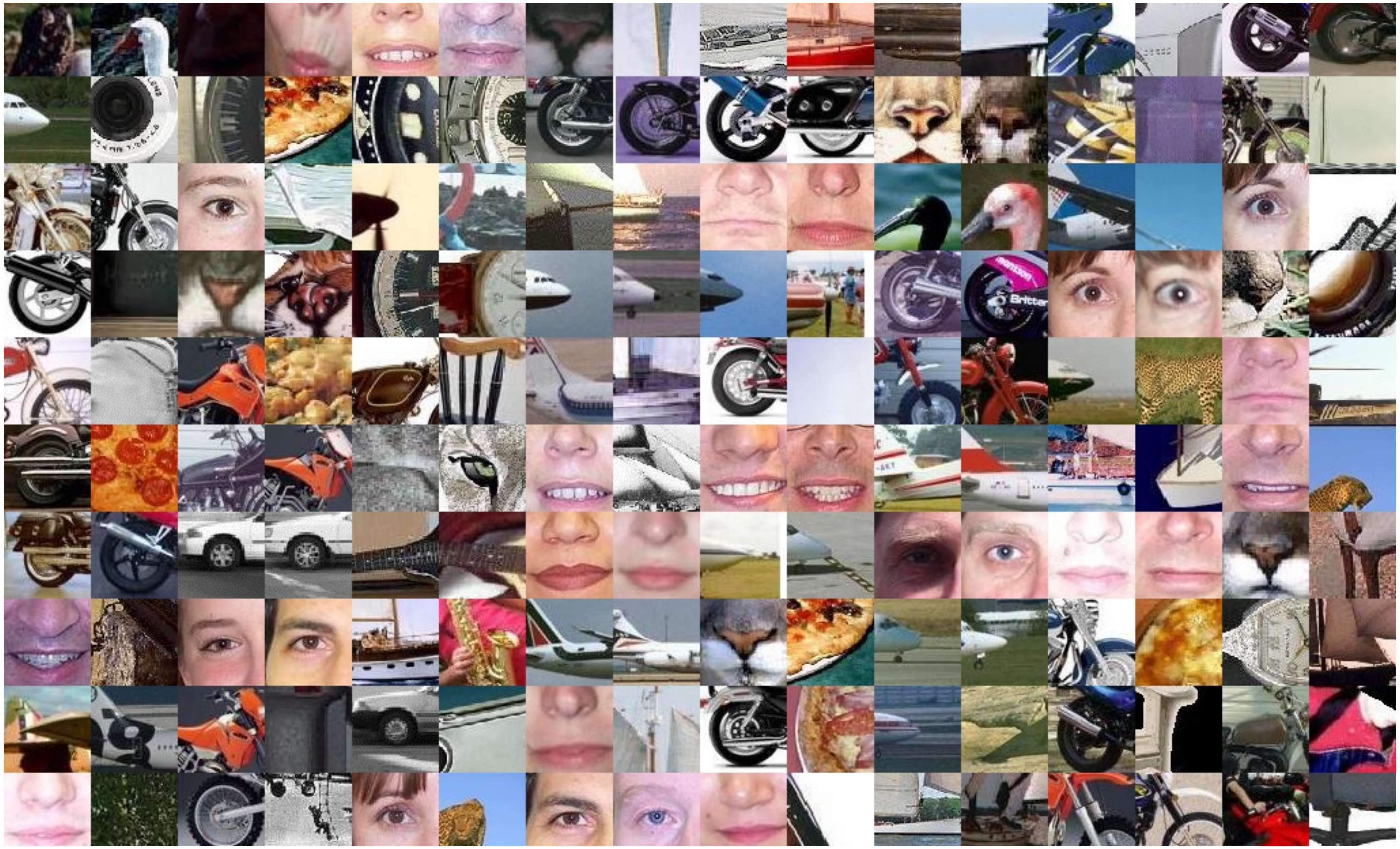
Feature detectors and descriptors



http://16385.courses.cs.cmu.edu/

16-385 Computer Vision
Spring 2022, Lecture 6

