CS5670: Computer Vision

Feature invariance

Reading

- Szeliski (first edition): 4.1

Announcements

- Project 1 code due tomorrow at 11:59pm
- Project 1 artifact due Monday, 3/1, at 11:59pm
- Project 2 (Feature Detection & Matching) will be out next week
  - To be done in groups of 2

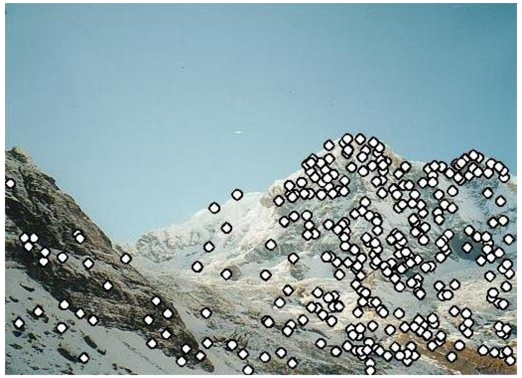
Panorama stitching

Panorama captured by Perseverence Rover, Feb. 20, 2021

https://www.space.com/nasa-perseverance-rover-first-panorama-mars

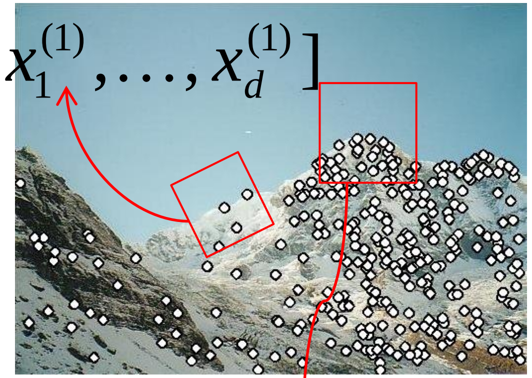
Local features: main components

1) **Detection**: Identify the interest points



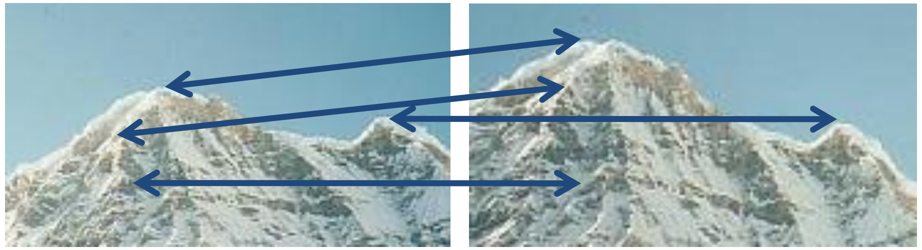
2) **Description**: Extract vector feature descriptor surrounding each interest point.

$$\mathbf{x}_1 = [x_1^{(1)}, \ldots, x_d^{(1)}]$$



$$\mathbf{x}_2 = [x_1^{(2)}, \ldots, x_d^{(2)}]$$

3) **Matching**: Determine correspondence between descriptors in two views



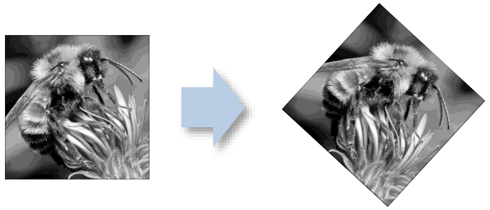
Kristen Grauman

Harris features (in red)

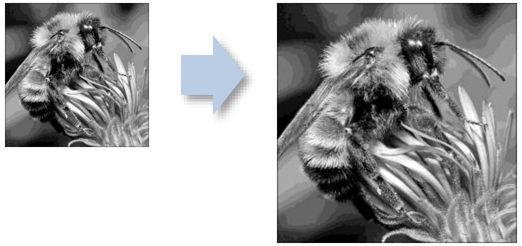
Image transformations

- Geometric

Rotation

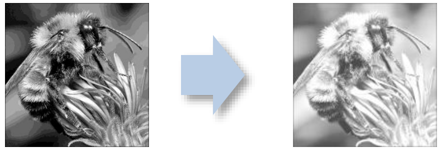


Scale



- Photometric

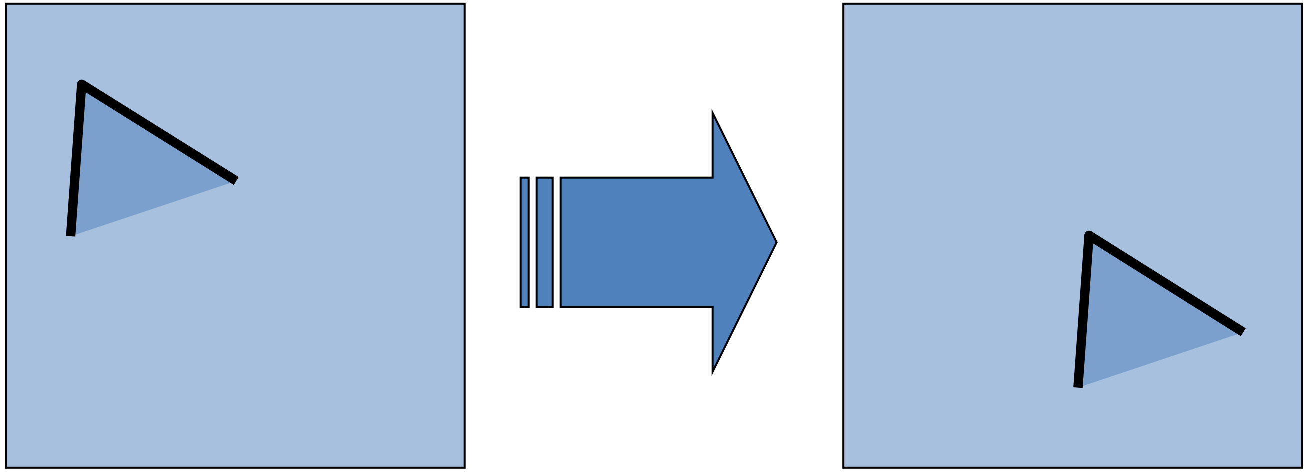
Intensity change



Invariance and equivariance

- We want corner locations to be *invariant* to photometric transformations and *equivariant* to geometric transformations
  - **Invariance:** image is transformed and corner locations do not change
  - **Equivariance:** if we have two transformed versions of the same image, features should be detected in corresponding locations
  - (Sometimes “invariant” and “equivariant” are both referred to as “invariant”)
  - (Sometimes “equivariant” is called “covariant”)

