Computer Vision

DATA.ML.300, 5 study credits

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Local image features

- Low-level features (corners, edges, texture patches) are needed for many tasks:
  - Image matching and registration
  - Structure-from-motion and image-based 3D modeling
  - Image segmentation
  - Object recognition
  - Image retrieval
- Relevant reading:
  - Chapter 4 of Szeliski's book
  - David Lowe's article (2004) http://www.cs.ubc.ca/~lowe/keypoints/

Acknowledgement: many slides from Svetlana Lazebnik, Steve Seitz, David Lowe, Kristen Grauman, and others (detailed credits on individual slides)

Why to extract local features?

- Motivation: panorama stitching
  - We have two images – how do we combine them?

Source: S. Lazebnik

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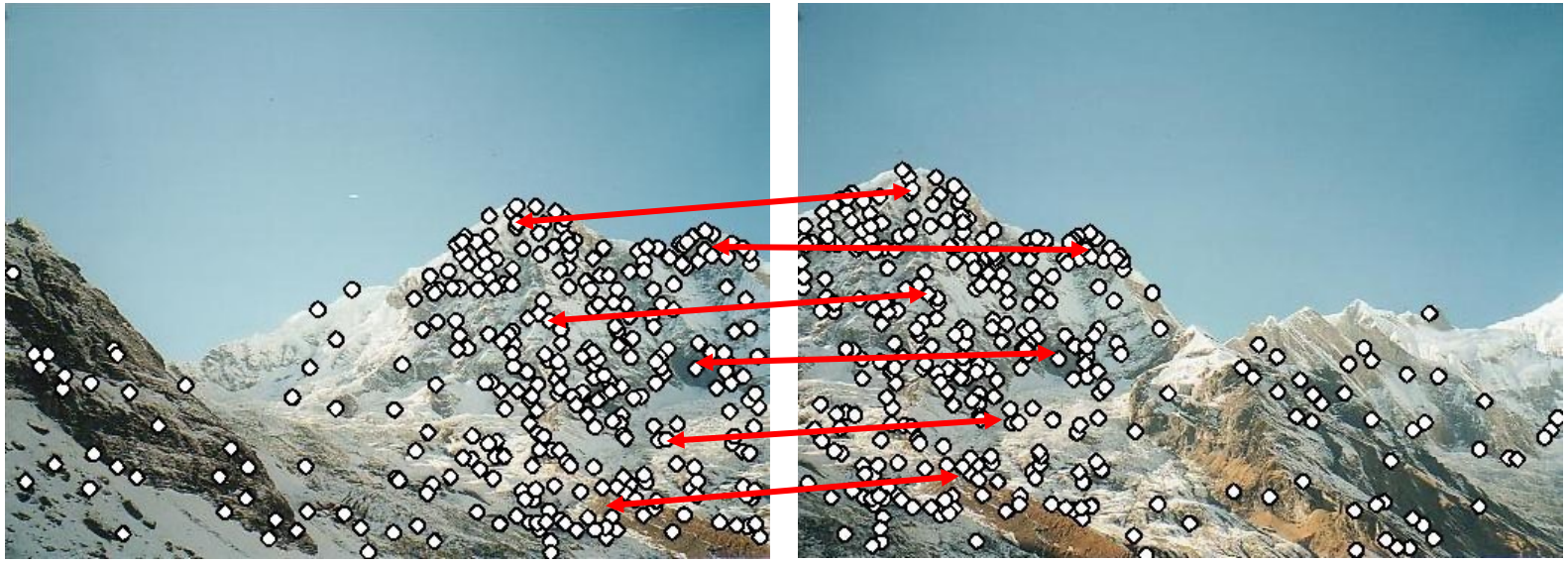


Step 1: extract local features (e.g. keypoints)

Step 2: find correspondences (e.g. match keypoint features)

Source: S. Lazebnik

Why to extract local features?

- Motivation: panorama stitching
  - We have two images – how do we combine them?

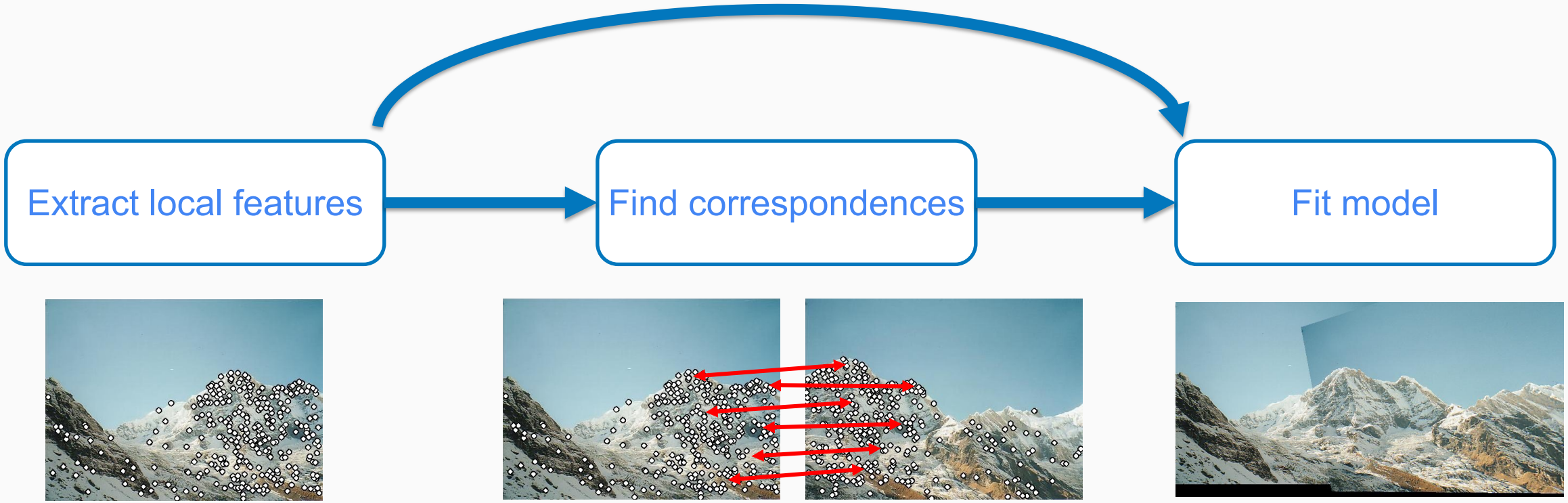
Step 1: extract local features (e.g. keypoints)

Step 2: find correspondences (e.g. match keypoint features)

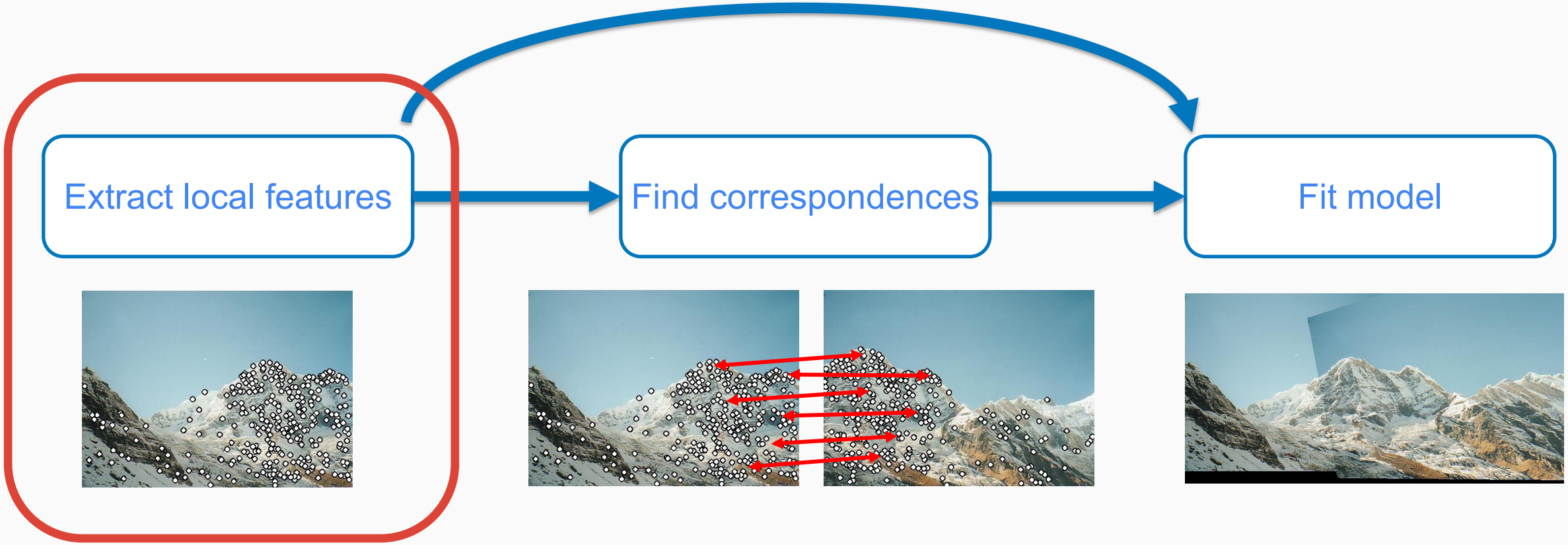
Step 3: align images (e.g. model fitting)

Source: S. Lazebnik

Usual steps in local feature extraction and matching



Usual steps in local feature extraction and matching



Edges

Edge detection

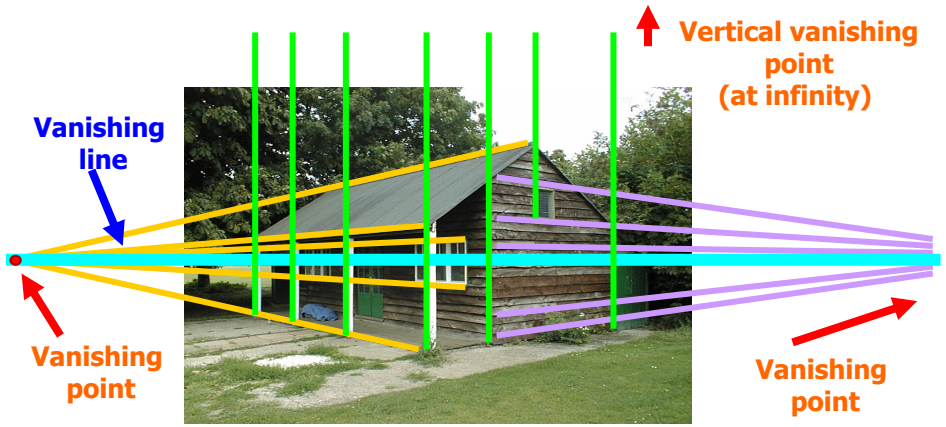
- Goal: Identify sudden changes (discontinuities) in an image
  - Intuitively, most semantic and shape information from the image can be encoded in the edges
  - More compact than pixels

- Ideal: artist's line drawing (but artist is also using object-level knowledge)

Source: D. Lowe

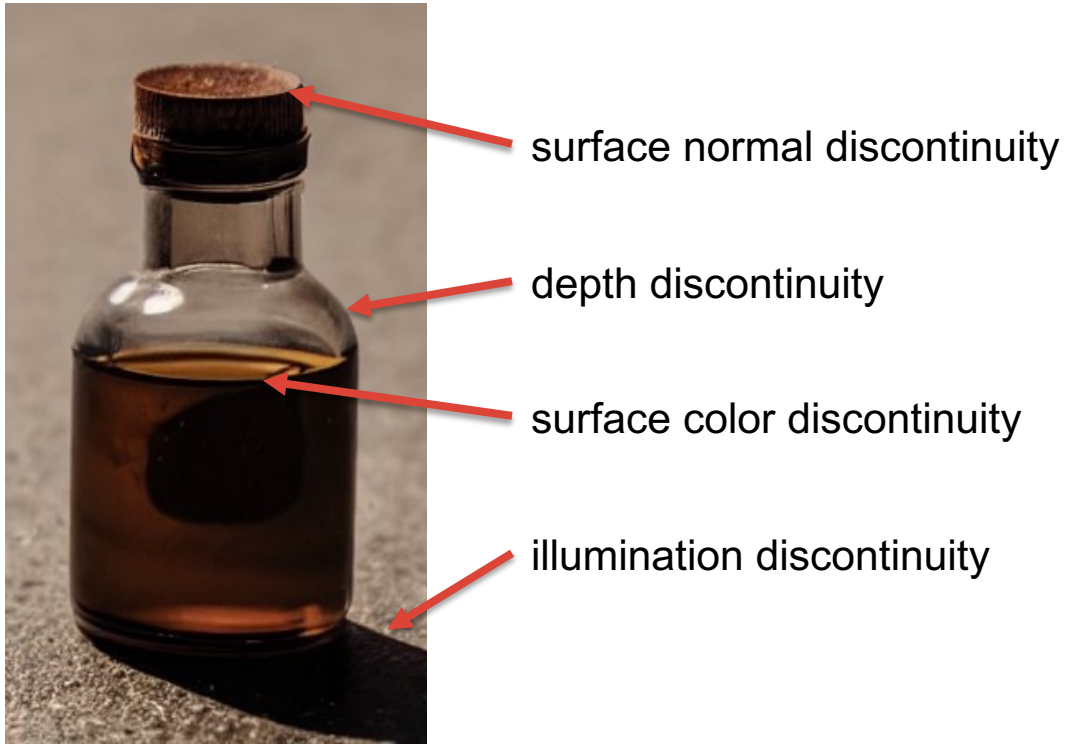
Why do we care about edges?

- Extract information, recognize objects
- Recover geometry and viewpoint



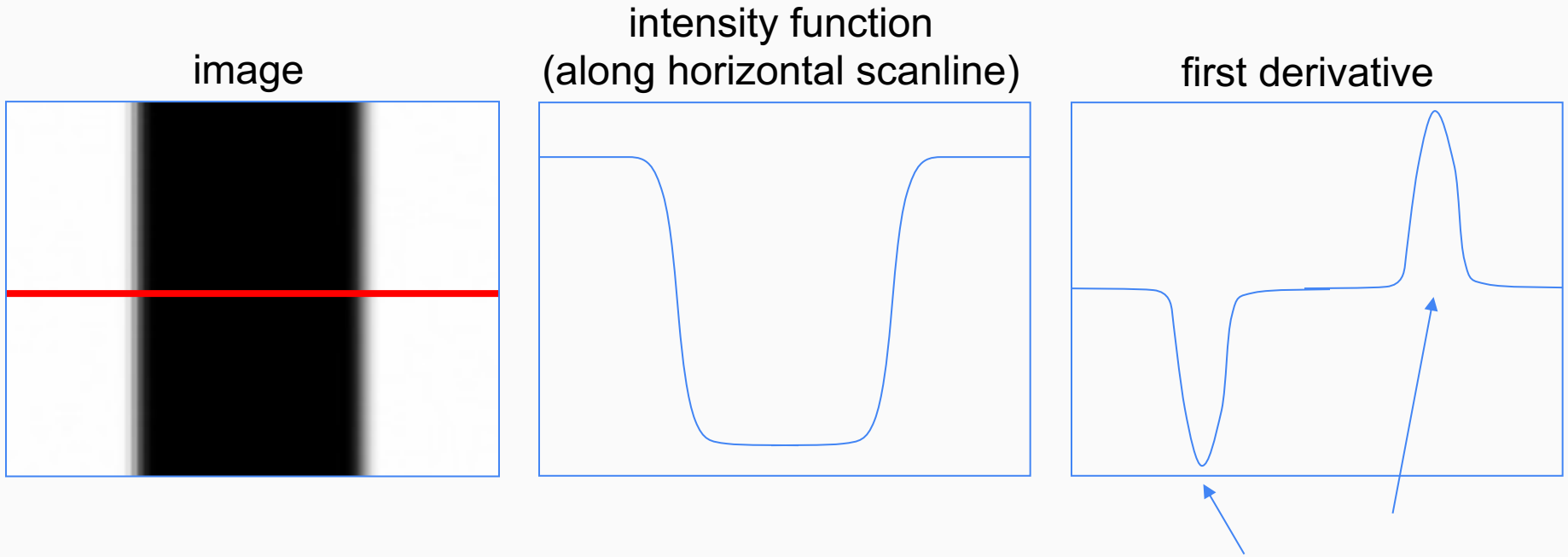
Origin of edges

- Edges are caused by a variety of factors:



Edge detection

- An edge is a place of rapid change in the image intensity function



Source: S. Lazebnik

Reminder: Derivatives with convolution

- For 2D function f(x,y), the partial derivative is:

$$\frac{\partial f(x,y)}{\partial x} = \lim_{\varepsilon \to 0} \frac{f(x+\varepsilon, y) - f(x,y)}{\varepsilon}$$

- For discrete data, we can approximate using finite differences:

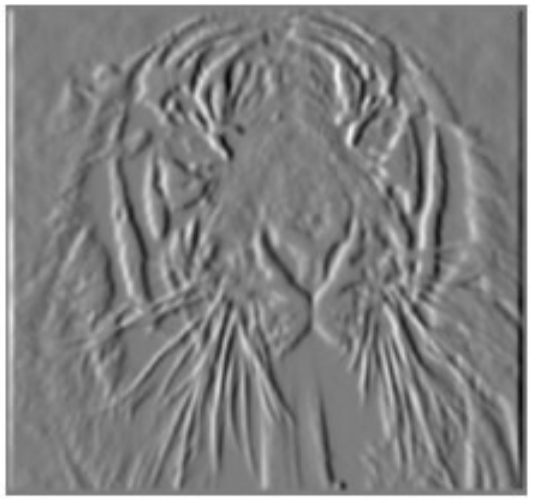
$$\frac{\partial f(x,y)}{\partial x} \approx \frac{f(x+1, y) - f(x,y)}{1}$$

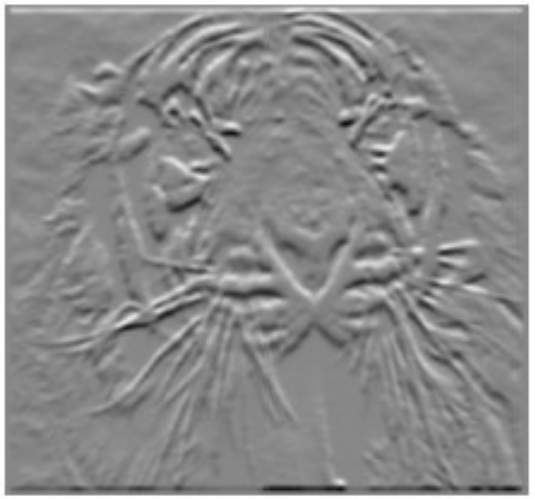
- To implement the above as convolution, what would be the associated filter?

Source: K. Grauman

Reminder: Partial derivatives of an image

$$\frac{\partial f(x,y)}{\partial x}$$





$$\frac{\partial f(x,y)}{\partial y}$$

-1	1

1
-1

Source: S. Lazebnik

Reminder: Finite difference filters

- Other approximations of derivative filters exist:

Prewitt: $M_x =$

-1	0	1
-1	0	1
-1	0	1

; $M_y =$

1	1	1
0	0	0
-1	-1	-1

Sobel: $M_x =$

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

; $M_y =$

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

Roberts: $M_x =$

0	1
-1	0

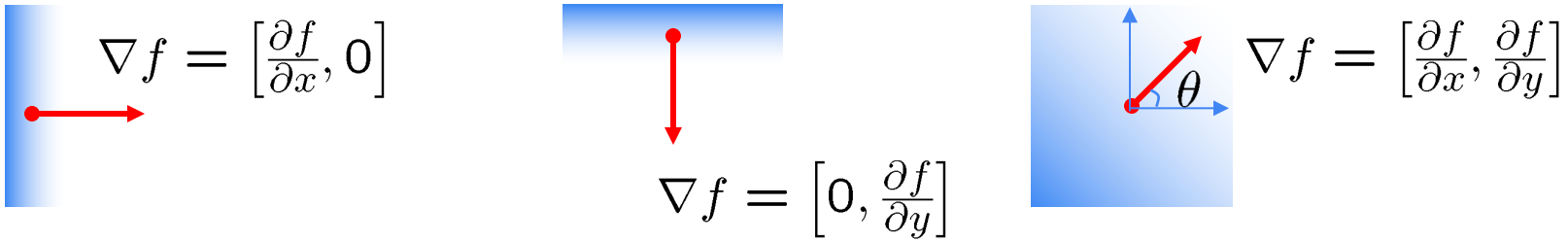
; $M_y =$

1	0
0	-1

Source: K. Grauman

Image gradient

The gradient of an image: $\nabla f = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$



The gradient points in the direction of most rapid increase in intensity

- How does this direction relate to the direction of the edge?

The gradient direction is given by $\theta = \tan^{-1}\left(\frac{\partial f}{\partial y} / \frac{\partial f}{\partial x}\right)$

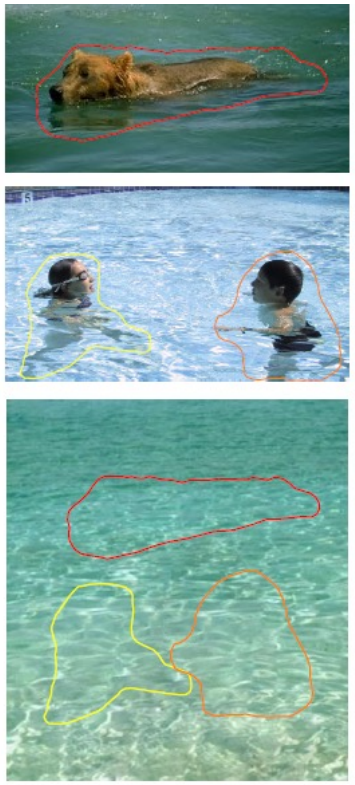
The edge strength is given by the gradient magnitude

$$\|\nabla f\| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$$

Source: Steve Seitz

Application: Gradient-domain image editing

- Goal: solve for pixel values in the target region to match gradients of the source region while keeping background pixels the same



sources/destinations

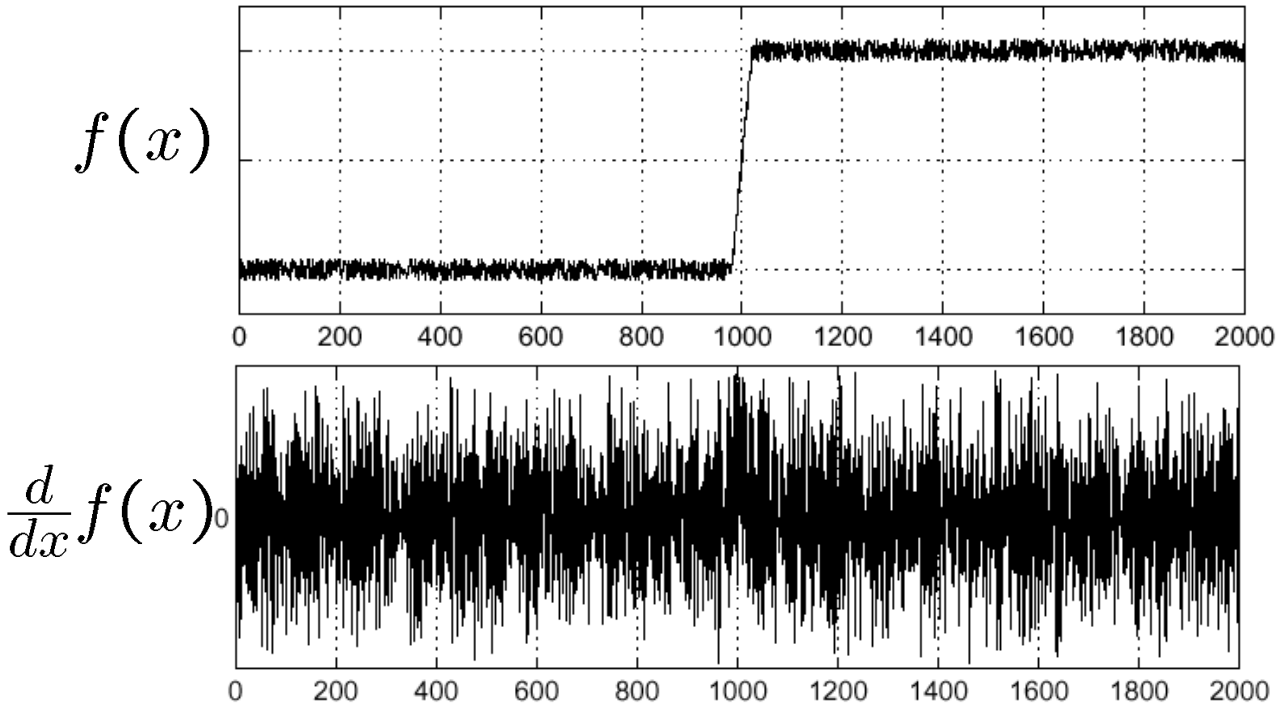
cloning

seamless cloning

P. Perez, M. Gangnet, A. Blake, Poisson Image Editing, SIGGRAPH 2003

Effects of noise

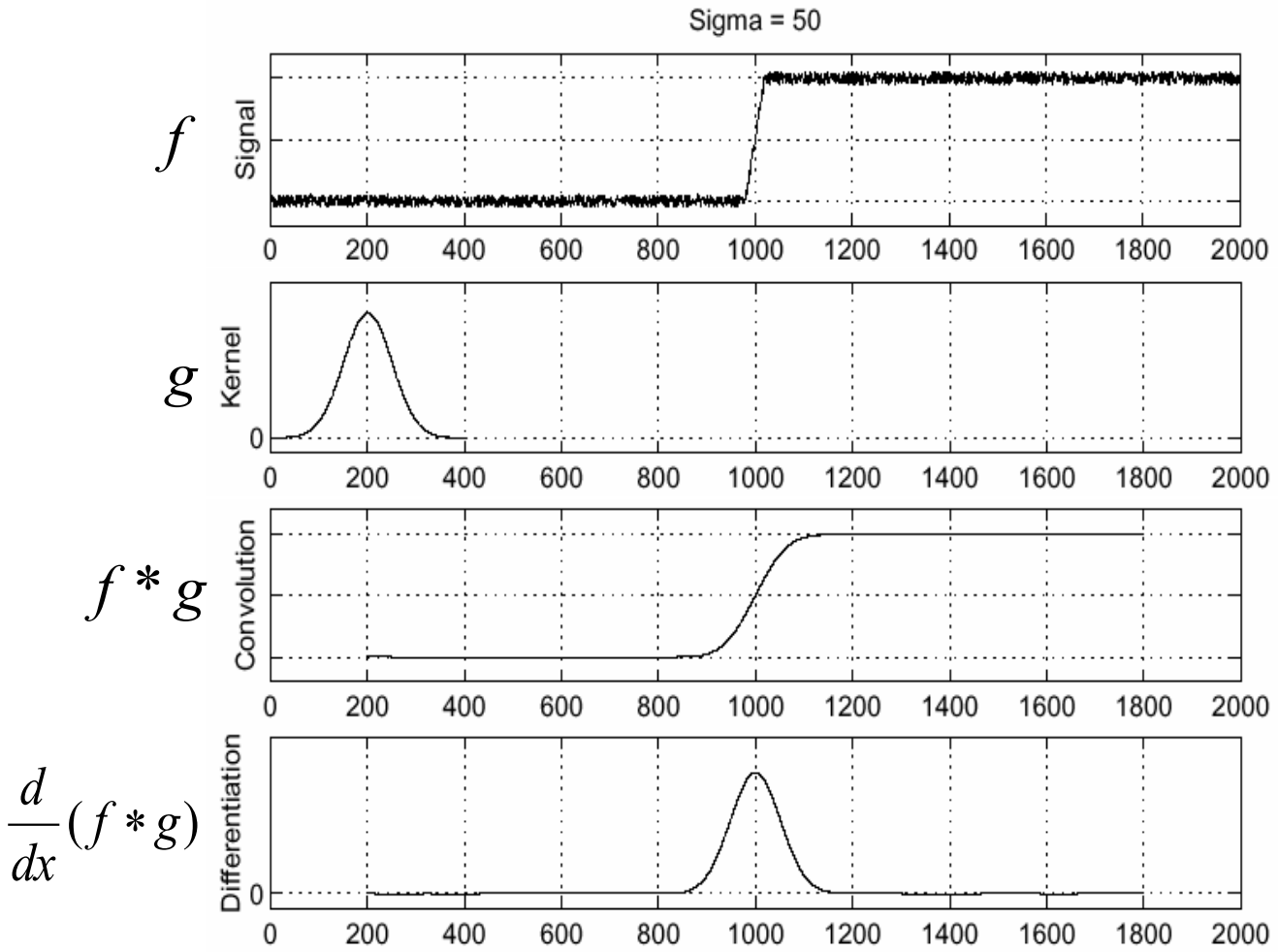
- Consider a single row or column of the image



Where is the edge?