Overview of today's lecture

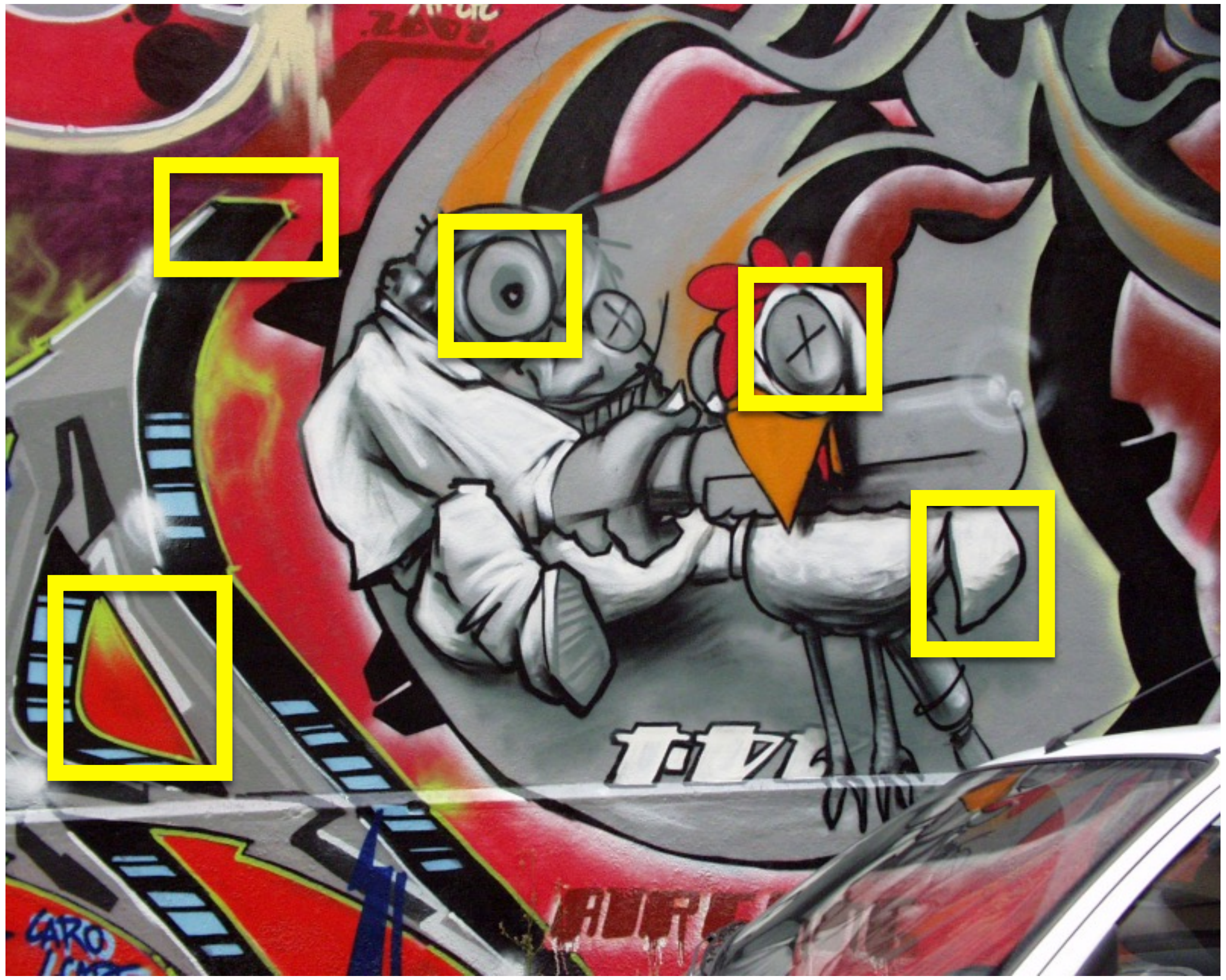
- Why do we need feature descriptors?
- Designing feature descriptors.
- MOPS descriptor.
- GIST descriptor.