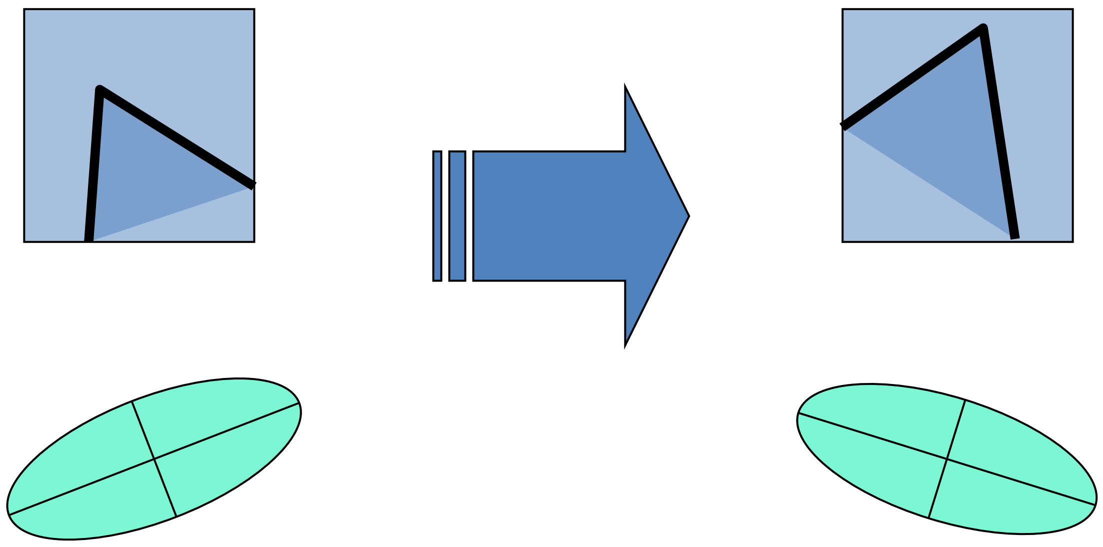
Harris detector invariance properties: image translation



- Derivatives and window function are equivariant

Corner location is equivariant w.r.t. translation

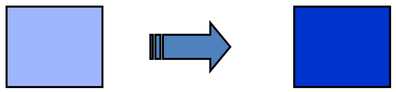
Harris detector invariance properties: image rotation



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

Corner location is equivariant w.r.t. image rotation

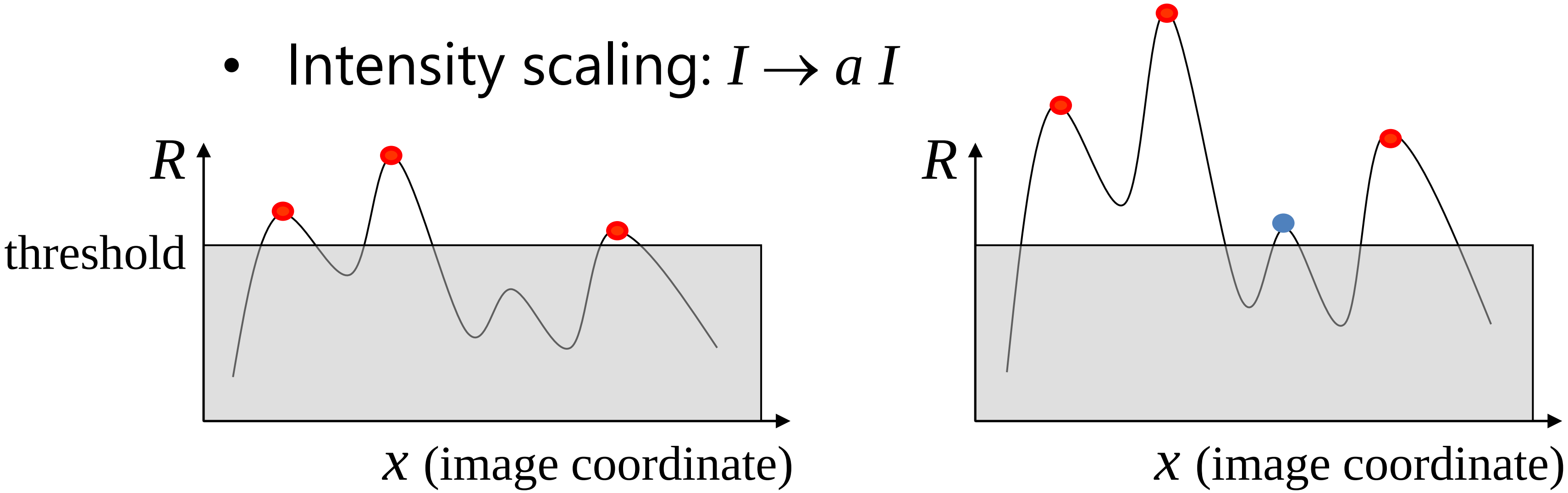
Harris detector invariance properties: Affine intensity change



$I \rightarrow a\,I + b$

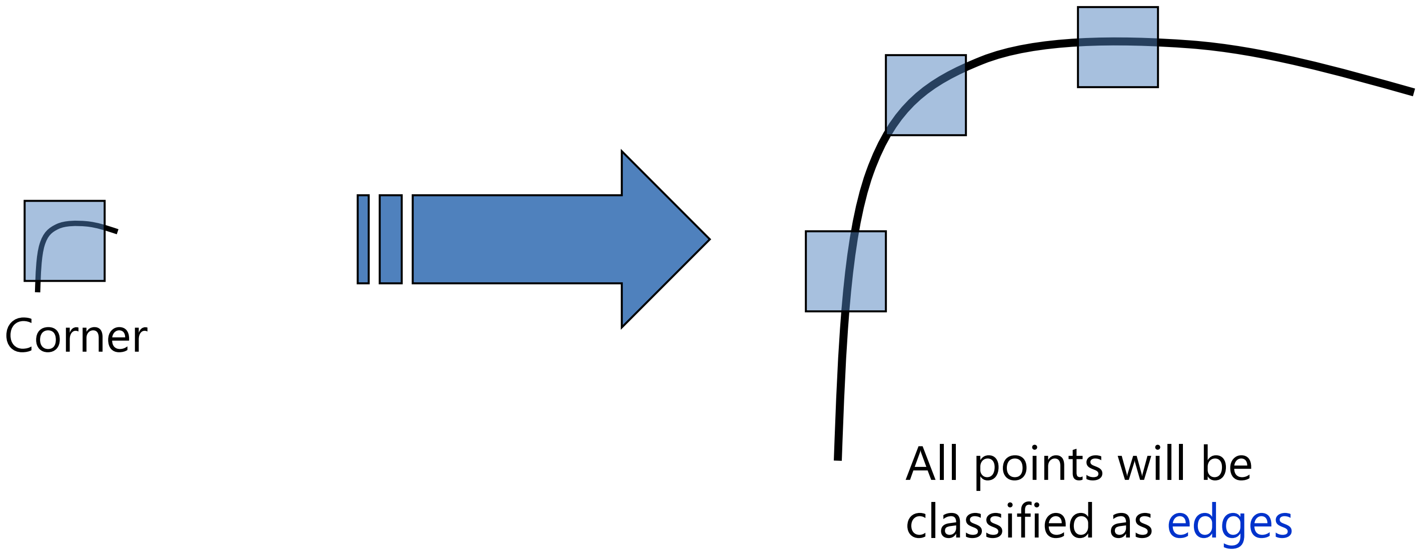
- Only derivatives are used → invariance to intensity shift $I \rightarrow I + b$