Source: S. Seitz

Solution: smooth first

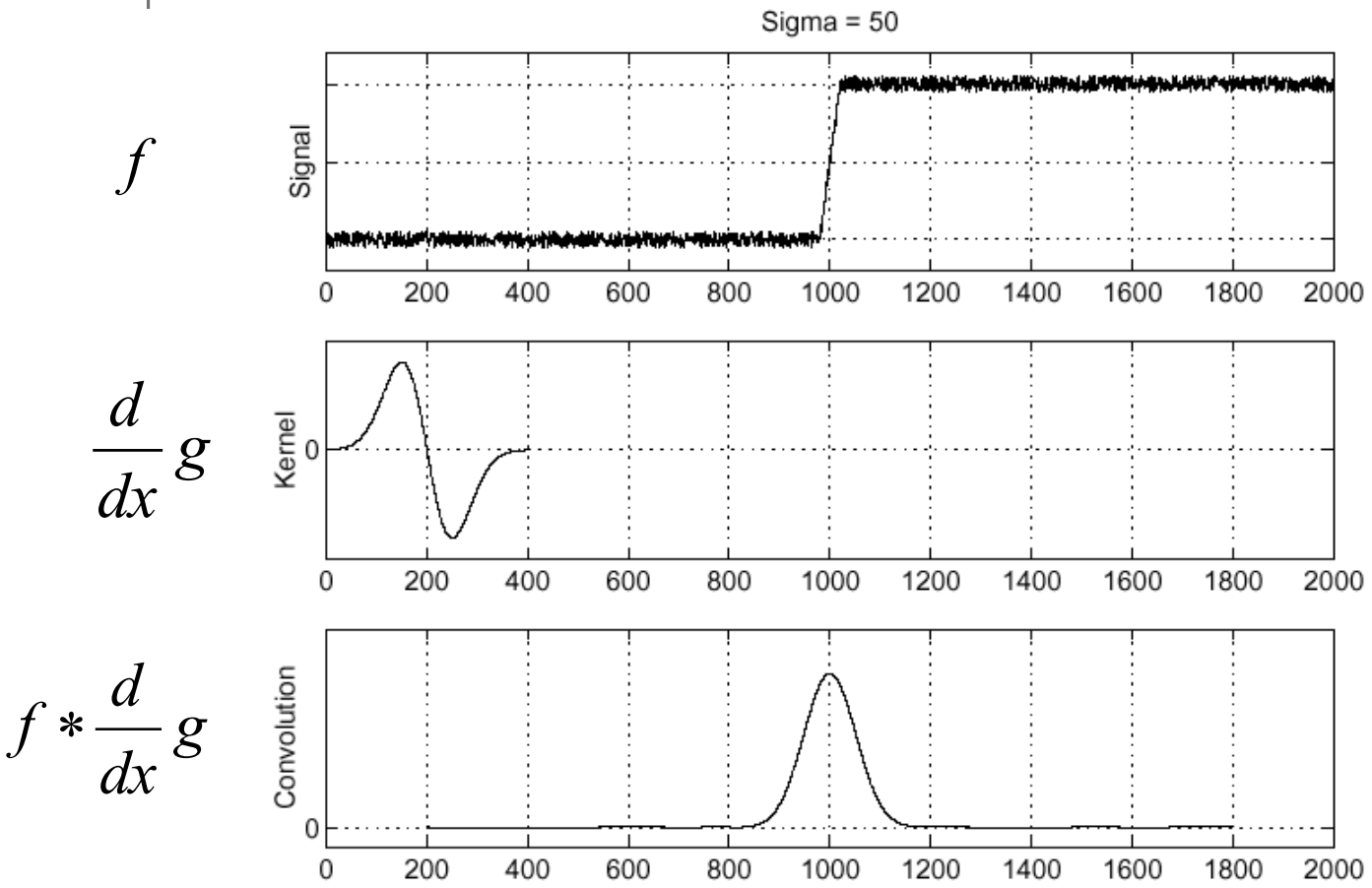


To find edges, look for peaks in $\frac{d}{dx}(f * g)$

Source: S. Seitz

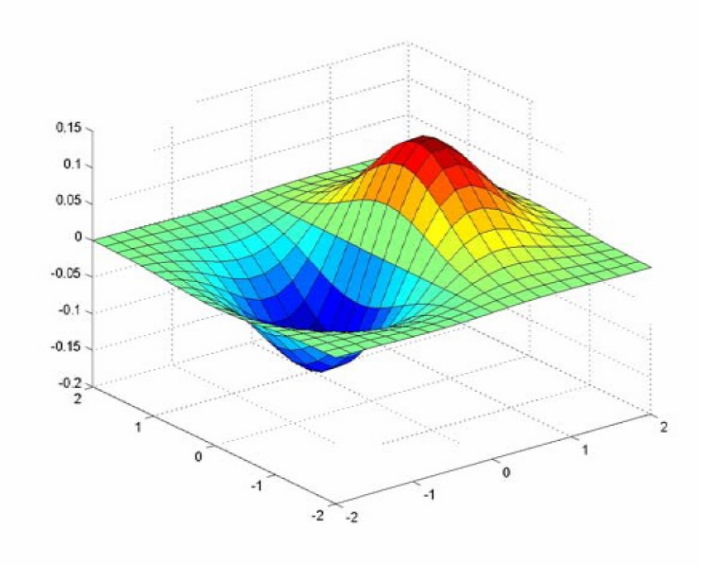
Derivative theorem of convolution

- Differentiation is convolution, and convolution is associative: $$\frac{d}{dx}(f * g) = f * \frac{d}{dx} g$$
- This saves us one operation:

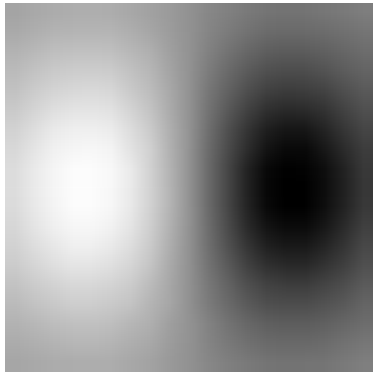


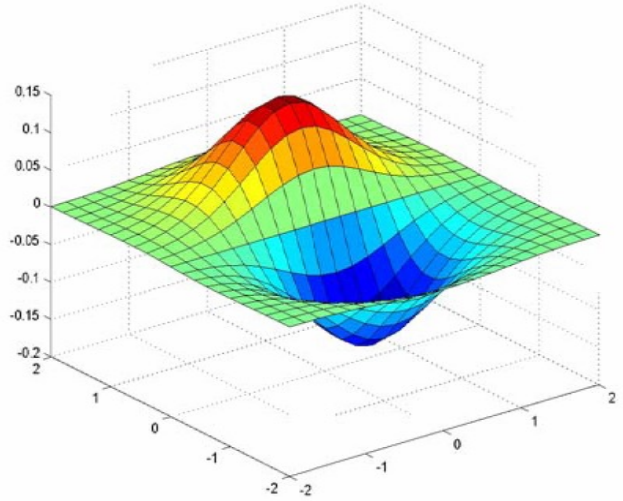
Source: S. Seitz

Derivative of Gaussian filters

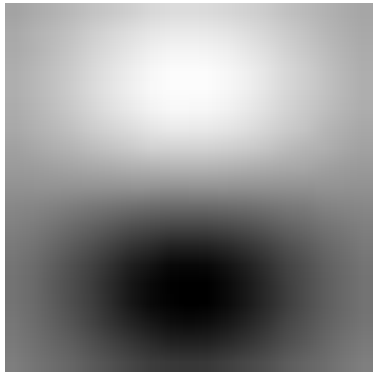


x-direction





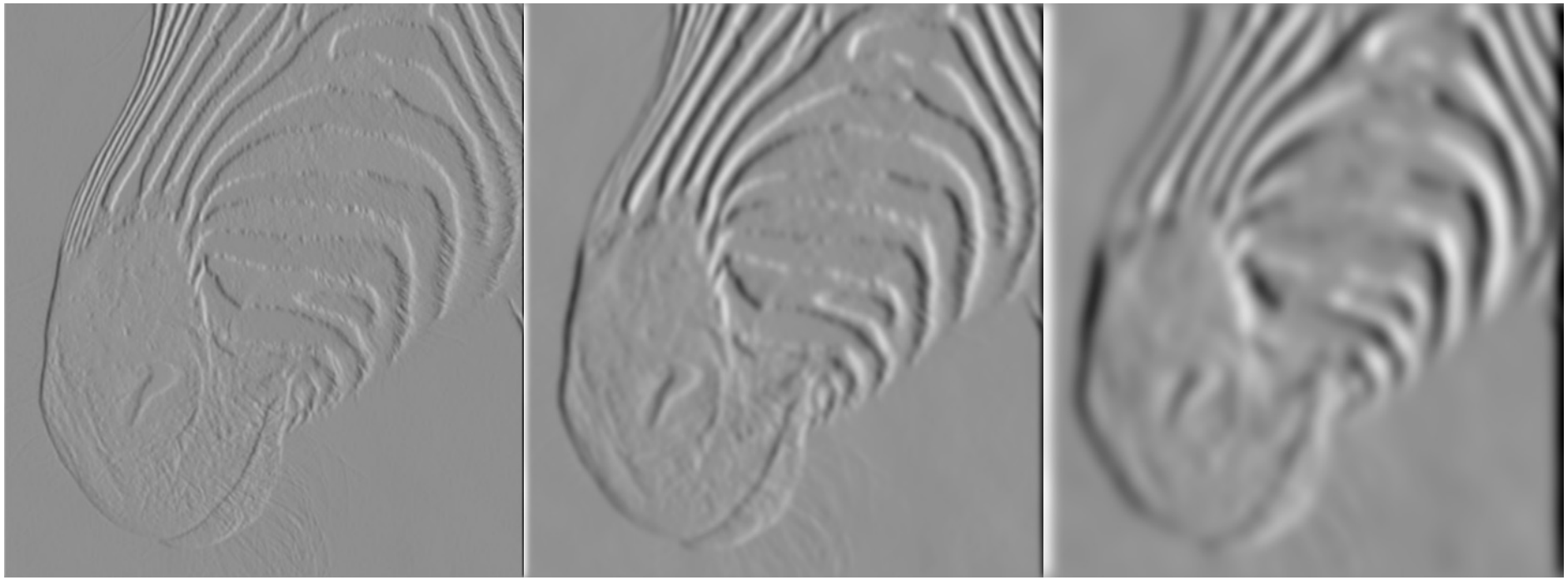
y-direction



Source: S. Lazebnik

Scale of Gaussian derivative filter

- Smoothed derivative removes noise, but blurs edge. Also finds edges at different “scales”



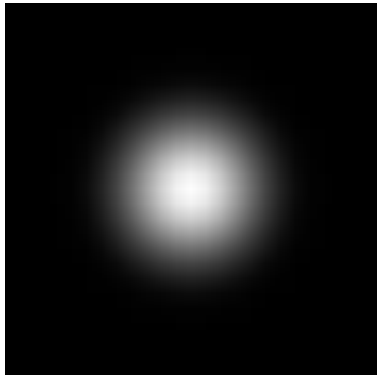
1 pixel 3 pixels 7 pixels

Source: D. Forsyth

Review: Smoothing vs. derivative filters

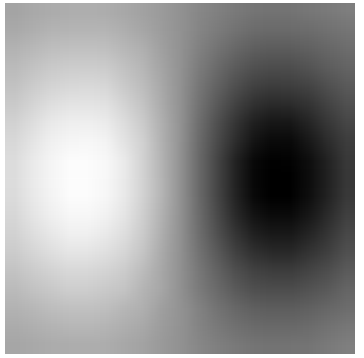
- Smoothing filters
  - Gaussian: remove “high-frequency” components; “low-pass” filter
  - Can the values of a smoothing filter be negative?
  - What should the values sum to?

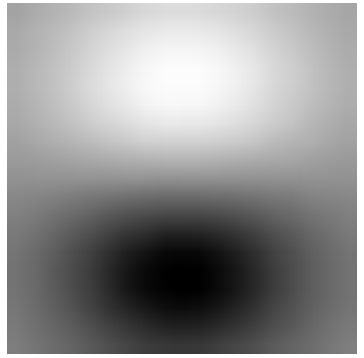
    One: constant regions are not affected by the filter



- Derivative filters
  - Derivatives of Gaussian
  - Can the values of a derivative filter be negative?
  - What should the values sum to?

    Zero: no response in constant regions





Source: S. Lazebnik

Building an edge detector

Original image

Final output

Source: S. Lazebnik

Building an edge detector

Norm of the gradient

Source: S. Lazebnik

Building an edge detector

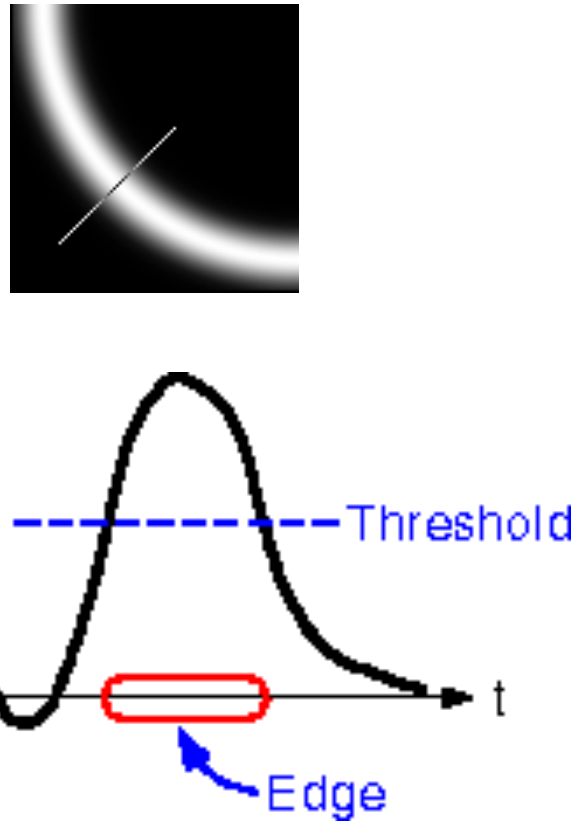
How to turn these thick regions of the gradient into curves?

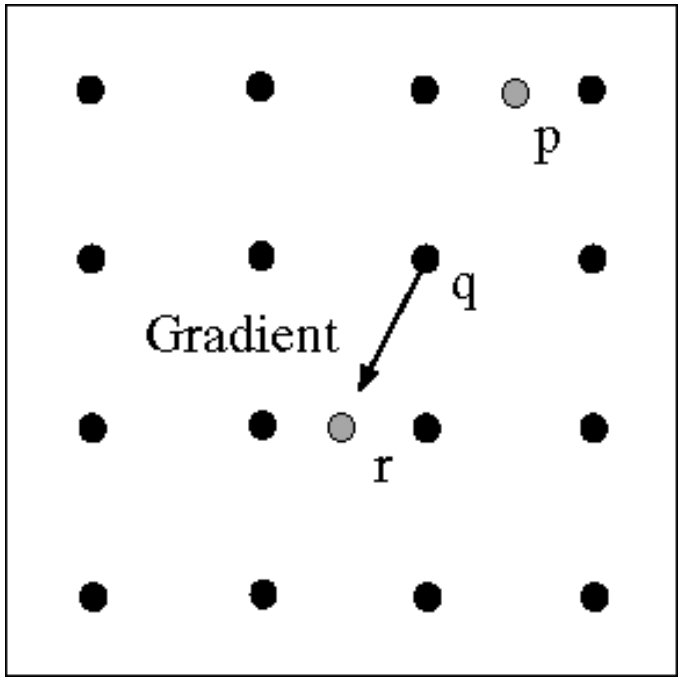
Thresholded norm of the gradient

Source: S. Lazebnik

Non-maximum suppression

- Check if pixel is local maximum along gradient direction, select single max across width of the edge
  - requires checking interpolated pixels p and r





Source: S. Lazebnik

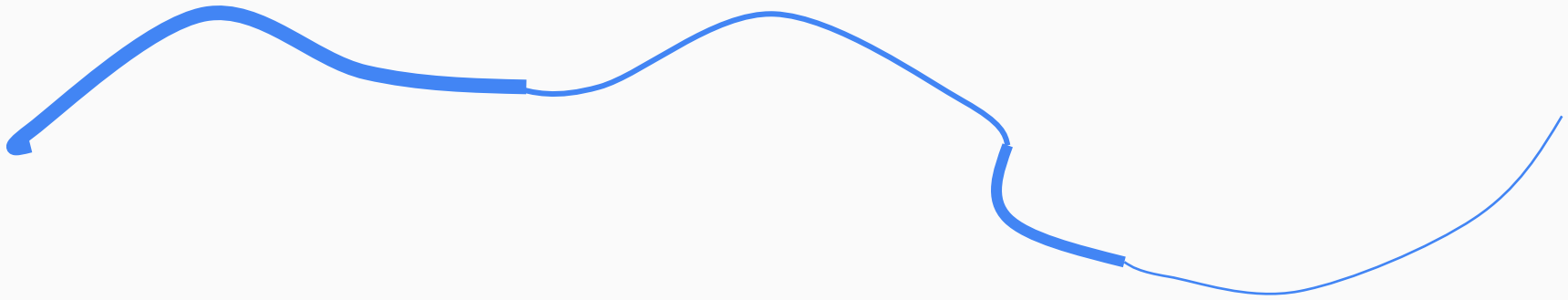
Non-maximum suppression

Another problem: pixels along this edge didn't survive the thresholding

Source: S. Lazebnik

Hysteresis thresholding

- Use a high threshold to start edge curves, and a low threshold to continue them.



Source: Steve Seitz

Hysteresis thresholding

original image

high threshold
(strong edges)

low threshold
(weak edges)

hysteresis threshold

Source: L. Fei-Fei

Recap: Canny edge detector

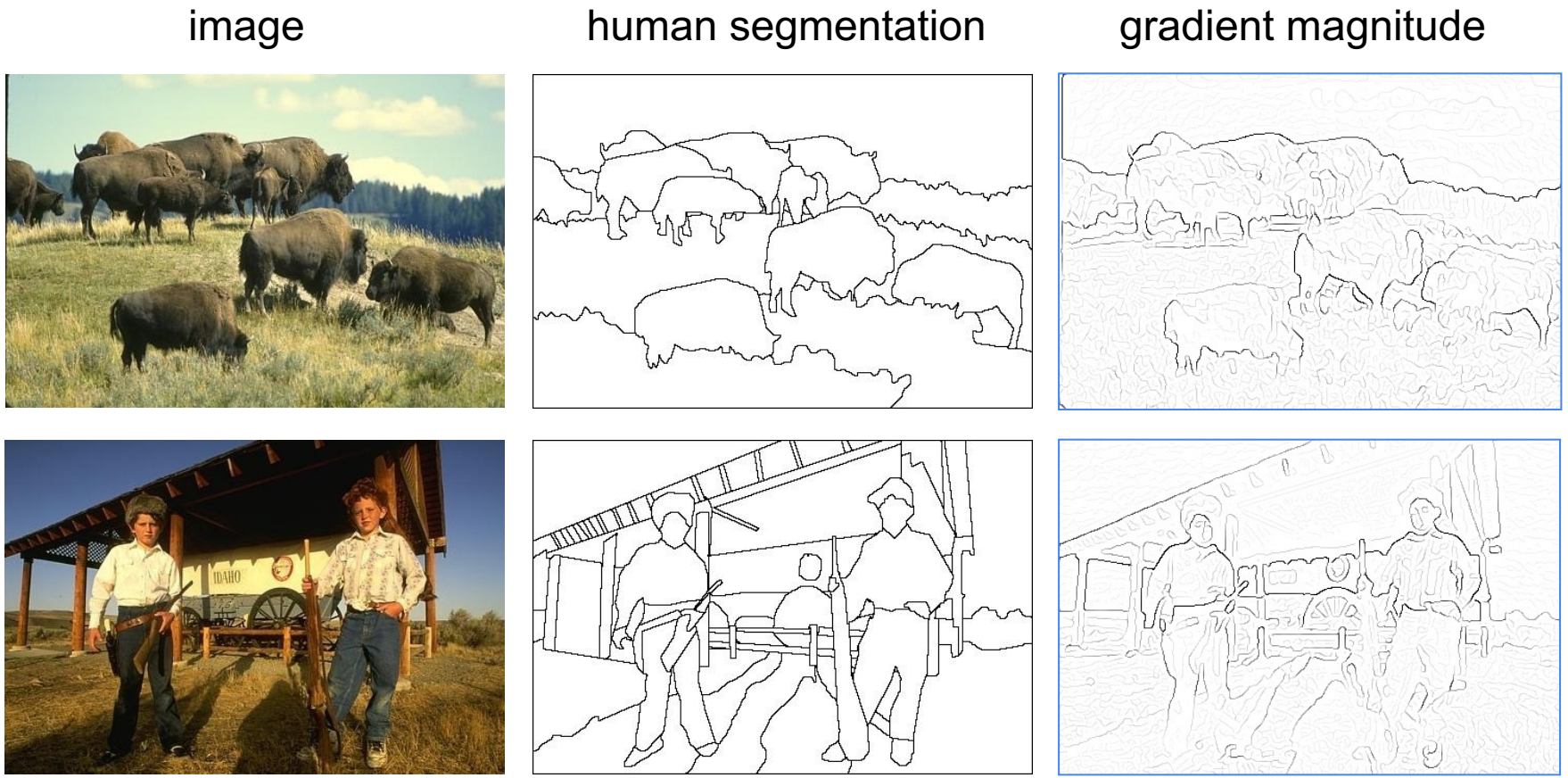
1. Compute x and y gradient images
2. Find magnitude and orientation of gradient
3. Non-maximum suppression:
   - Thin wide “ridges” down to single pixel width
4. Linking and thresholding (hysteresis):
   - Define two thresholds: low and high
   - Use the high threshold to start edge curves and the low threshold to continue them

MATLAB: `edge(image, 'canny');`

J. Canny, ***A Computational Approach To Edge Detection***, IEEE Trans. Pattern Analysis and Machine Intelligence, 8:679-714, 1986.