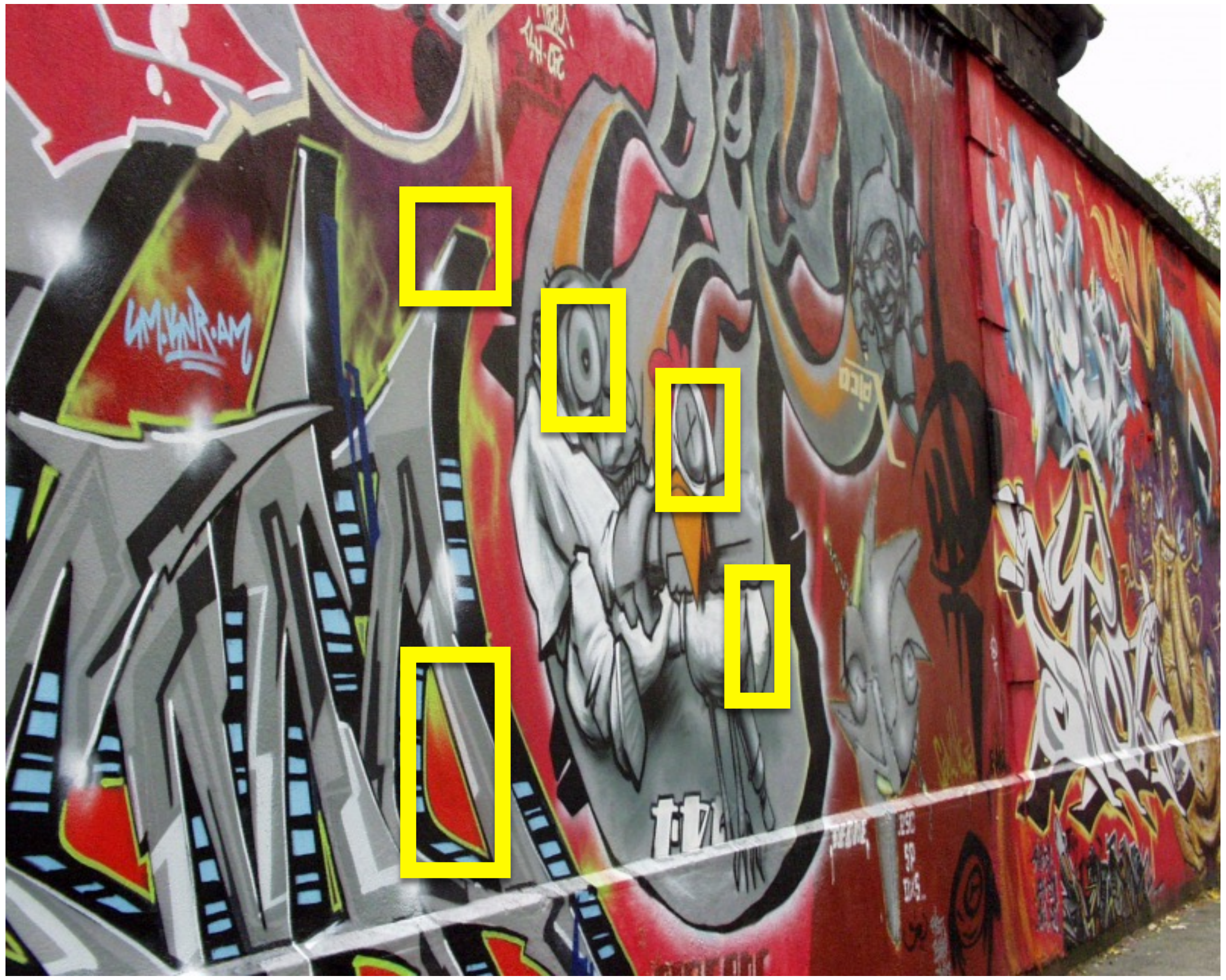
Slide credits

Most of these slides were adapted from:

- Kris Kitani (16-385, Spring 2017).

Why do we need feature descriptors?





If we know where the good features are,
how do we match them?

How do we describe an image patch?

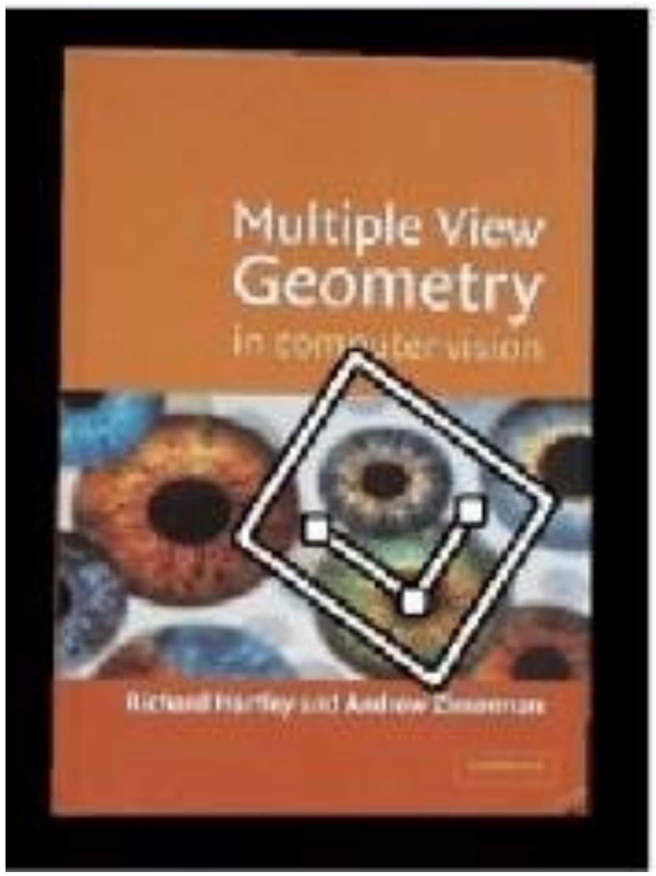
Patches with similar content should have similar descriptors.

Designing feature descriptors

What is the best descriptor for an image feature?

