Workshops in Creative Computing: Computer Vision Module

Lecture 2: Image Features

Wednesday, Feb 27, 2013

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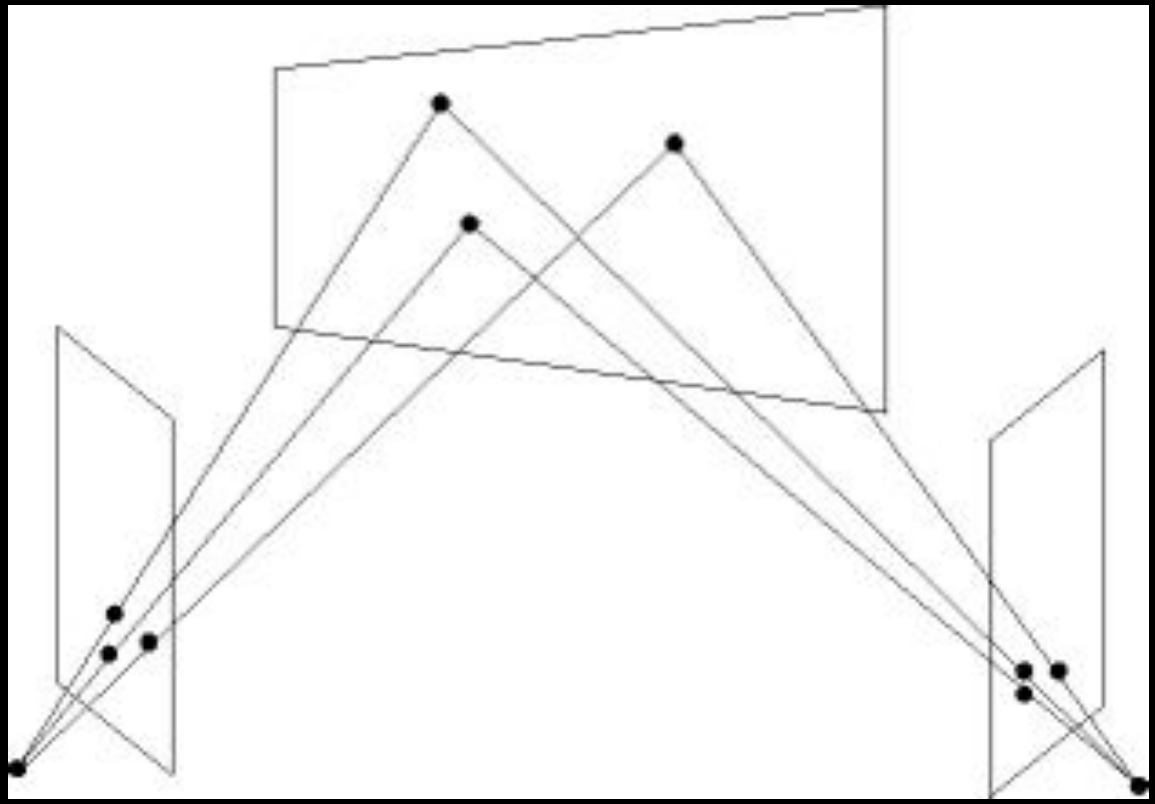
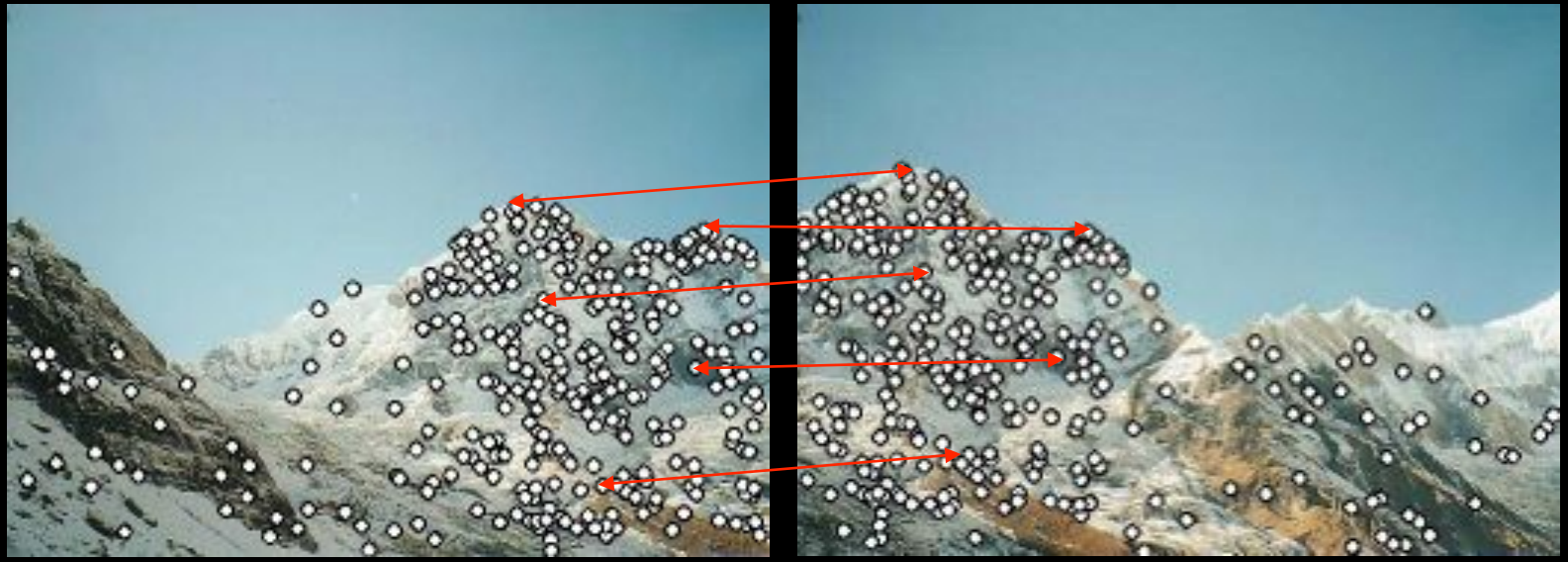
Assignment 1: Still need to solve Computer Vision

