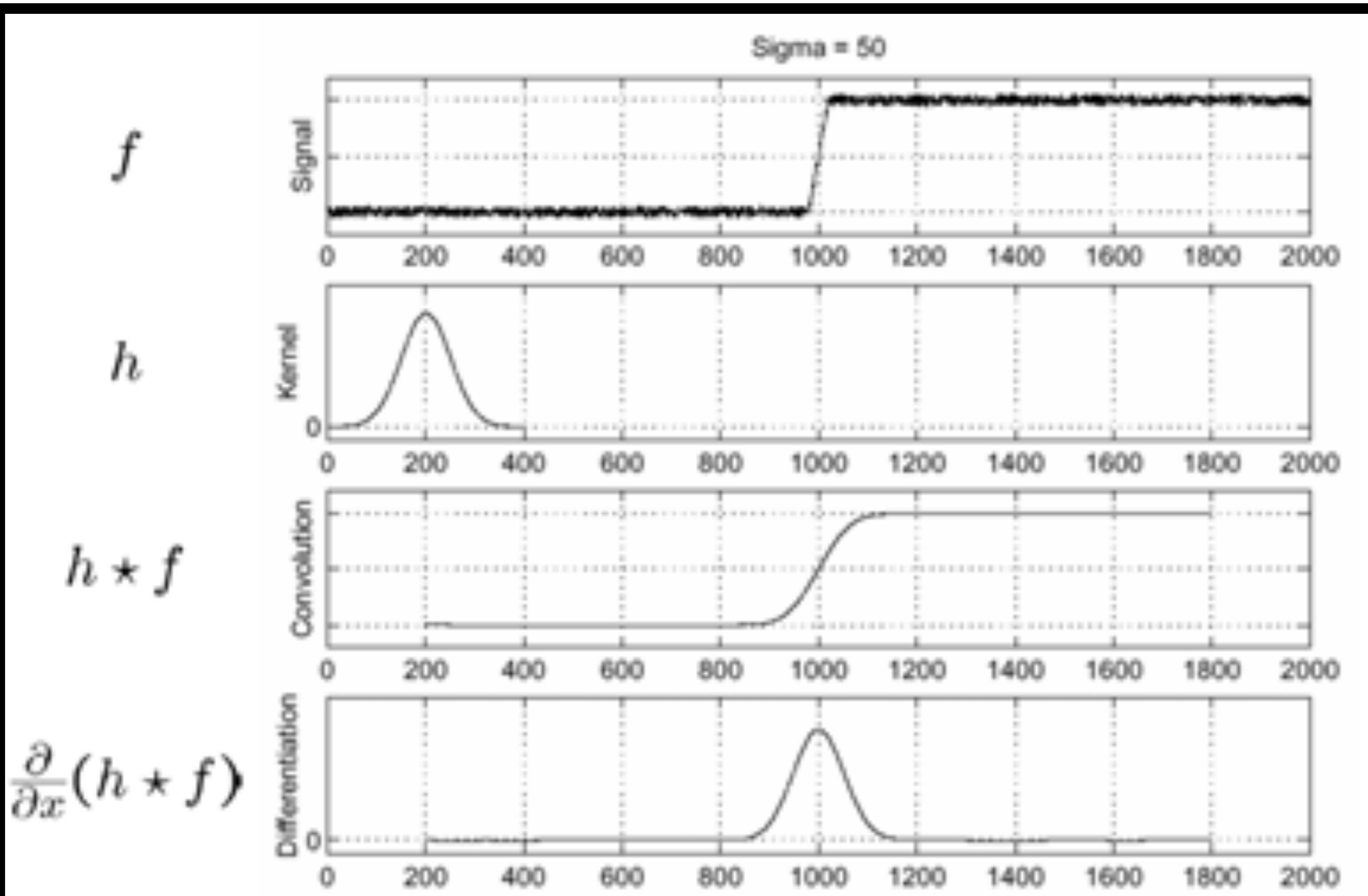
$$\frac{1}{8}\begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

s_y

$$\frac{1}{8}\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

s_x


$f(x)$
$\frac{d}{dx}f(x)$
0
0 200 400 600 800 1000 1200 1400 1600 1800 2000
0 200 400 600 800 1000 1200 1400 1600 1800 2000