Photometric transformations

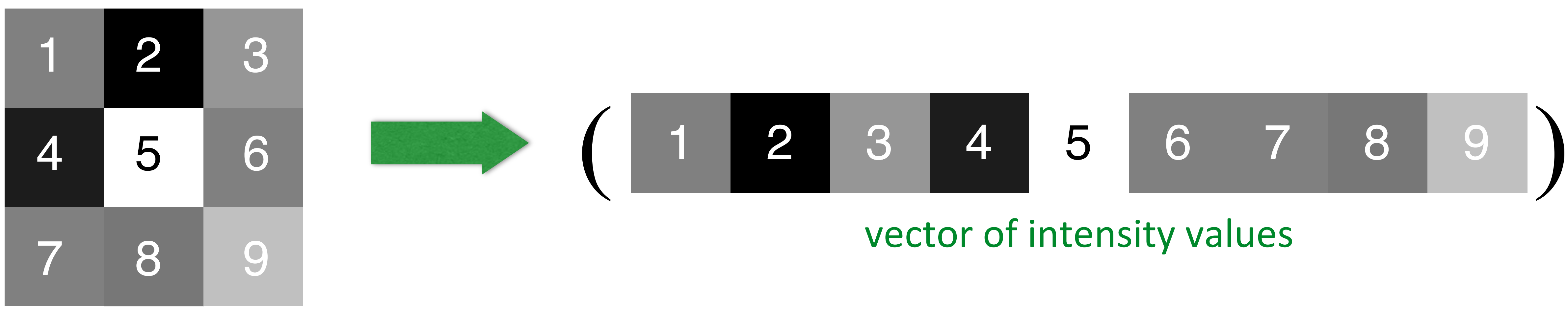
Geometric transformations



objects will appear at different scales,
translation and rotation

Image patch

Just use the pixel values of the patch!

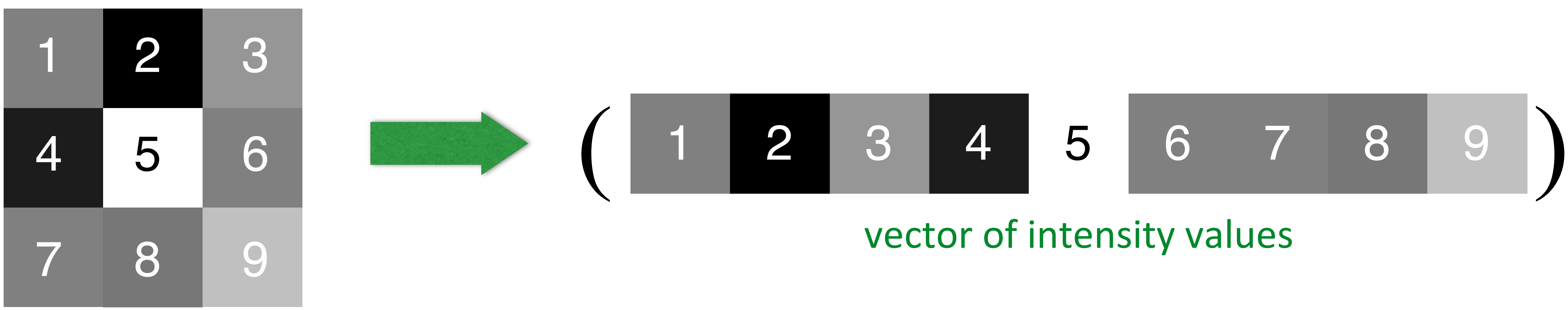


Perfectly fine if geometry and appearance is unchanged

(a.k.a. template matching)

Image patch

Just use the pixel values of the patch!



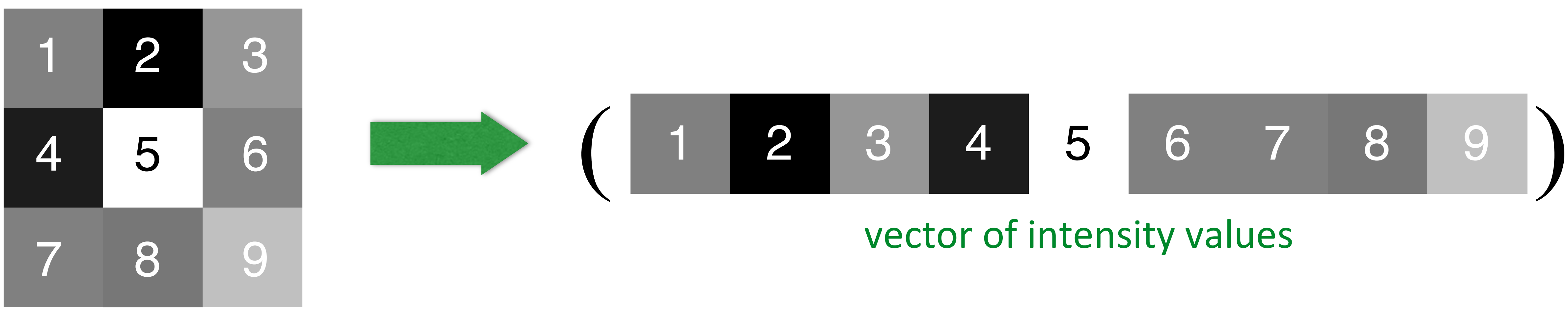
Perfectly fine if geometry and appearance is unchanged

(a.k.a. template matching)

What are the problems?