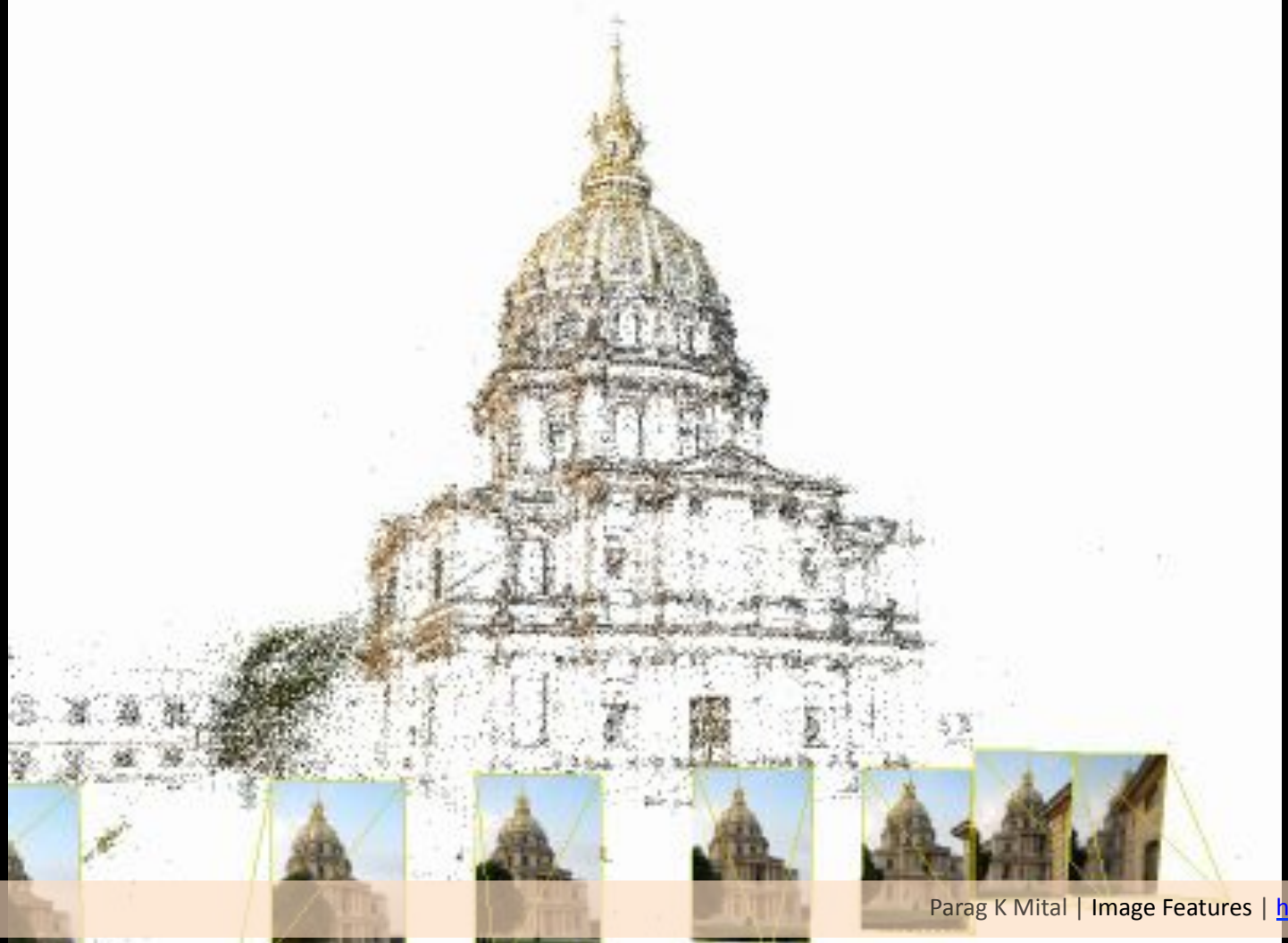
Vision is based on inference

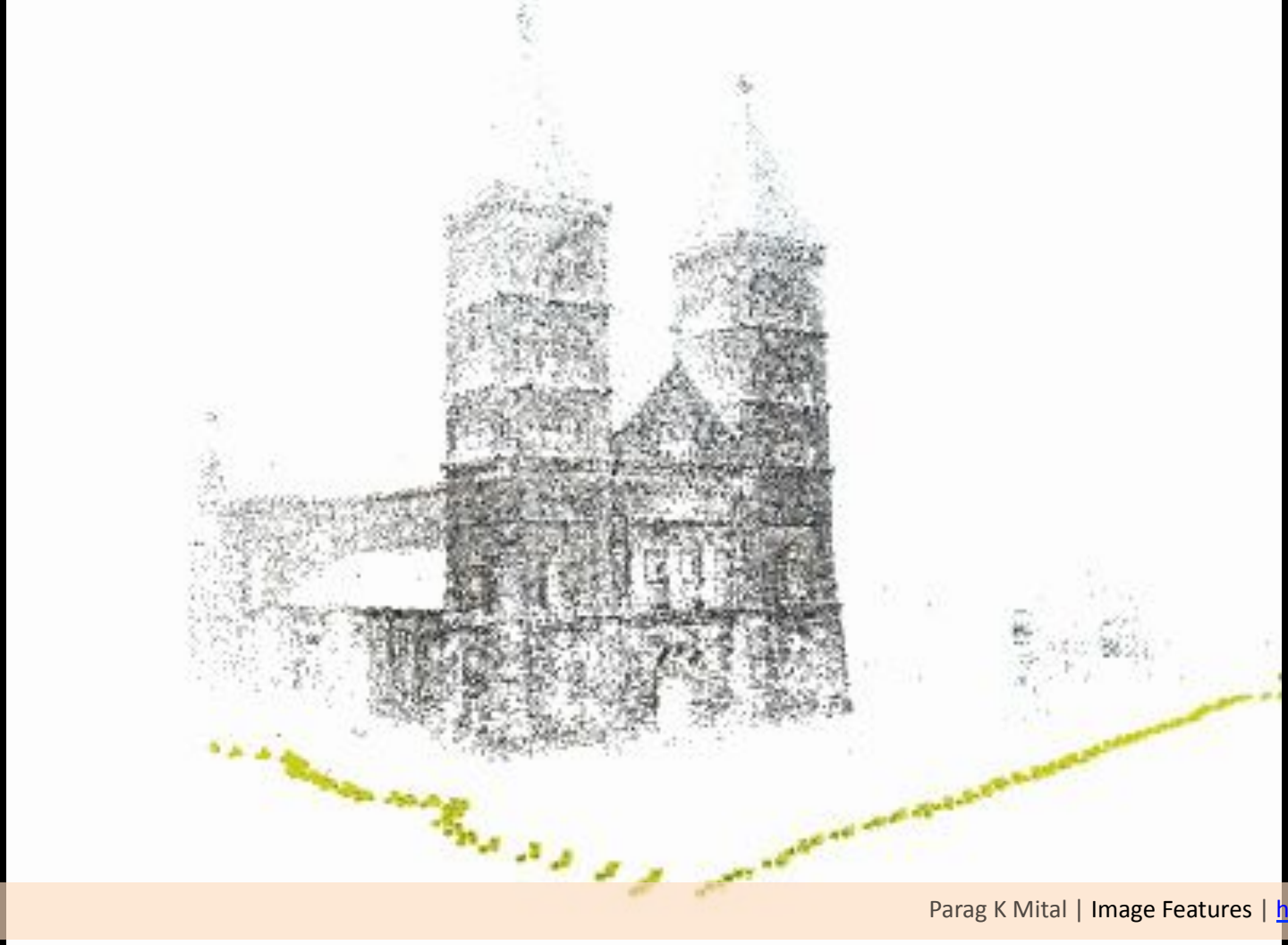
Popular Uses of Feature Detection:

