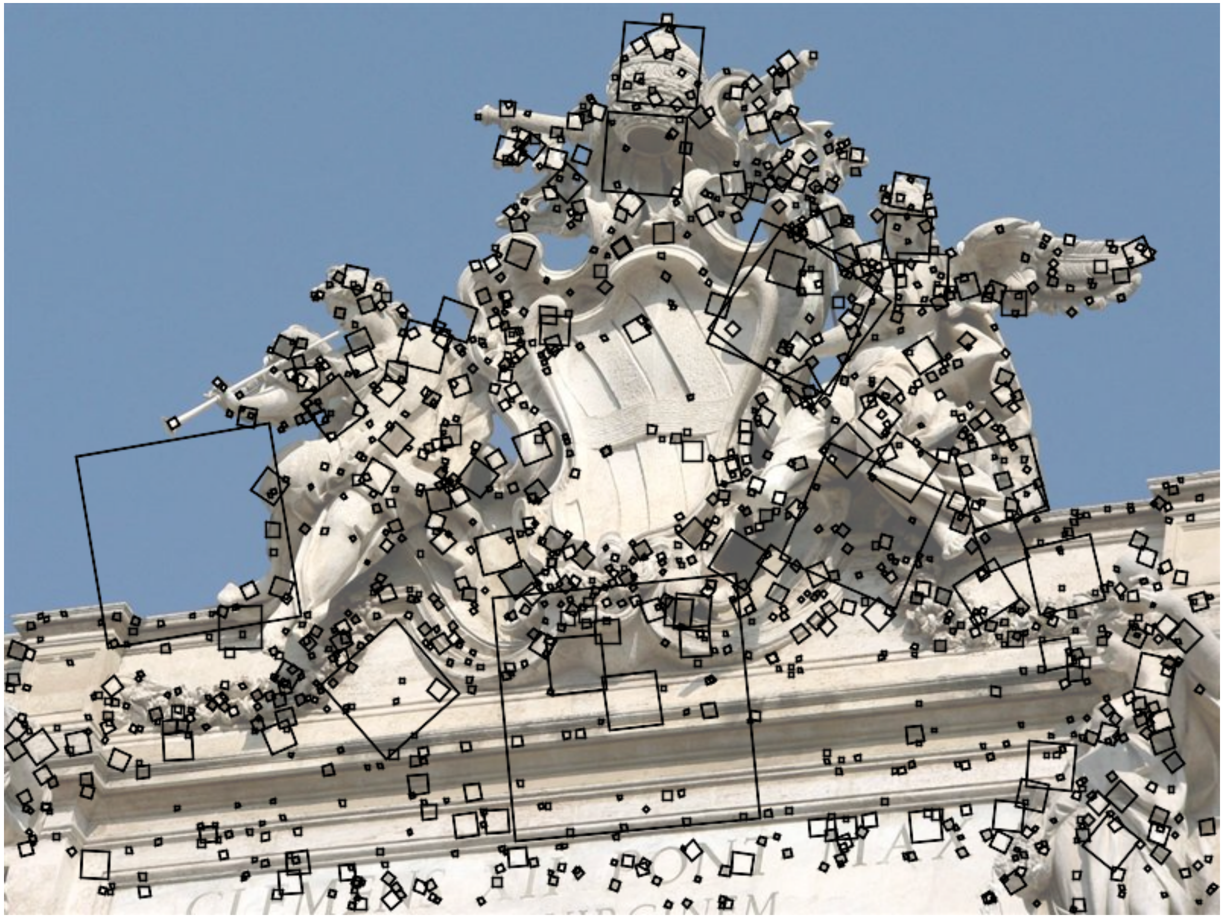
SIFT keypoint detection

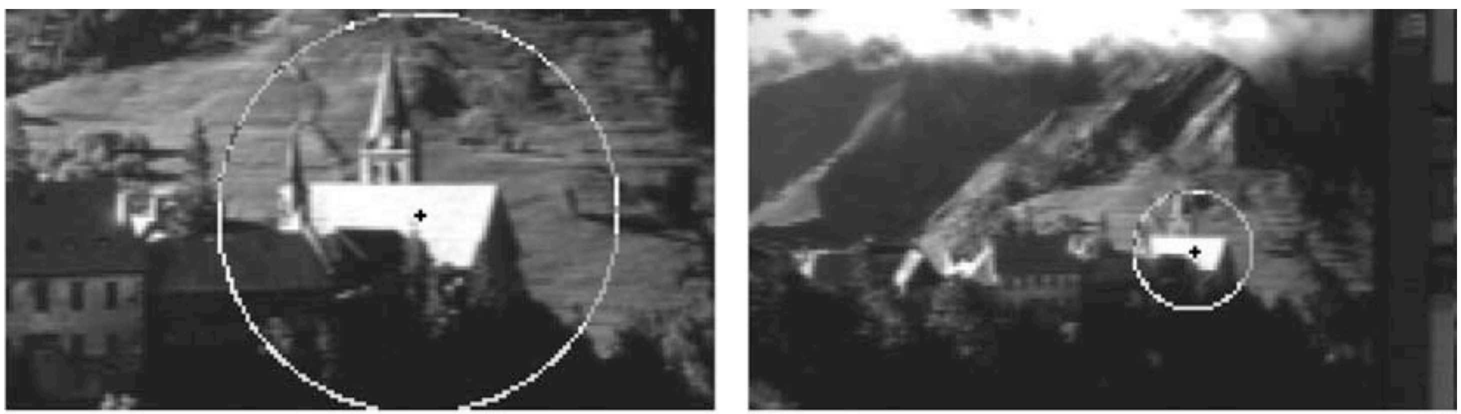


D. Lowe, [Distinctive image features from scale-invariant keypoints](), *IJCV* 60 (2), pp. 91-110, 2004

Slides from S. Lazebnik.

Keypoint detection with scale selection

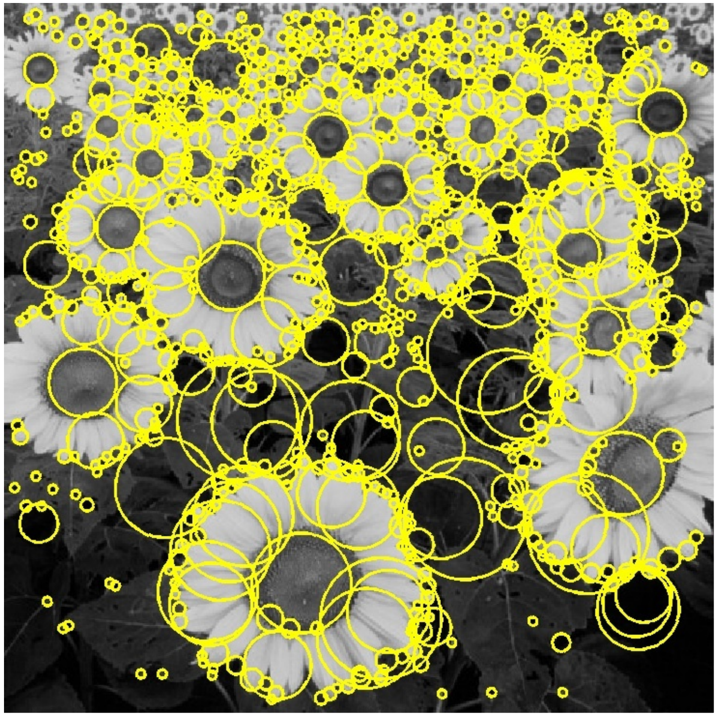
- We want to extract keypoints with *characteristic scales* that are *covariant* w.r.t. the image transformation