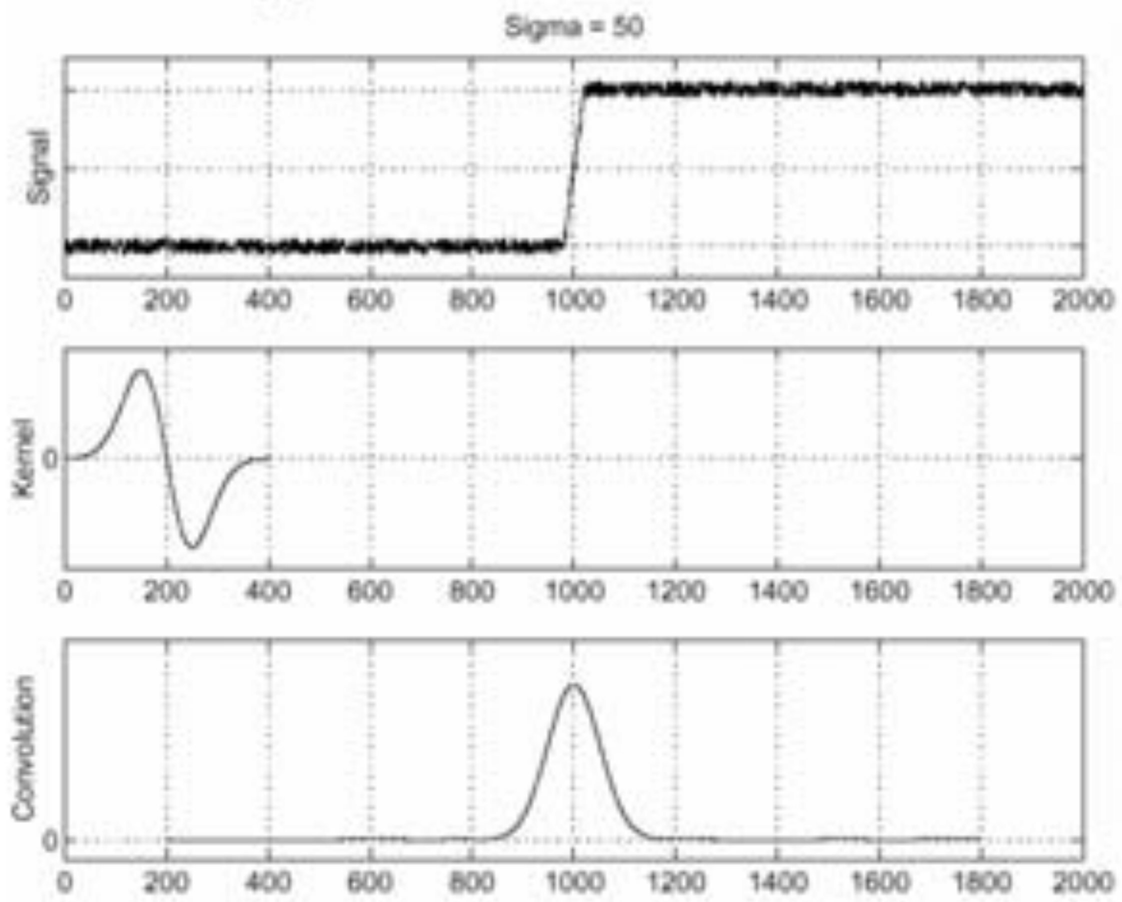


Sigma = 50
f
Signal
h
Kernel
0
$h \star f$
Convolution
$\frac{\partial}{\partial x}(h \star f)$
Differentiation
0
0 200 400 600 800 1000 1200 1400 1600 1800 2000