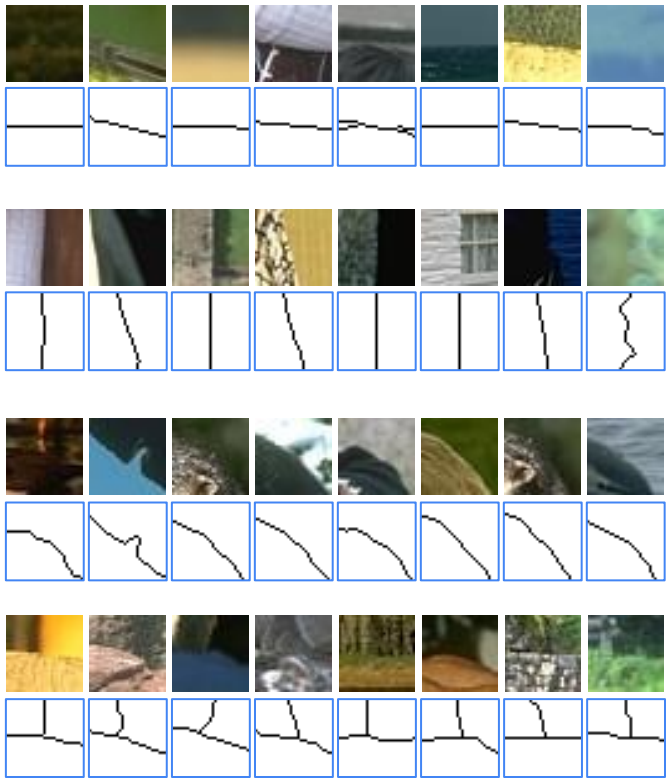
Image gradients vs. meaningful contours

- Berkeley segmentation database:
  http://www.eecs.berkeley.edu/Research/Projects/CS/vision/grouping/segbench/



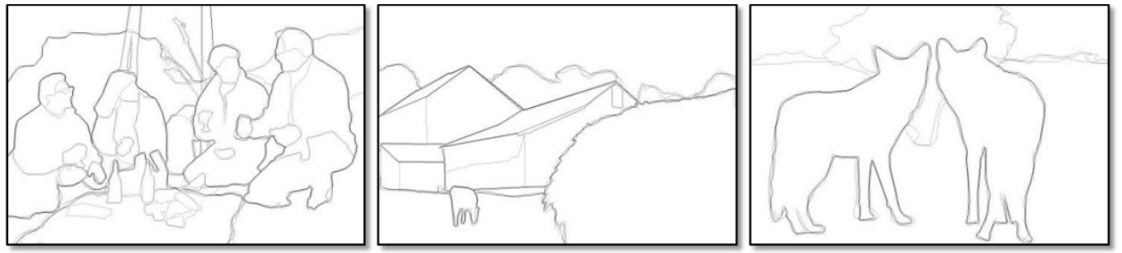
Data-driven edge detection

Training data



Input images

Ground truth



Output

P. Dollar and L. Zitnick, Structured forests for fast edge detection, ICCV 2013

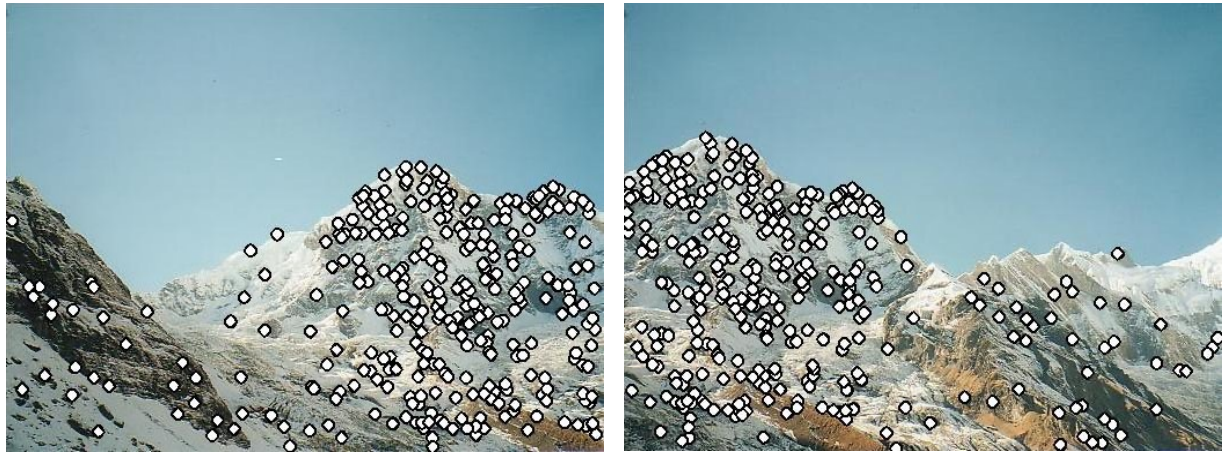
Keypoints

Keypoint extraction: Corners

Source: S. Lazebnik

Reminder: Panorama stitching

- Motivation: panorama stitching
  - We have two images – how do we combine them?



Step 1: extract keypoints

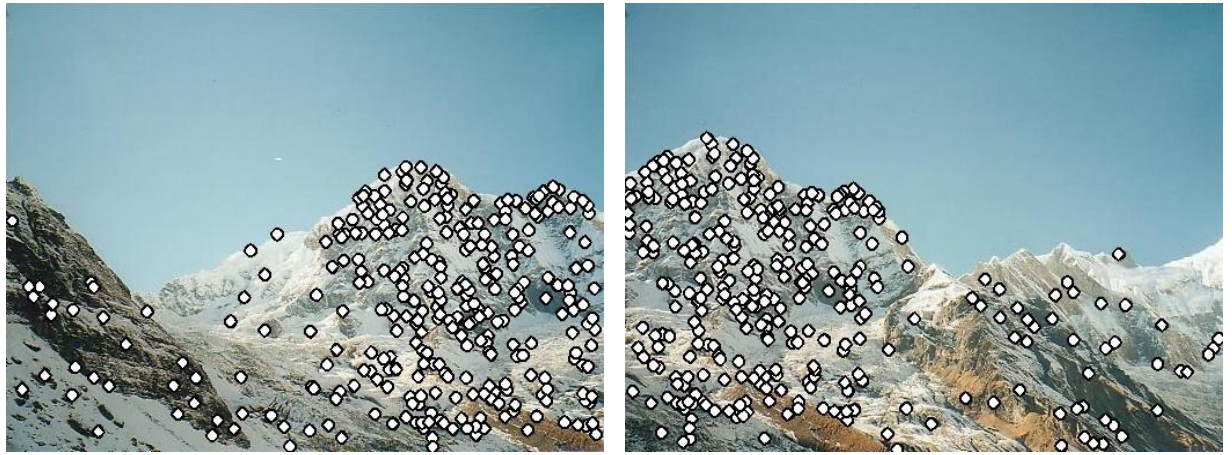
Step 2: match keypoint features

Step 3: align images

Source: S. Lazebnik

Characteristics of good keypoints

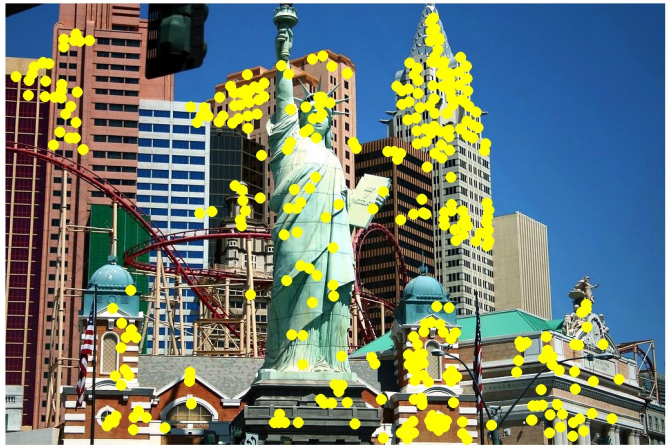
- Repeatability
  - The same keypoint can be found in several images despite geometric and photometric transformations
- Saliency
  - Each keypoint is distinctive
- Compactness and efficiency
  - Many fewer keypoints than image pixels
- Locality
  - A keypoint occupies a relatively small area of the image; robust to clutter and occlusion



Source: S. Lazebnik

Applications

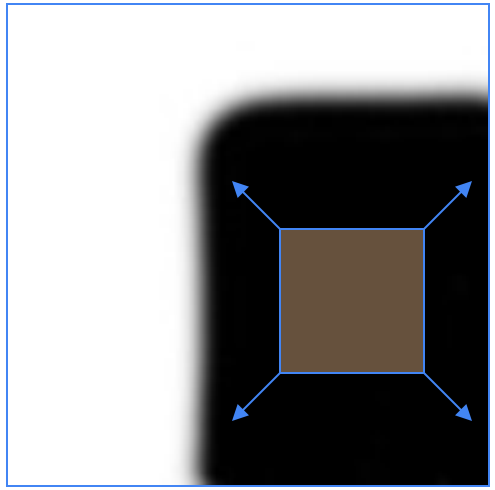
- Keypoints are used for:
  - Image alignment
  - 3D reconstruction
  - Motion tracking
  - Robot navigation
  - Indexing and database retrieval
  - Object recognition



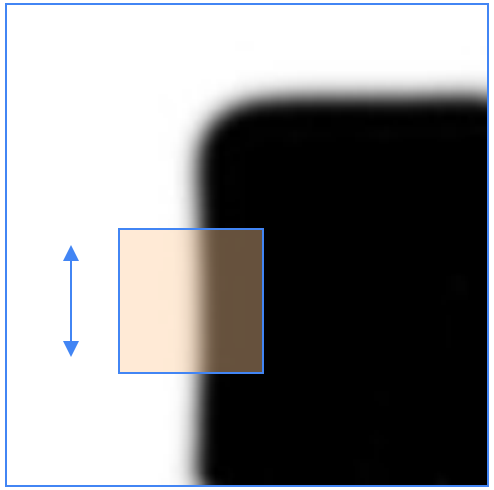
Source: S. Lazebnik

Corner Detection: Basic Idea

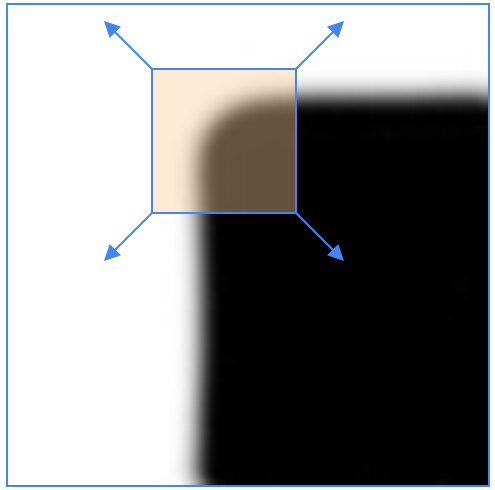
- We should easily recognize the point by looking through a small window
- Shifting a window in any direction should give a large change in intensity



"flat" region:
no change in
all directions



"edge":
no change
along the edge
direction



"corner":
significant
change in all
directions

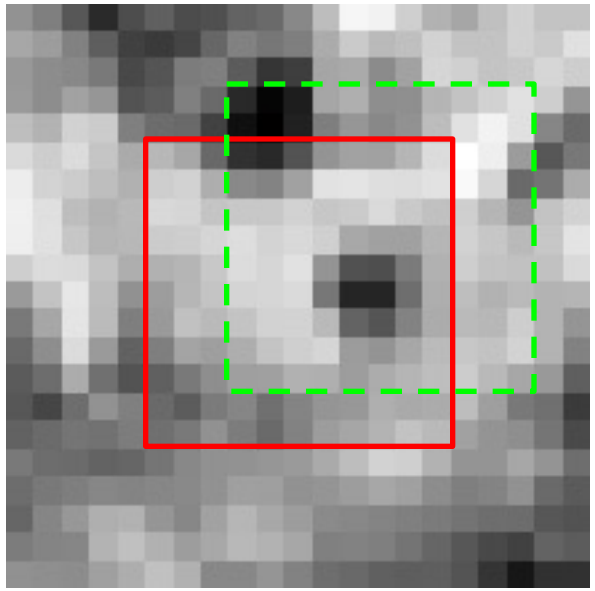
Source: S. Lazebnik

Corner Detection: Mathematics

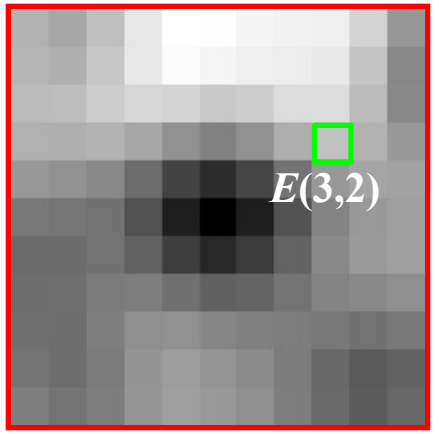
Change in appearance of window W for the shift [u,v]:

$$E(u,v) = \sum_{(x,y)\in W} [I(x+u, y+v) - I(x,y)]^2$$

$I(x, y)$



$E(u, v)$



Source: S. Lazebnik

Corner Detection: Mathematics

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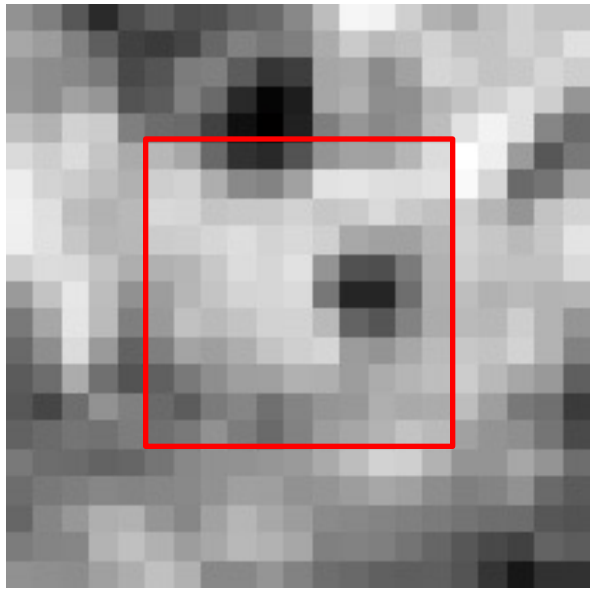
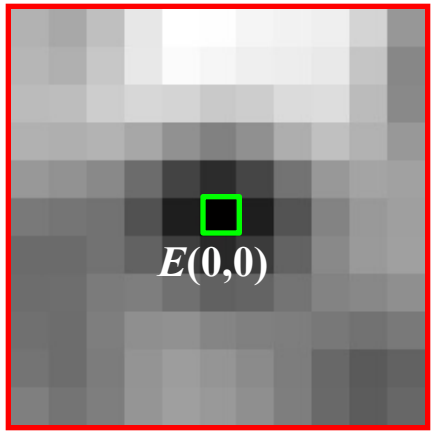


$E(u, v)$



Source: S. Lazebnik

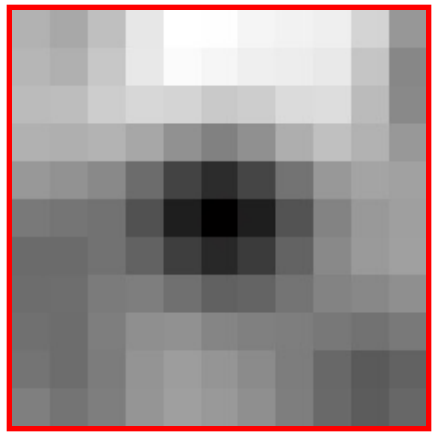
Corner Detection: Mathematics

Change in appearance of window W for the shift [u,v]:

$$E(u,v) = \sum_{(x,y)\in W} [I(x+u, y+v) - I(x,y)]^2$$

We want to find out how this function behaves for small shifts

$E(u, v)$



Source: S. Lazebnik

Corner Detection: Mathematics

- First-order Taylor approximation for small motions [u, v]:

$$I(x+u, y+v) \approx I(x,y) + I_x u + I_y v$$

- Let's plug this into E(u,v):

$$\begin{aligned} E(u,v) &= \sum_{(x,y)\in W} [I(x+u,y+v) - I(x,y)]^2 \\ &\approx \sum_{(x,y)\in W} [I(x,y) + I_x u + I_y v - I(x,y)]^2 \\ &= \sum_{(x,y)\in W} [I_x u + I_y v]^2 = \sum_{(x,y)\in W} I_x^2 u^2 + 2 I_x I_y uv + I_y^2 v^2 \end{aligned}$$

Source: S. Lazebnik

Corner Detection: Mathematics

The quadratic approximation can be written as

$$\sum_{(x,y)\in W} I_x^2 u^2 + 2 I_x I_y uv + I_y^2 v^2$$

$$E(u,v) \approx \begin{bmatrix} u & v \end{bmatrix} M \begin{bmatrix} u \\ v \end{bmatrix}$$

where M is a **second moment matrix** computed from image derivatives:

$$M = \begin{bmatrix} \sum_{x,y} I_x^2 & \sum_{x,y} I_x I_y \\ \sum_{x,y} I_x I_y & \sum_{x,y} I_y^2 \end{bmatrix}$$

(the sums are over all the pixels in the window W)

Source: S. Lazebnik

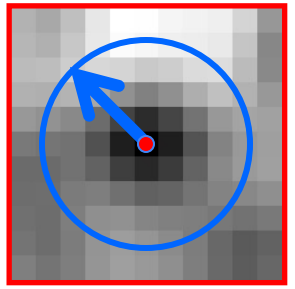
Interpreting the second moment matrix

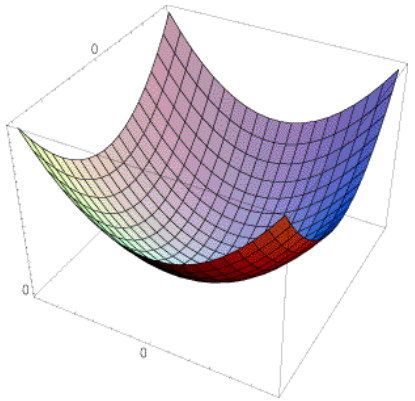
- The surface E(u,v) is locally approximated by a quadratic form. Let's try to understand its shape.
  - Specifically, in which directions does it have the smallest/greatest change?

$$E(u,v) \approx [u \;\; v] \; M \begin{bmatrix} u \\ v \end{bmatrix}$$

$$M = \begin{bmatrix} \sum_{x,y} I_x^2 & \sum_{x,y} I_x I_y \\ \sum_{x,y} I_x I_y & \sum_{x,y} I_y^2 \end{bmatrix}$$

$E(u, v)$



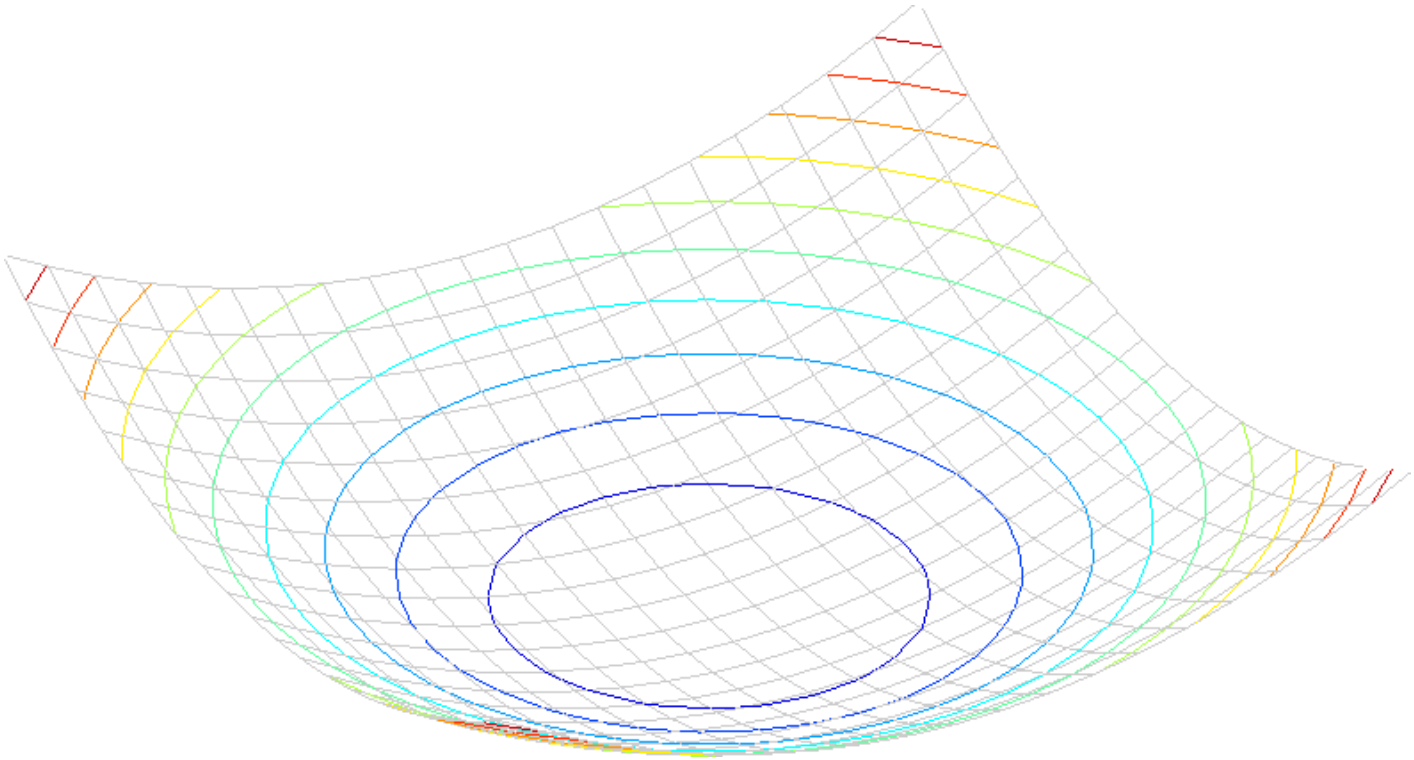


Interpreting the second moment matrix

Consider a horizontal “slice” of E(u, v):

This is the equation of an ellipse.

$$[u \;\; v] \; M \begin{bmatrix} u \\ v \end{bmatrix} = \text{const}$$



Source: S. Lazebnik

Interpreting the second moment matrix

Consider a horizontal "slice" of E(u, v):

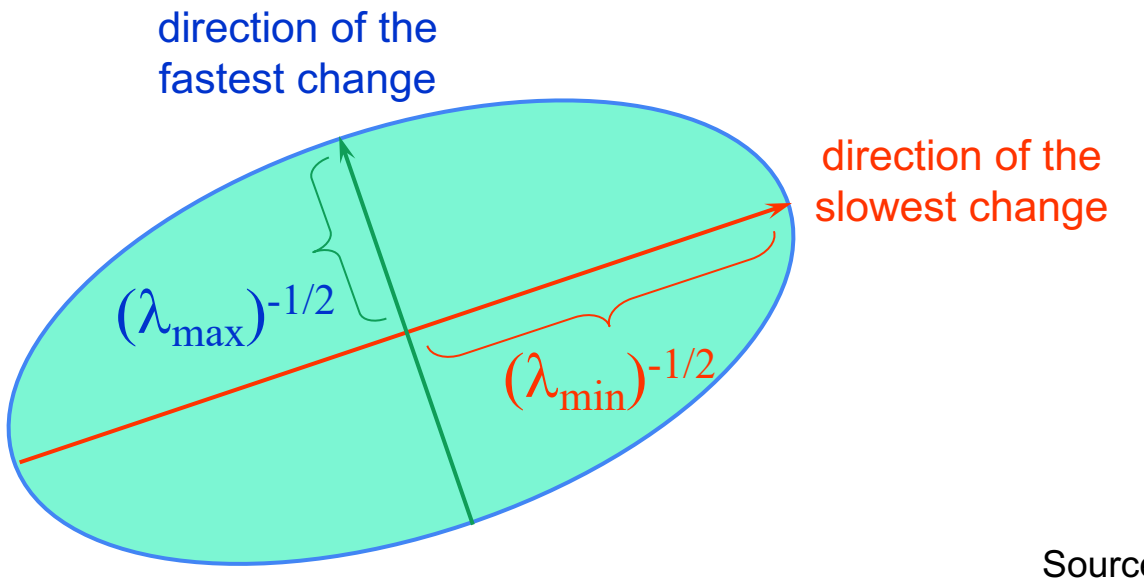
$$\begin{bmatrix} u & v \end{bmatrix} M \begin{bmatrix} u \\ v \end{bmatrix} = \text{const}$$

This is the equation of an ellipse.