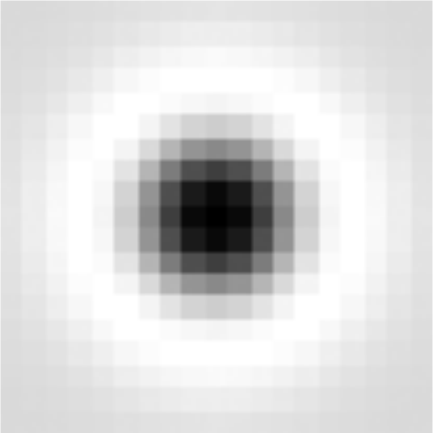


Source: L. Lazebnik

Basic idea

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

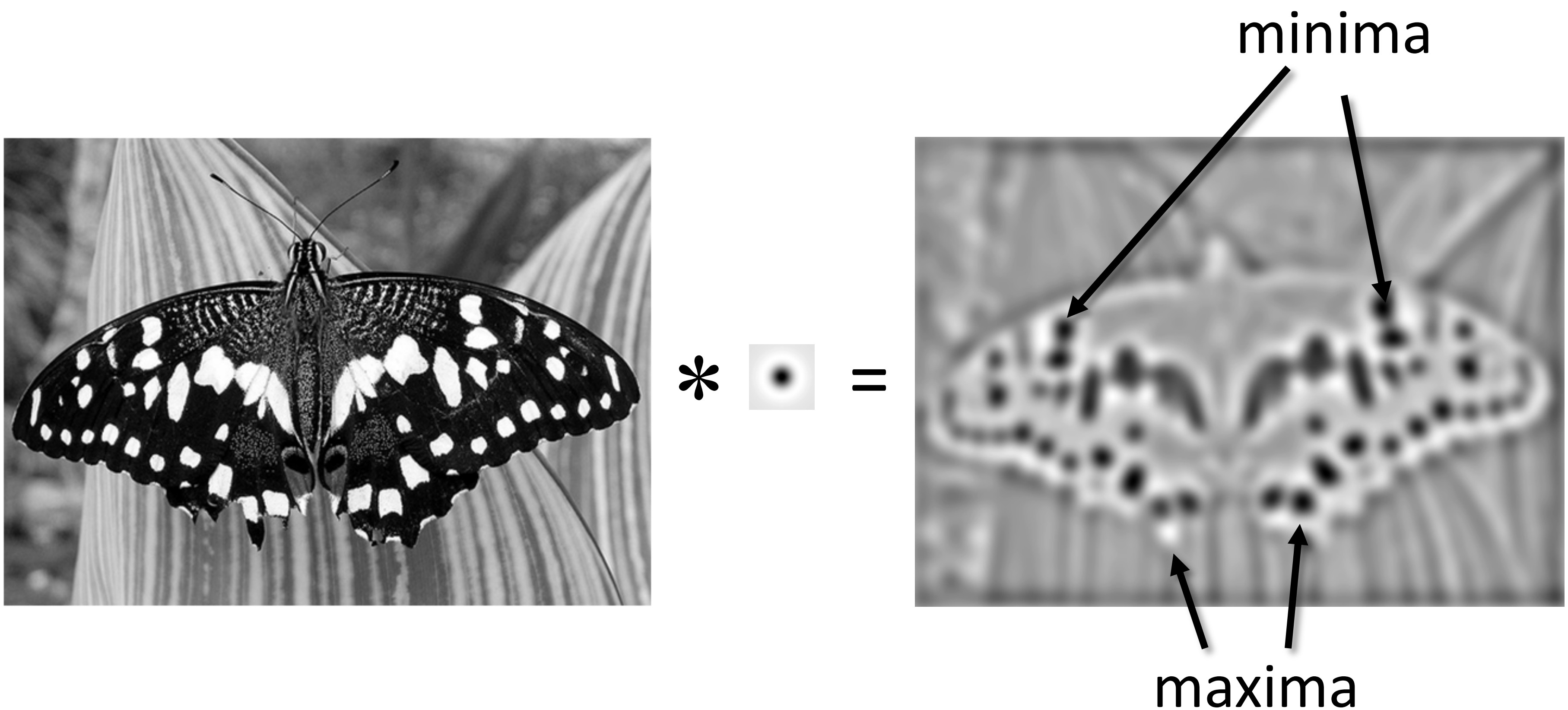




T. Lindeberg, [Feature detection with automatic scale selection](), *IJCV* 30(2), pp 77-116, 1998

Source: L. Lazebnik

Blob detection



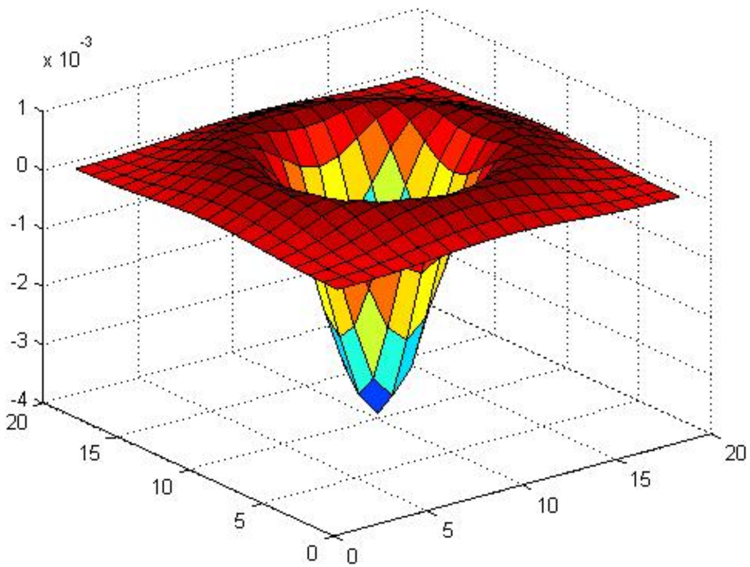
Find maxima *and minima* of blob filter response in space *and scale*