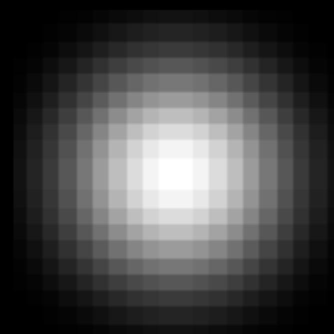
$$f$$

$$\frac{\partial}{\partial x}h$$

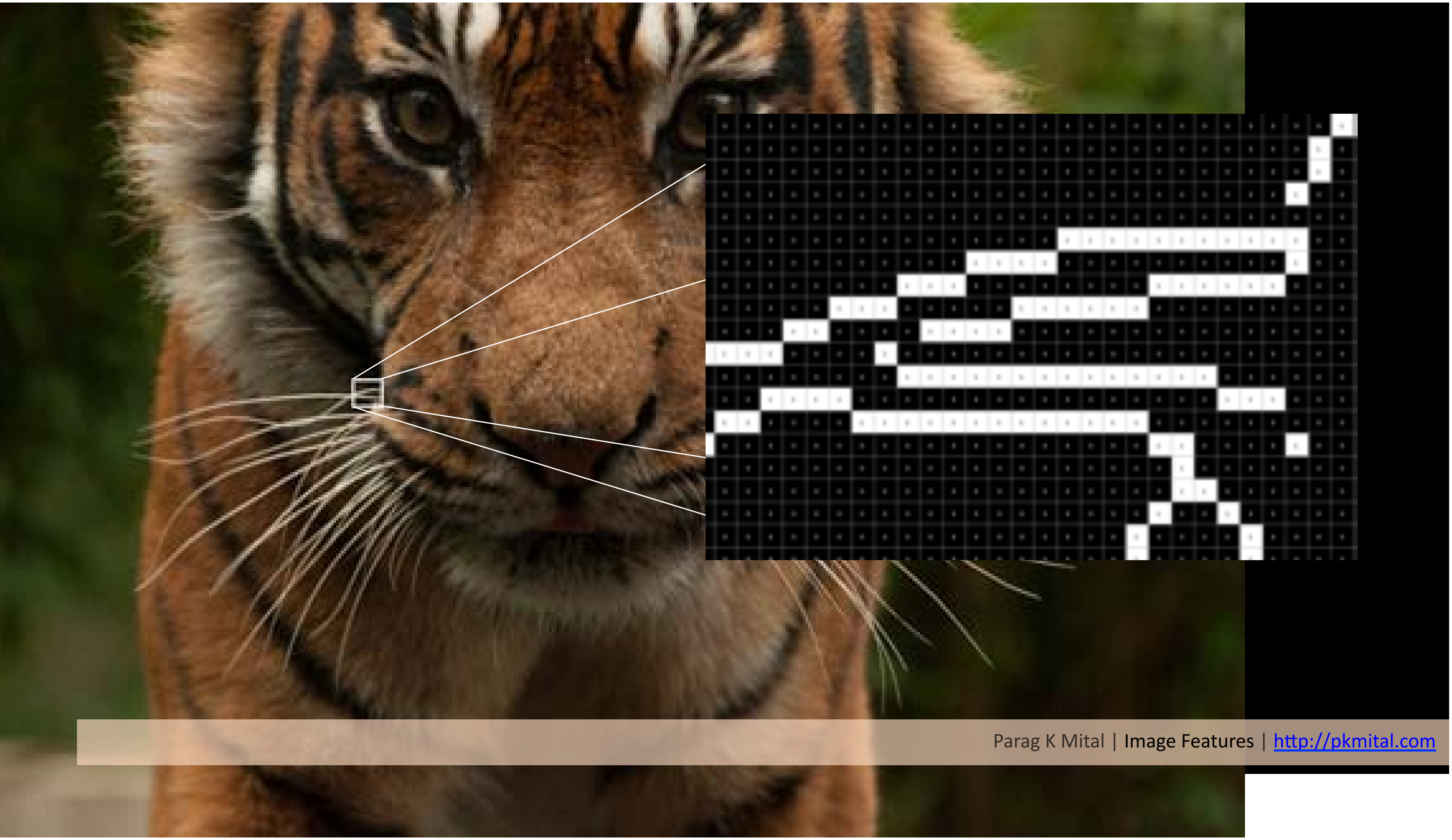
$$(\frac{\partial}{\partial x}h) \star f$$



Gaussian Kernel



At what scale are our edges defined?



What kind of invariance does our algorithm have?

Luminance?
Color?
Translation?
Rotation?
Scale?
Skew? (Perspective?)

128 element vector * 320 pixels wide * 240 pixels high

= 38 MB per image!