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





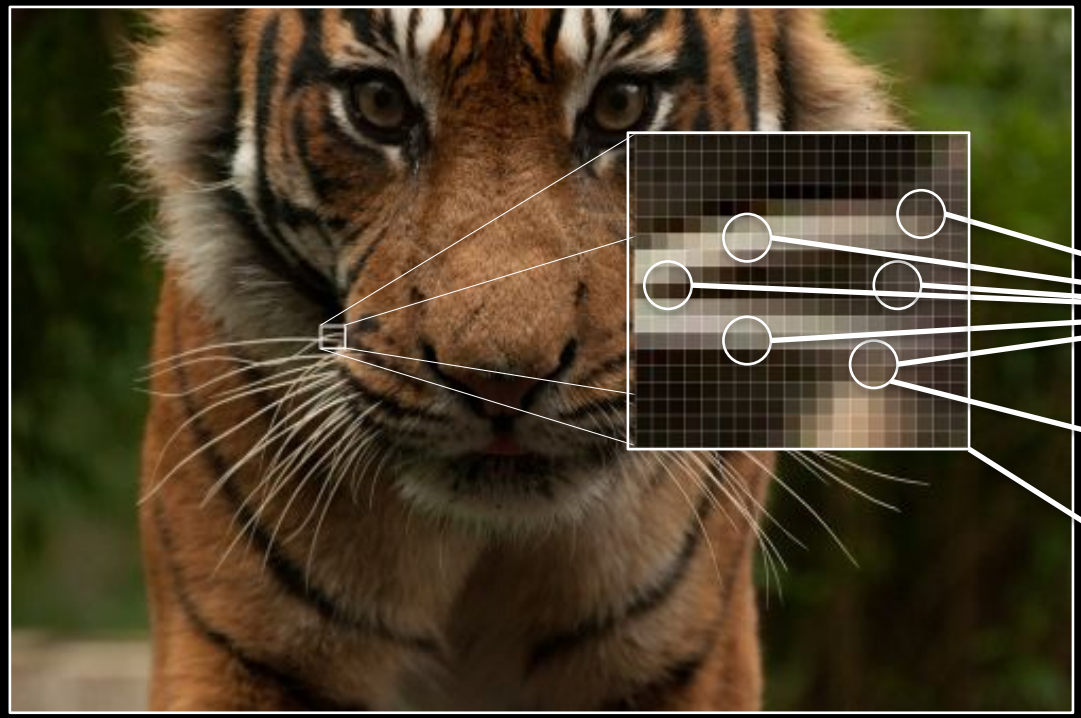




Google Image Search,
Google Goggles,
etc…

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

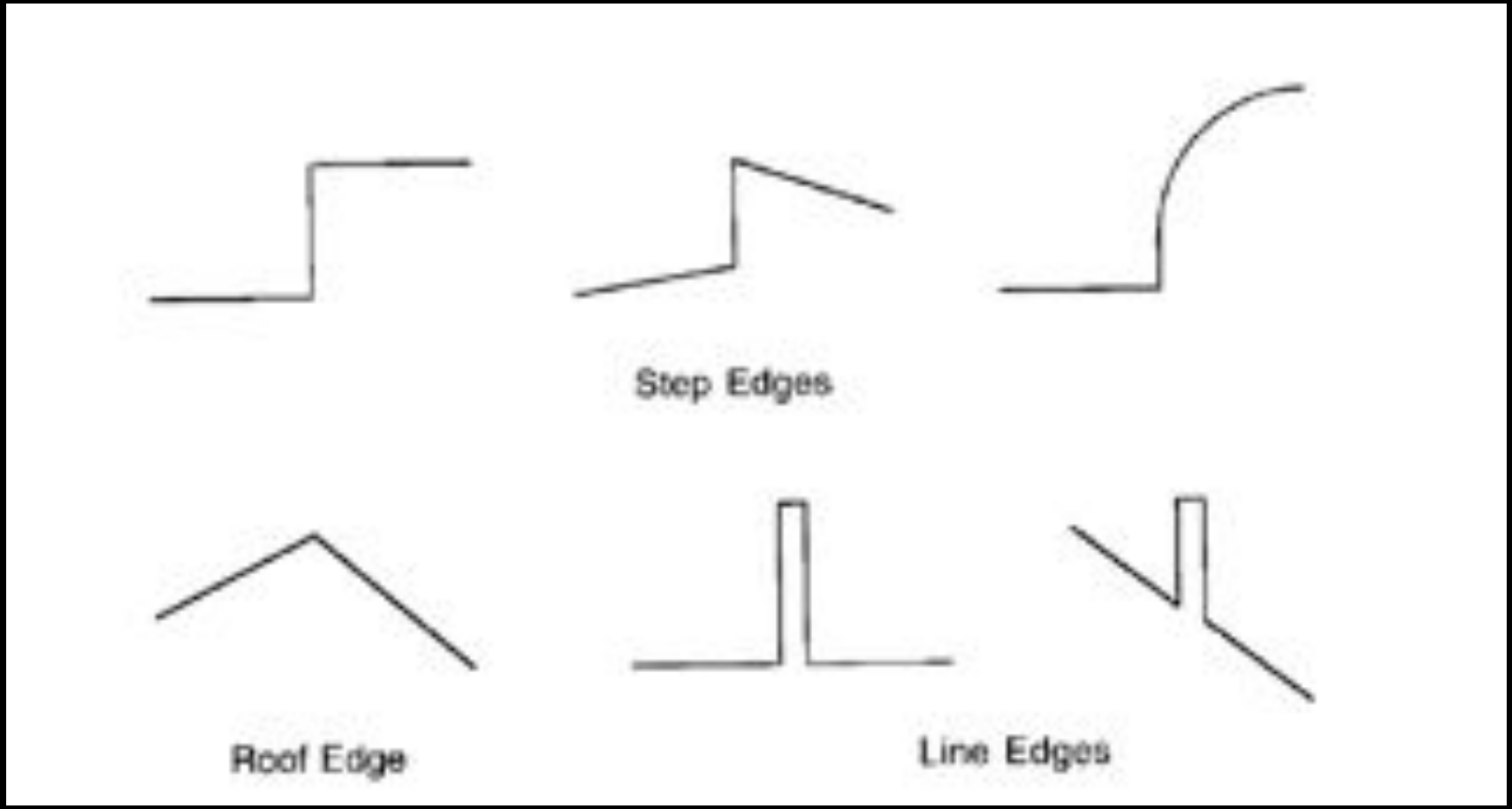
Single feature =
Low-level description

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

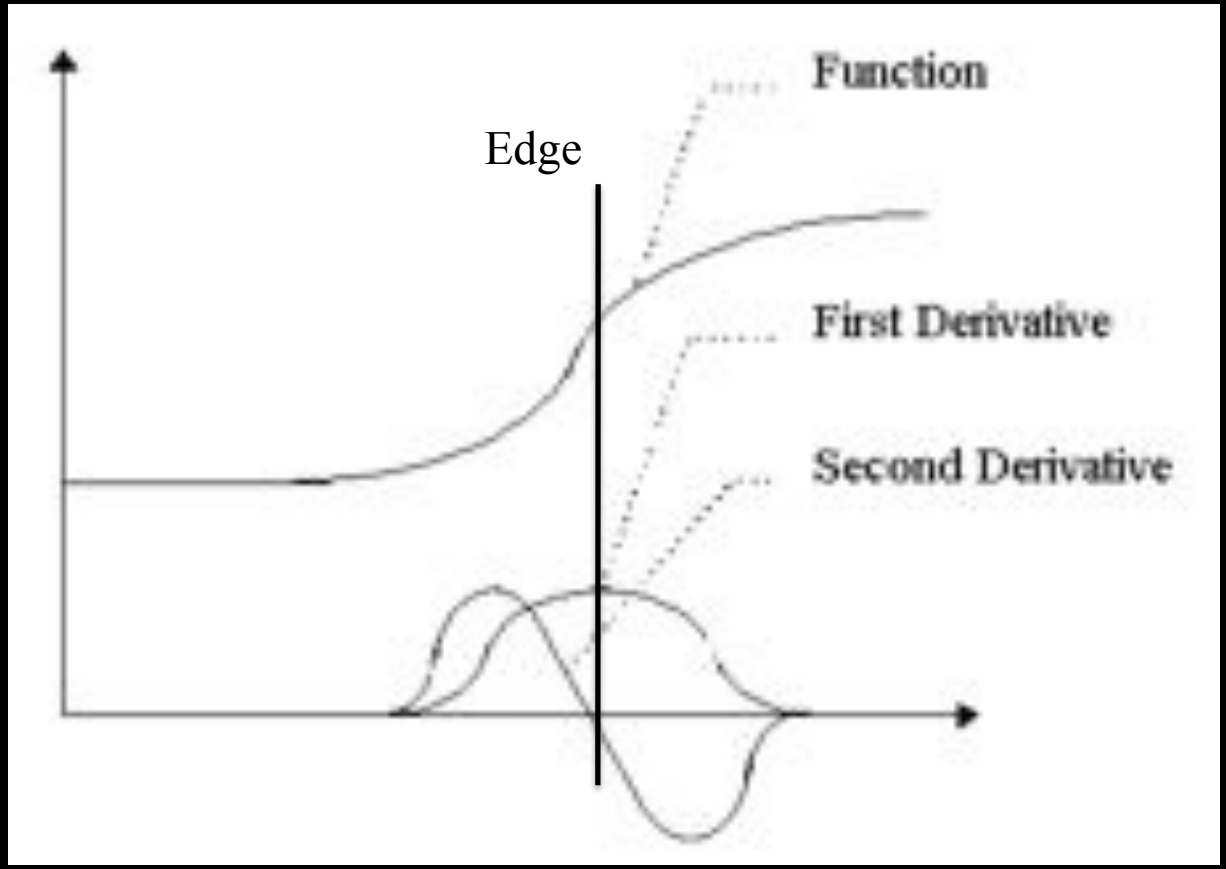
Edges are where change occurs

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

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

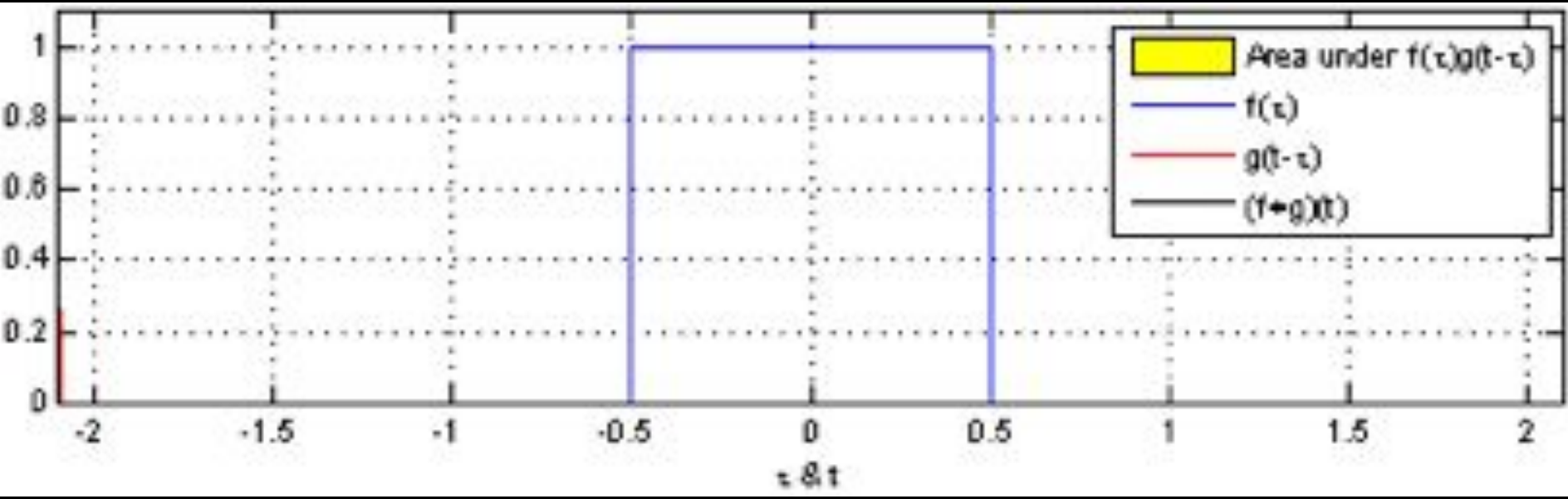
Images are Discrete Functions

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

Sobel: Convolution Operators

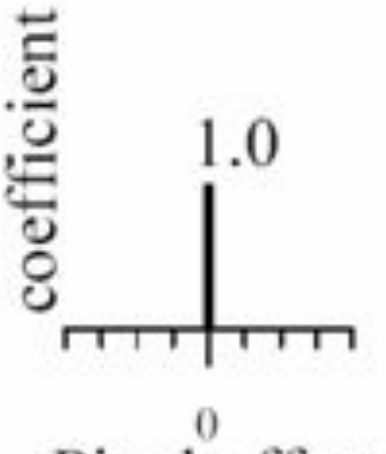