- Intensity scaling: $I \rightarrow a\,I$



Partially invariant to affine intensity change

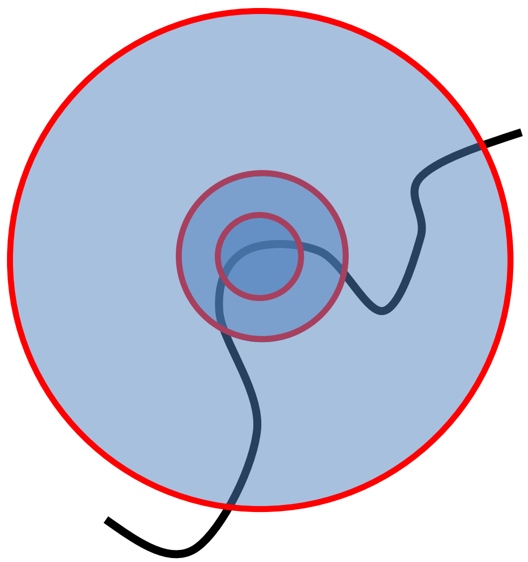
Harris detector invariance properties: scaling



Neither invariant nor equivariant to scaling

Scale invariant detection

Suppose you're looking for corners

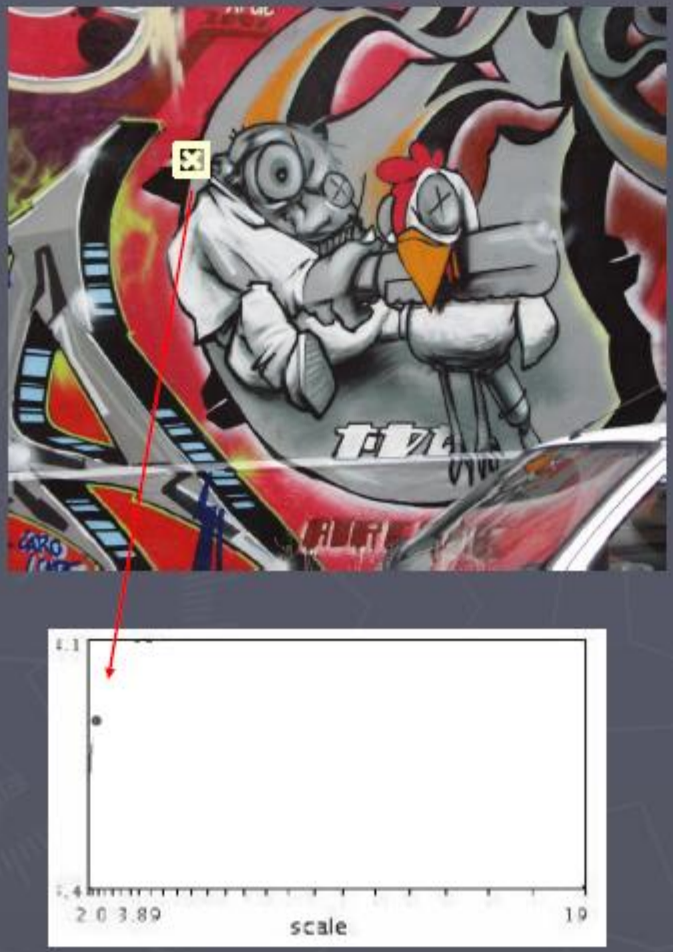


Key idea: find scale that gives local maximum of f

- in both position and scale
- One definition of f: the Harris operator

Automatic scale selection

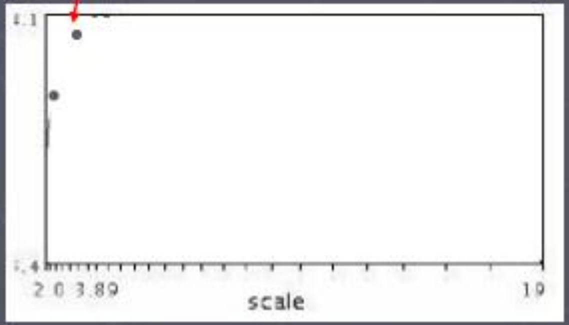