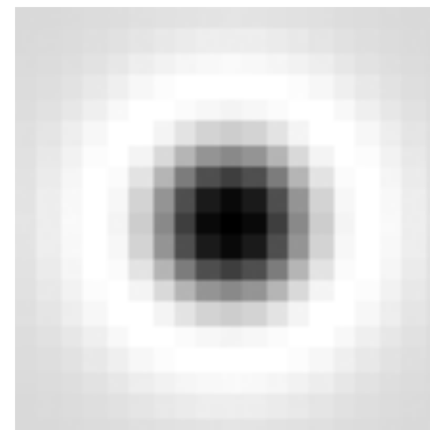
Source: L. Lazebnik

Source: N. Snavely

Blob filter

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

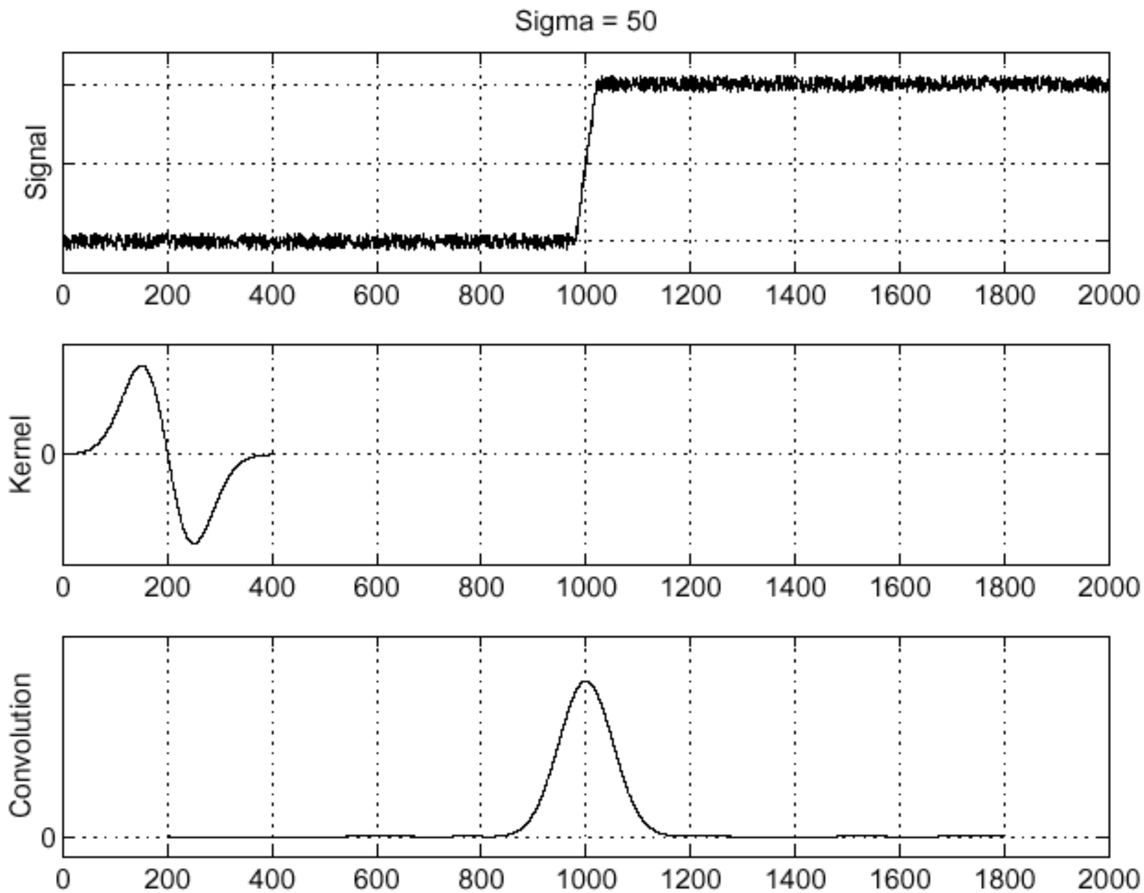




$$\nabla^2 g = \frac{\partial^2 g}{\partial x^2} + \frac{\partial^2 g}{\partial y^2}$$

Source: L. Lazebnik

Recall: Edge detection



f — Edge

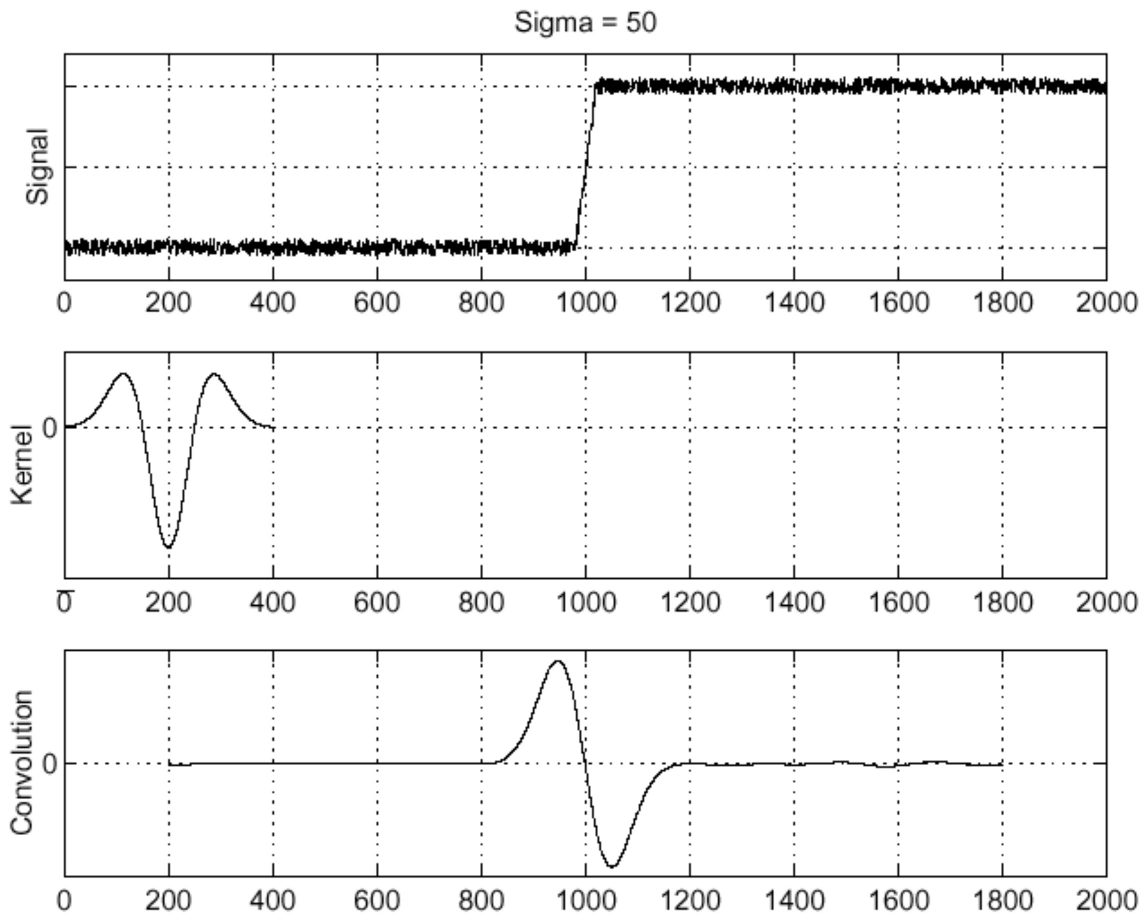
$\frac{d}{dx} g$ — Derivative of Gaussian

$f * \frac{d}{dx} g$ — Edge = maximum of derivative

Source: L. Lazebnik

Source: S. Seitz

Edge detection, Take 2



f — Edge

$\frac{d^2}{dx^2} g$ — Second derivative of Gaussian (Laplacian)

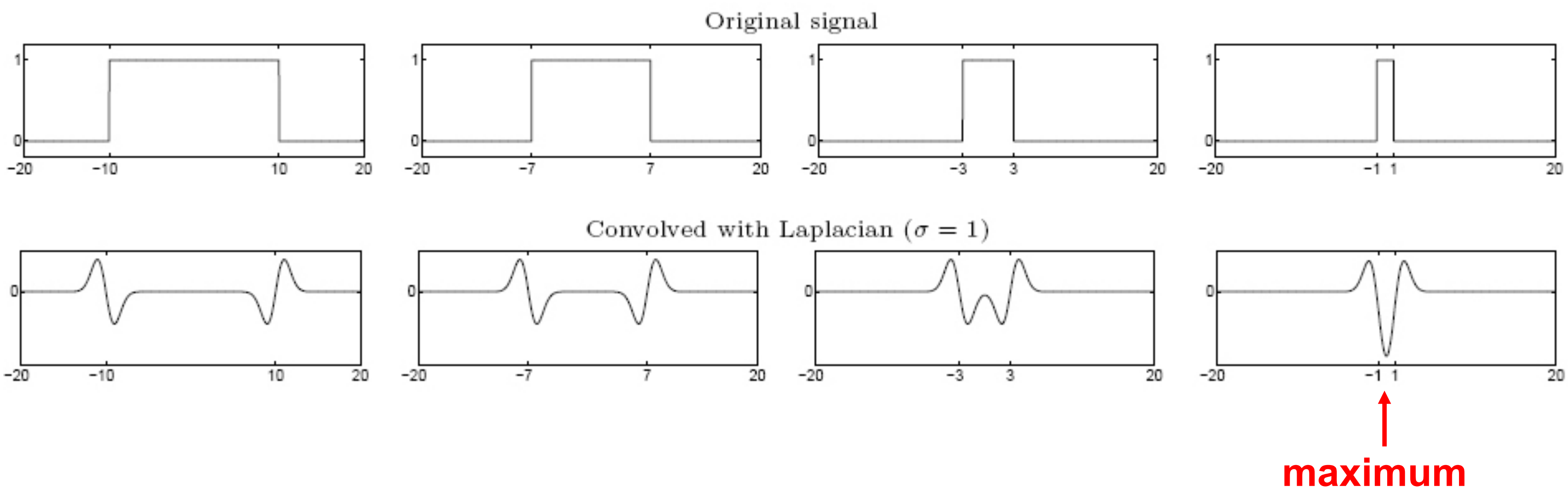
$f * \frac{d^2}{dx^2} g$ — Edge = zero crossing of second derivative