$$\frac{1}{8}\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} = s_x \qquad \frac{1}{8}\begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} = s_y$$

Convolution



Convolution

original

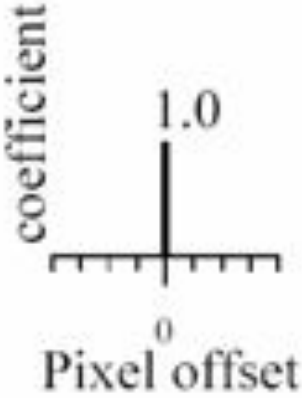


[0,0,0,0,1,0,0,0,0]

?

Convolution

original

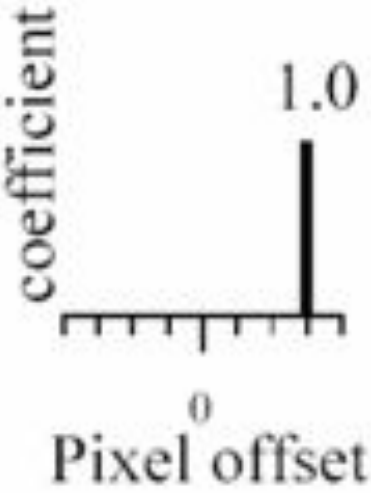


[0,0,0,0,1,0,0,0,0]

Filtered
(no change)

Convolution

original

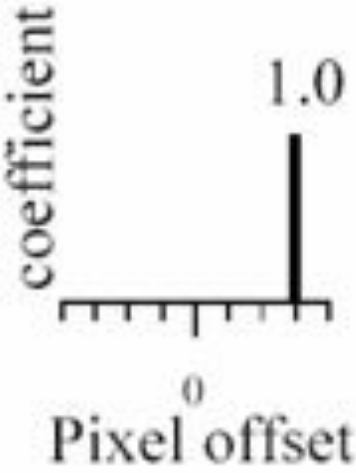


[0,0,0,0,0,0,0,1,0]

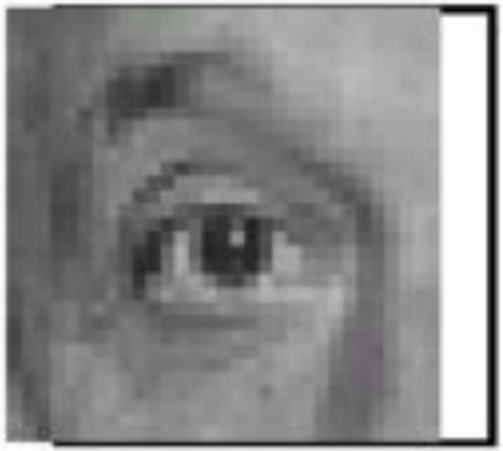
?

Convolution

original



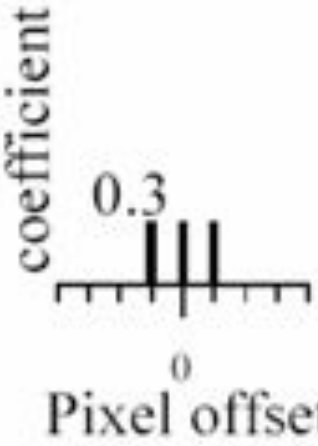
[0,0,0,0,0,0,0,1,0]



shifted

Convolution

original

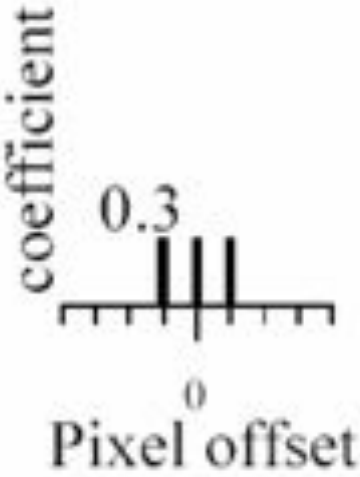


[0,0,0,0.333,0.333,0.333,0,0,0]

?

Convolution

original

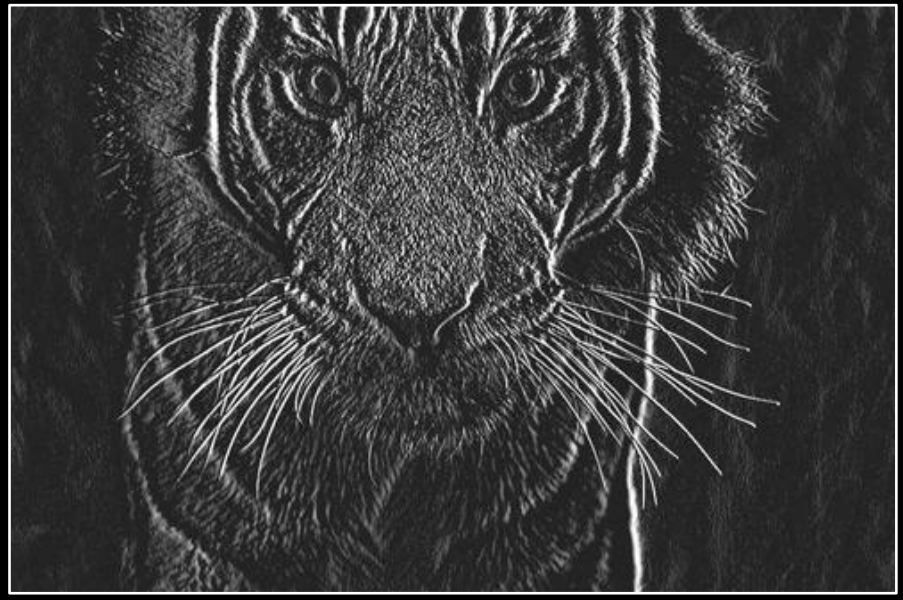


[0,0,0,0.333,0.333,0.333,0,0,0]

Blurred (filter applied in both dimensions).