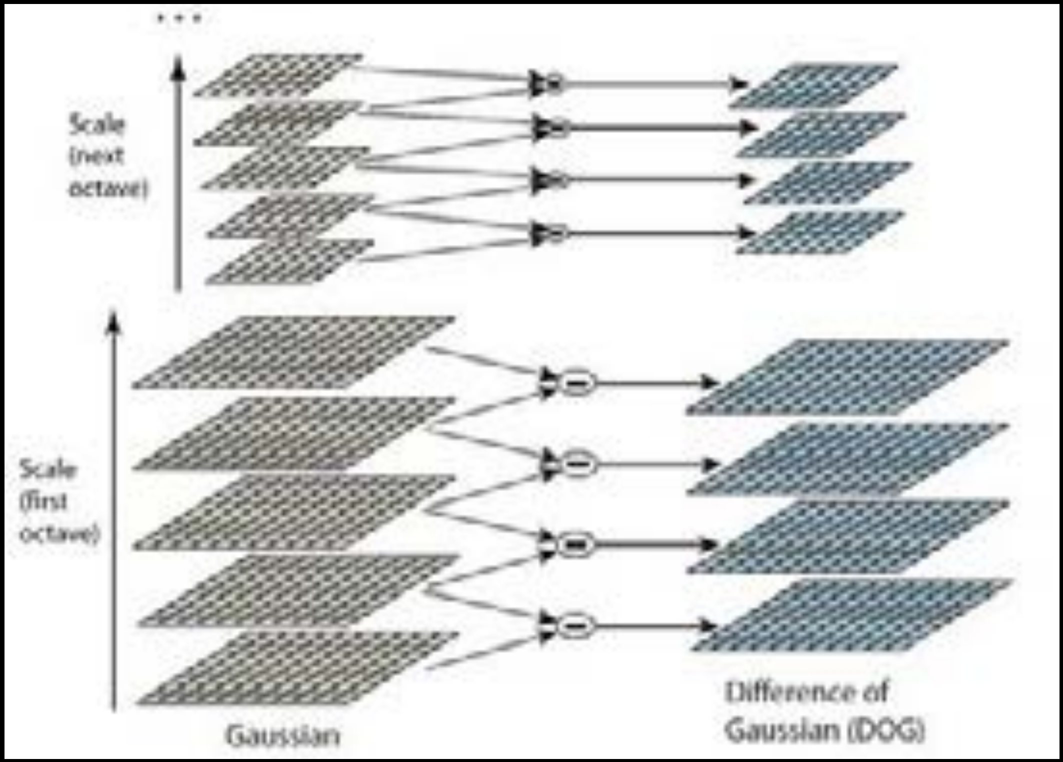
Rather than describe every pixel of an image, we need to find the keypoints