Source: S. Seitz

Source: L. Lazebnik

From edges to blobs

- Edge = ripple
- Blob = superposition of two ripples

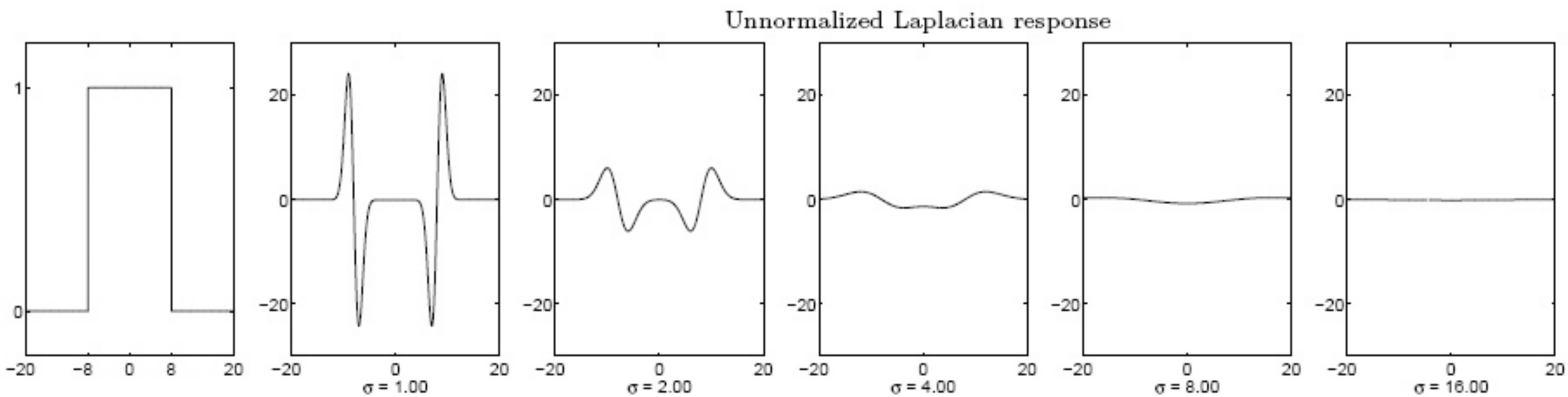


Spatial selection: the magnitude of the Laplacian response will achieve a maximum at the center of the blob, provided the scale of the Laplacian is “matched” to the scale of the blob

Source: L. 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:



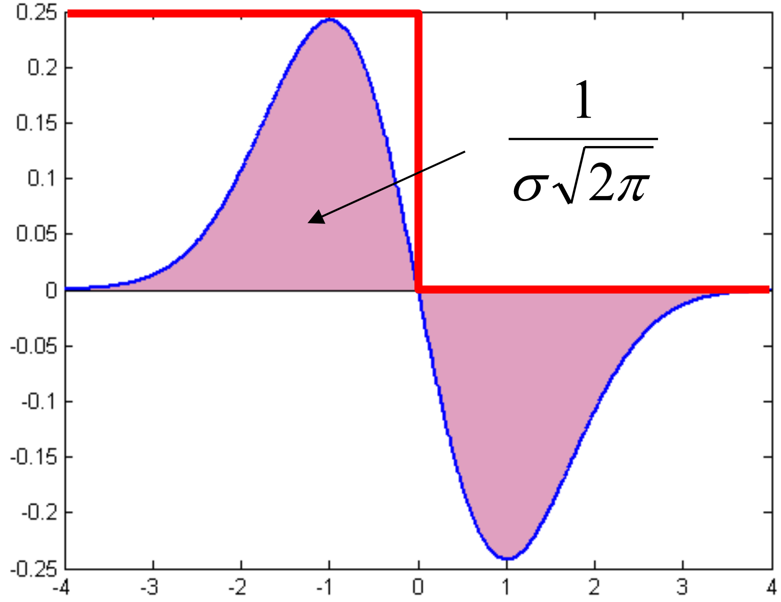
original signal (radius=8)

increasing σ

Source: L. Lazebnik

Scale normalization

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



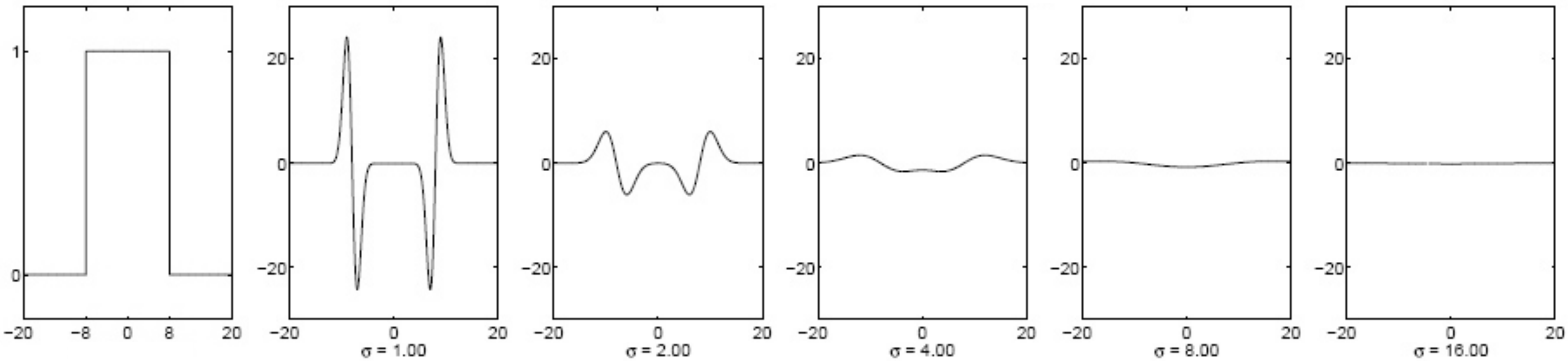
- To keep response the same (scale-invariant), must multiply Gaussian derivative by σ
- Laplacian is the second Gaussian derivative, so it must be multiplied by σ^2