Diagonalization of M:

$$M = R^{-1} \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} R$$

The axis lengths of the ellipse are determined by the eigenvalues and the orientation is determined by R



Source: S. Lazebnik

Interpreting the second moment matrix

Consider the axis-aligned case (gradients are either horizontal or vertical)

$$M = \begin{bmatrix} \sum_{x,y} I_x^2 & \sum_{x,y} I_x I_y \\ \sum_{x,y} I_x I_y & \sum_{x,y} I_y^2 \end{bmatrix} = \begin{bmatrix} a & 0 \\ 0 & b \end{bmatrix}$$

If either a or b is close to 0, then this is not a corner, so look for locations where both are large.

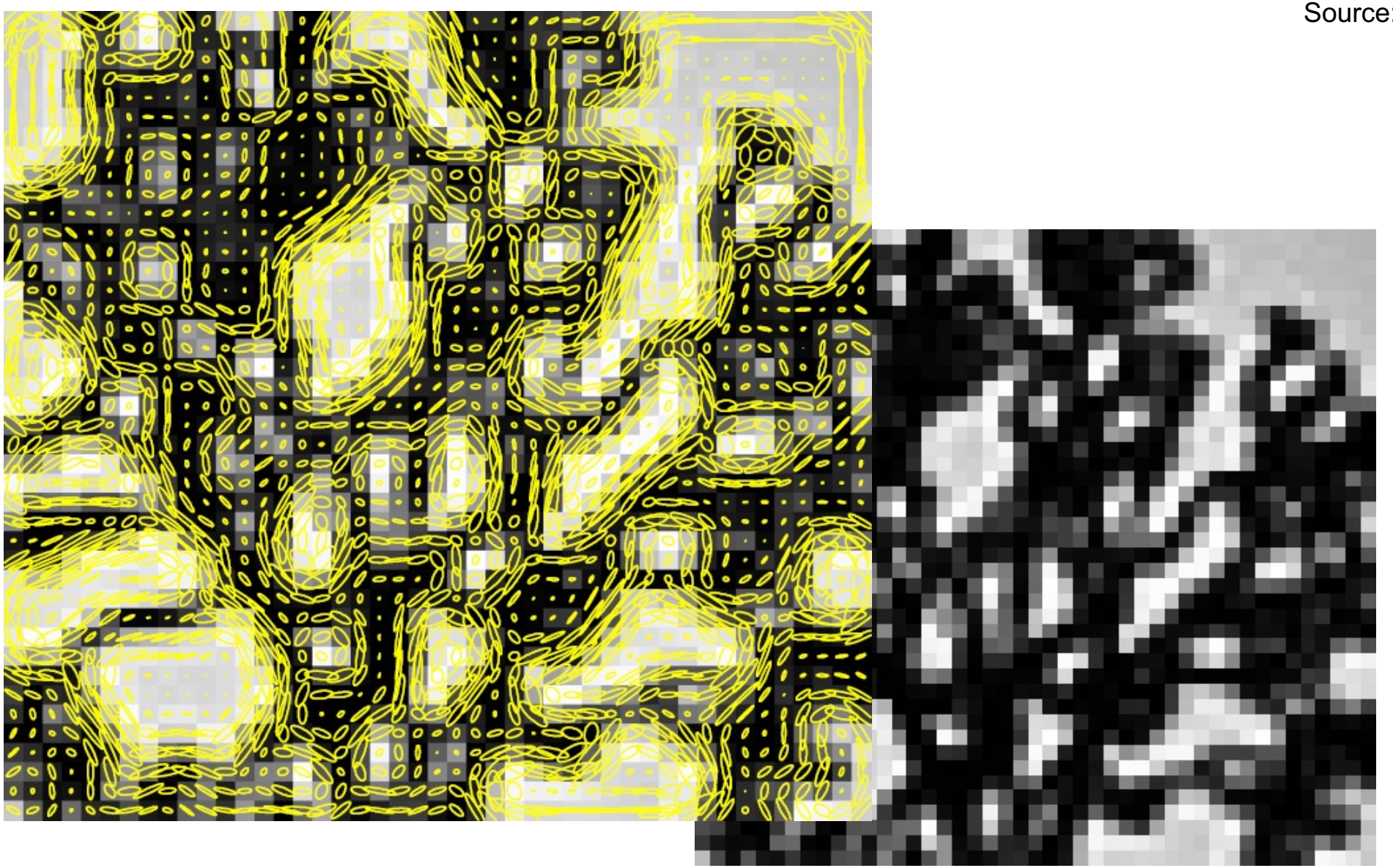
Source: S. Lazebnik

Visualization of second moment matrices

Source: S. Lazebnik

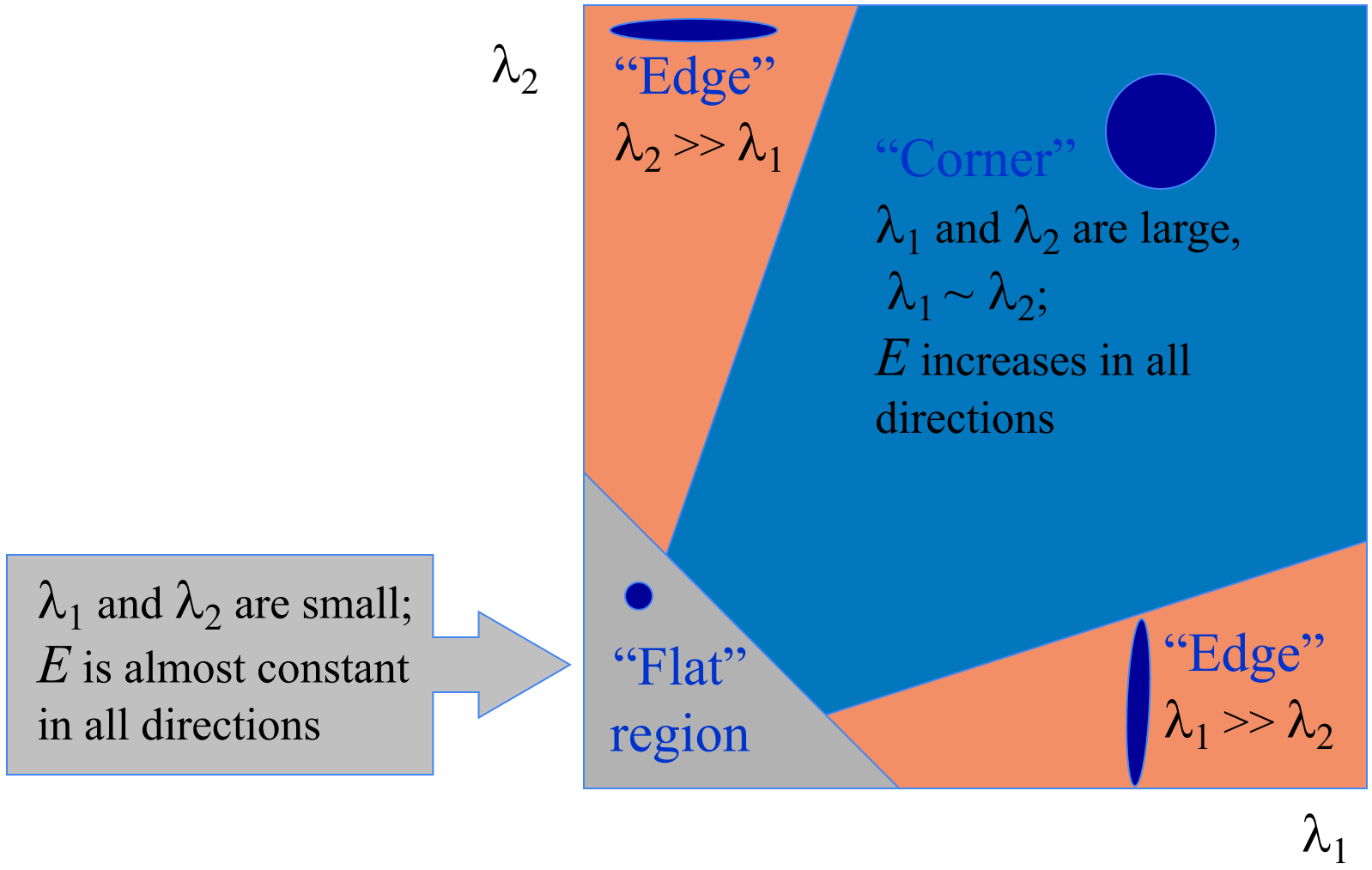
Visualization of second moment matrices

Source: S. Lazebnik



Interpreting the eigenvalues

Classification of image points using eigenvalues of M:

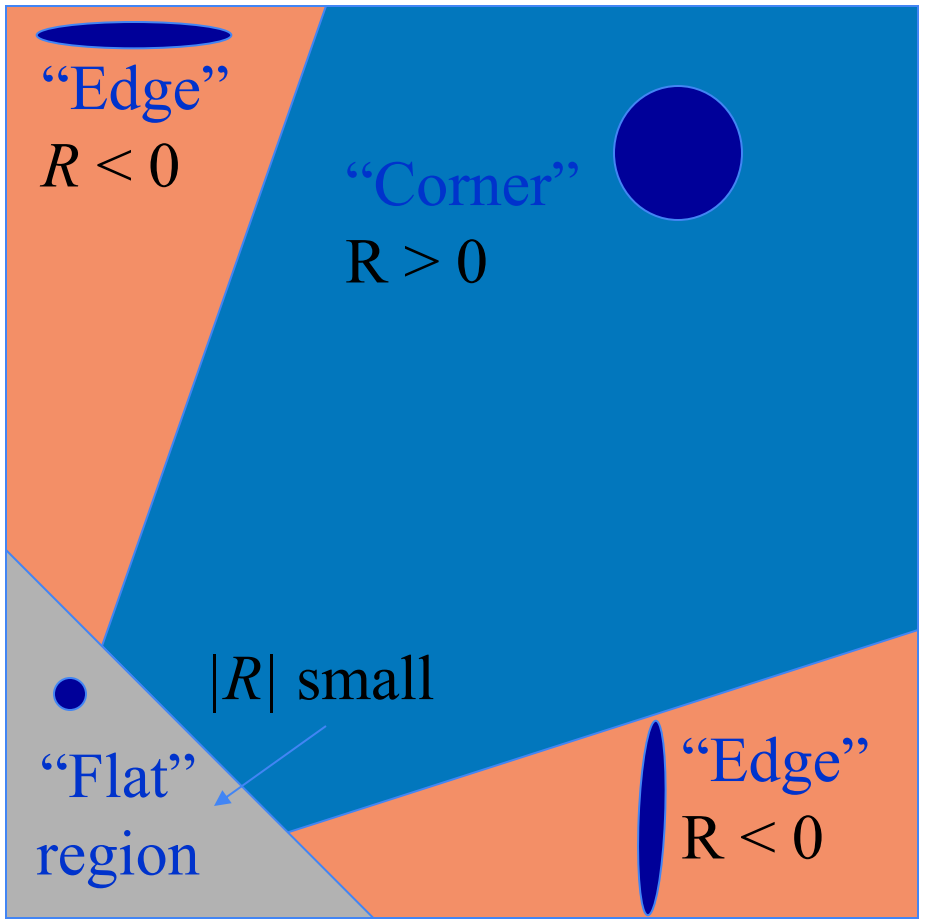


Source: S. Lazebnik

Corner response function

$$R = \det(M) - \alpha \operatorname{trace}(M)^2 = \lambda_1 \lambda_2 - \alpha(\lambda_1 + \lambda_2)^2$$

α: constant (0.04 to 0.06)



Source: S. Lazebnik

Keypoints – Harris corner detector

The Harris corner detector

- Compute partial derivatives at each pixel
- Compute second moment matrix M in a Gaussian window around each pixel:

$$M = \begin{bmatrix} \sum_{x,y} w(x,y) I_x^2 & \sum_{x,y} w(x,y) I_x I_y \\ \sum_{x,y} w(x,y) I_x I_y & \sum_{x,y} w(x,y) I_y^2 \end{bmatrix}$$

C.Harris and M.Stephens. "A Combined Corner and Edge Detector."
Proceedings of the 4th Alvey Vision Conference: pages 147—151, 1988.

Source: S. Lazebnik

The Harris corner detector

- Compute partial derivatives at each pixel
- Compute second moment matrix M in a Gaussian window around each pixel
- Compute corner response function R

$$R = \det(M) - \alpha \operatorname{trace}(M)^2 = \lambda_1 \lambda_2 - \alpha(\lambda_1 + \lambda_2)^2$$

C.Harris and M.Stephens. "A Combined Corner and Edge Detector."
Proceedings of the 4th Alvey Vision Conference: pages 147—151, 1988.

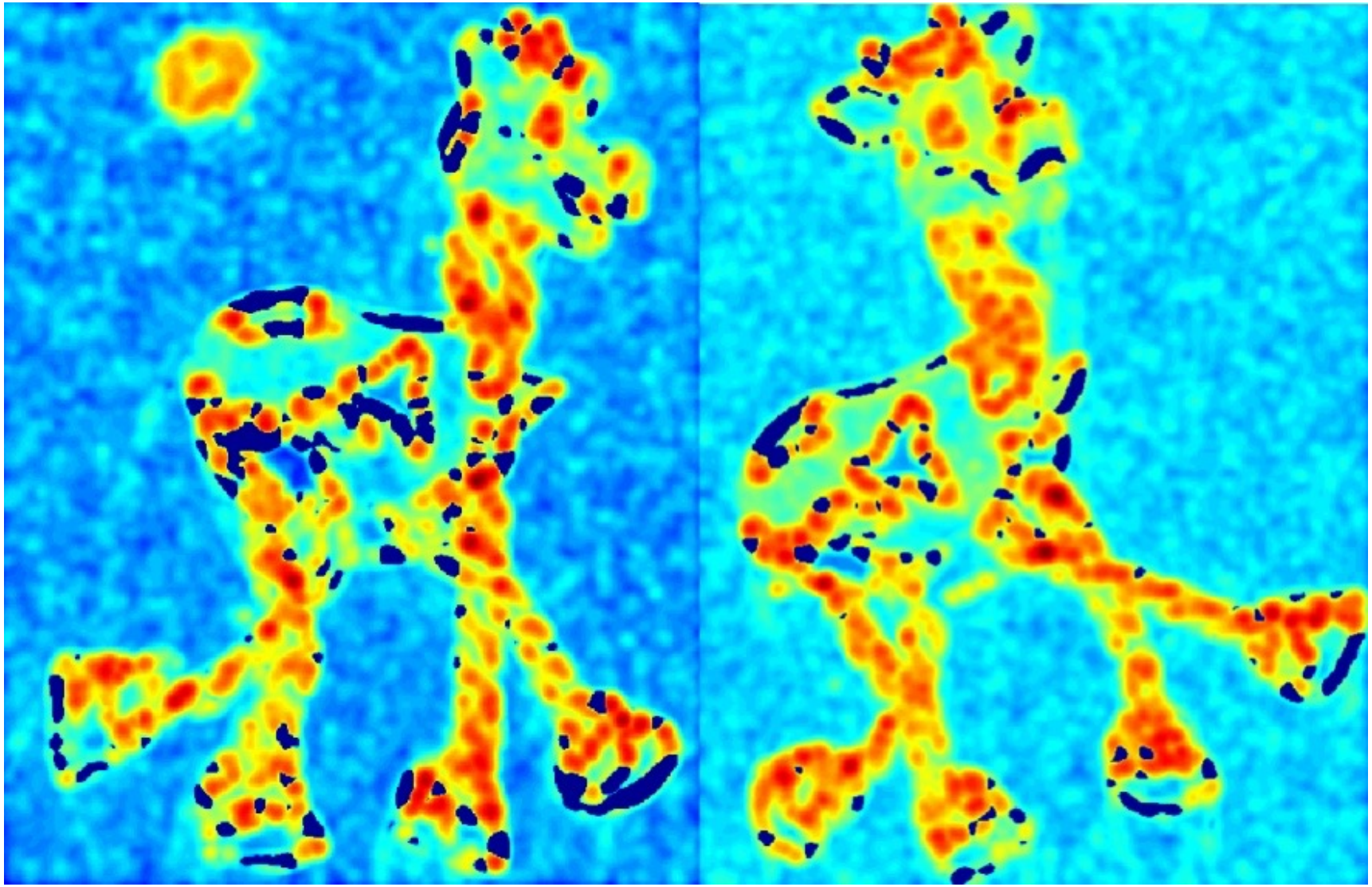
Source: S. Lazebnik

Harris Detector: Steps

Source: S. Lazebnik

Harris Detector: Steps

Compute corner response R



Source: S. Lazebnik

The Harris corner detector

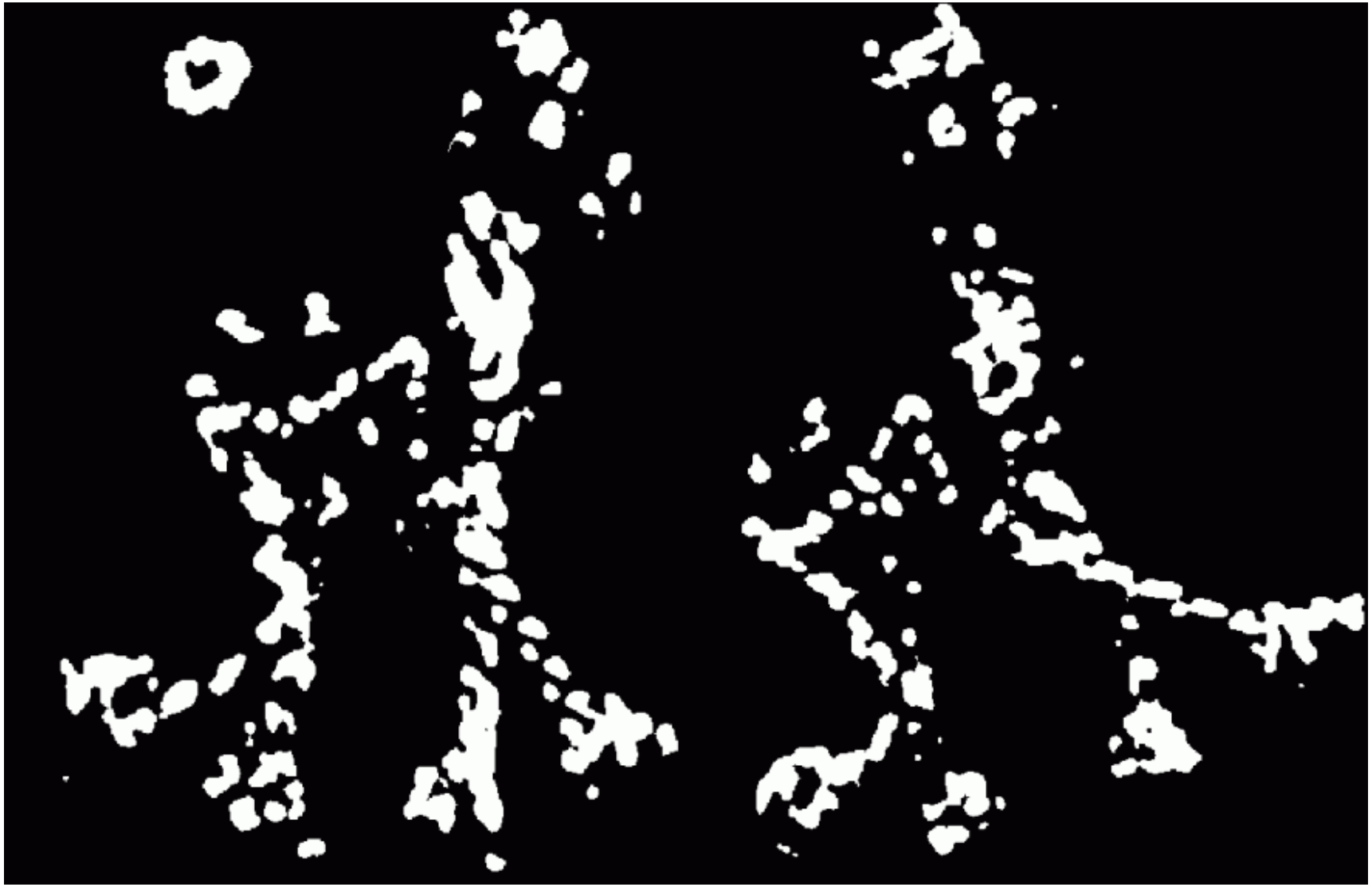
- Compute partial derivatives at each pixel
- Compute second moment matrix M in a Gaussian window around each pixel
- Compute corner response function R
- Threshold R
- Find local maxima of response function (nonmaximum suppression)

C.Harris and M.Stephens. "A Combined Corner and Edge Detector."
Proceedings of the 4th Alvey Vision Conference: pages 147—151, 1988.

Source: S. Lazebnik

Harris Detector: Steps

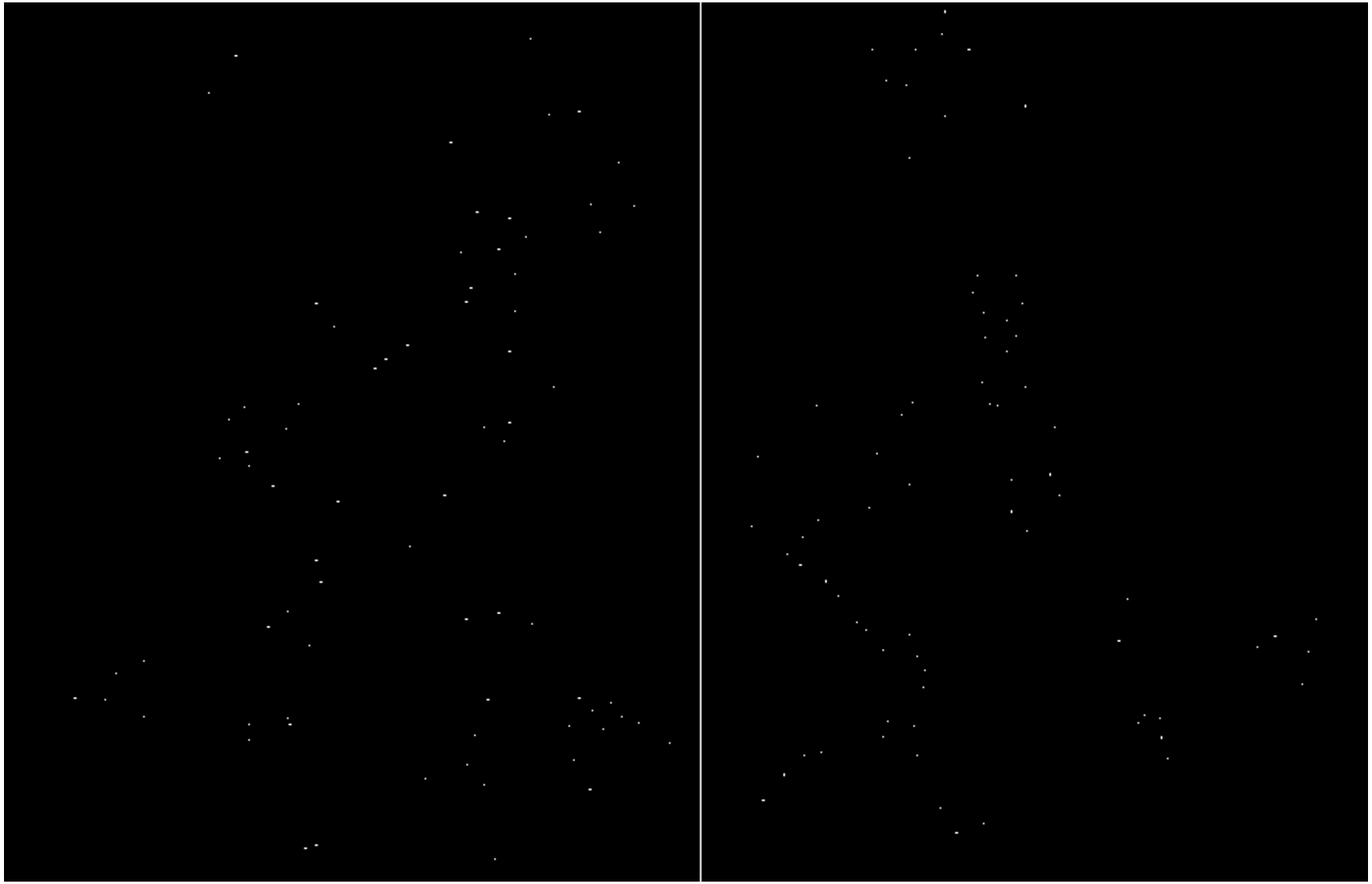
Find points with large corner response: R > threshold



Source: S. Lazebnik

Harris Detector: Steps

Take only the points of local maxima of R



Source: S. Lazebnik

Harris Detector: Steps

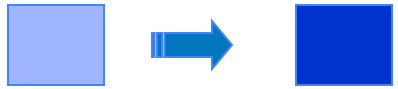
Source: S. Lazebnik

Robustness of corner features

- What happens to corner features when the image undergoes geometric or photometric transformations?