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

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



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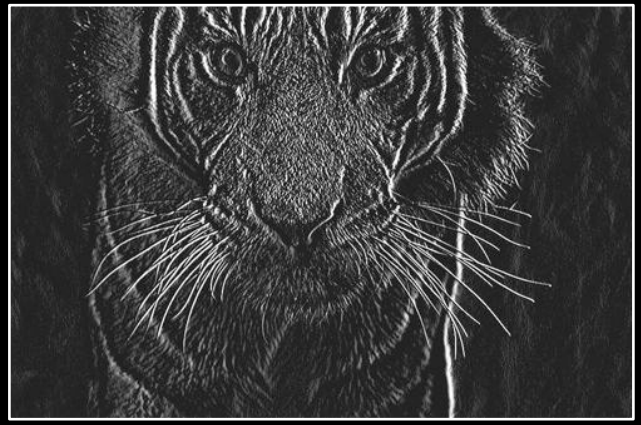

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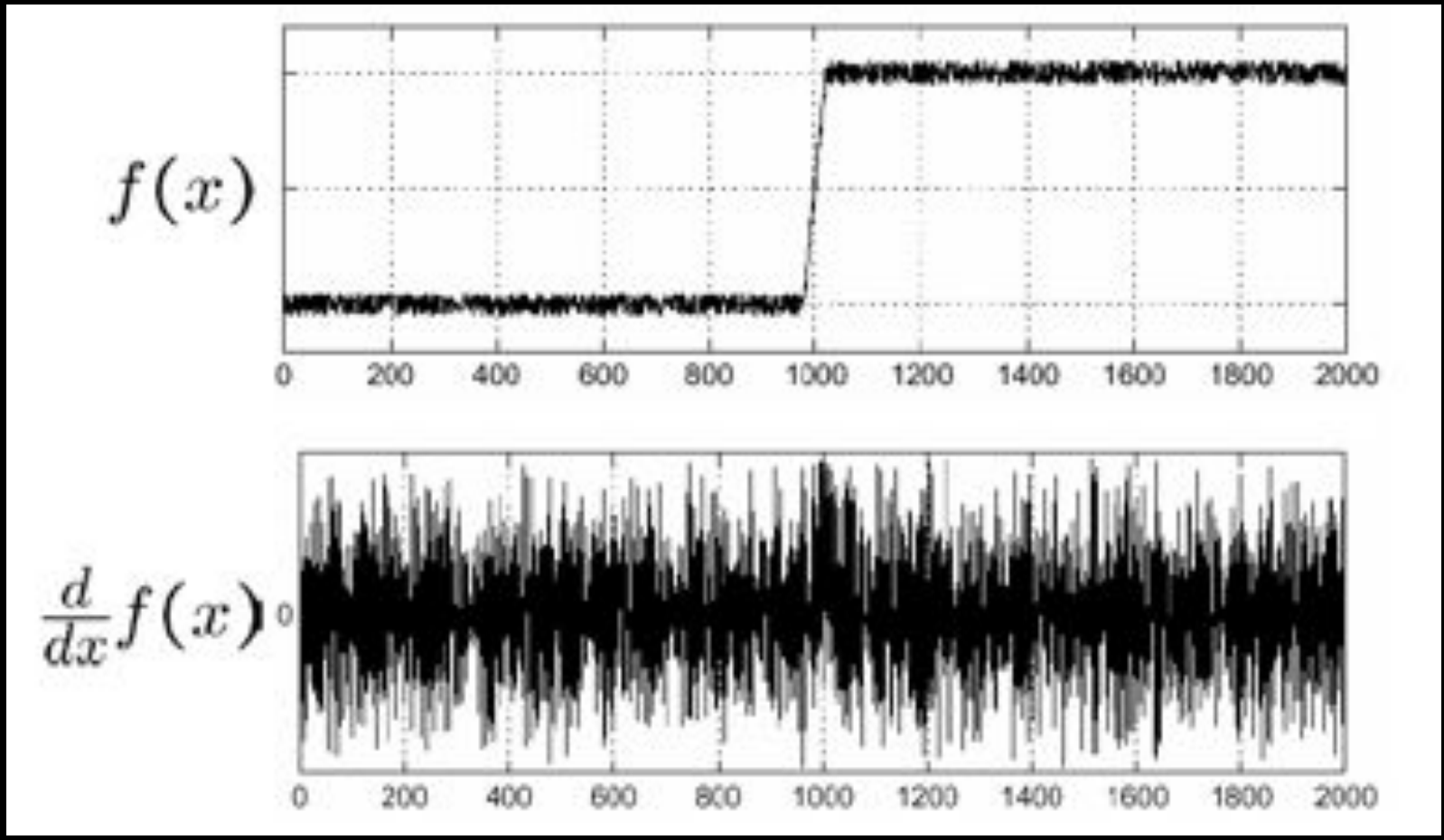
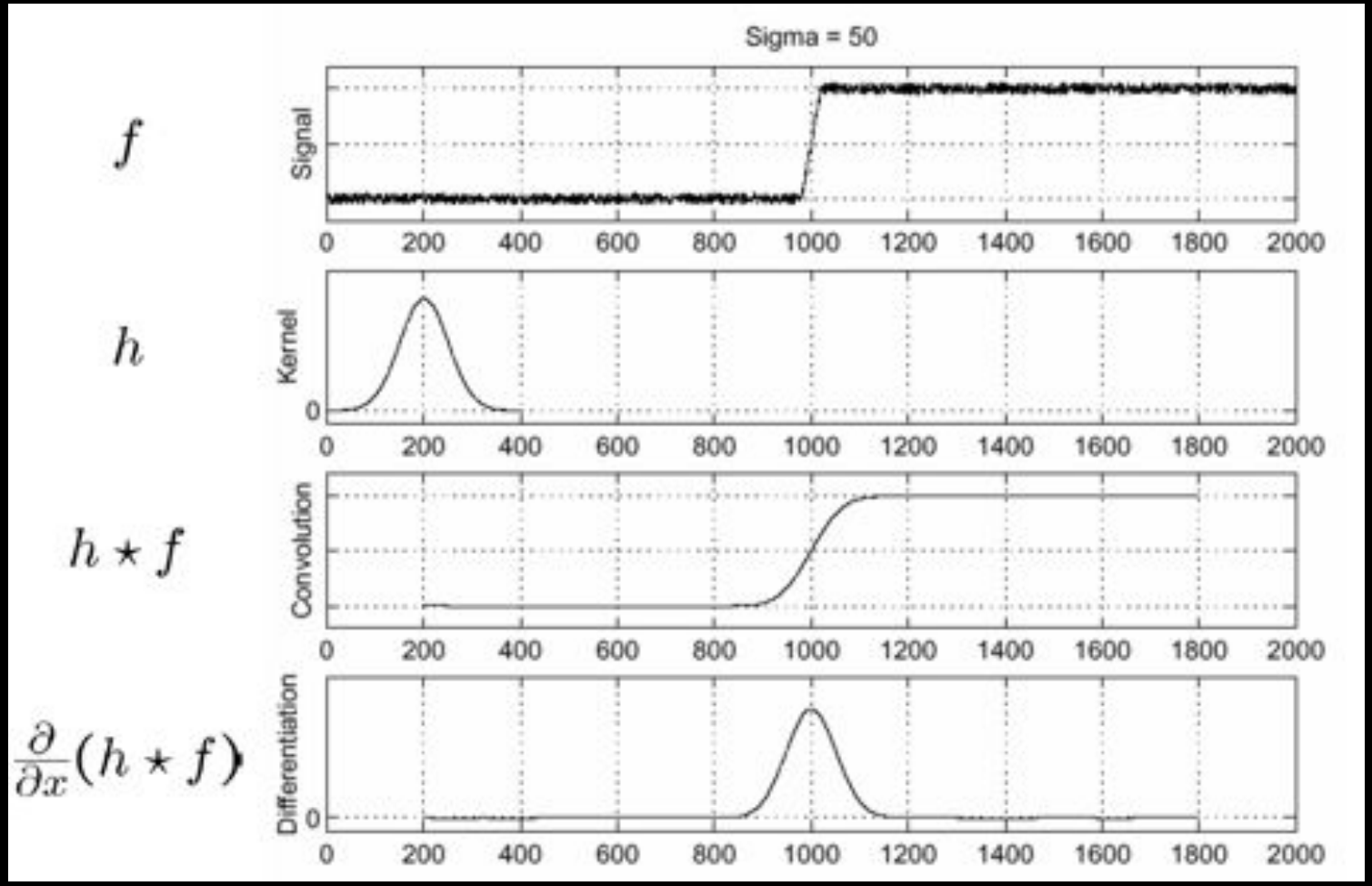
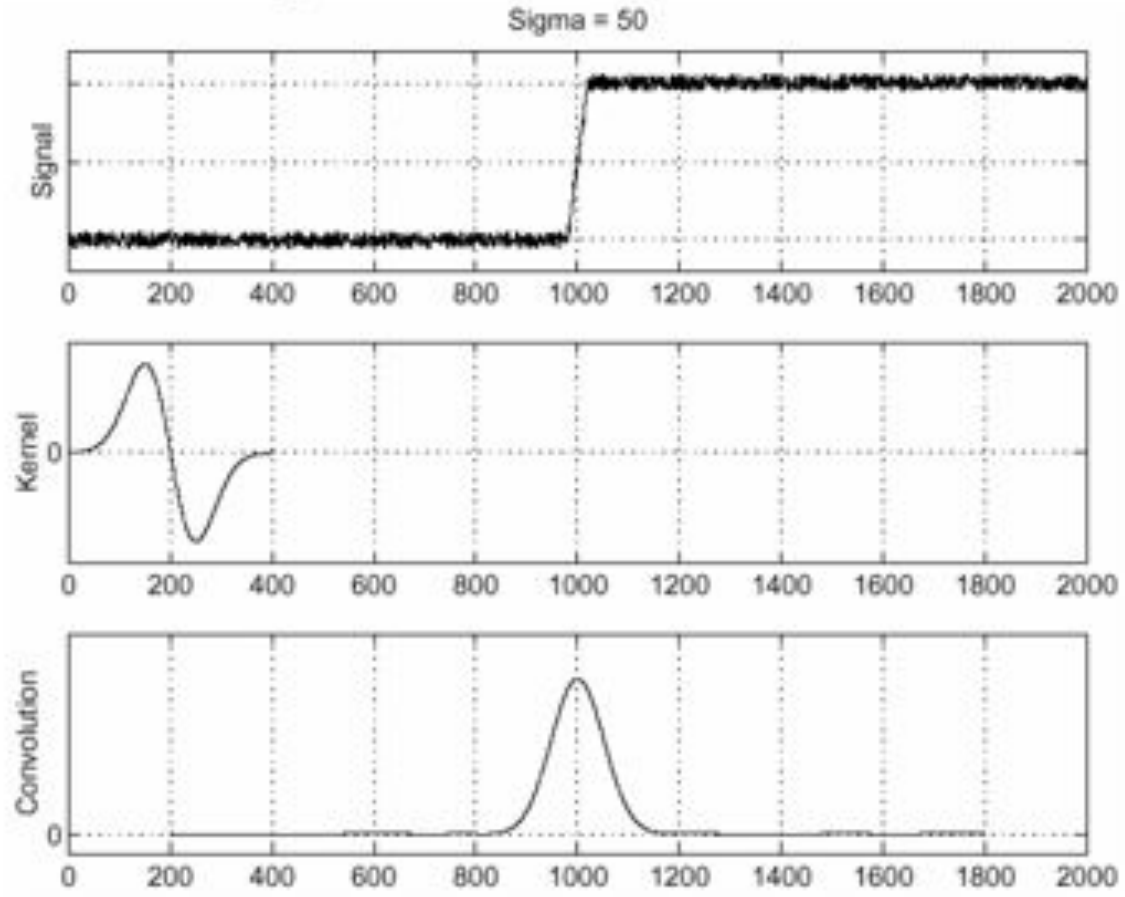