Image patch

Just use the pixel values of the patch!



Perfectly fine if geometry and appearance is unchanged

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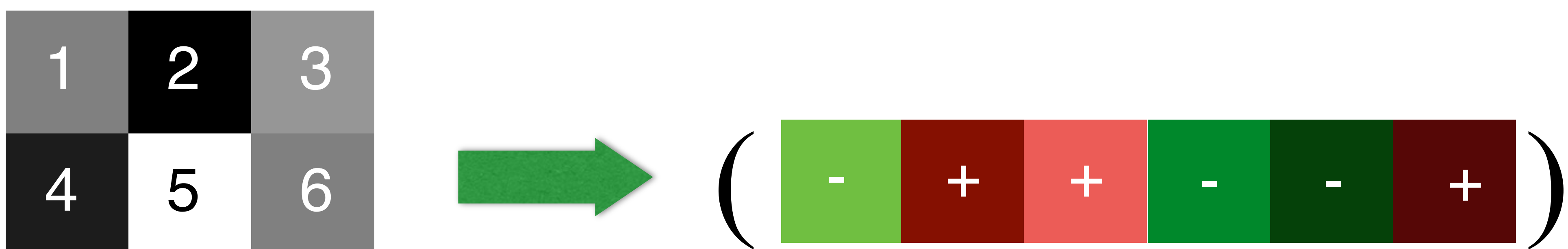
What are the problems?

How can you be less sensitive to absolute intensity values?

Image gradients

Use pixel differences



vector of x derivatives

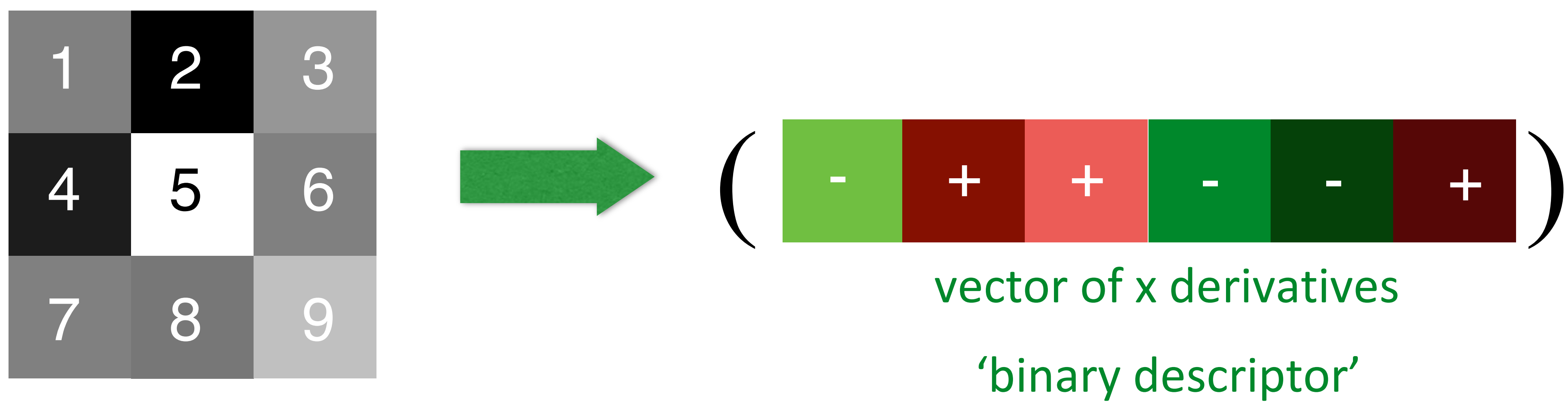
‘binary descriptor’

Feature is invariant to absolute intensity values

What are the problems?