Source: L. Lazebnik

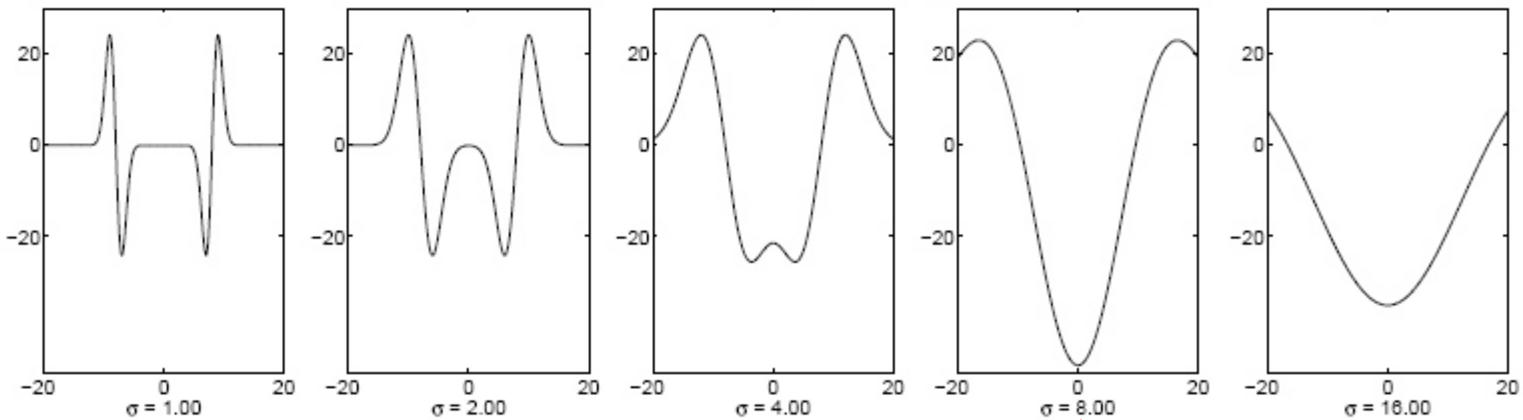
Effect of scale normalization

Original signal

Unnormalized Laplacian response



Scale-normalized Laplacian response



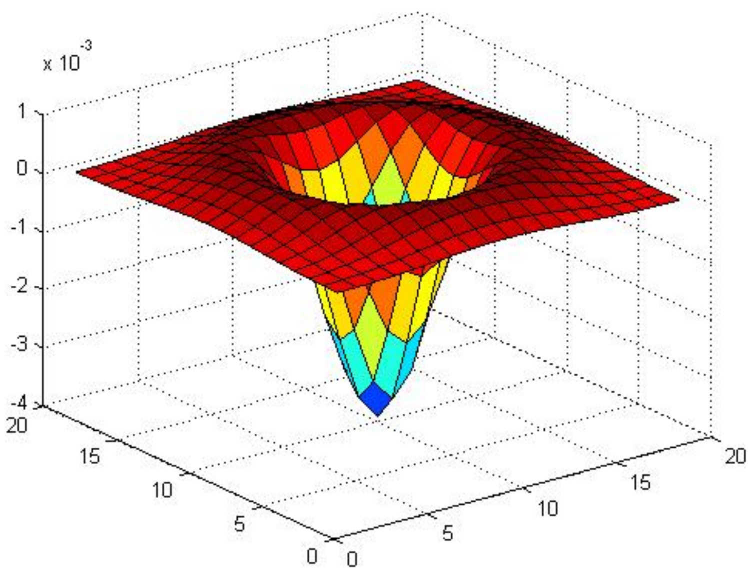
maximum

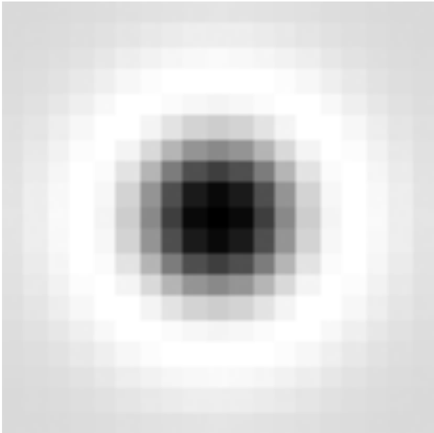
Source: L. Lazebnik

Blob detection in 2D

- *Scale-normalized* Laplacian of Gaussian:

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

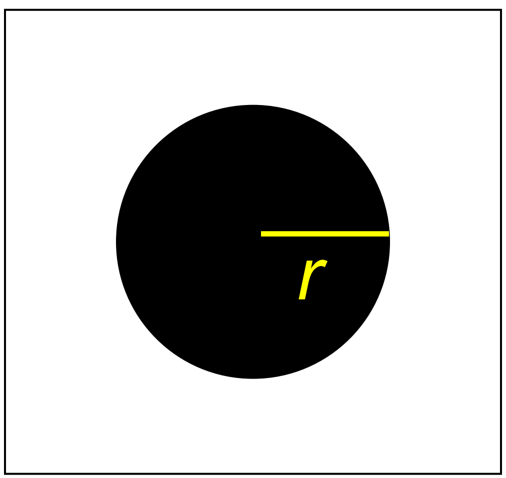




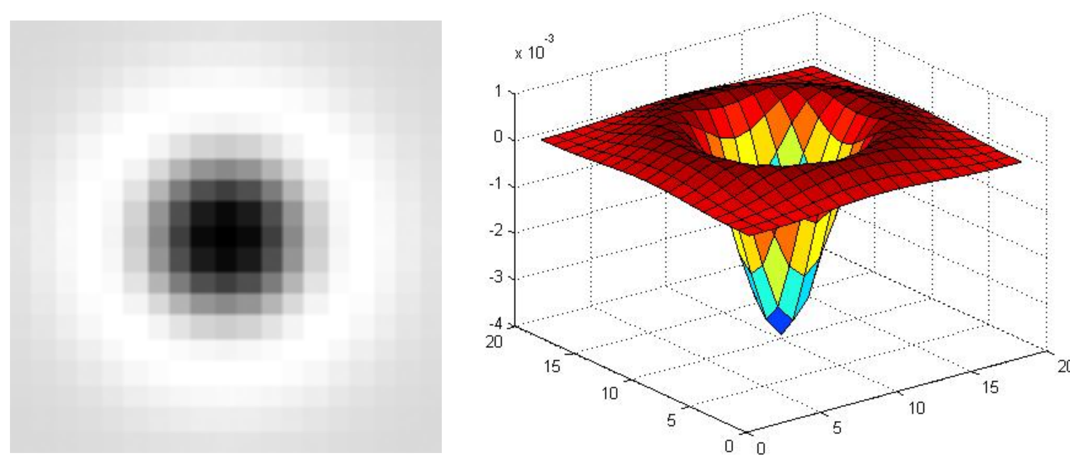
Source: L. Lazebnik

Blob detection in 2D

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



image



Laplacian

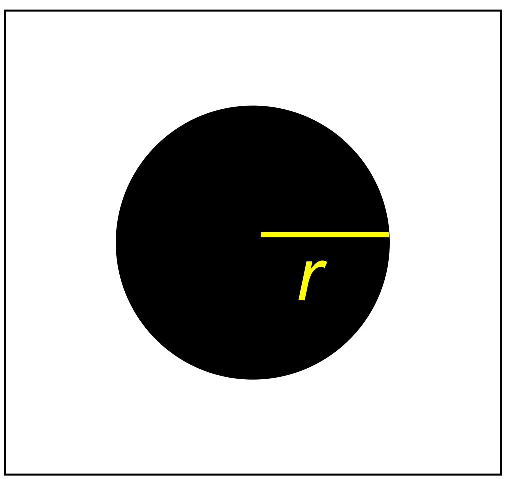
Source: L. Lazebnik

Blob detection in 2D

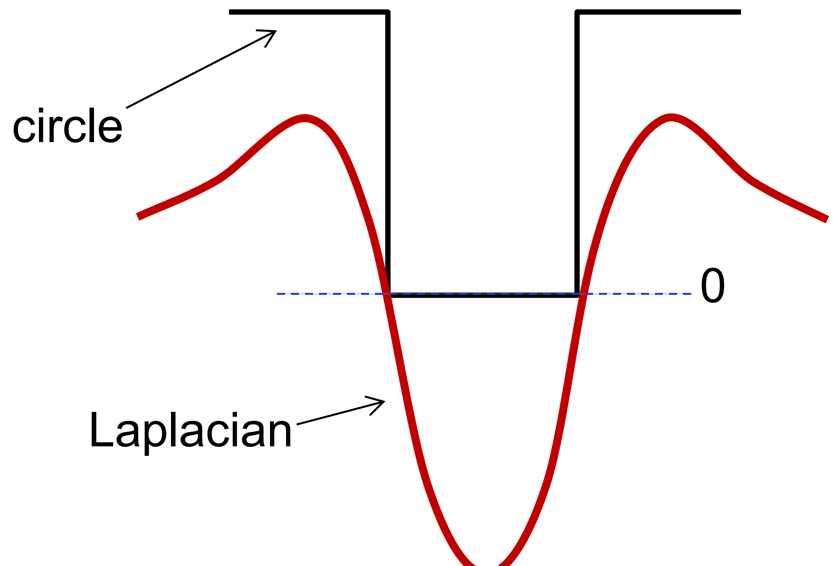
- At what scale does the Laplacian achieve a maximum response to a binary circle of radius r?
- To get maximum response, the zeros of the Laplacian have to be aligned with the circle
- The Laplacian is given by (up to scale):