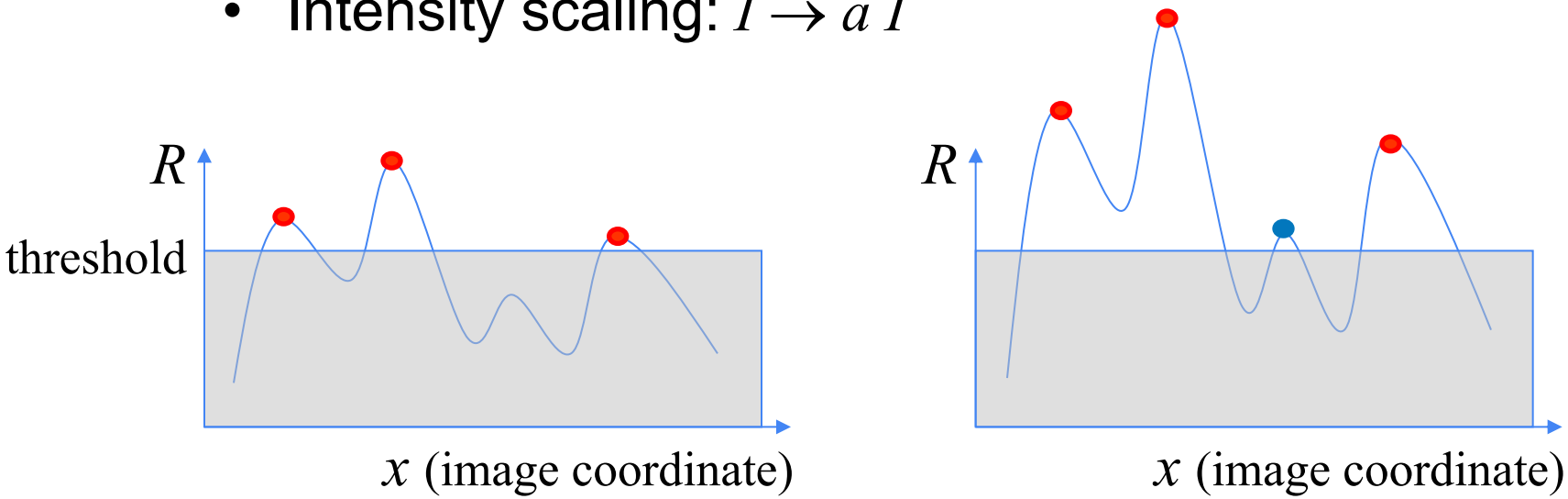
Source: S. Lazebnik

Affine intensity change



$$I \rightarrow a\,I + b$$

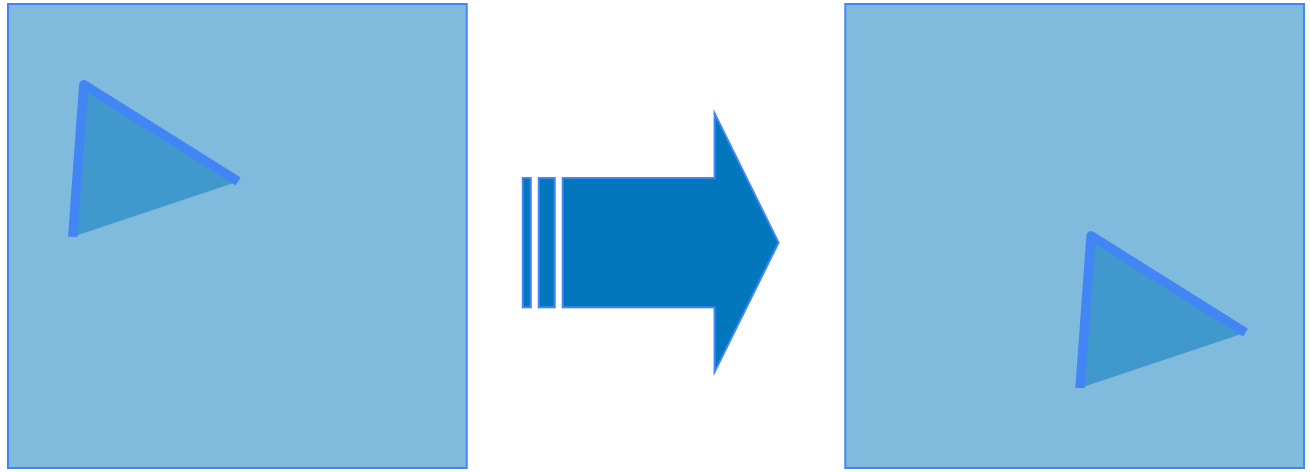
- Only derivatives are used => invariance to intensity shift $I \rightarrow I + b$
- Intensity scaling: $I \rightarrow a\,I$



Partially invariant to affine intensity change

Source: S. Lazebnik

Image translation

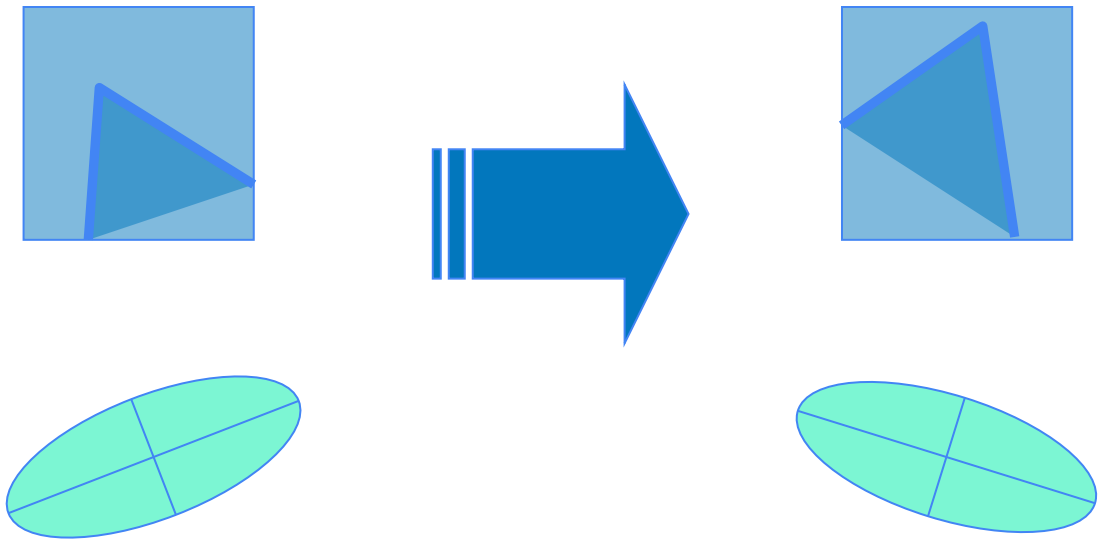


- Derivatives and window function are shift-invariant

Corner location is *covariant* w.r.t. translation

Source: S. Lazebnik

Image rotation

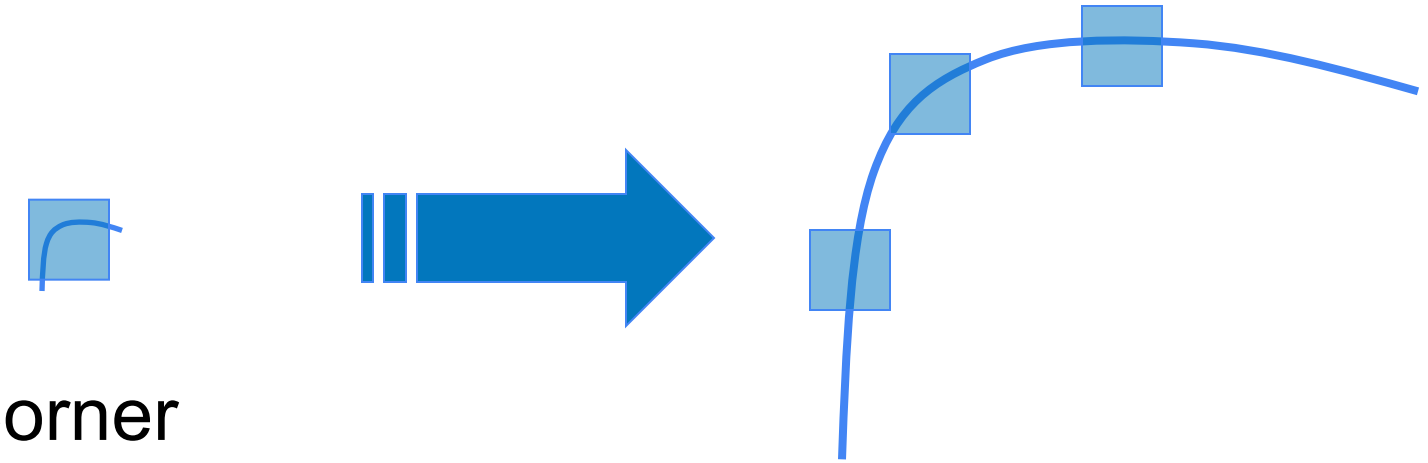


Second moment ellipse rotates but its shape (i.e. eigenvalues) remains the same

Corner location is covariant w.r.t. rotation

Source: S. Lazebnik

Scaling



Corner

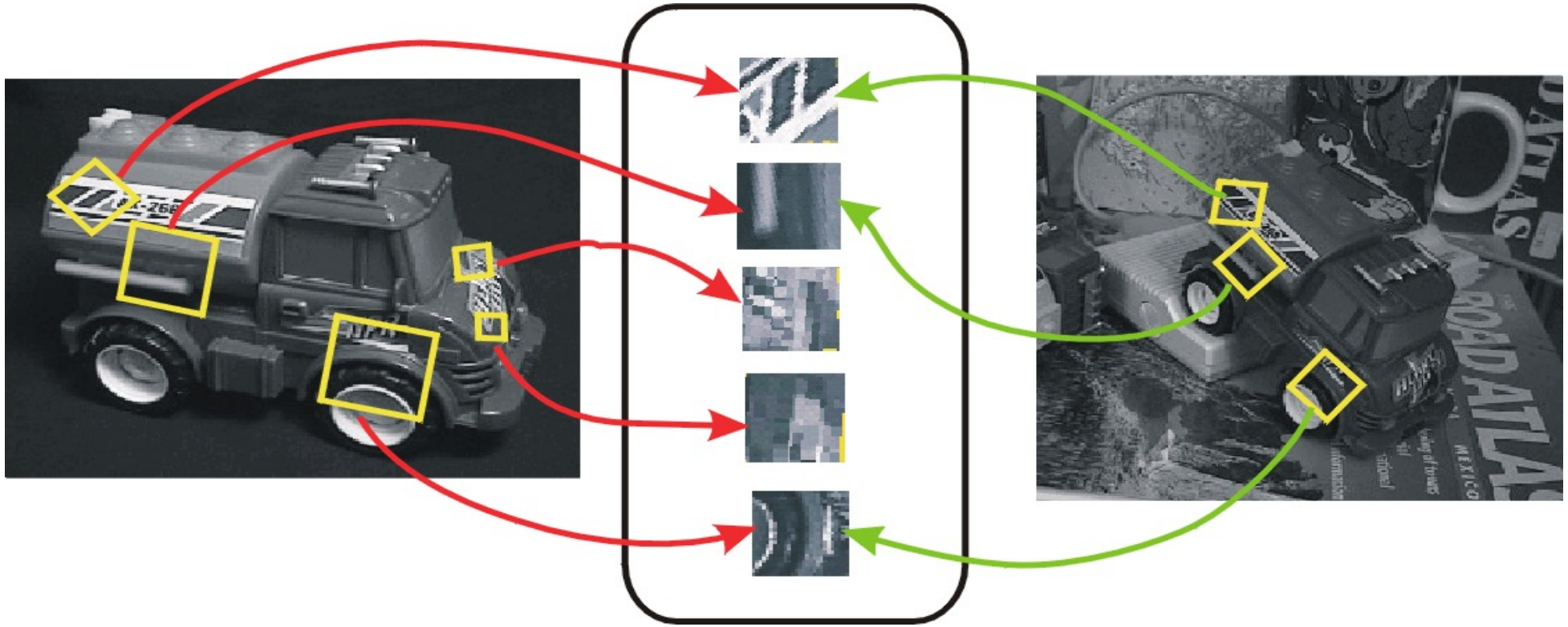
All points will be classified as edges

Corner location is not covariant to scaling!

Source: S. Lazebnik

Sneak peak: from feature detection to feature description

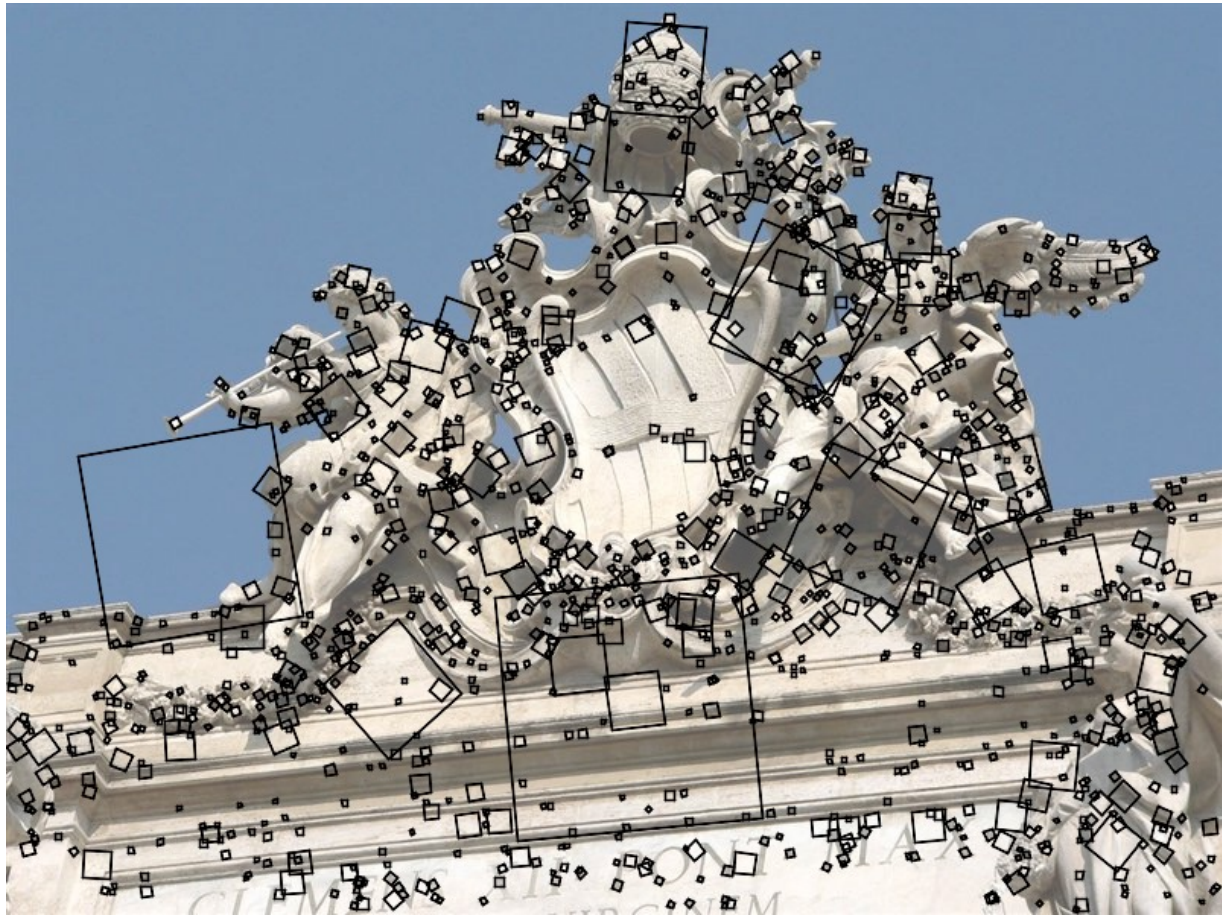
- Detection is covariant:
  - features(transform(image)) = transform(features(image))



Source: S. Lazebnik

Keypoints – Scale Invariant Feature Transform (SIFT)

SIFT keypoint detection

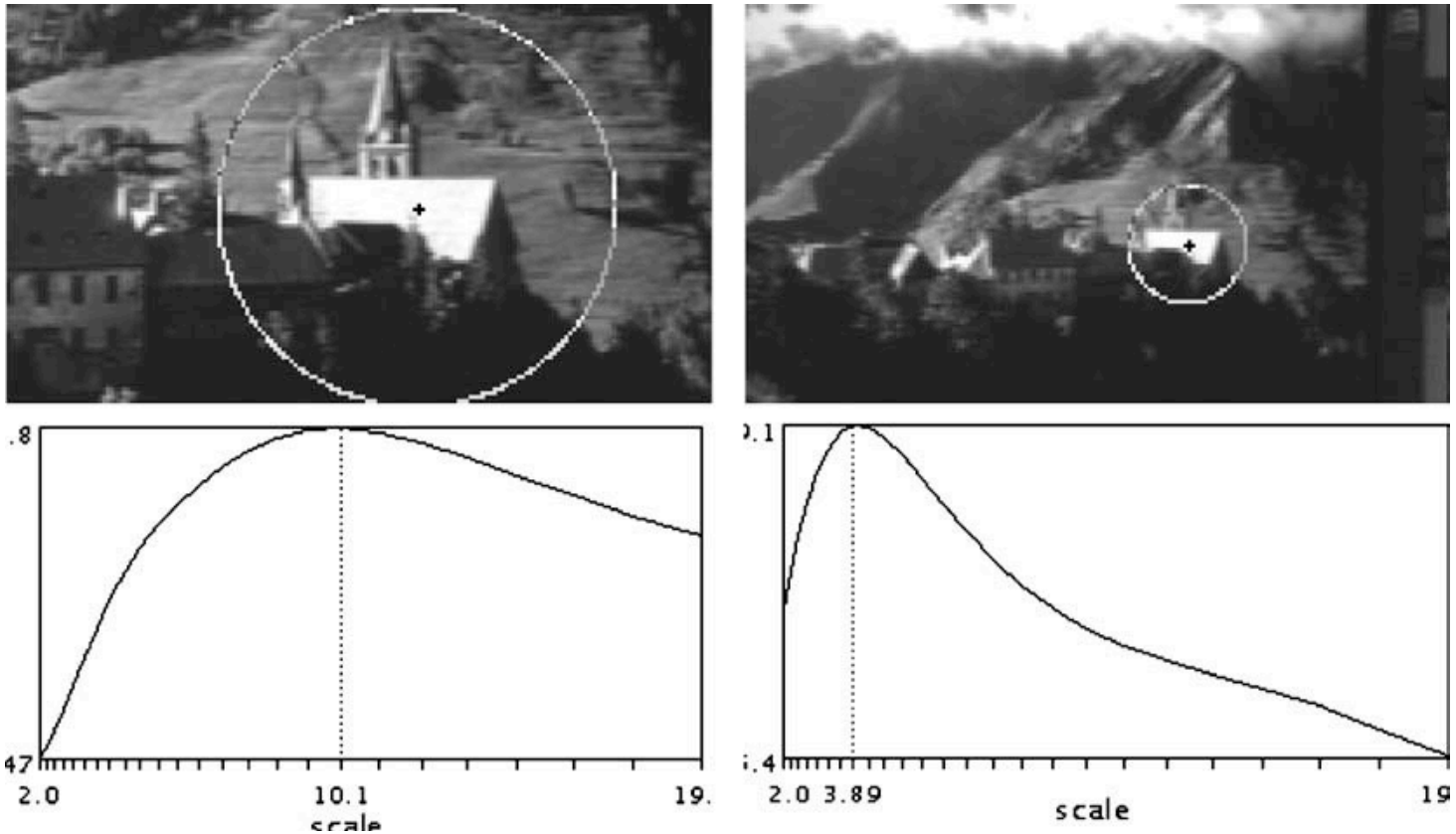


D. Lowe, **Distinctive image features from scale-invariant keypoints**, *IJCV* 60 (2), pp. 91-110, 2004.

Source: S. Lazebnik

Keypoint detection with scale selection

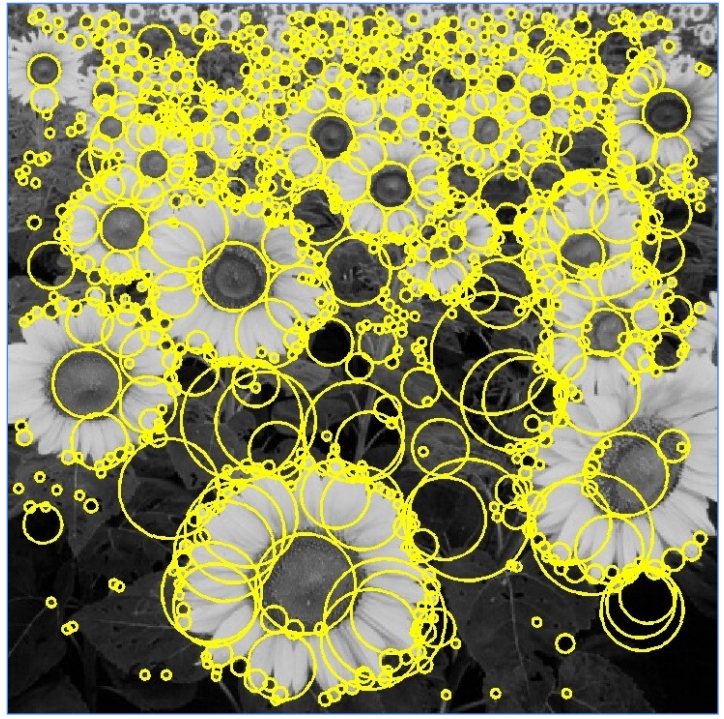
- We want to extract keypoints with characteristic scale that is covariant with the image transformation

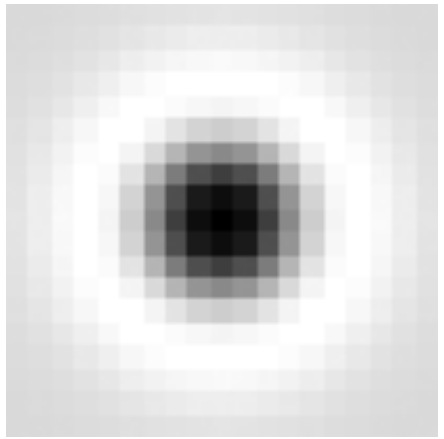


Source: S. Lazebnik

Basic idea

- Convolve the image with a “blob filter” at multiple scales and look for extrema of filter response in the resulting scale space