Image gradients

Use pixel differences



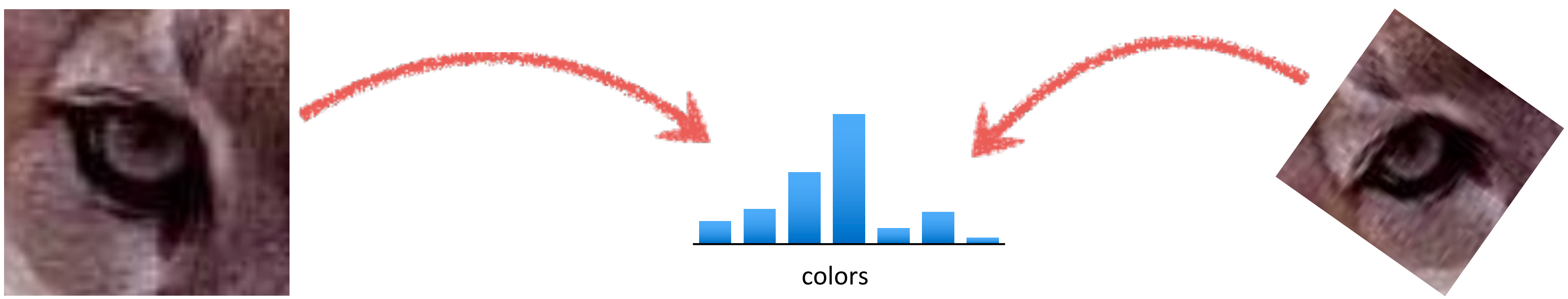
Feature is invariant to absolute intensity values

What are the problems?

How can you be less sensitive to deformations?

Color histogram

Count the colors in the image using a histogram

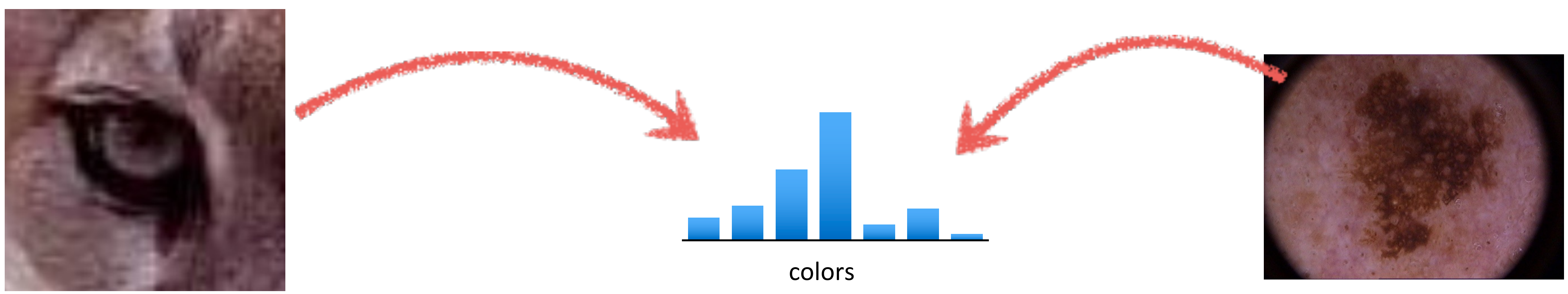


Invariant to changes in scale and rotation

What are the problems?

Color histogram

Count the colors in the image using a histogram



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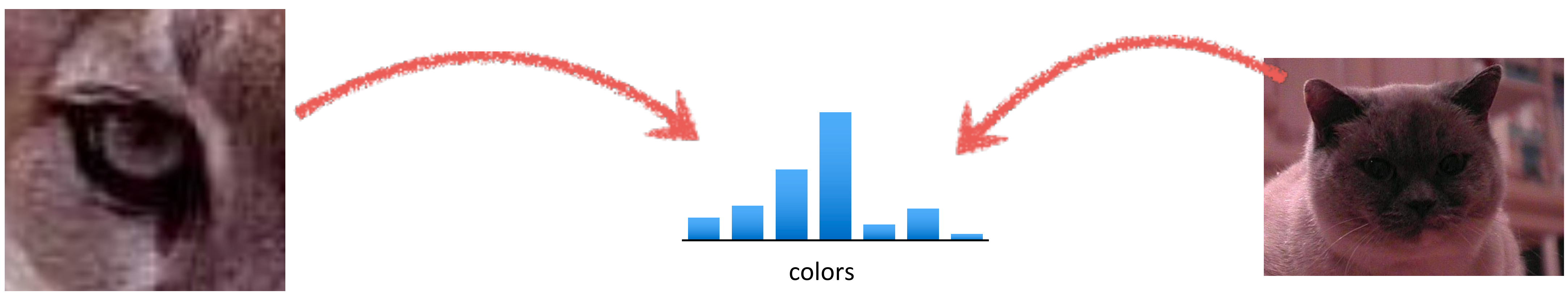