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

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



image



Source: L. Lazebnik

Scale-space blob detector

1. Convolve image with scale-normalized Laplacian at several scales

Source: L. Lazebnik

Scale-space blob detector: Example

Source: L. Lazebnik

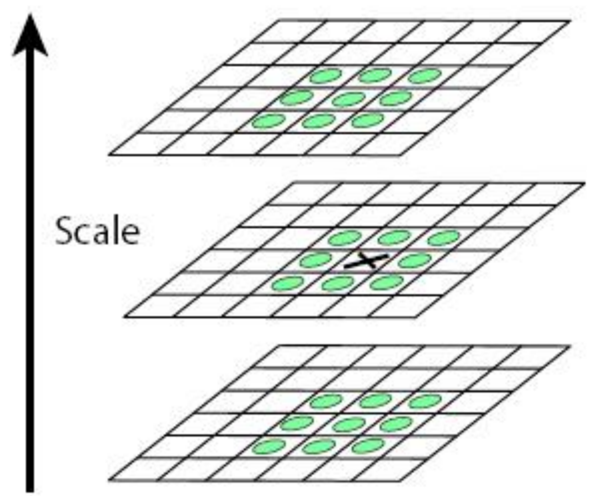
Scale-space blob detector: Example

sigma = 11.9912

Source: L. Lazebnik

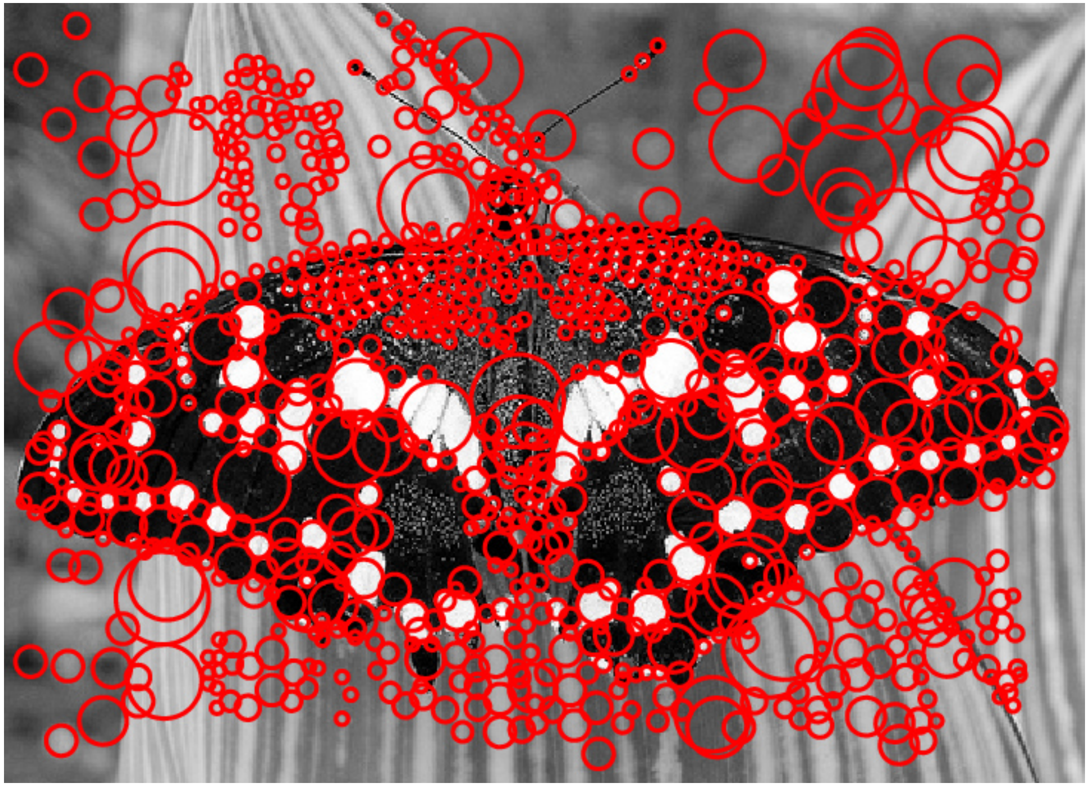
Scale-space blob detector

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



Source: L. Lazebnik

Scale-space blob detector: Example



Source: L. Lazebnik

Efficient implementation

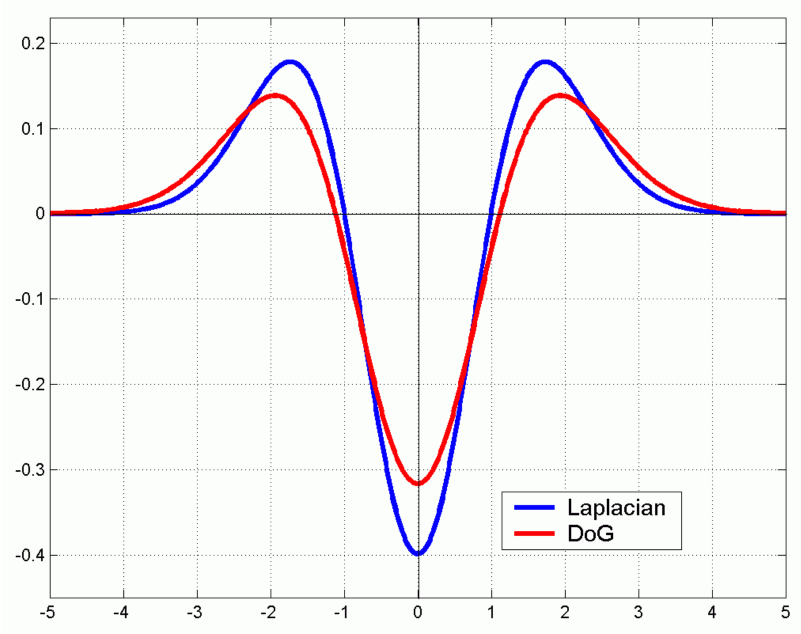
- Approximating the Laplacian with a difference of Gaussians:

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

(Laplacian)

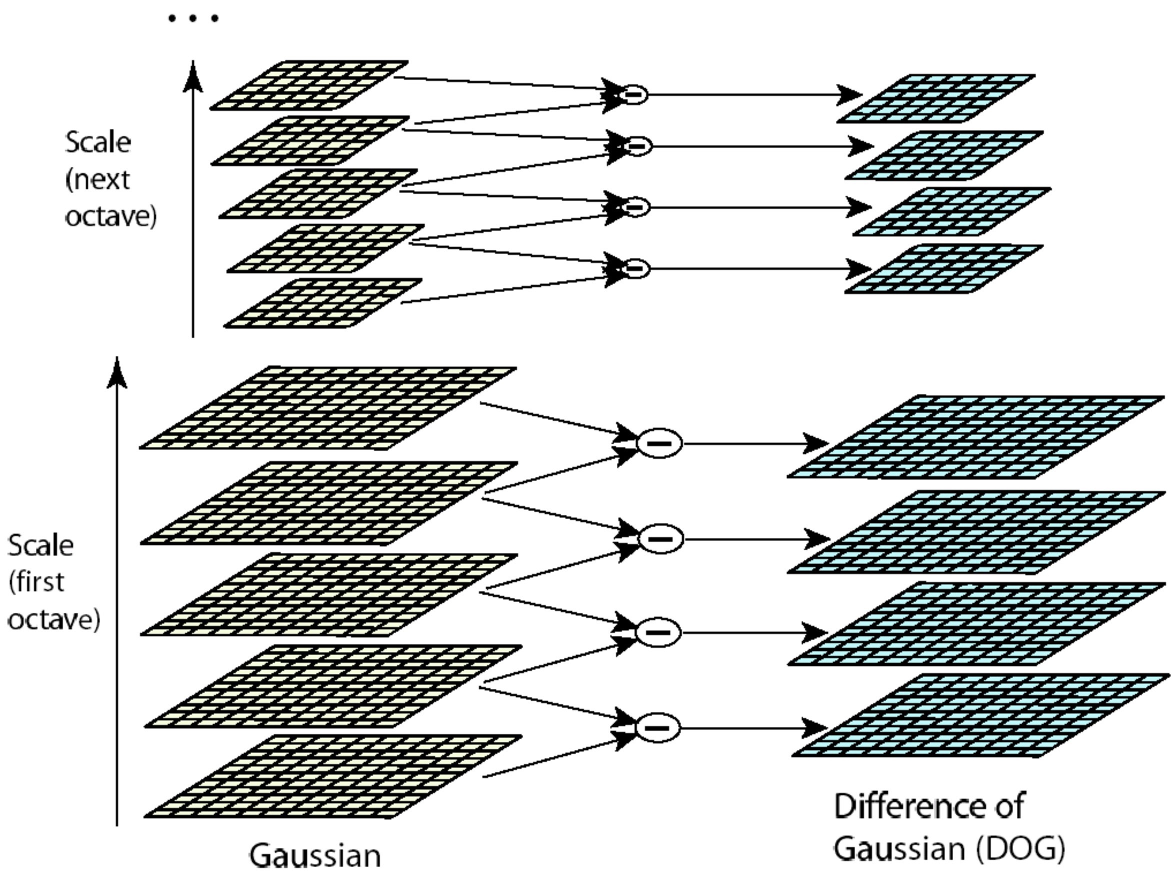
$$DoG = G(x, y, k\sigma) - G(x, y, \sigma)$$

(Difference of Gaussians)