$f(x)$
0
200
400
600
800
1000
1200
1400
1600
1800
2000
$\frac{d}{dx}f(x)$
0
200
400
600
800
1000
1200
1400
1600
1800
2000


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

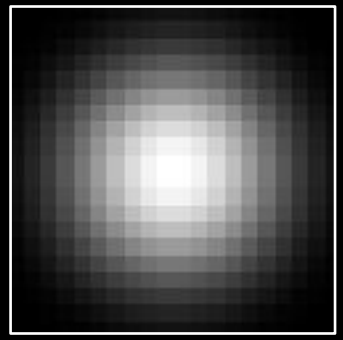
f

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

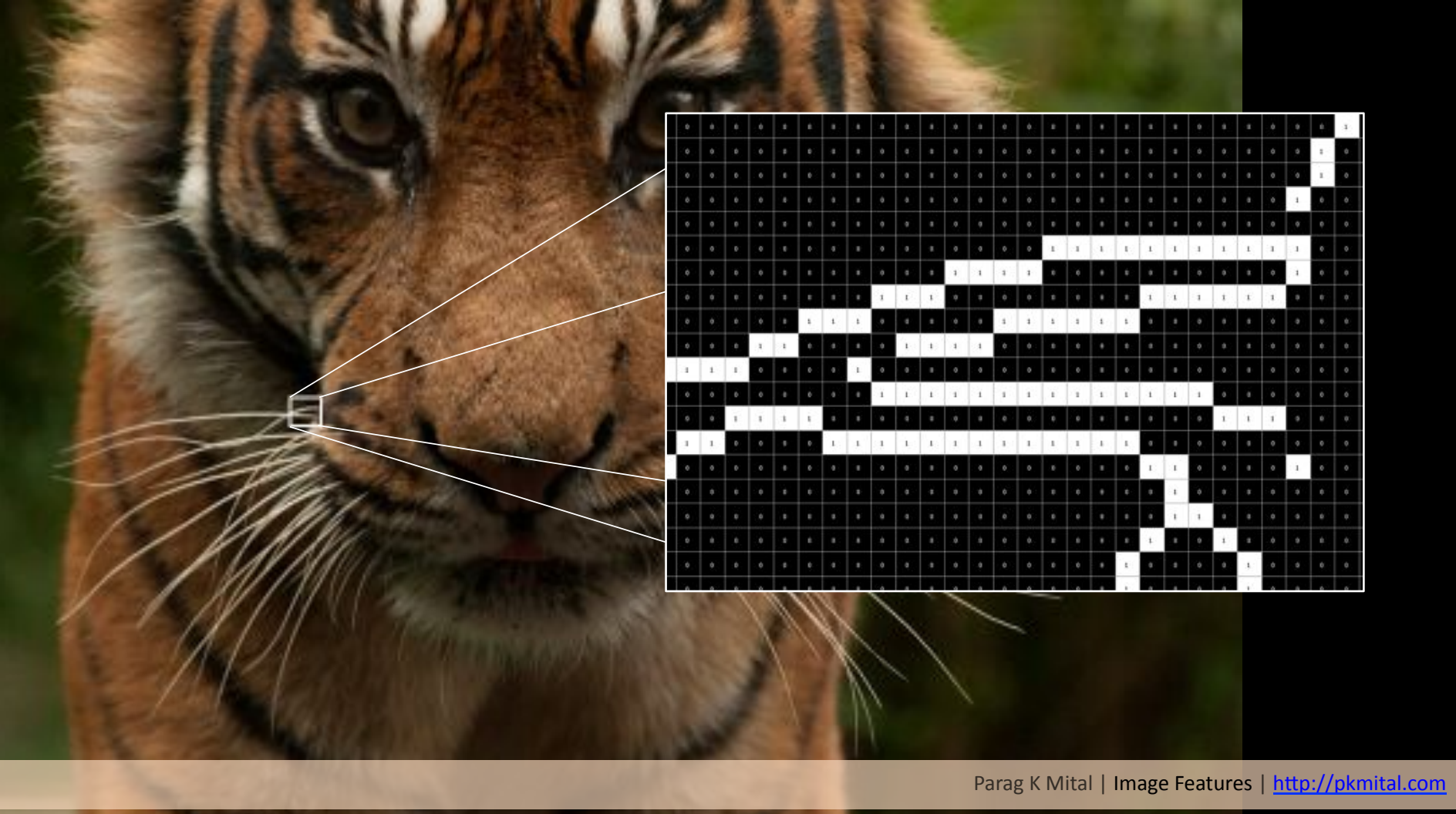
$(\frac{\partial}{\partial x}h) \star f$



Gaussian Kernel



At what scale are our edges defined?