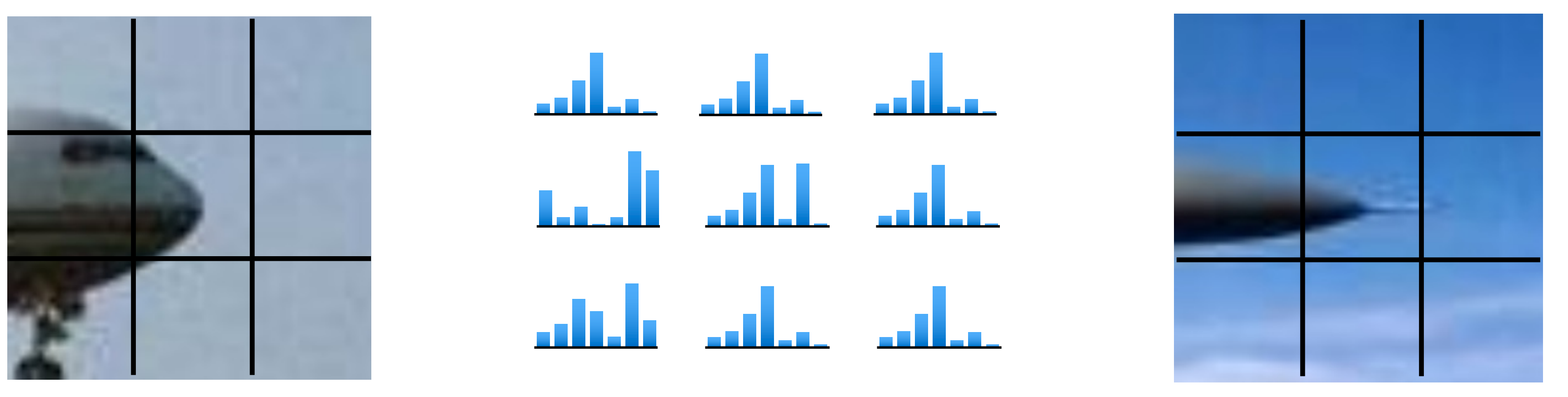
Invariant to changes in scale and rotation

What are the problems?

How can you be more sensitive to spatial layout?

Spatial histograms

Compute histograms over spatial ‘cells’



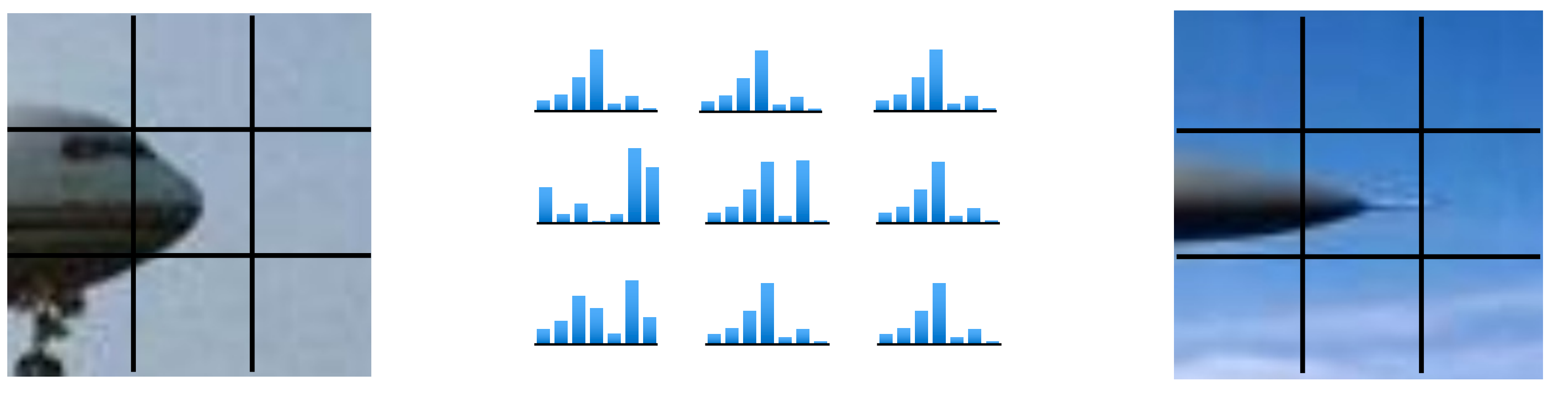
Retains rough spatial layout

Some invariance to deformations

What are the problems?

Spatial histograms

Compute histograms over spatial 'cells'



Retains rough spatial layout

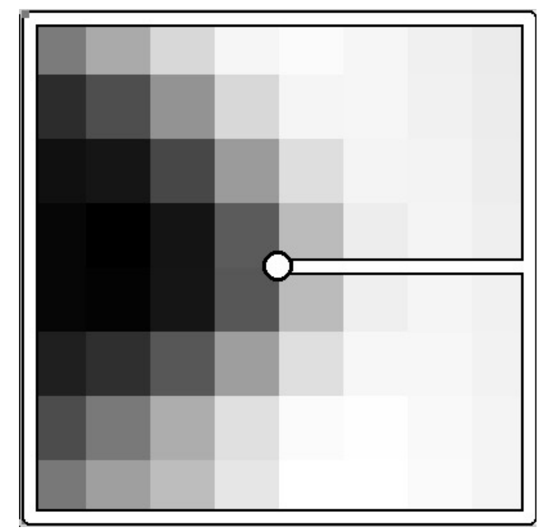
Some invariance to deformations

What are the problems?