Lindeberg et al., 1996



$f(I_{i_1 \ldots i_m}(x,\sigma))$

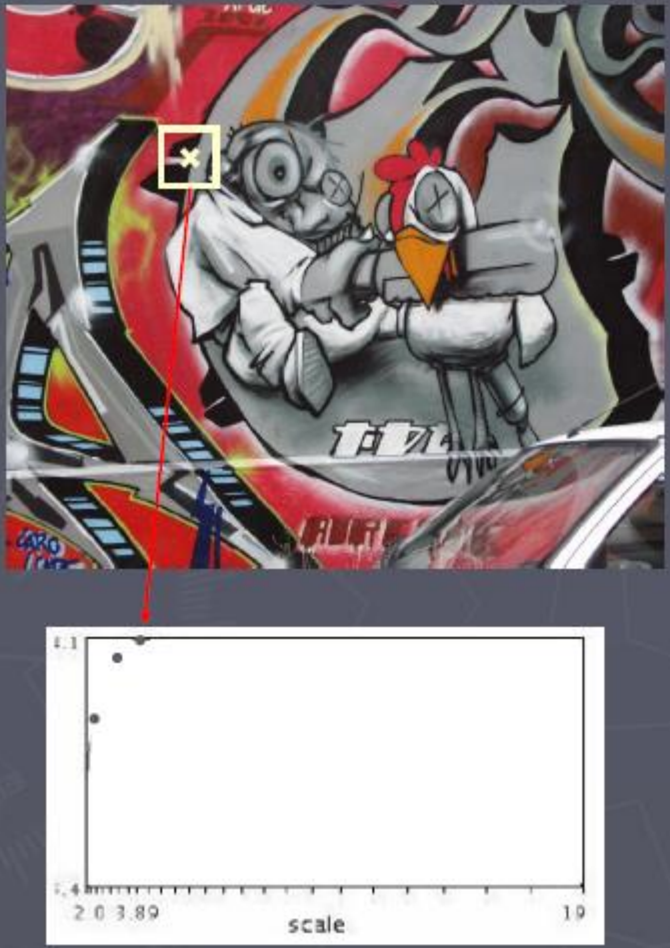
Slide from Tinne Tuytelaars

Automatic scale selection



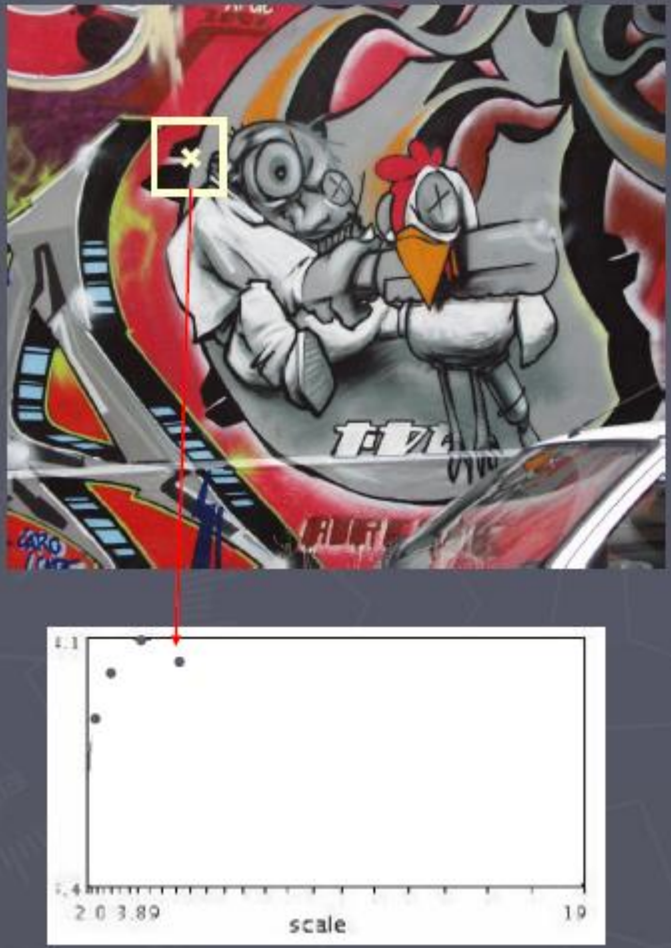
$f(I_{i_1 \dots i_m}(x,\sigma))$

Automatic scale selection



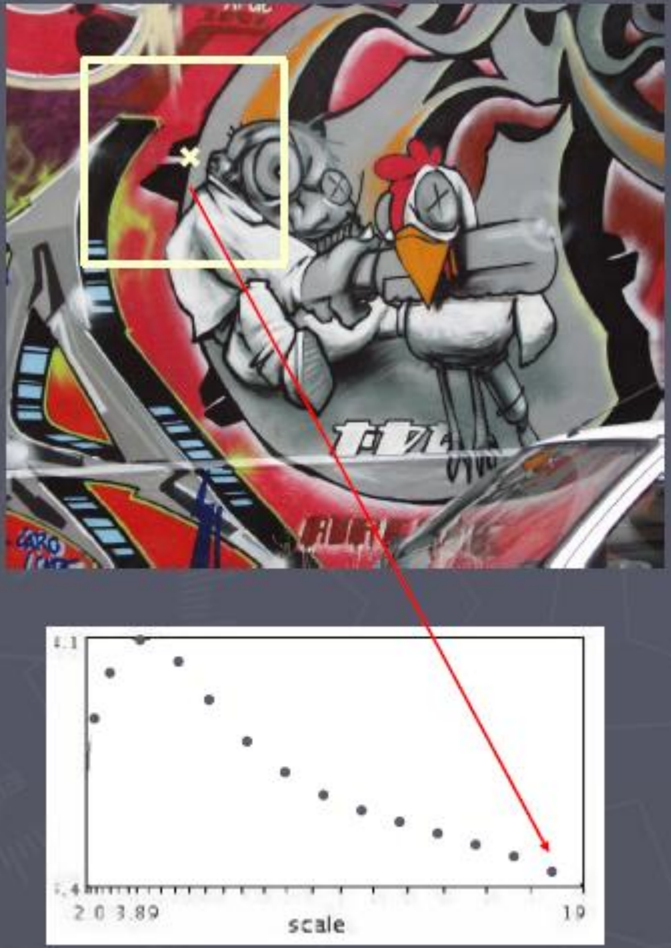
$$f(I_{i_1 \ldots i_m}(x,\sigma))$$

Automatic scale selection



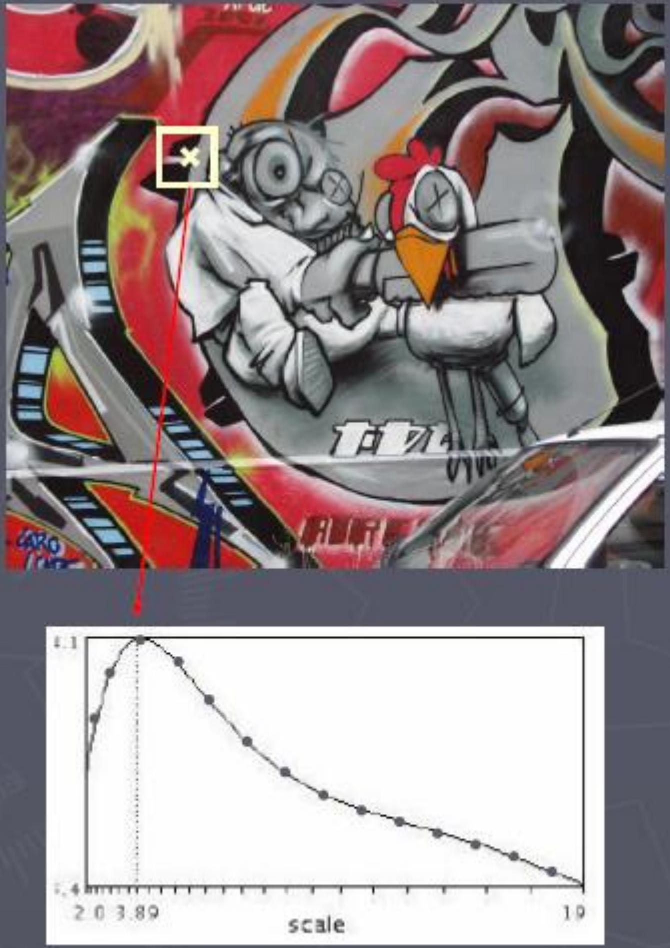
$$f(I_{i_1 \ldots i_m}(x,\sigma))$$

Automatic scale selection