What kind of invariance does our algorithm have?

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

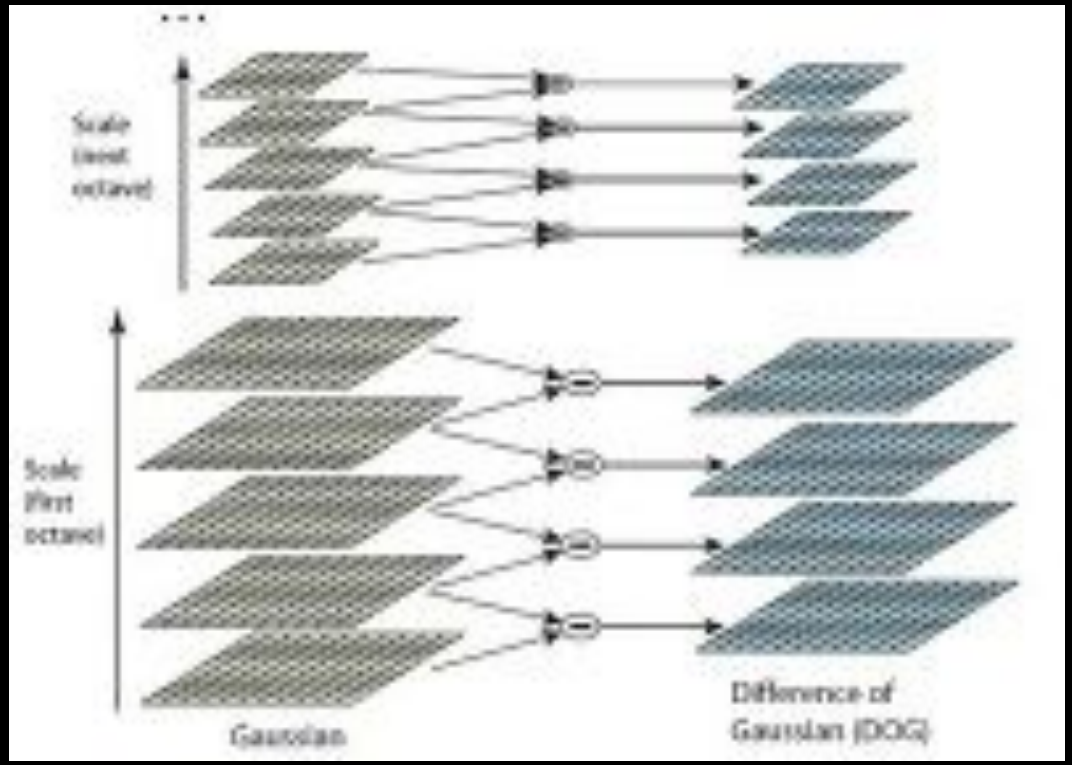
Rather than describe every pixel of an image, we need to find the keypoints

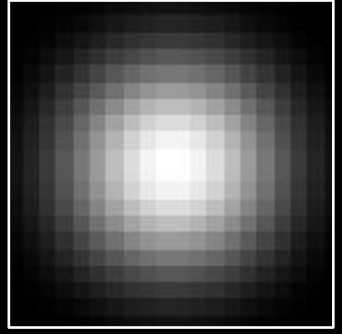
Invariance to: luminance, color, rotation, translation, scale, skew…

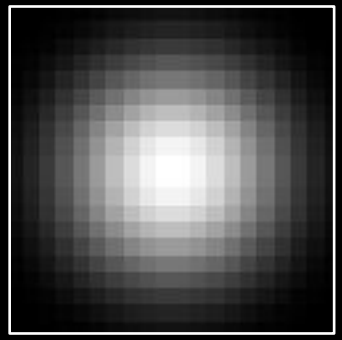
Should be fast to detect, and cheap to store!

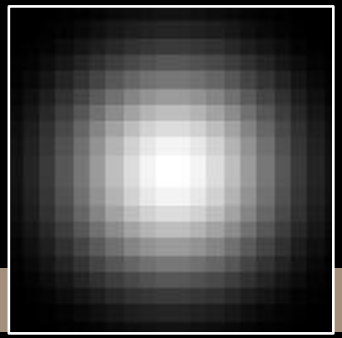
Scale Invariant Feature Transform (SIFT)

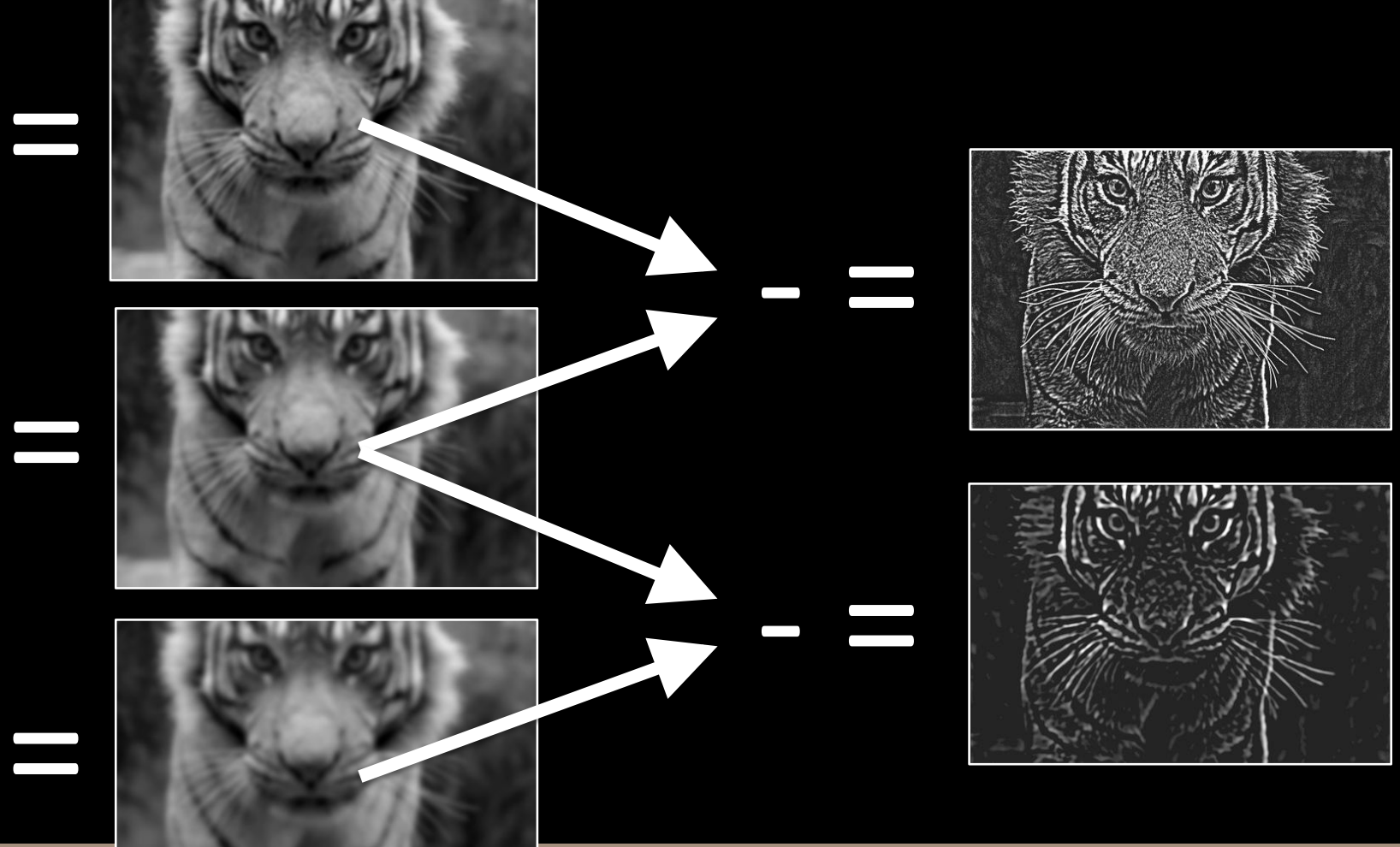
- Generate a Difference of Gaussian(DoG) or a laplacian pyramid
- Extrema detection from the DoG pyramid which is the local maxima and minima, the point found is an extrema
- Eliminate low contrast or poorly localized points, what remains are the keypoints
- Assign an orientation to the points based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