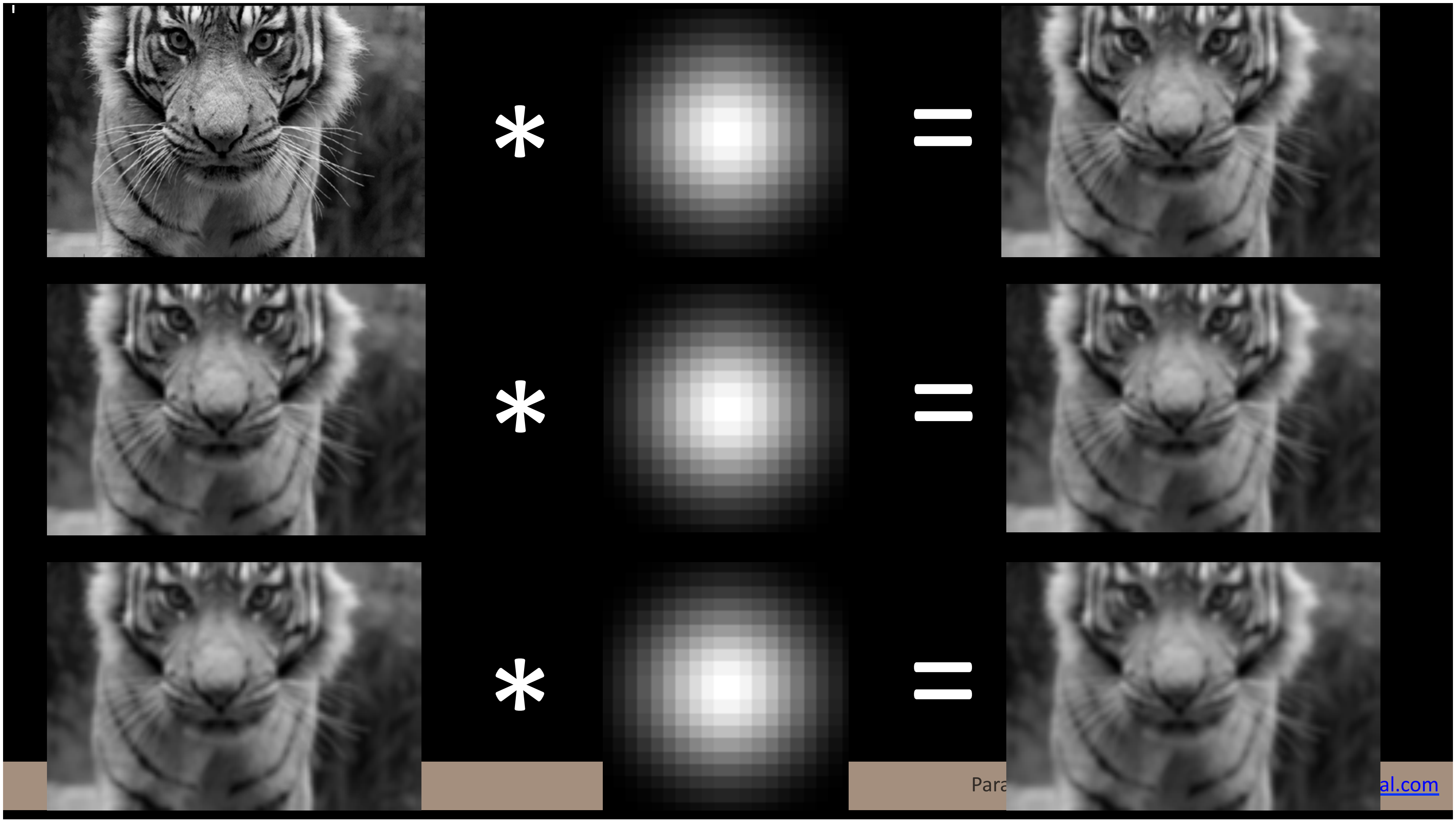
Invariance to: luminance, color, rotation, translation, scale, skew…

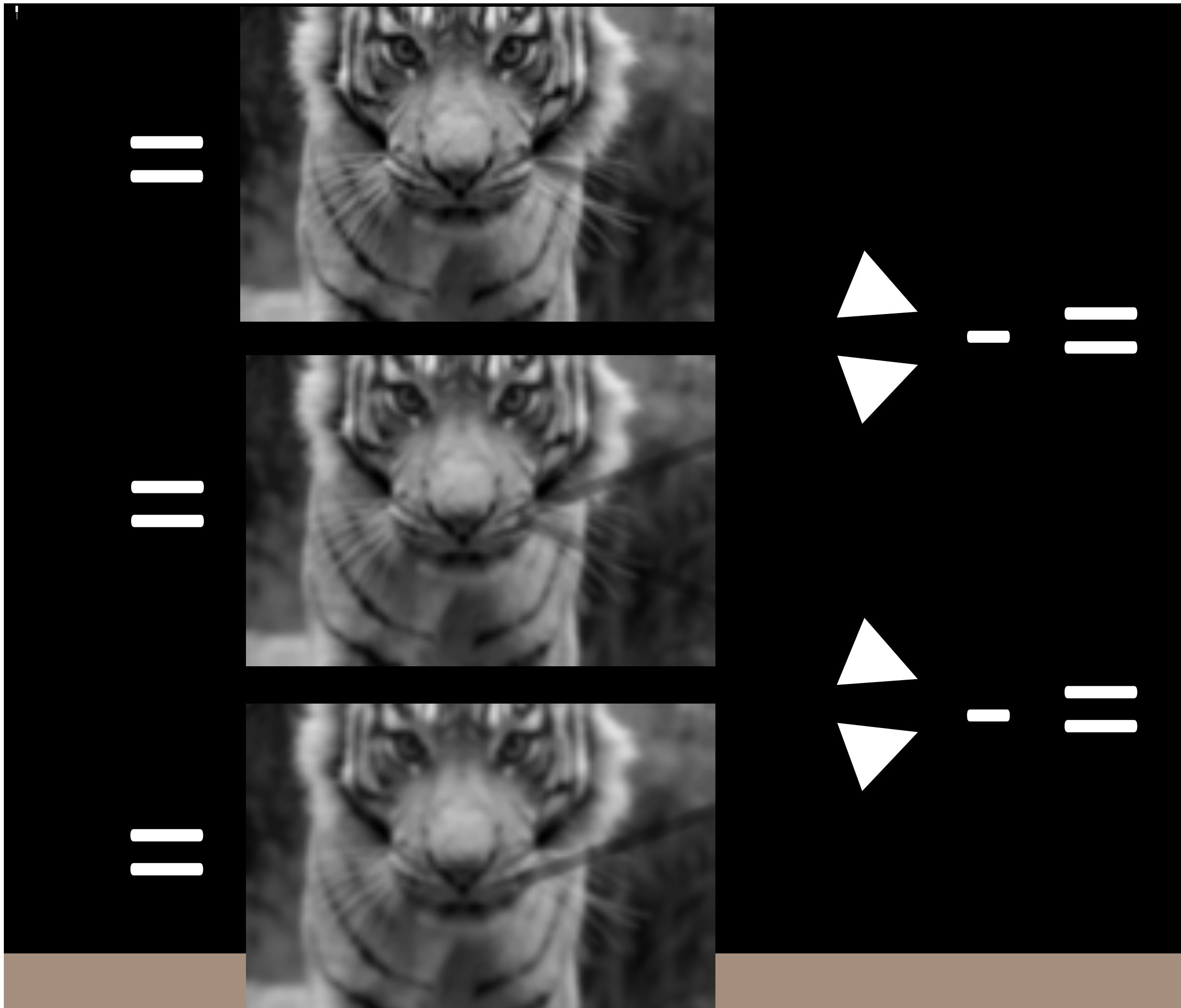
Should be fast to detect, and cheap to store!