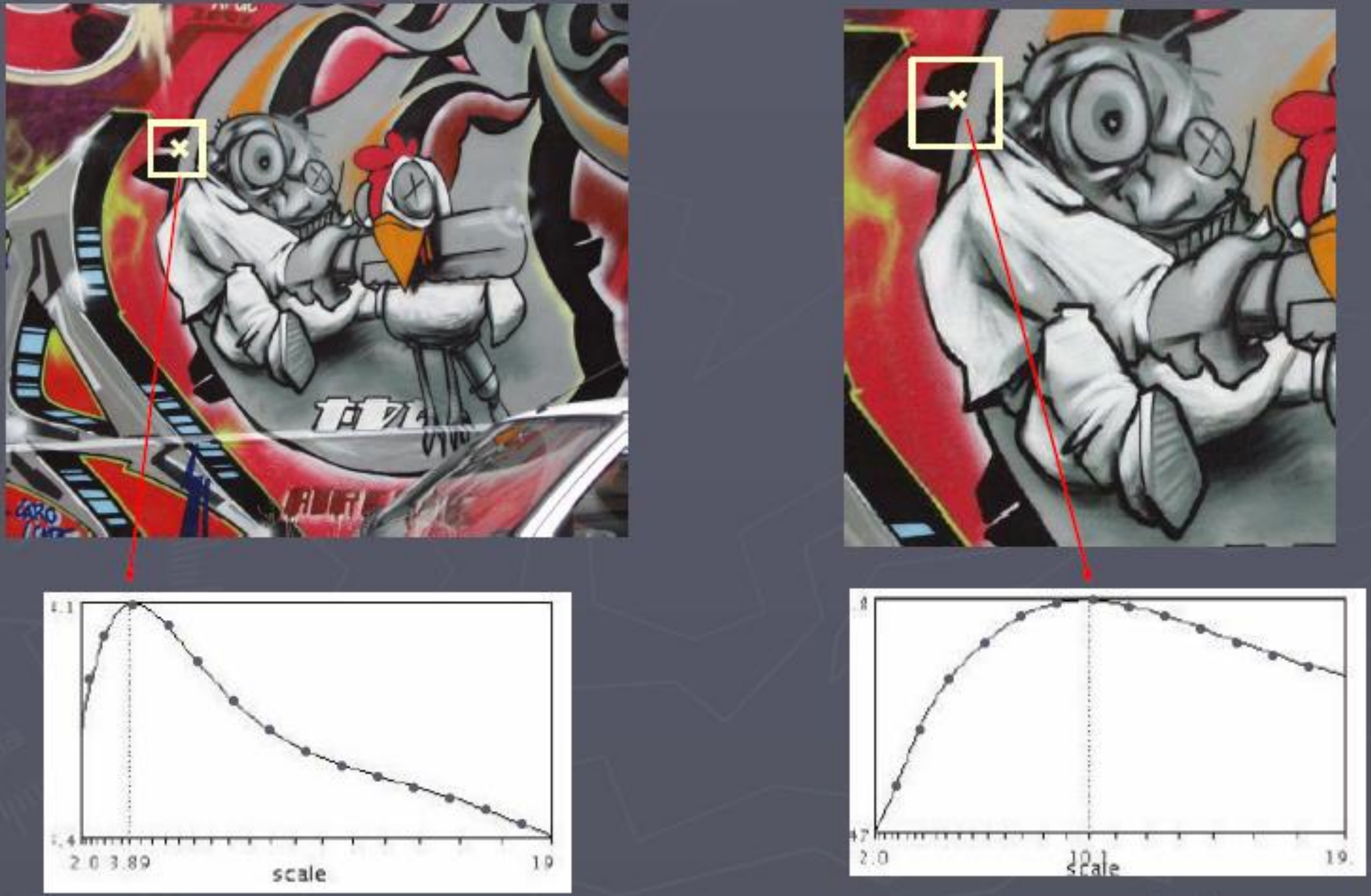
$f(I_{i_1 \ldots i_m}(x,\sigma))$

Automatic scale selection



$$f(I_{i_1 \ldots i_m}(x,\sigma))$$

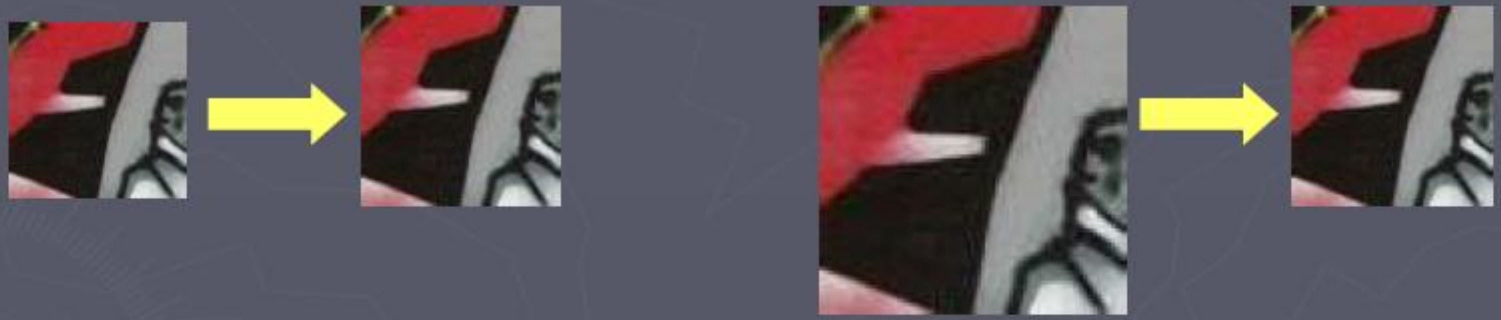
Automatic scale selection



$f(I_{i_1 \ldots i_m}(x,\sigma))$ $f(I_{i_1 \ldots i_m}(x',\sigma'))$

Automatic scale selection

Normalize: rescale to fixed size

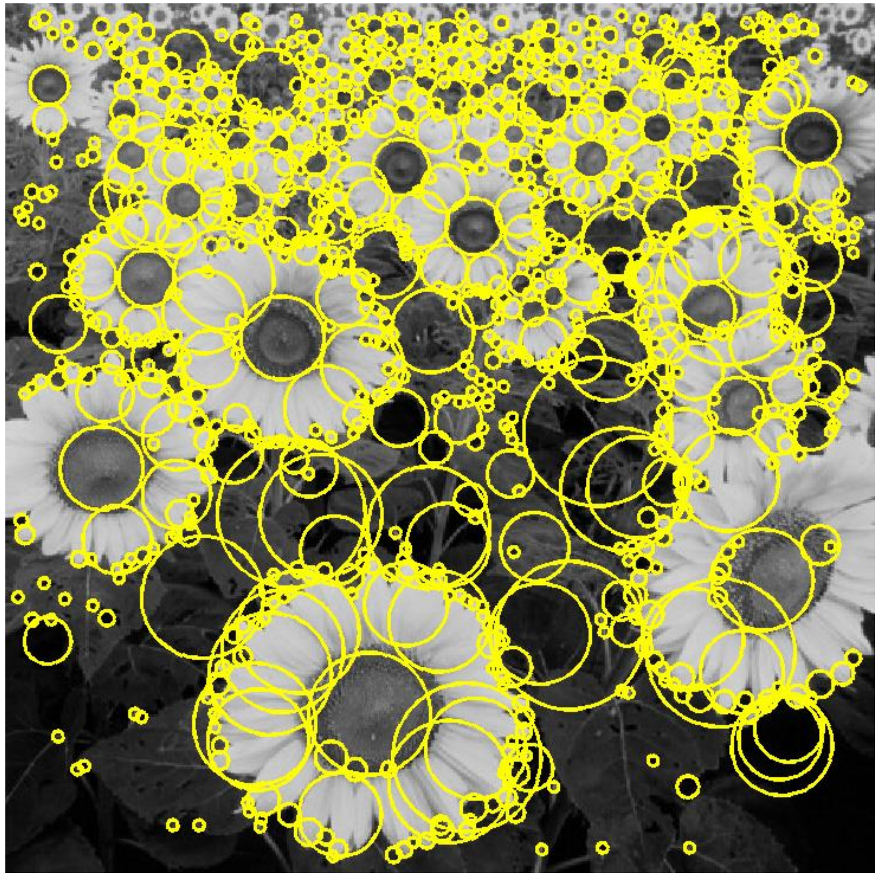


Implementation

- Instead of computing *f* for larger and larger windows, we can implement using a fixed window size with a Gaussian pyramid