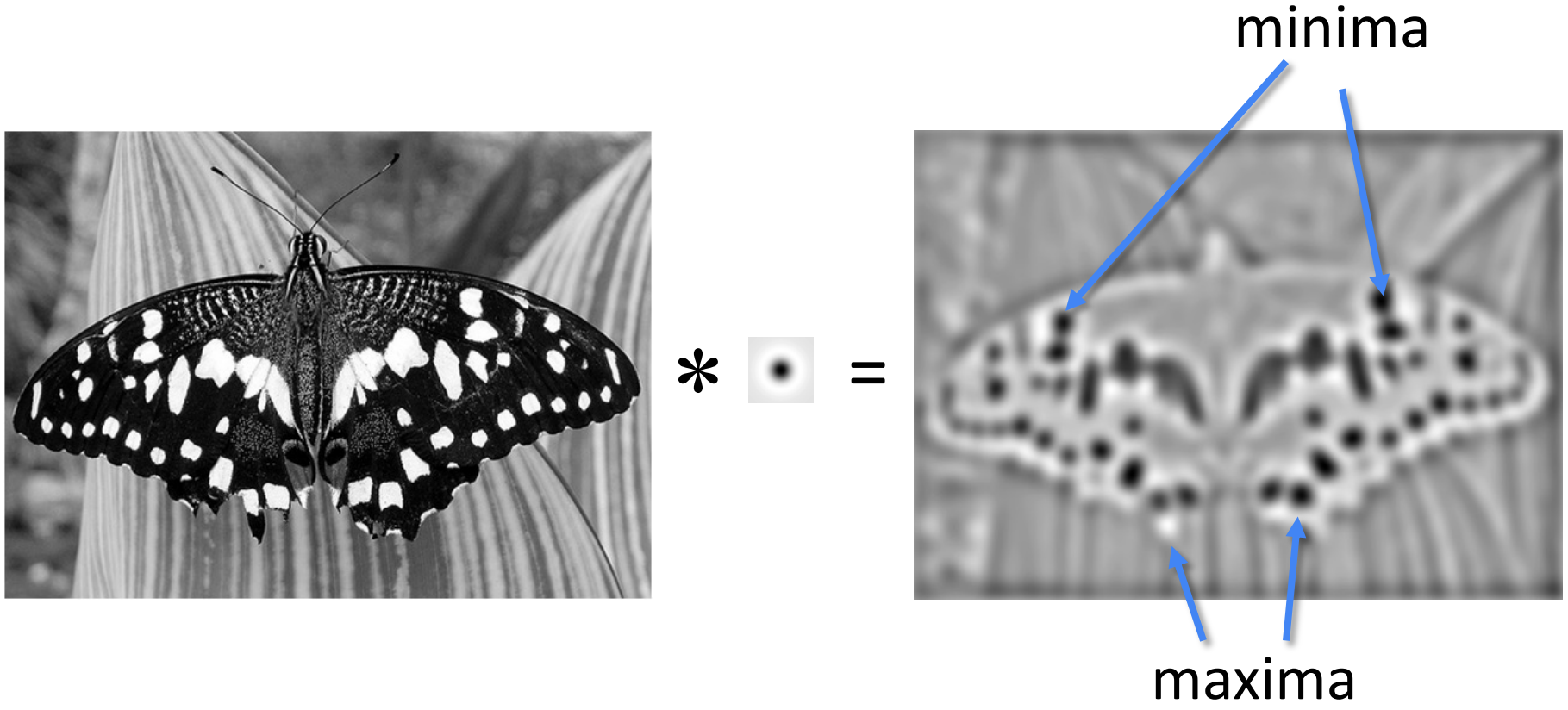


T. Lindeberg. Feature detection with automatic scale selection.
IJCV 30(2), pp 77-116, 1998.

Source: S. Lazebnik

Blob detection

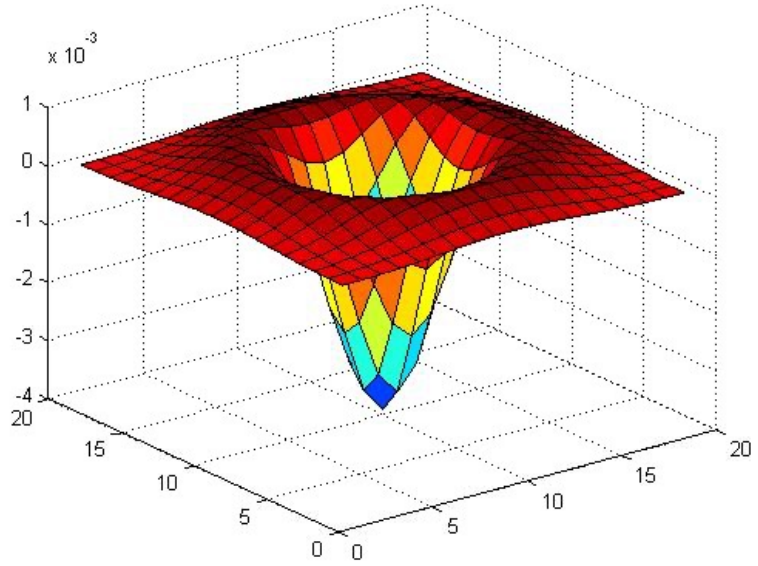
- Find maxima and minima of blob filter response in space and scale

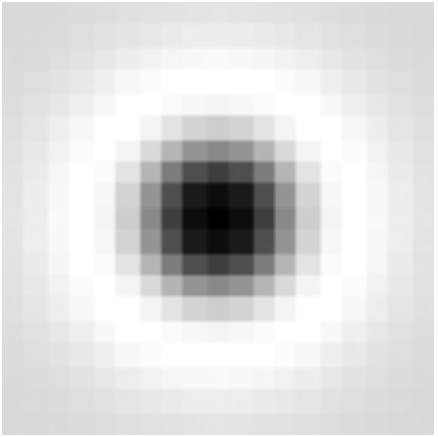


Source: N. Snavely

Blob filter

- Laplacian of Gaussian: Circularly symmetric operator for blob detection in 2D



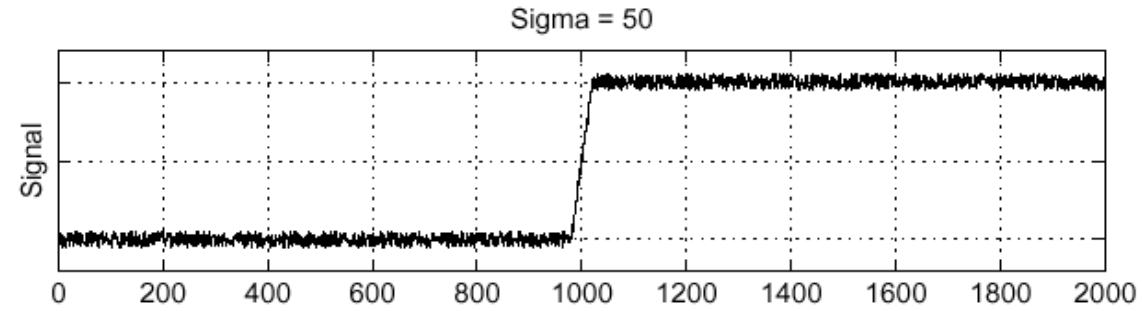


$$\nabla^2 g = \frac{\partial^2 g}{\partial x^2} + \frac{\partial^2 g}{\partial y^2}$$

Source: S. Lazebnik

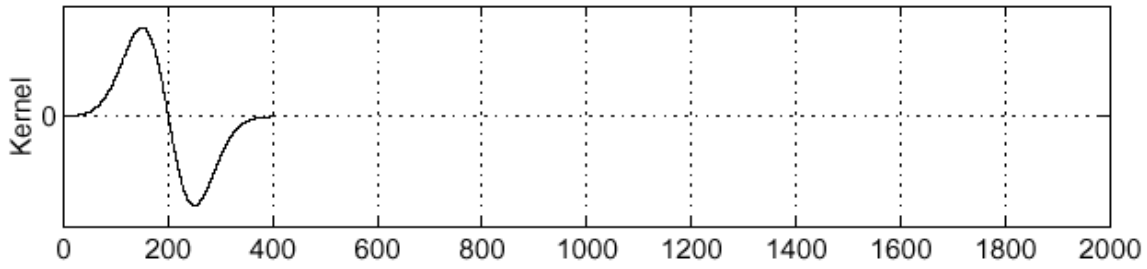
Recall: Edge detection

f



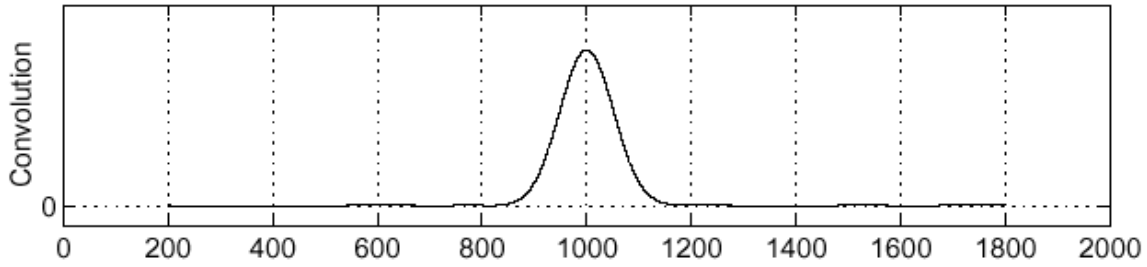
Edge

$\frac{d}{dx} g$



Derivative of Gaussian

$f * \frac{d}{dx} g$

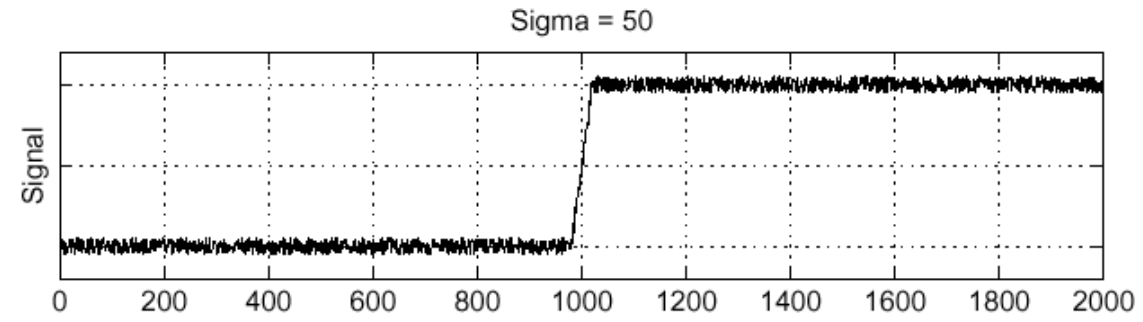


Edge = maximum of derivative

Source: S. Seitz

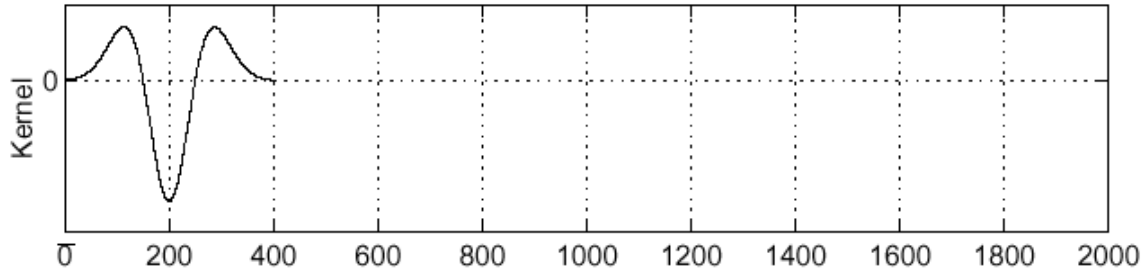
Edge detection, Take 2

f



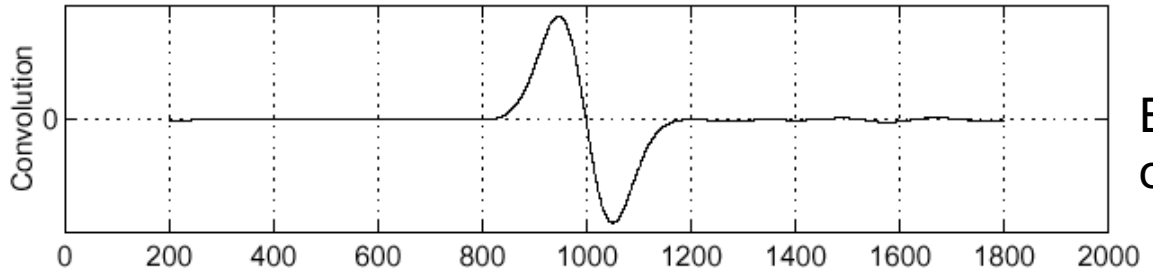
Edge

$\frac{d^2}{dx^2} g$



Second derivative of Gaussian (Laplacian)

$f * \frac{d^2}{dx^2} g$

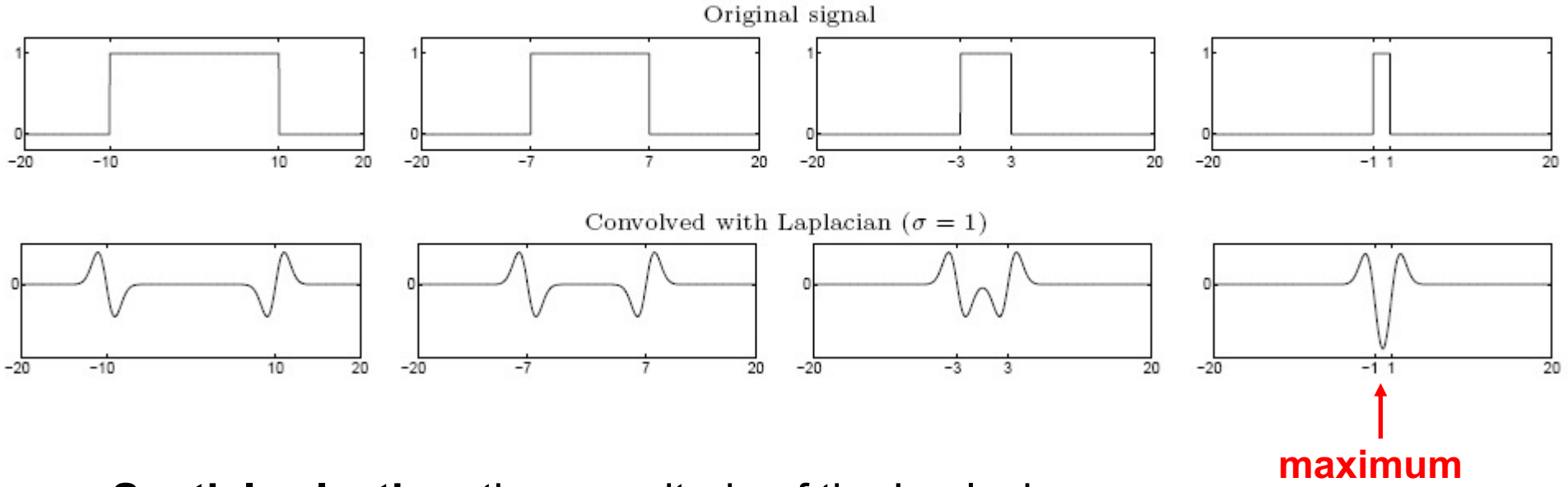


Edge = zero crossing of second derivative

Source: S. Seitz

From edges to blobs

- Edge = ripple
- Blob = superposition of two ripples

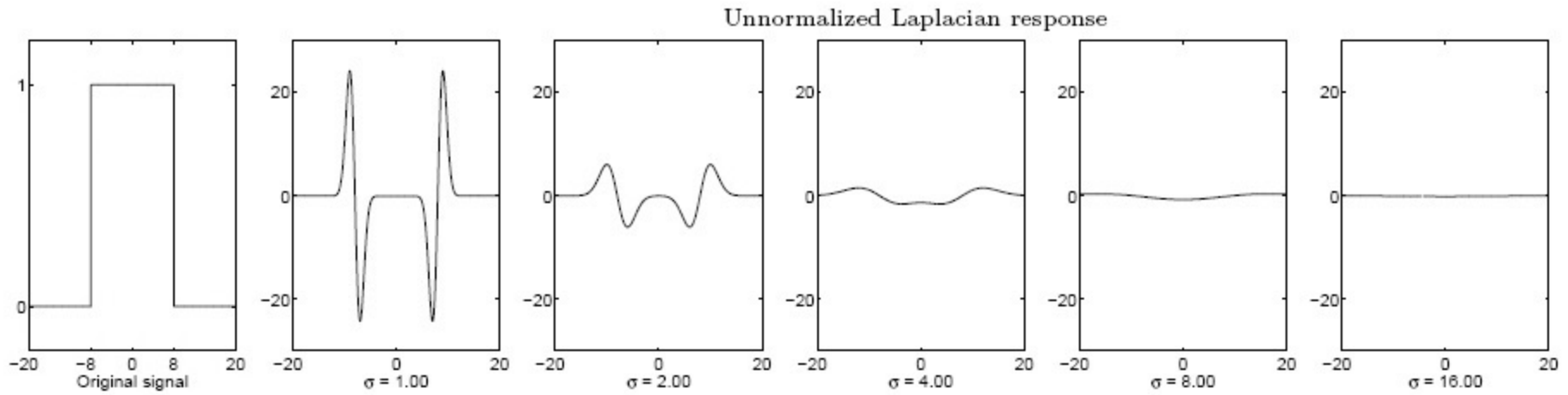


Spatial selection: the magnitude of the Laplacian response will achieve a maximum at the center of the blob, provided the scale of the Laplacian is "matched" to the scale of the blob

Source: S. Lazebnik

Scale selection

- We want to find the characteristic scale of the blob by convolving it with Laplacians at several scales and looking for the maximum response
- However, Laplacian response decays as scale increases:



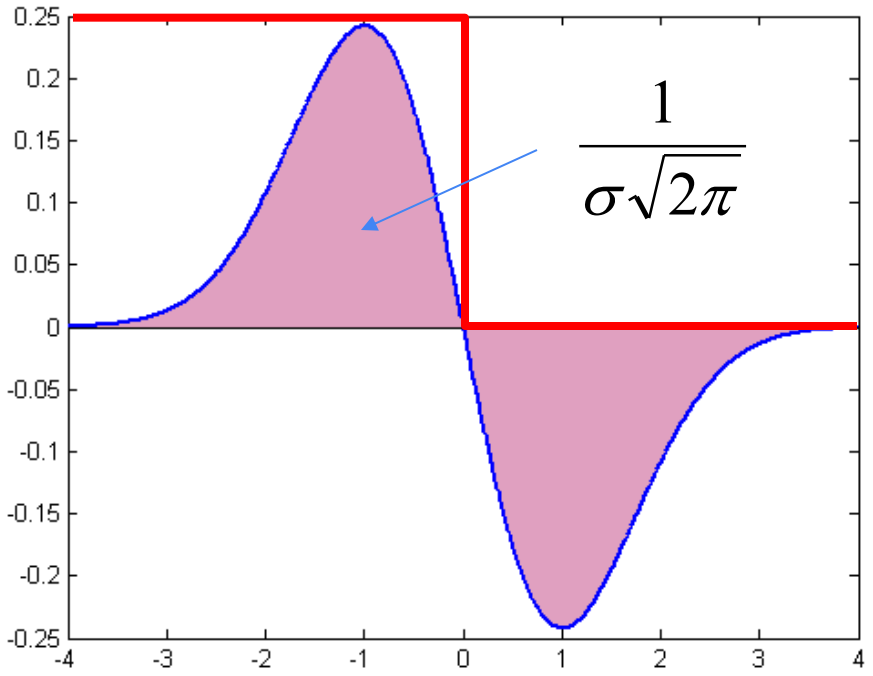
original signal (radius=8)

increasing σ

Source: S. Lazebnik

Scale normalization

- The response of a derivative of Gaussian filter to a perfect step edge decreases as σ increases



Source: S. Lazebnik

Scale normalization

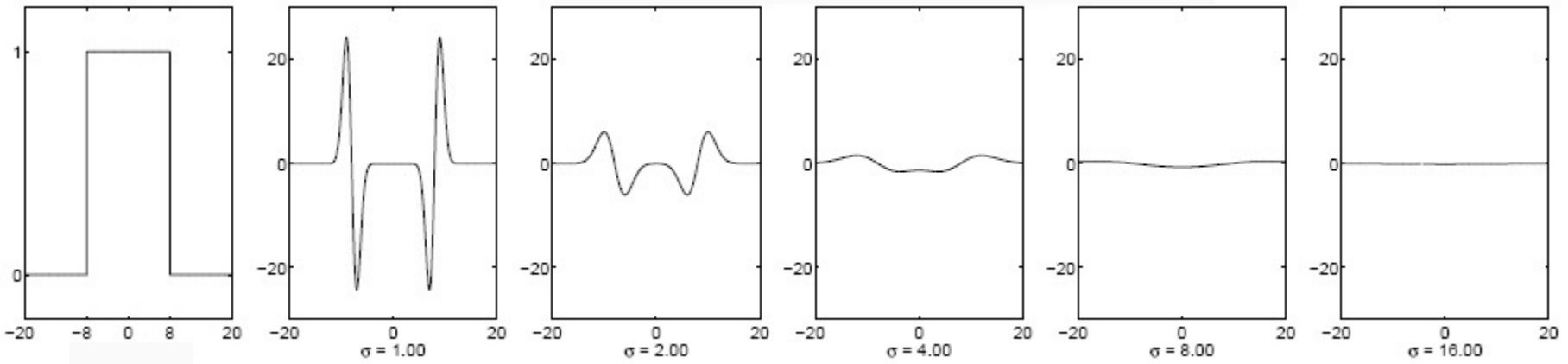
- The response of a derivative of Gaussian filter to a perfect step edge decreases as σ increases
- To keep response the same (scale-invariant), must multiply Gaussian derivative by σ
- Laplacian is the second Gaussian derivative, so it must be multiplied by σ^2

Source: S. Lazebnik

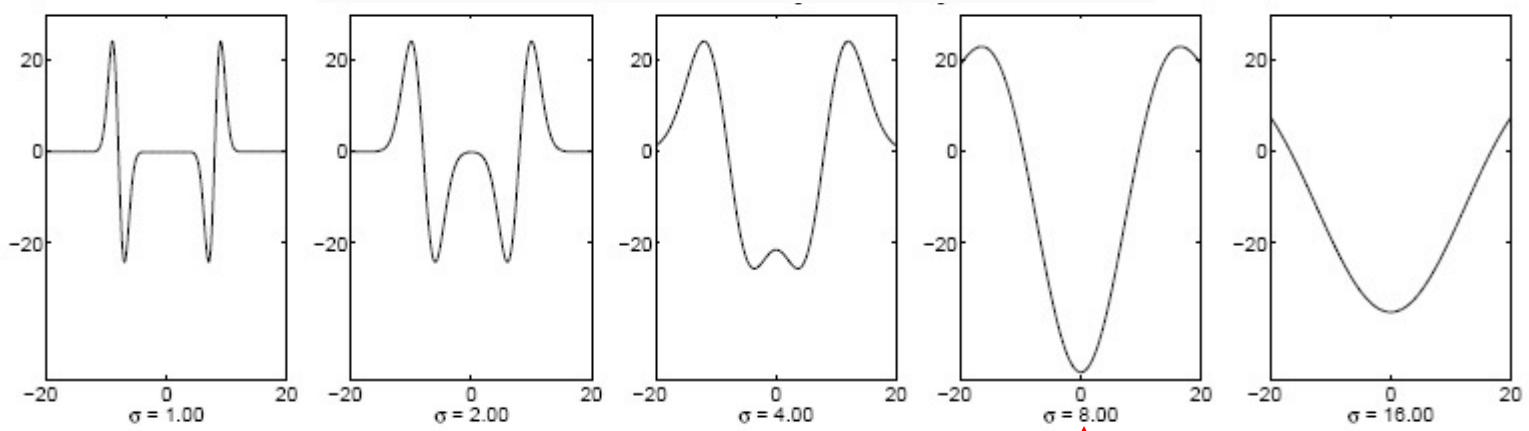
Effect of scale normalization

Original signal

Unnormalized Laplacian response



Scale-normalized Laplacian response



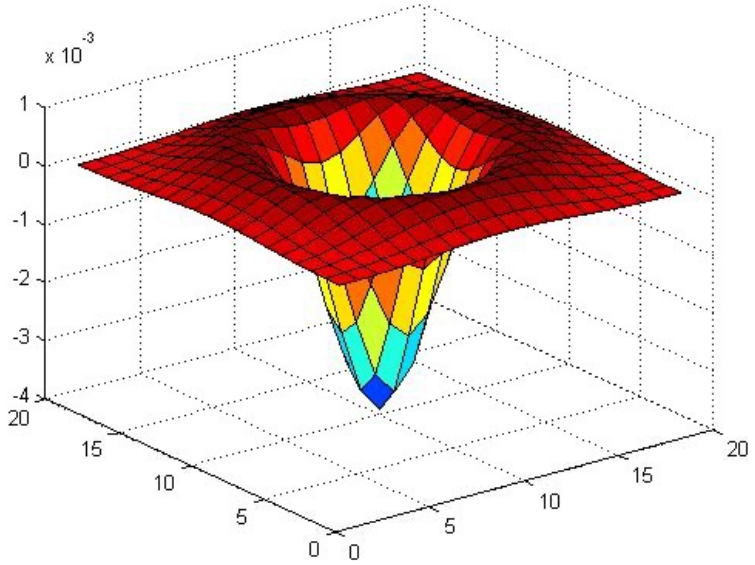
maximum

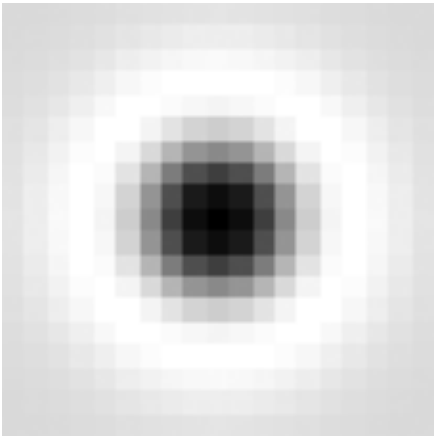
Source: S. Lazebnik

Blob detection in 2D

- Scale-normalized Laplacian of Gaussian:

$$\nabla^2_{\text{norm}} g = \sigma^2 \left(\frac{\partial^2 g}{\partial x^2} + \frac{\partial^2 g}{\partial y^2} \right)$$