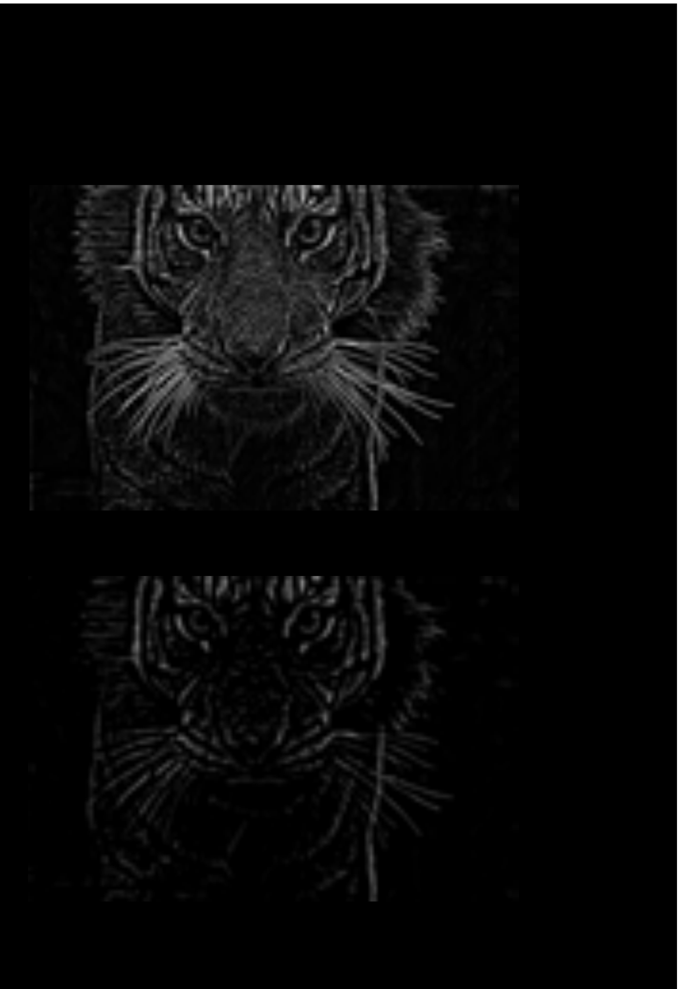
Scale Invariant Feature Transform (SIFT)