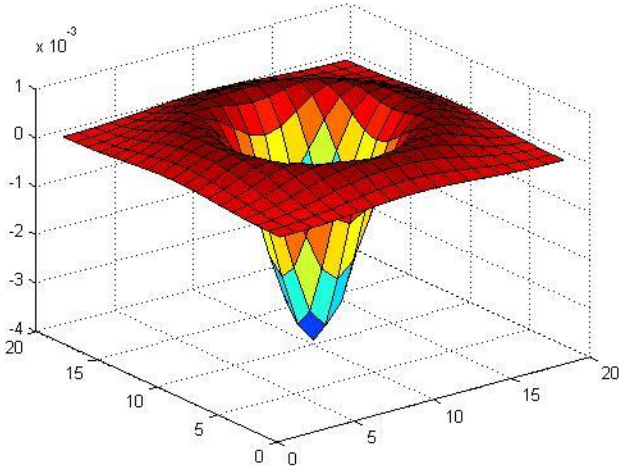
(sometimes need to create in-between levels, e.g. a ¾-size image)

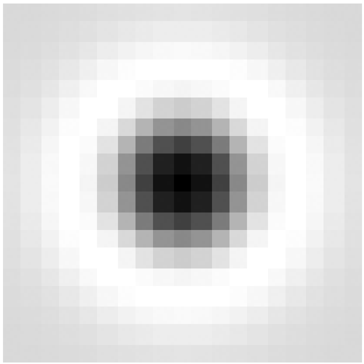
Feature extraction: Corners and blobs



Another common definition of *f*

- The *Laplacian of Gaussian* (*LoG*)



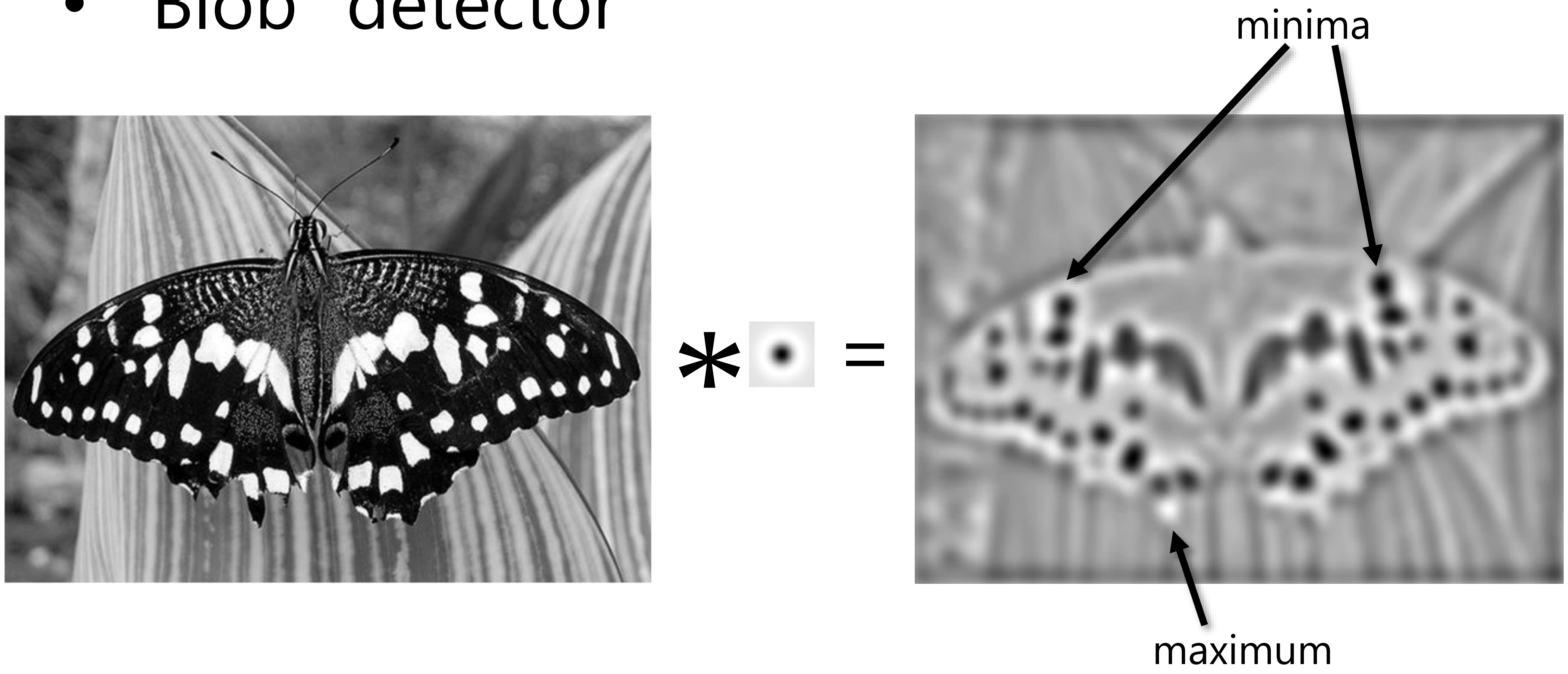


$$\nabla^2 g = \frac{\partial^2 g}{\partial x^2} + \frac{\partial^2 g}{\partial y^2}$$

(very similar to a Difference of Gaussians (DoG) – i.e. a Gaussian minus a slightly smaller Gaussian)