Source: L. Lazebnik

Efficient implementation

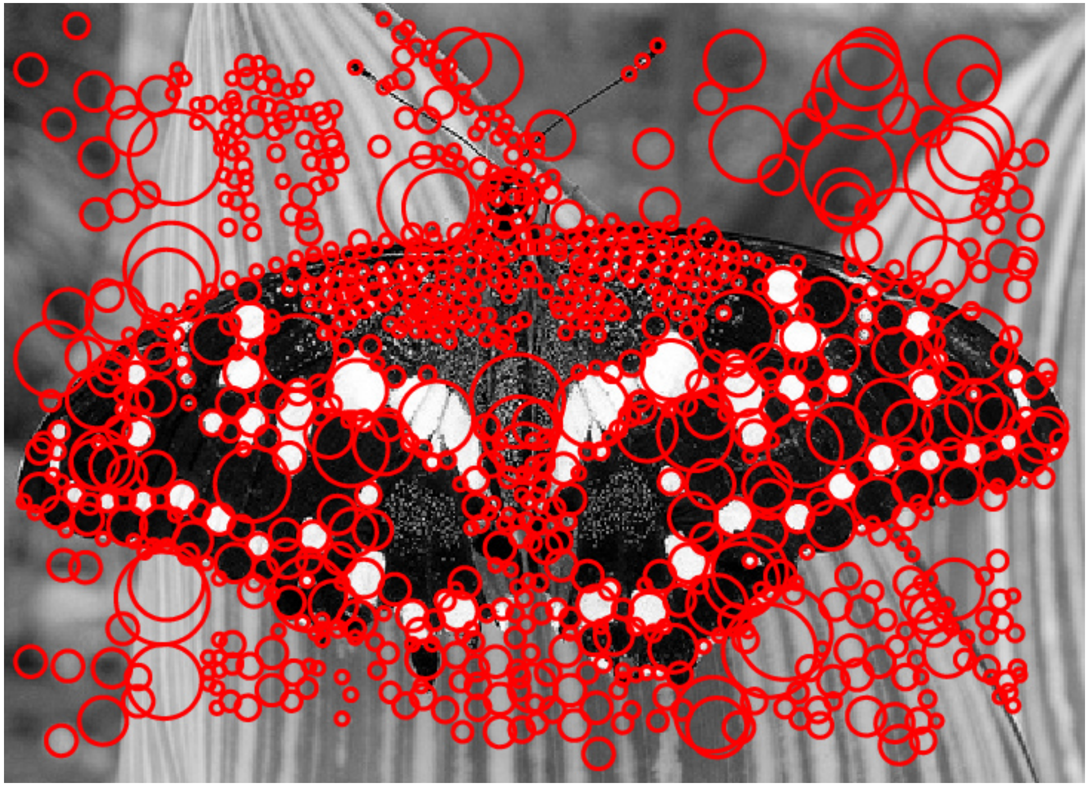


David G. Lowe. **"Distinctive image features from scale-invariant keypoints."** *IJCV* 60 (2), pp. 91-110, 2004.

Source: L. Lazebnik

Eliminating edge responses

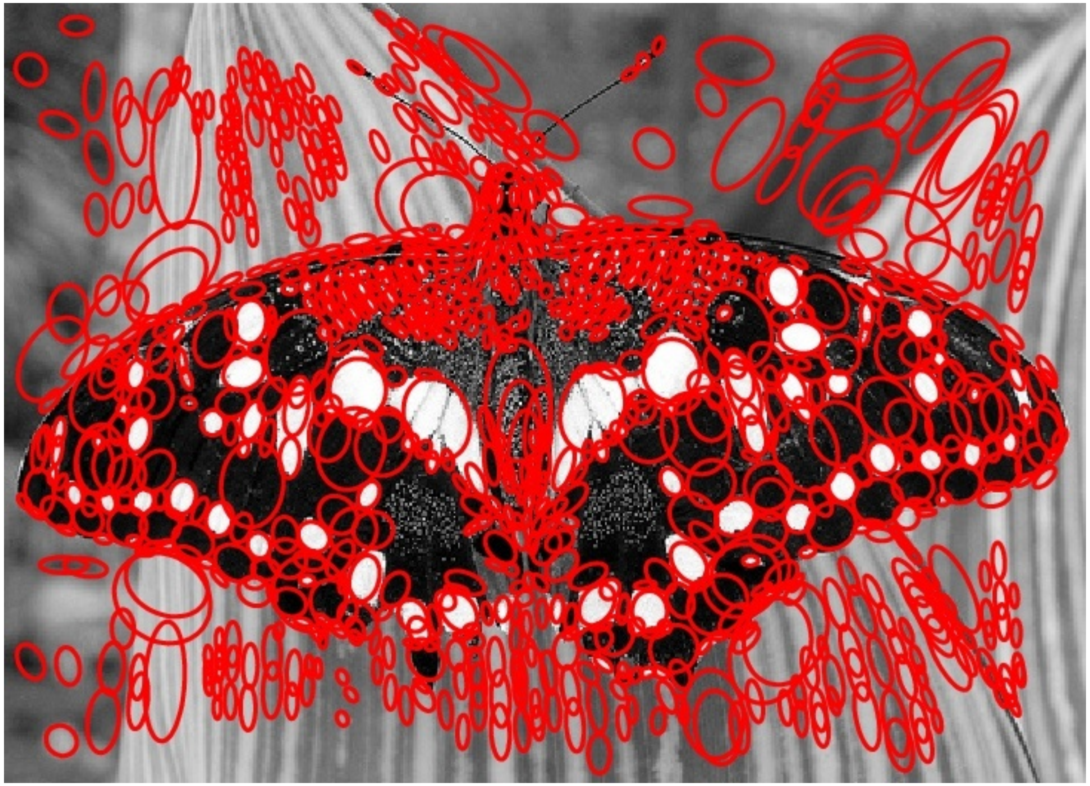
- Laplacian has strong response along edges



Source: L. Lazebnik

Eliminating edge responses

- Laplacian has strong response along edges

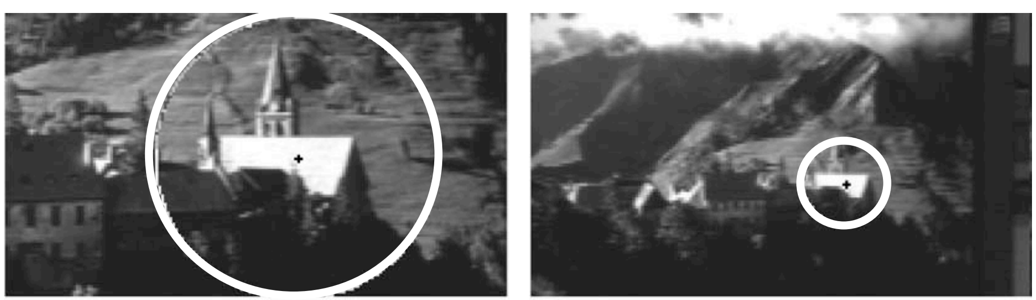


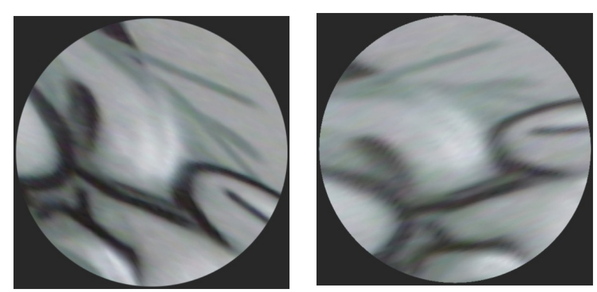
- Solution: filter based on Harris response function over neighborhoods containing the “blobs”

Source: L. Lazebnik

From feature detection to feature description

- To recognize the same pattern in multiple images, we need to match appearance "signatures" in the neighborhoods of extracted keypoints
  - But corresponding neighborhoods can be related by a scale change or rotation
  - We want to *normalize* neighborhoods to make signatures invariant to these transformations