- Generate a Difference of Gaussian(DoG) or a laplacian pyramid
- Extrema detection from the DoG pyramid which is the local maxima and minima, the point found is an extrema
- Eliminate low contrast or poorly localized points, what remains are the keypoints
- Assign an orientation to the points based on the image properties
- Compute and generate keypoint descriptors


Scale
(next
octave)
Scale
(first
octave)
Gaussian
Difference of
Gaussian (DOG)







Popular Feature Detectors:

SIFT: Scale Invariant Feature Transform

SURF: Speeded-Up Robust Features

Harris: Corner detector

FAST: It's a really fast Corner detector

STAR: Center Surround Extractor (CenSurE)

MSER: Maximally Stable Extremal Regions

GFTT: Good Features To Track

GIST: Global scene feature

HOG: Histogram of Oriented Gradients

1. ~~How do we detect features?~~
2. How do we describe features?
3. How do we match features?

Now we've detected features, but how do we describe them, and match similar groups of them?

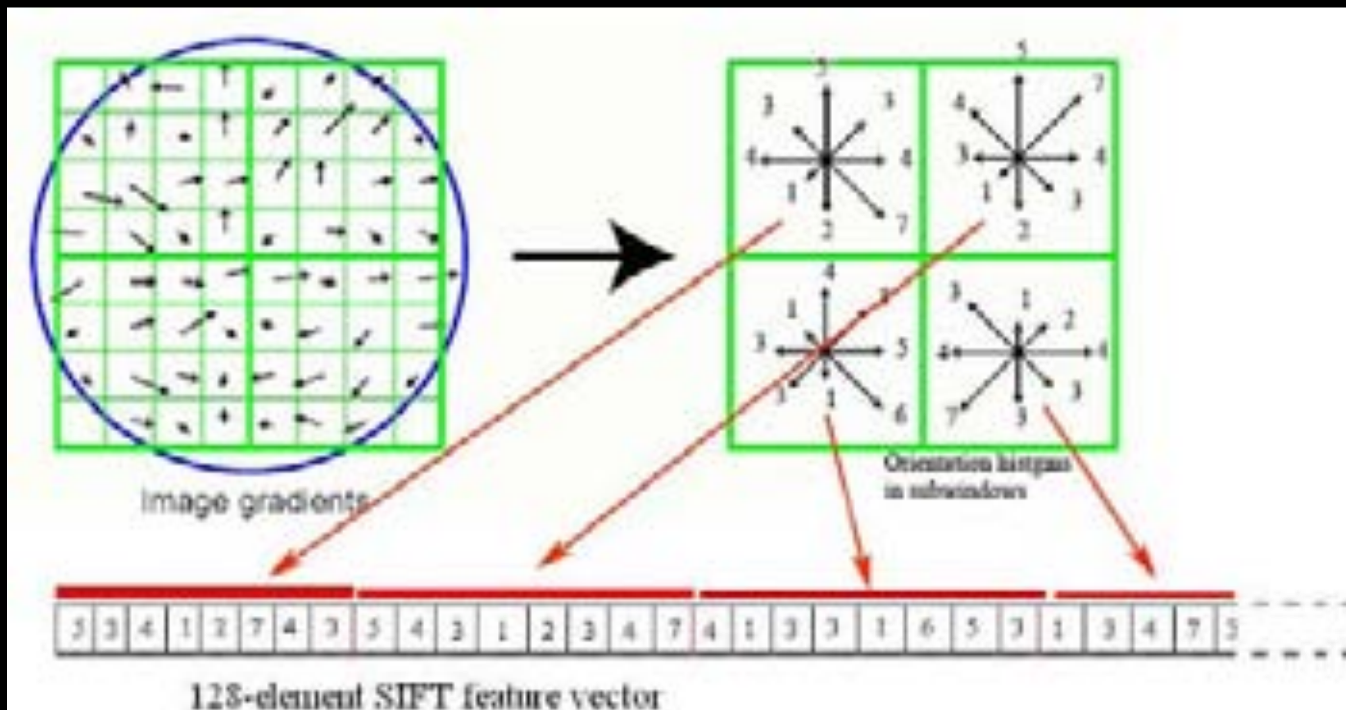


Image gradients
128-element SIFT feature vector

Store all keypoints describing our object in a matrix

128 element vector * 500 keypoints

= 0.25 MB per image!