Laplacian of Gaussian

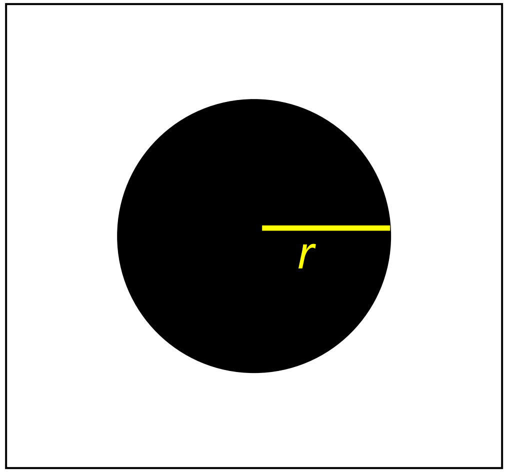
- "Blob" detector



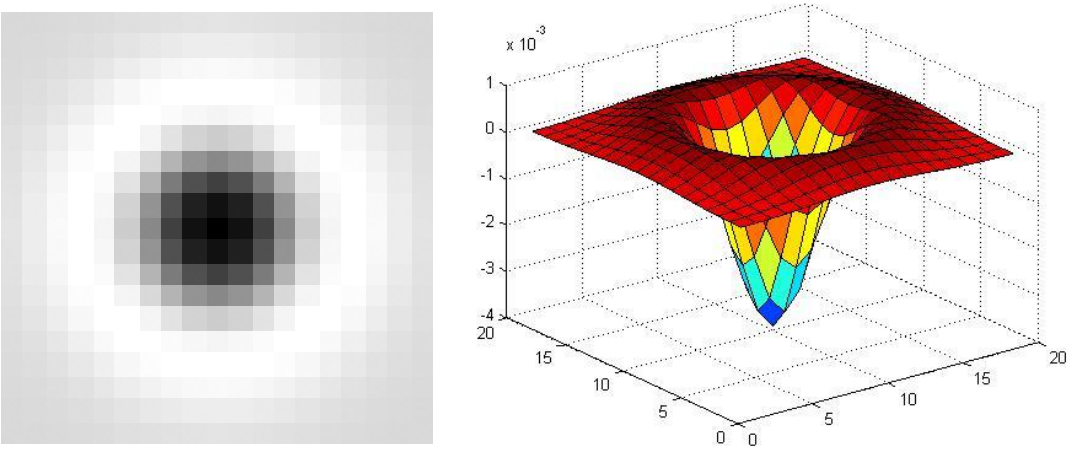
- Find maxima *and minima* of LoG operator in space and scale

Scale selection

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



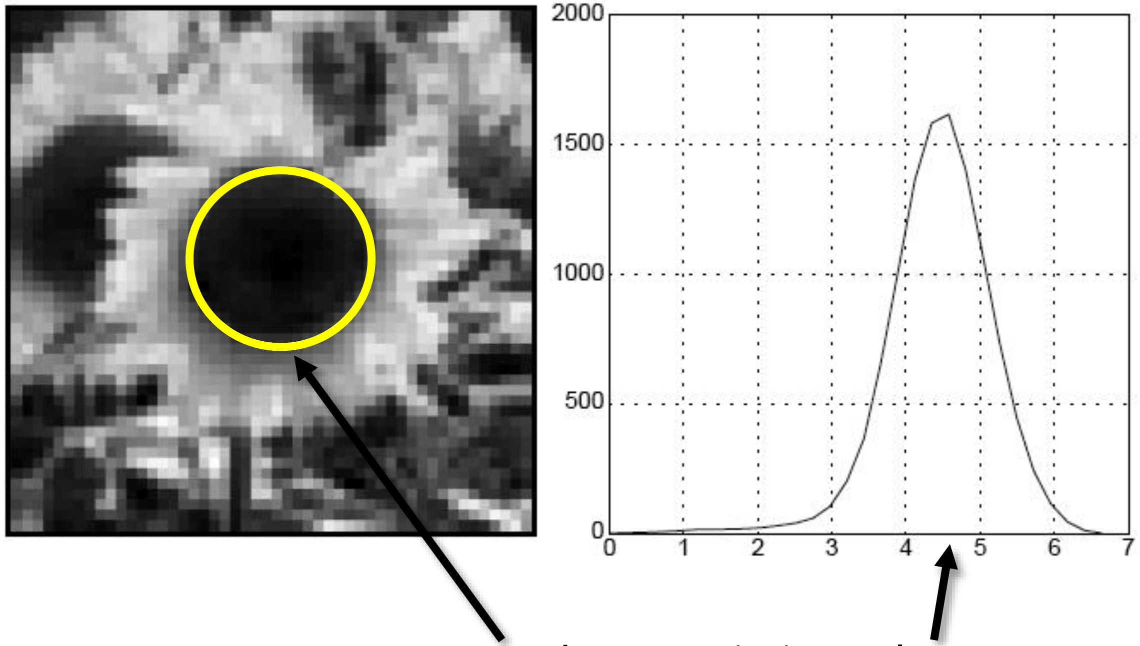
image



Laplacian

Characteristic scale

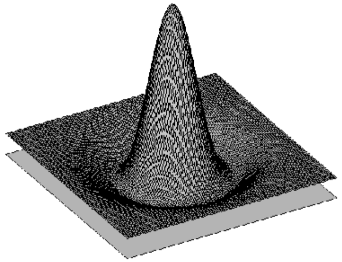
- We define the characteristic scale as the scale that produces peak of Laplacian response



characteristic scale

T. Lindeberg (1998). ["Feature detection with automatic scale selection."]() *International Journal of Computer Vision* **30** (2): pp 77--116.