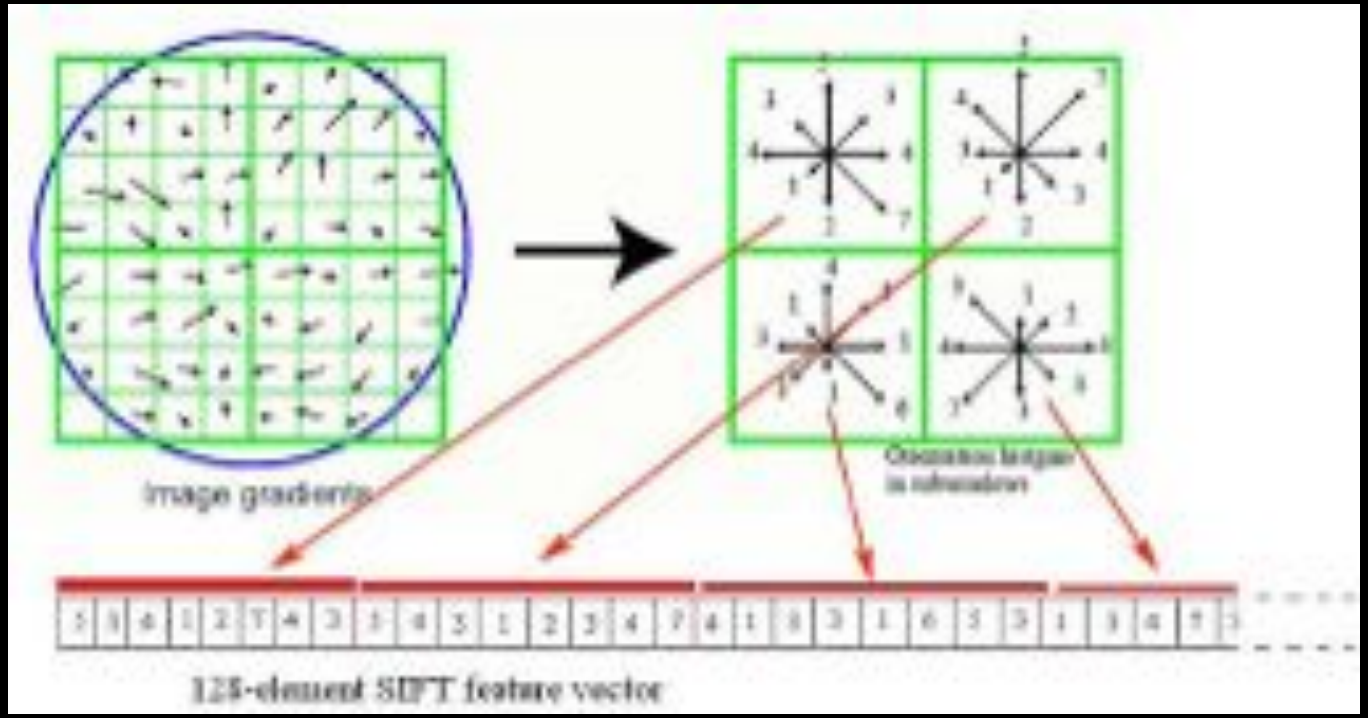


Image gradients
128-element SIFT feature vector

128 element vector * 320 pixels wide * 240 pixels high

= 38 MB per image!

128 element vector * 300 features =

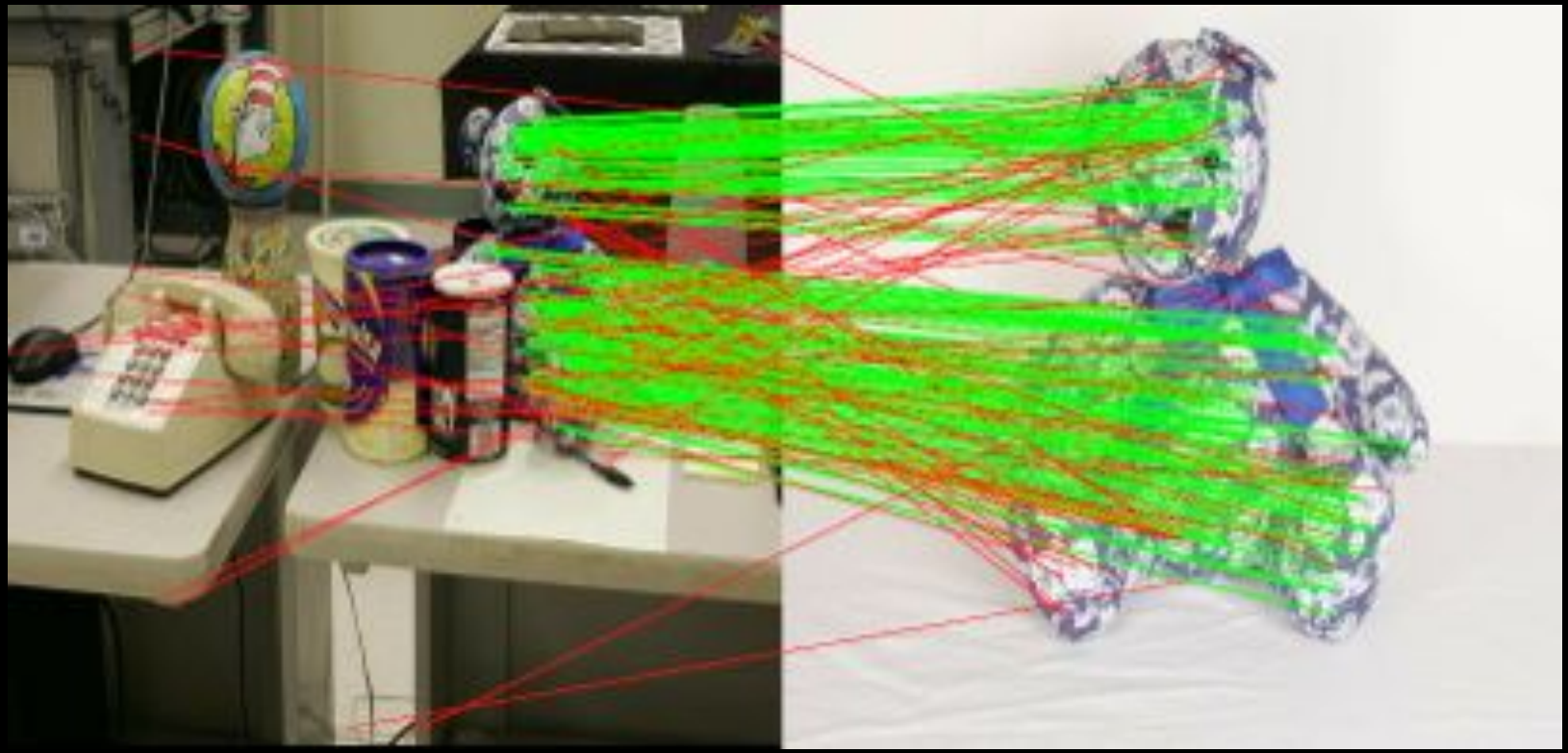
0.15 MB per image

Store all keypoints describing our object in a matrix

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