Popular Feature Descriptors:

SIFT: Scale Invariant Feature Transform

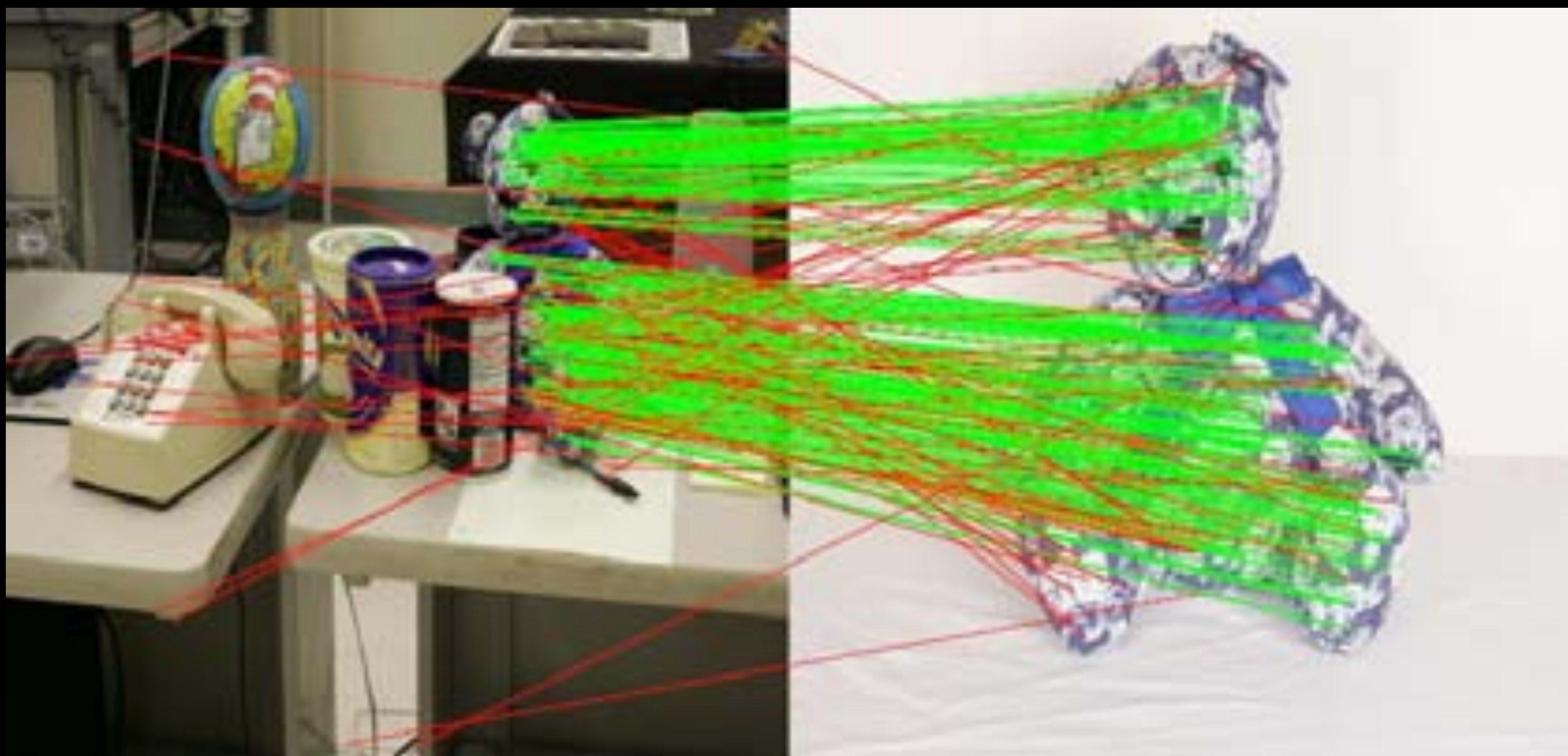
SURF: Speeded-Up Robust Features

BRIEF: Binary string descriptor

Geometric Blur: Samples image from small deviations

Self-Similarity

1. ~~How do we detect features?~~
2. ~~How do we describe features?~~
3. How do we match features?



Nearest neighbors

Hash Table

Approximate Nearest Neighbors

PCA

ICP