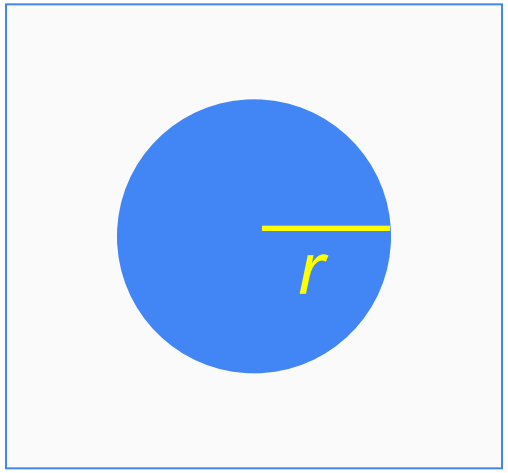




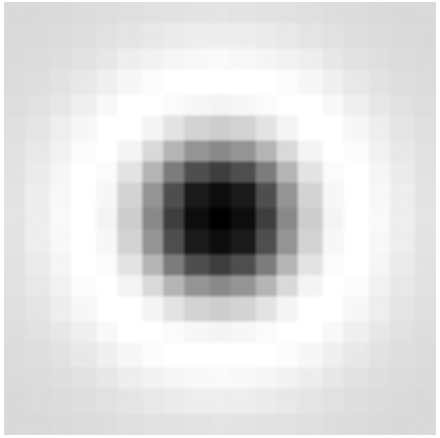
Source: S. Lazebnik

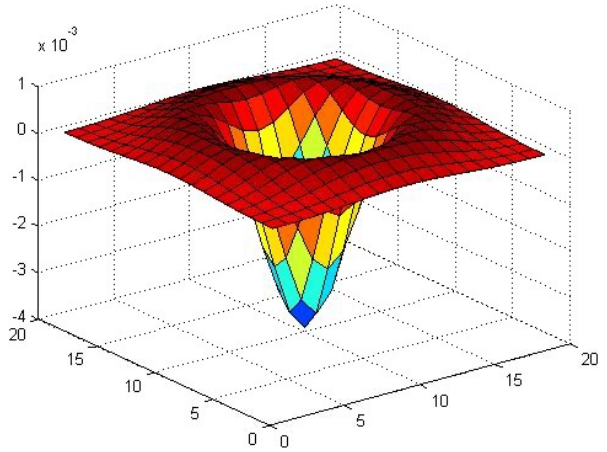
Blob detection in 2D

- At what scale does the Laplacian achieve a maximum response to a binary circle of radius r?



image





Laplacian

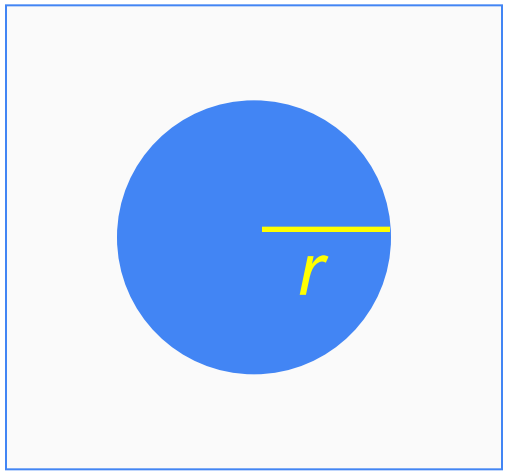
Source: S. Lazebnik

Blob detection in 2D

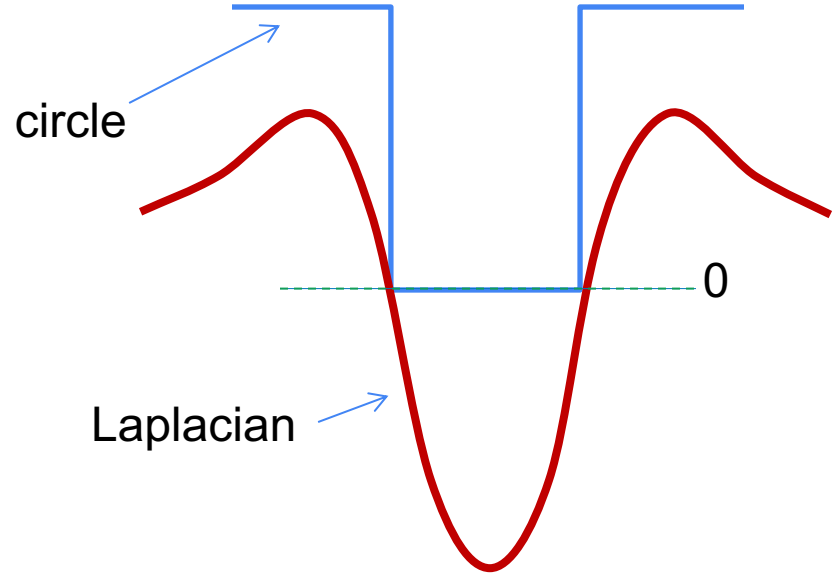
- At what scale does the Laplacian achieve a maximum response to a binary circle of radius r?
- To get maximum response, the zeros of the Laplacian have to be aligned with the circle
- The Laplacian is given by (up to scale):

$$(x^2 + y^2 - 2\sigma^2)\, e^{-(x^2+y^2)/2\sigma^2}$$

- Therefore, the maximum response occurs at $\sigma = r/\sqrt{2}.$



image



Source: S. Lazebnik

Scale-space blob detector

- Convolve image with scale-normalized Laplacian at several scales

Source: S. Lazebnik

Scale-space blob detector: Example

Source: S. Lazebnik

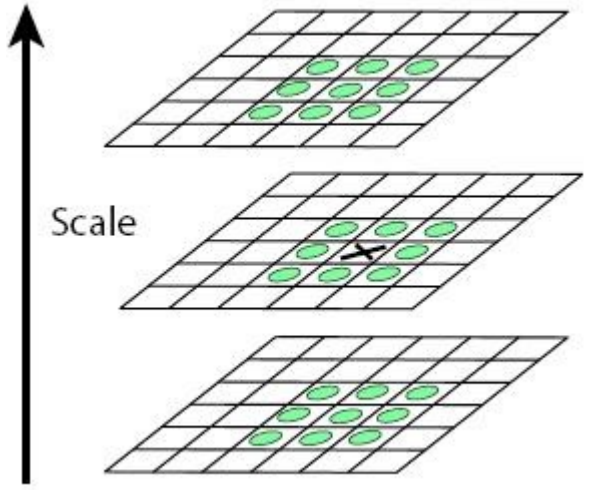
Scale-space blob detector: Example

sigma = 11.9912

Source: S. Lazebnik

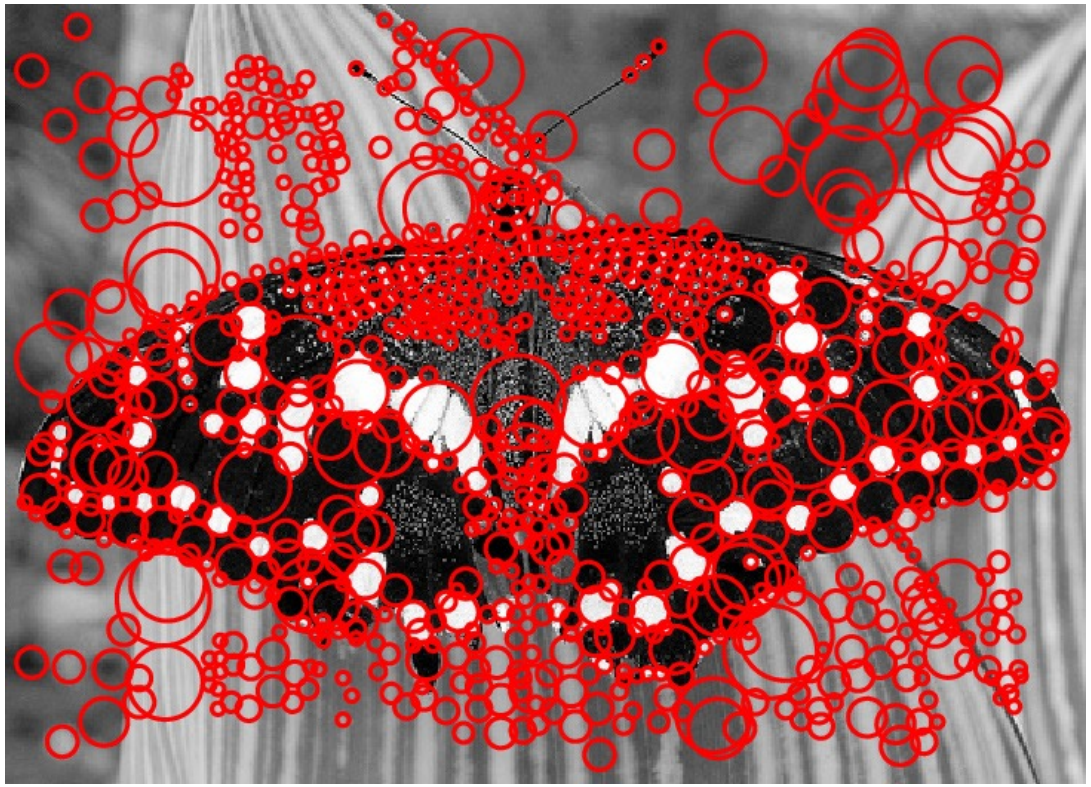
Scale-space blob detector

- Convolve image with scale-normalized Laplacian at several scales
- Find maxima of squared Laplacian response in scale-space



Source: S. Lazebnik

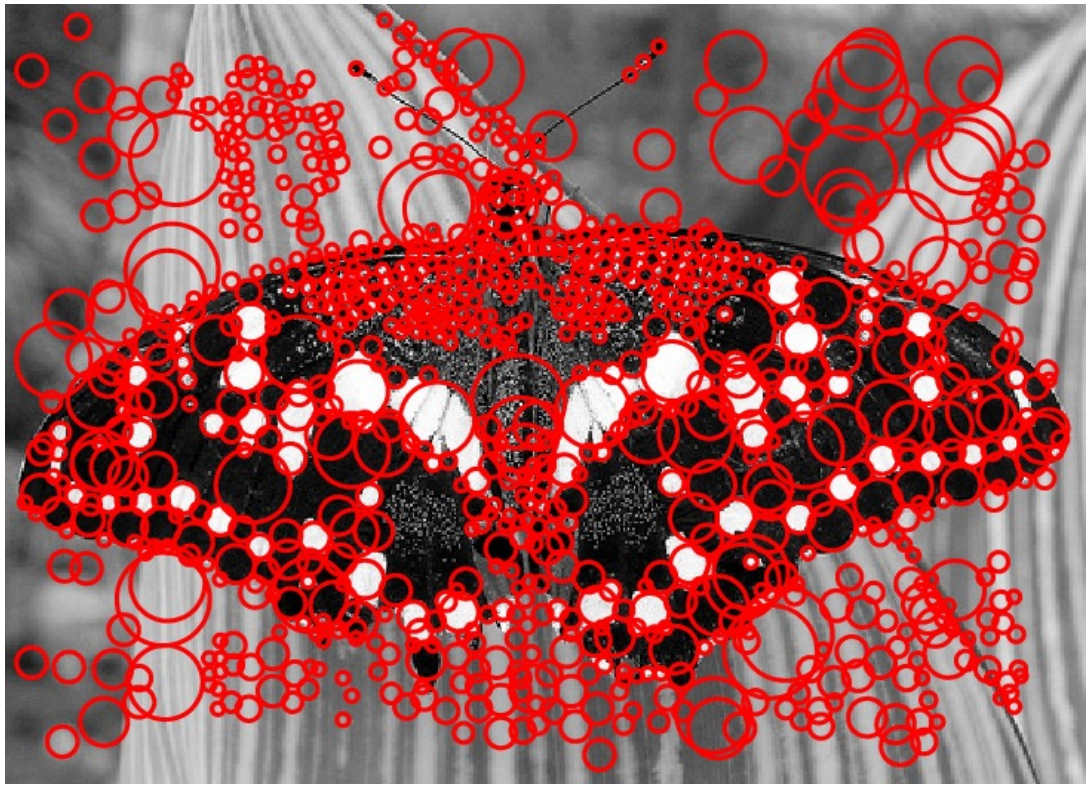
Scale-space blob detector: Example



Source: S. Lazebnik

Eliminating edge responses

- Laplacian has strong response along edge



Source: S. Lazebnik

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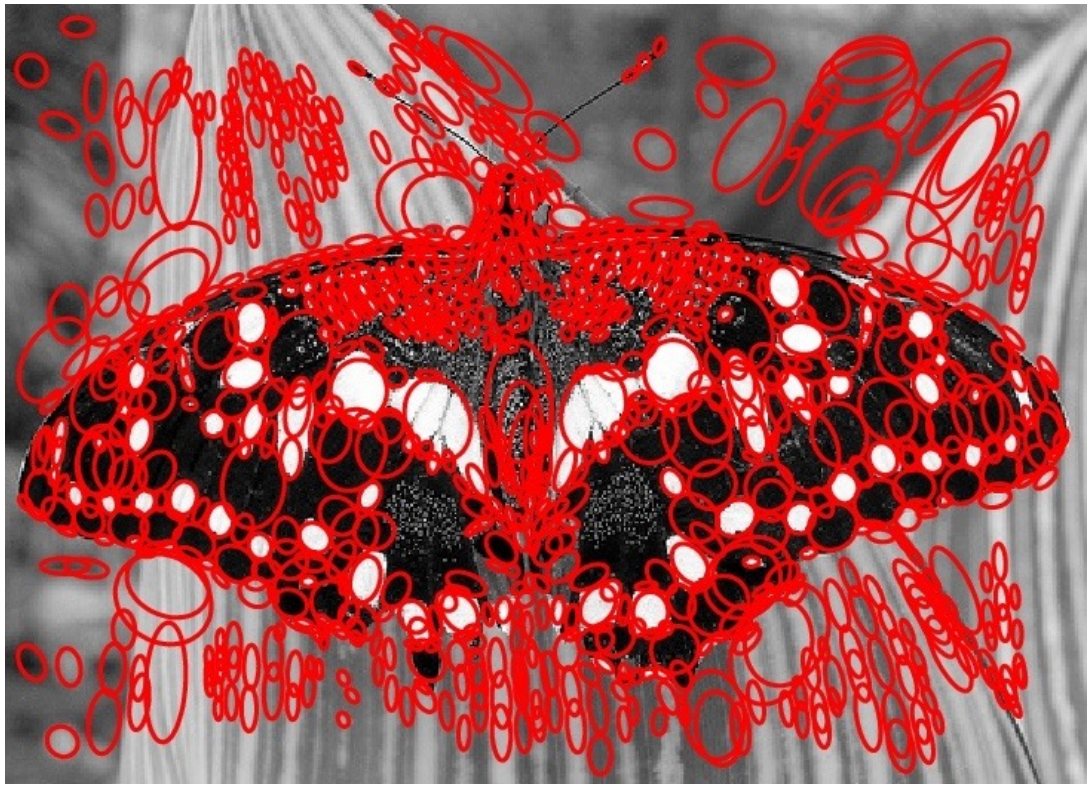


- Solution: filter based on Harris response function over neighborhoods containing the “blobs”

Source: S. Lazebnik

Efficient implementation

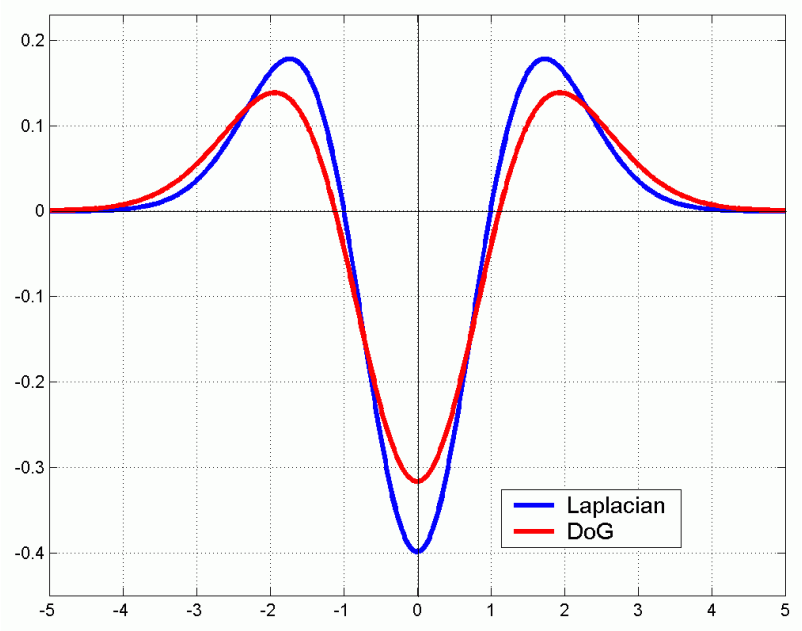
- Approximating the Laplacian with a difference of Gaussians:

$$L = \sigma^2 \left(G_{xx}(x, y, \sigma) + G_{yy}(x, y, \sigma) \right)$$

(Laplacian)

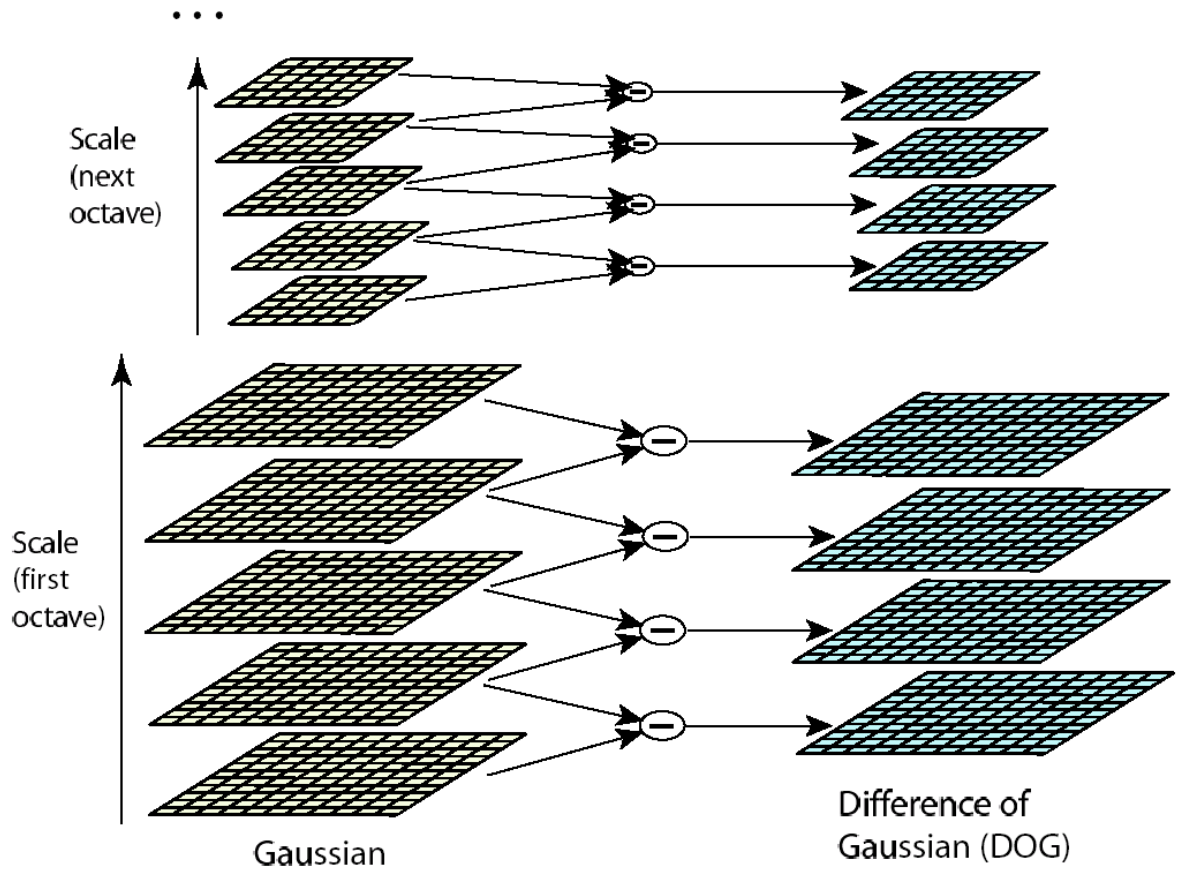
$$DoG = G(x, y, k\sigma) - G(x, y, \sigma)$$

(Difference of Gaussians)



Source: S. Lazebnik

Efficient implementation

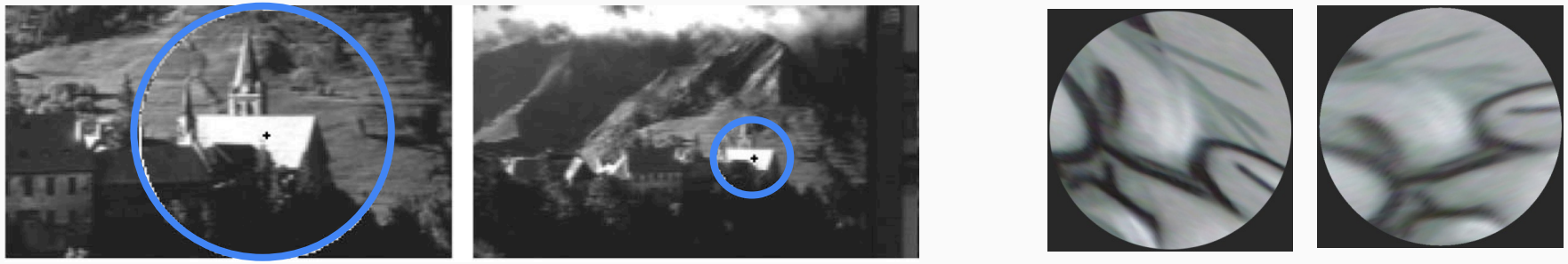


David G. Lowe. **"Distinctive image features from scale-invariant keypoints."** *IJCV* 60 (2), pp. 91-110, 2004.

Source: S. Lazebnik

From feature detection to feature description

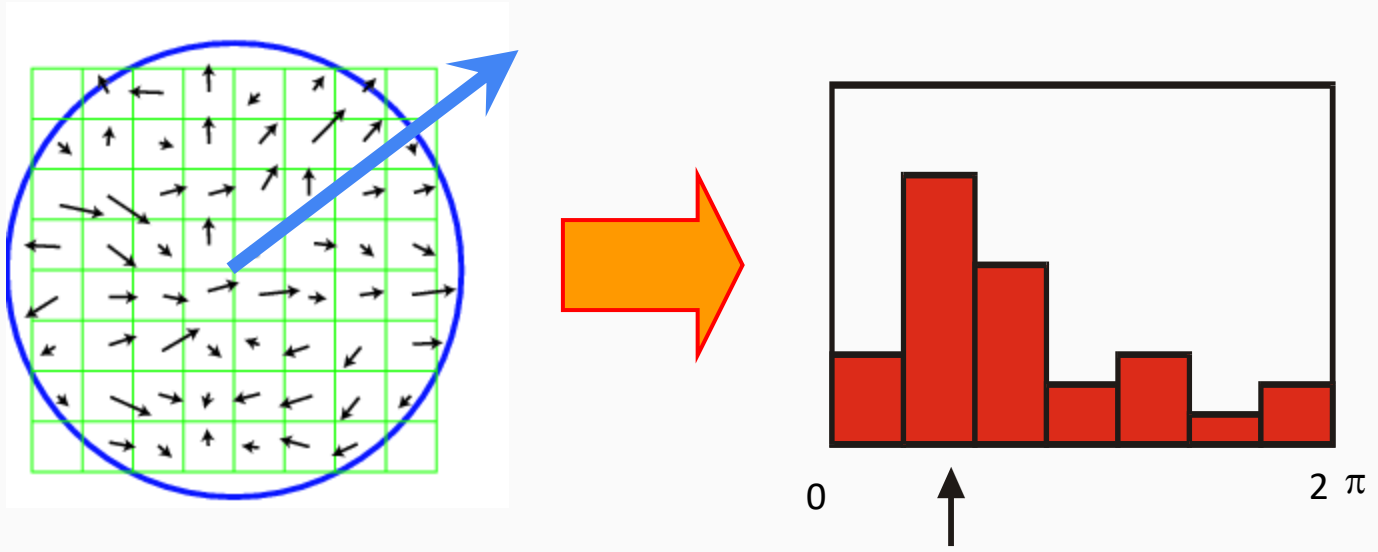
- Scaled and rotated versions of the same neighborhood will give rise to blobs that are related by the same transformation
- What to do if we want to compare the appearance of these image regions?
  - Normalization: transform these regions into same-size circles
  - Problem: rotational ambiguity



Source: S. Lazebnik

Eliminating rotation ambiguity

- To assign a unique orientation to circular image windows:
  - Create histogram of local gradient directions in the patch
  - Assign canonical orientation at peak of smoothed histogram