Find local maxima in 3D position-scale space



$$L_{xx}(\sigma) + L_{yy}(\sigma) \rightarrow$$

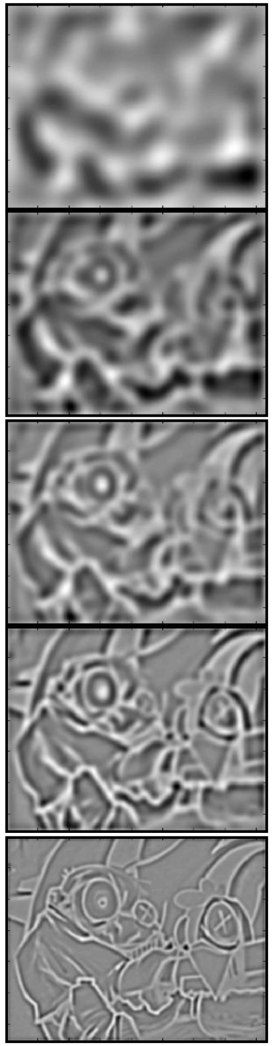
σ^5

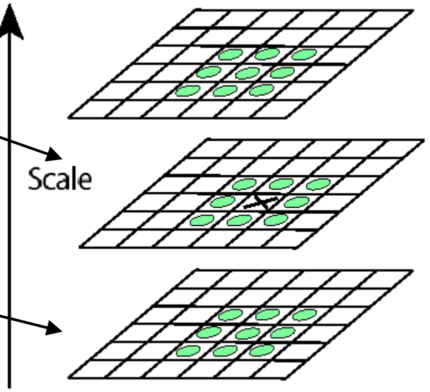
σ^4

σ^3

σ^2

σ





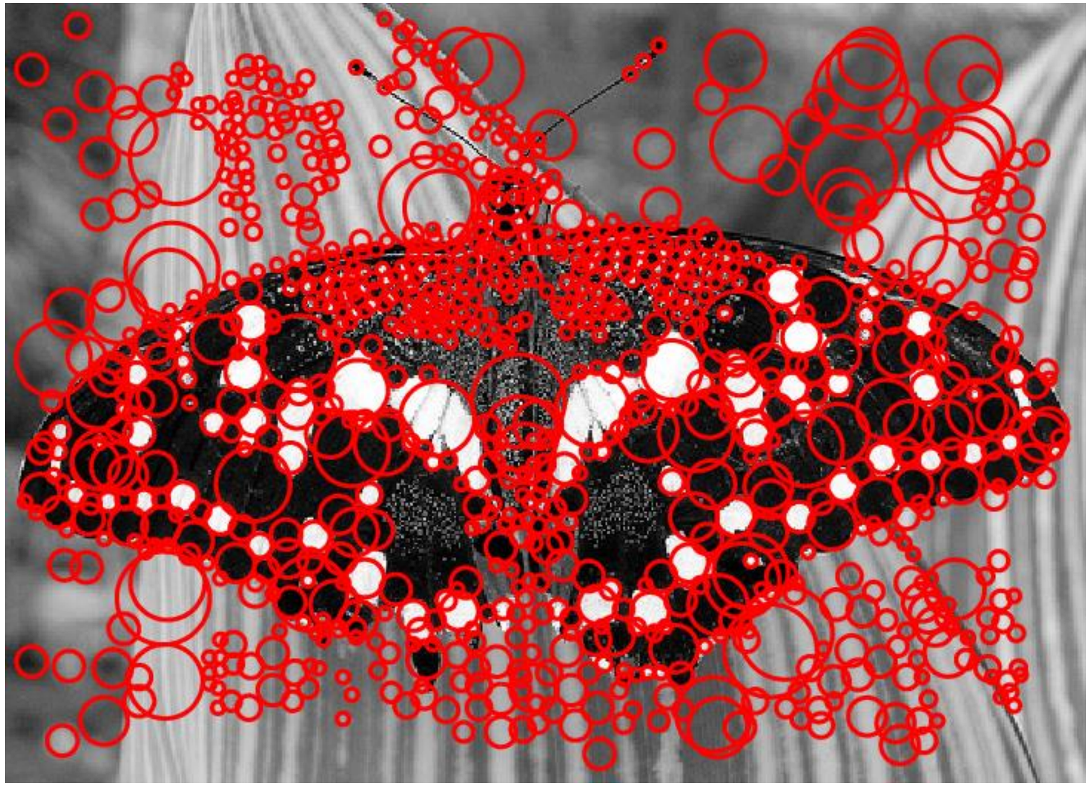
$\Rightarrow$ **List of**
(x, y, s)

Scale-space blob detector: Example

Scale-space blob detector: Example

sigma = 11.9912

Scale-space blob detector: Example



Scale Invariant Detection

- Functions for determining scale $f = \text{Kernel} * \text{Image}$

Kernels:

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

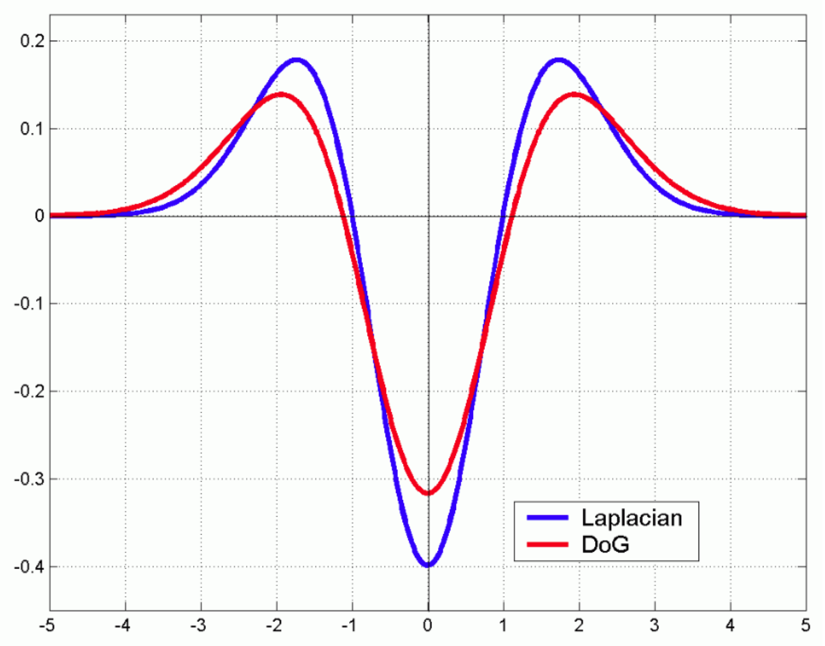
(Laplacian)

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

(Difference of Gaussians)

where Gaussian

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

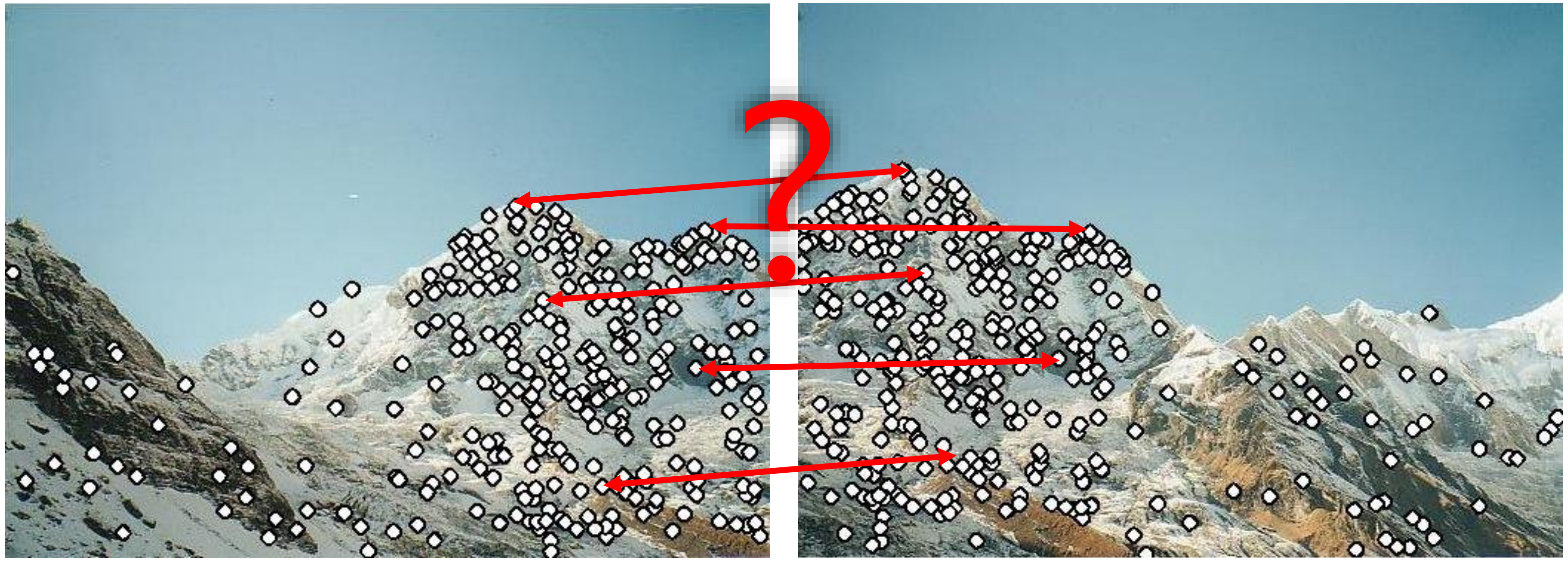


Note: The LoG and DoG operators are both rotation equivariant

Questions?

Feature descriptors

We know how to detect good points
Next question: **How to match them?**



Answer: Come up with a *descriptor* for each point, find similar descriptors between the two images