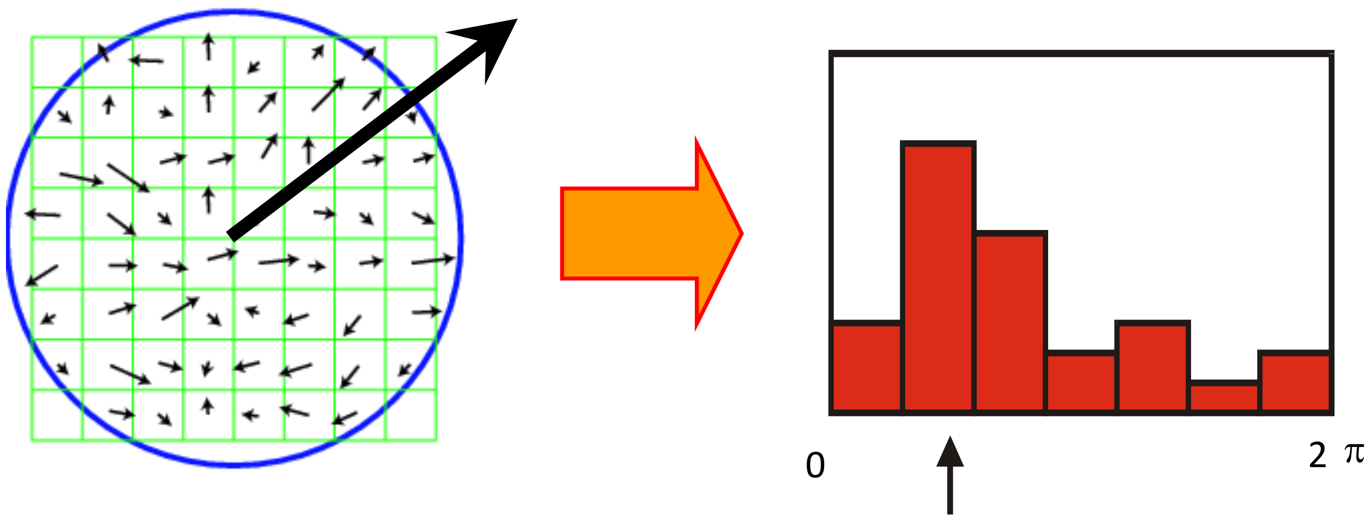




Source: L. Lazebnik

Finding a reference orientation

- Create histogram of local gradient directions in the patch
- Assign reference orientation at peak of smoothed histogram



Source: L. Lazebnik

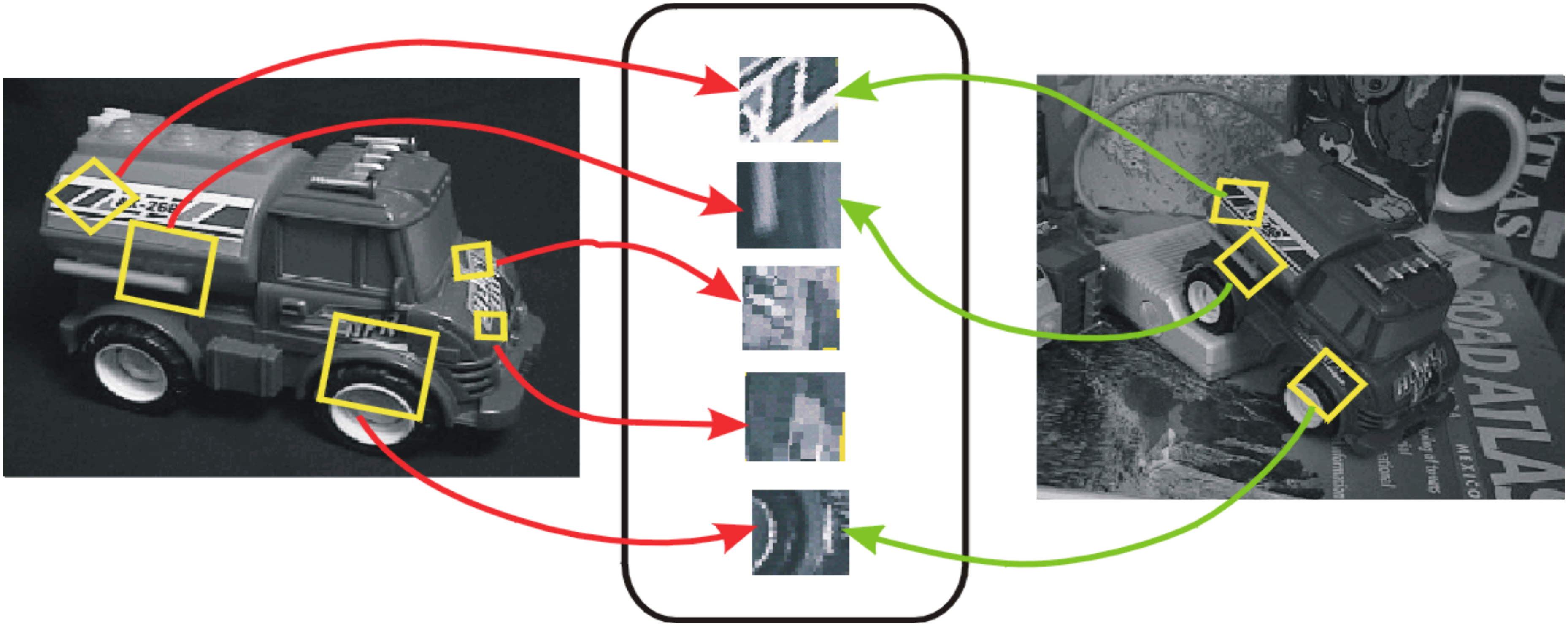
SIFT features

- 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: L. Lazebnik

From keypoint detection to feature description



Detection is *covariant*:

features(transform(image)) = transform(features(image))

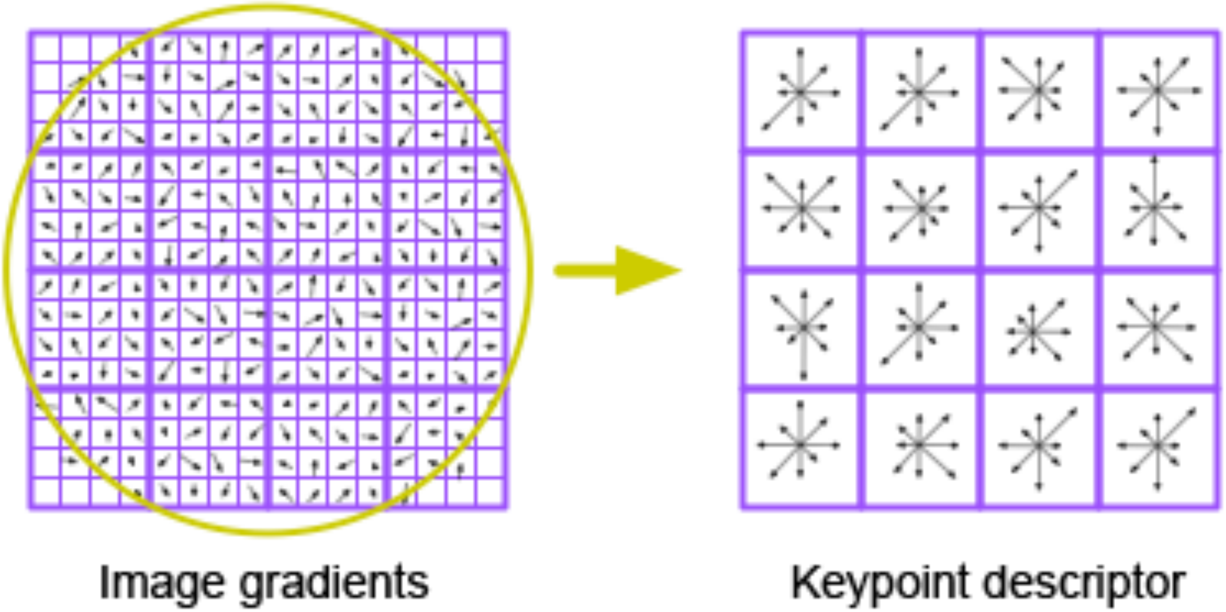
Description is *invariant*:

features(transform(image)) = features(image)

Source: L. 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: L. Lazebnik

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