Source: S. Lazebnik

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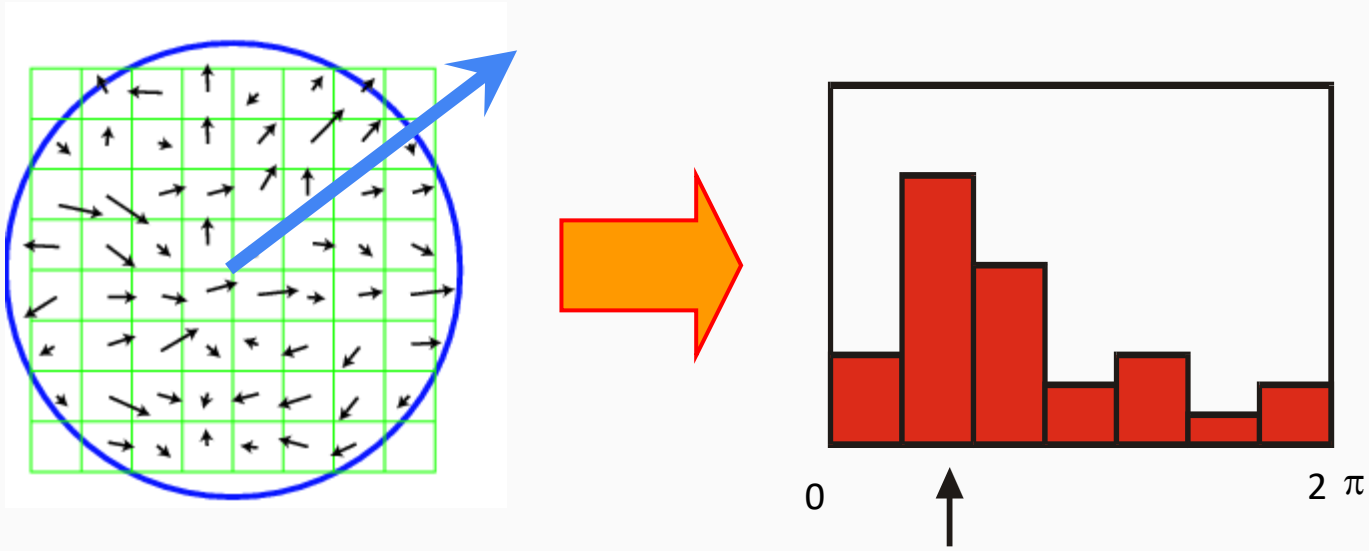
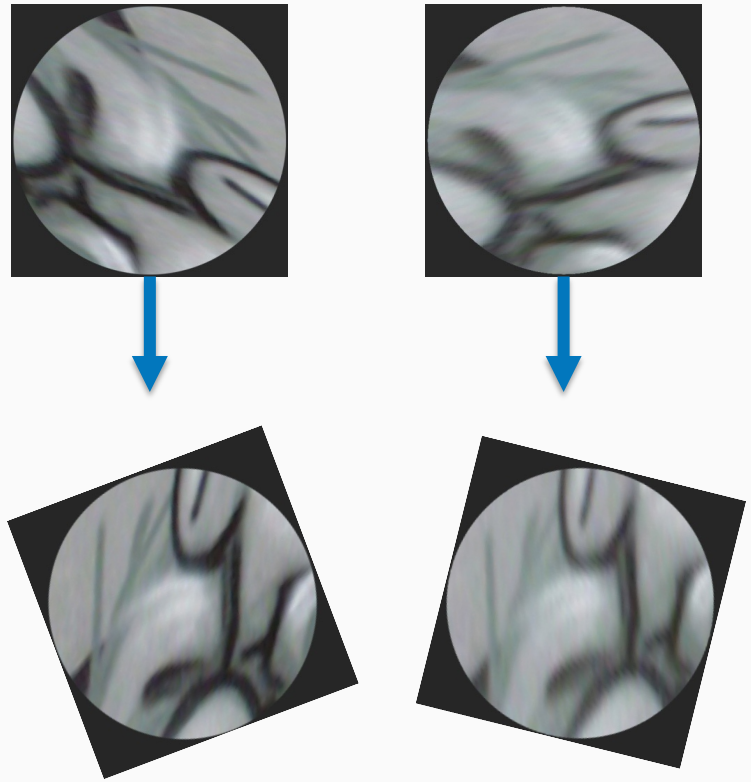
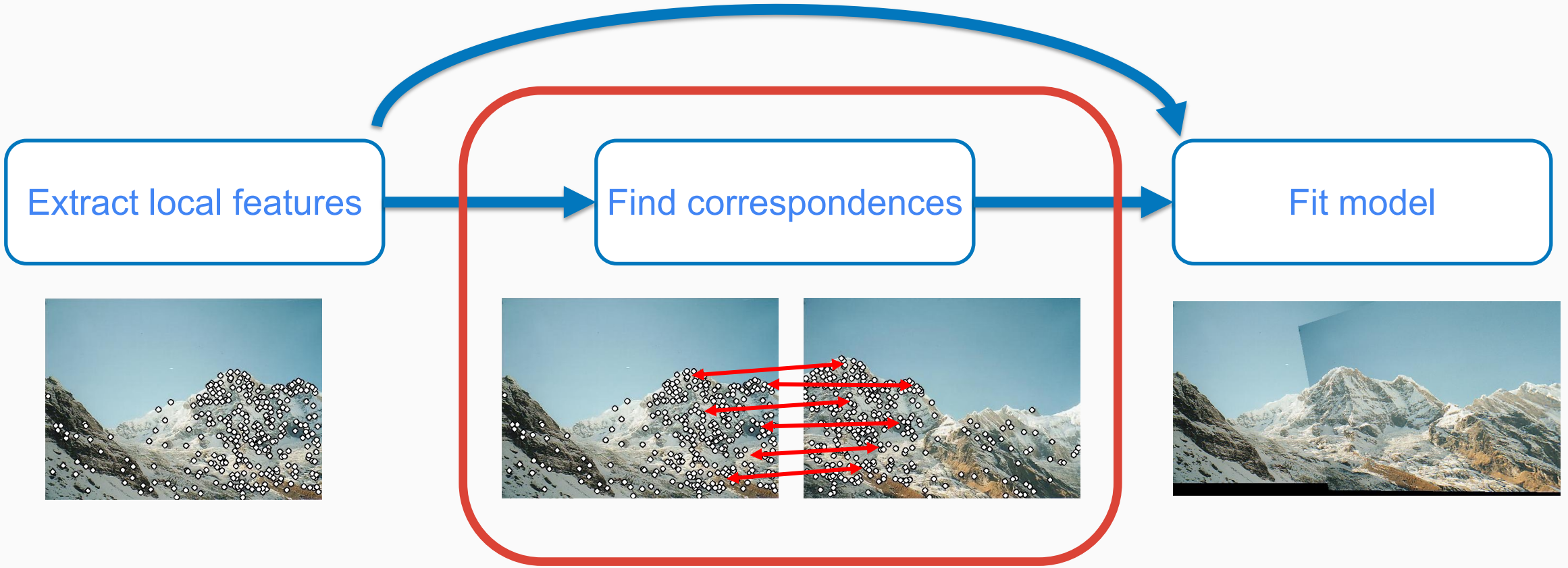




Source: S. Lazebnik

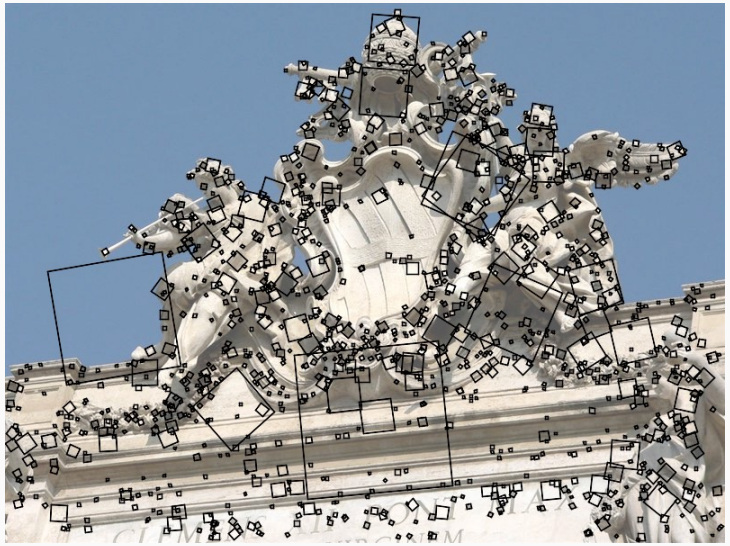
Usual steps in local feature extraction and matching



Local feature descriptors – SIFT cont.

SIFT features

- Detected features with characteristic scales and orientations:

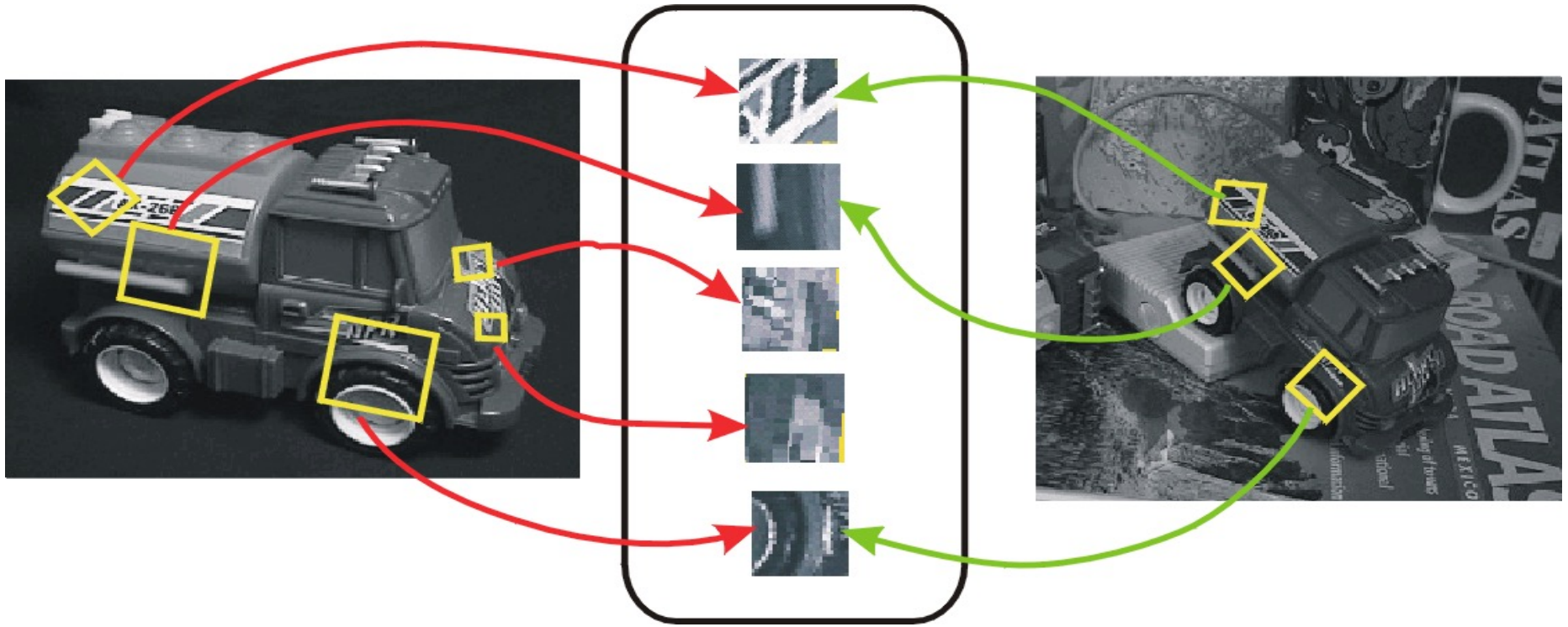


David G. Lowe. **"Distinctive image features from scale-invariant keypoints."** *IJCV* 60 (2), pp. 91-110, 2004.

Source: S. Lazebnik

From feature detection to feature description

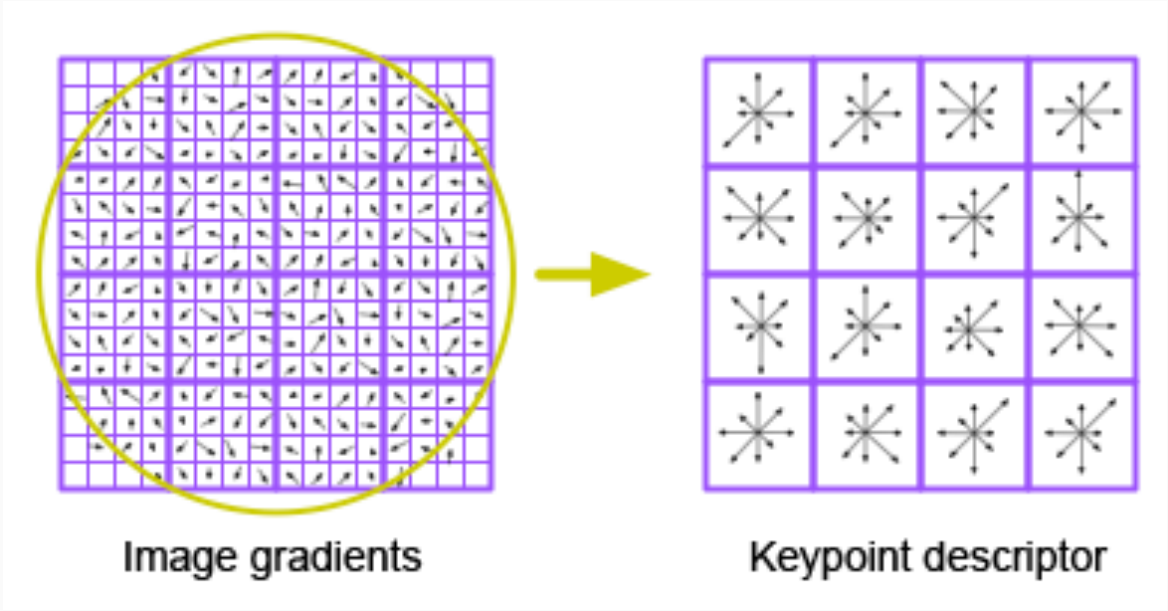
- Detection is covariant:
  - features(transform(image)) = transform(features(image))
- Description is invariant:
  - features(transform(image)) = features(image)



Source: S. Lazebnik

SIFT descriptors

- Inspiration: complex neurons in the primary visual cortex



D. Lowe. **Distinctive image features from scale-invariant keypoints.** *IJCV* 60 (2), pp. 91-110, 2004.

Source: S. Lazebnik

SIFT descriptor computation

- use the normalized region about the keypoint
- compute gradient magnitude and orientation at each point in the region
- weight them by a Gaussian window overlaid on the circle
- create an orientation histogram over the 4 X 4 subregions of the window
- 4 X 4 descriptors over 16 X 16 sample array were used in practice. 4 X 4 times 8 directions gives a vector of 128 values.

Summary of SIFT feature detection and description

1. Scale-space extrema detection

   Search over multiple scales and image locations.

2. Keypoint localization

   Fit a model to determine location and scale.
   Select keypoints based on a measure of stability.

3. Orientation assignment

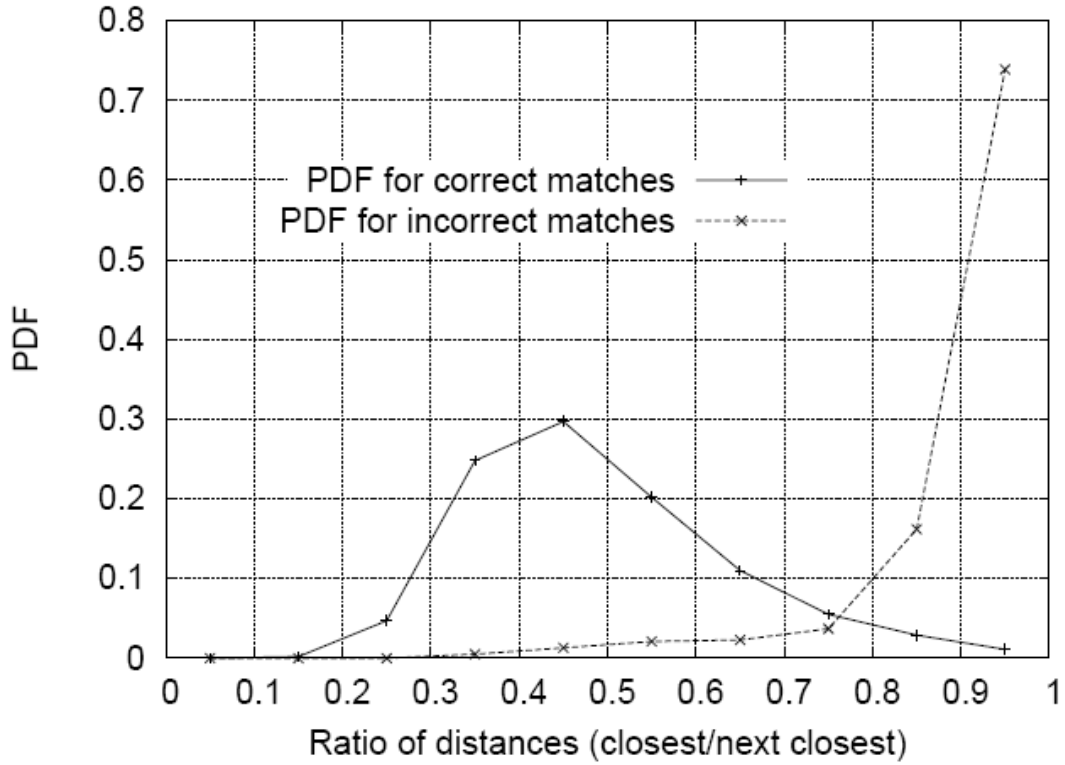
   Compute best orientation(s) for each keypoint region.

4. Keypoint description

   Use local image gradients at selected scale and rotation
   to describe each keypoint region.

Matching SIFT Descriptors

- Nearest neighbor (Euclidean distance)
- Threshold ratio of nearest to 2nd nearest descriptor



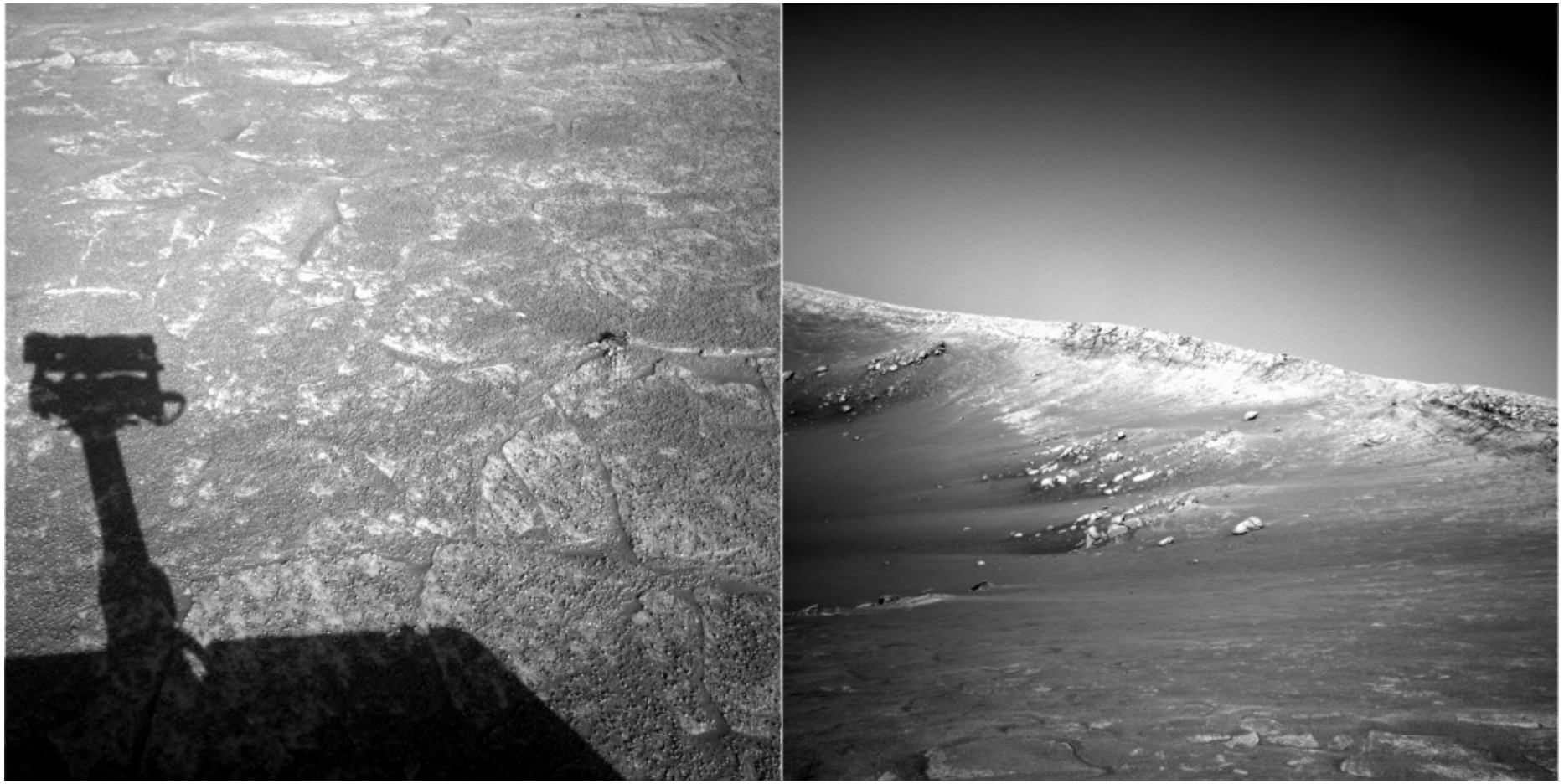
Lowe IJCV 2004

Properties of SIFT

- Extraordinarily robust detection and description technique
  - Can handle changes in viewpoint
    Up to about 60 degree out-of-plane rotation
  - Can handle significant changes in illumination
    Sometimes even day vs. night
  - Fast and efficient—can run in real time
  - Lots of code available

Source: N. Snavely

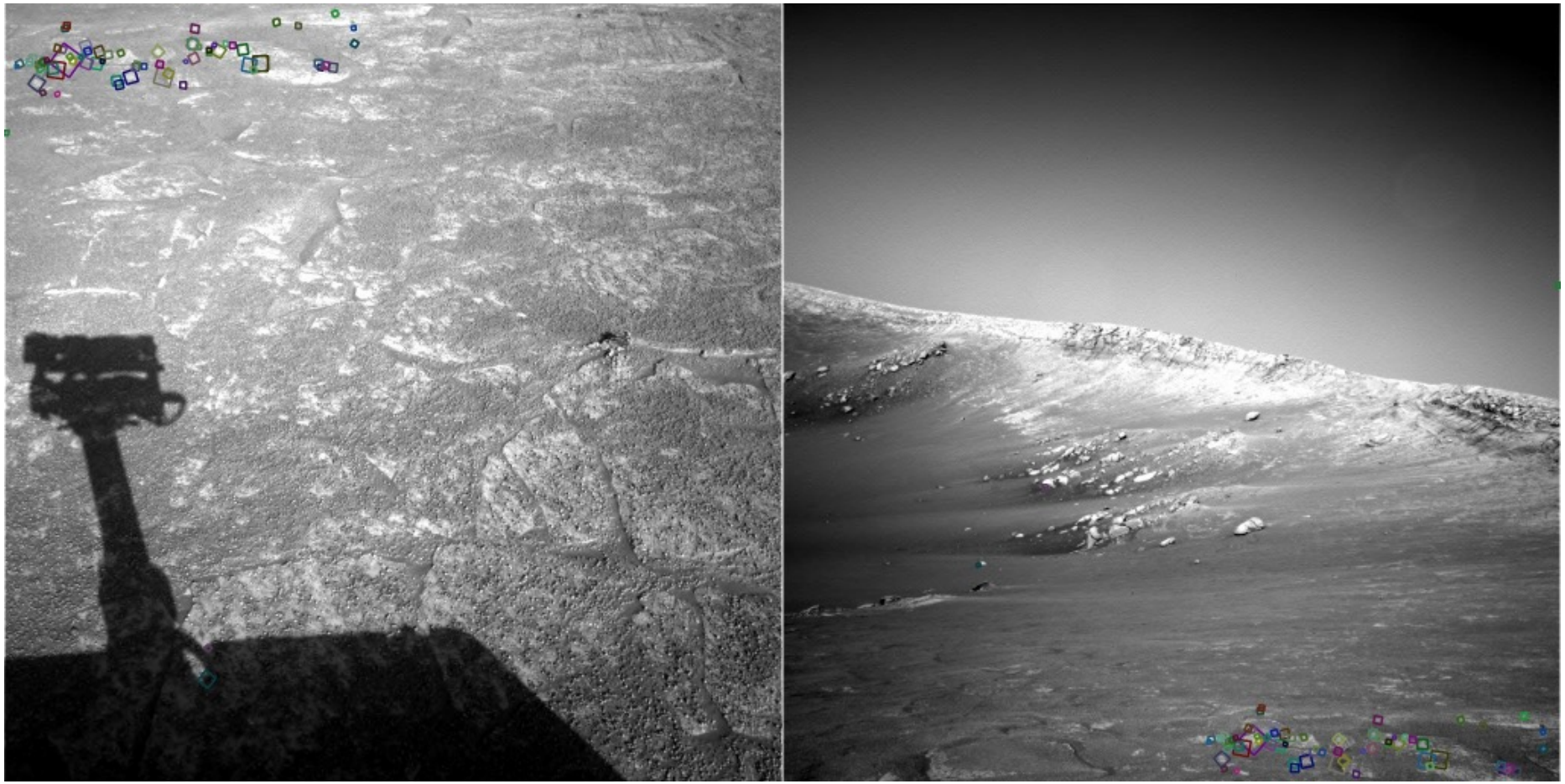
A hard keypoint matching problem



NASA Mars Rover images

Source: S. Lazebnik

Answer below (look for tiny colored squares…)



NASA Mars Rover images
with SIFT feature matches
Figure by Noah Snavely

Source: S. Lazebnik

That’s all folks!