How can you be completely invariant to rotation?

Orientation normalization

Use the dominant image gradient direction to normalize the orientation of the patch

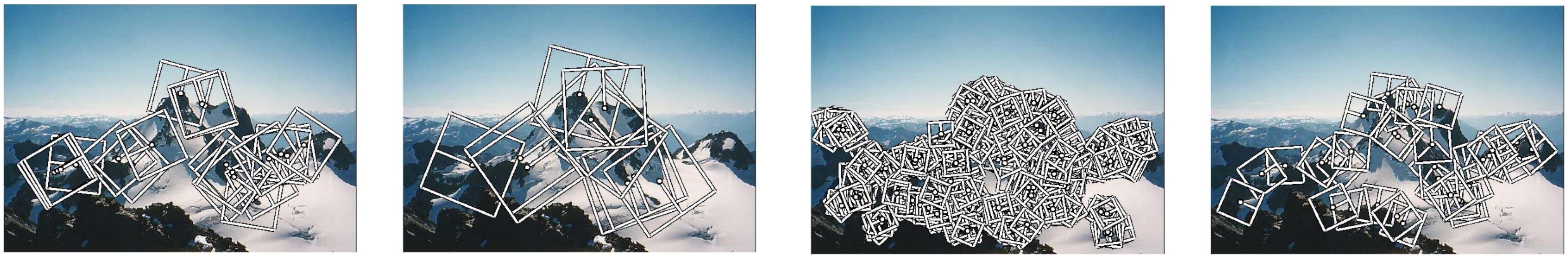


save the orientation angle θ along with (x, y, s)

MOPS descriptor

Multi-Scale Oriented Patches (MOPS)

Multi-Image Matching using Multi-Scale Oriented Patches. M. Brown, R. Szeliski and S. Winder. International Conference on Computer Vision and Pattern Recognition (CVPR2005). pages 510-517

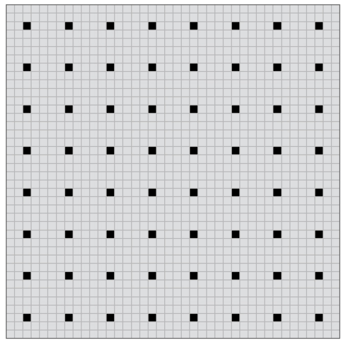


Multi-Scale Oriented Patches (MOPS)

Multi-Image Matching using Multi-Scale Oriented Patches. M. Brown, R. Szeliski and S. Winder.
International Conference on Computer Vision and Pattern Recognition (CVPR2005). pages 510-517

Given a feature (x, y, s, θ)

Get 40 x 40 image patch, subsample every 5th pixel
(*what's the purpose of this step?*)



Subtract the mean, divide by standard deviation
(*what's the purpose of this step?*)

Haar Wavelet Transform
(*what's the purpose of this step?*)

Multi-Scale Oriented Patches (MOPS)

Multi-Image Matching using Multi-Scale Oriented Patches. M. Brown, R. Szeliski and S. Winder.
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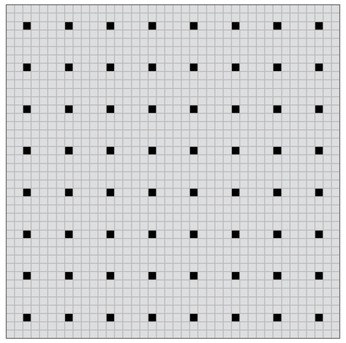
Given a feature (x, y, s, θ)

Get 40 x 40 image patch, subsample every 5th pixel

(low frequency filtering, absorbs localization errors)



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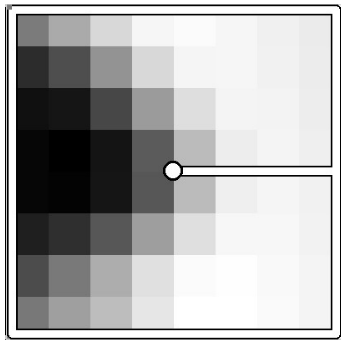

Haar Wavelet Transform

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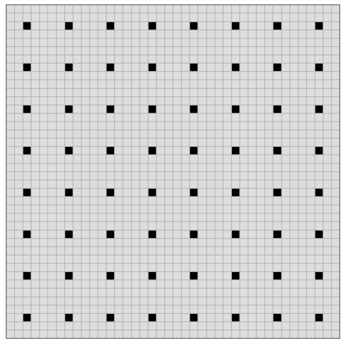
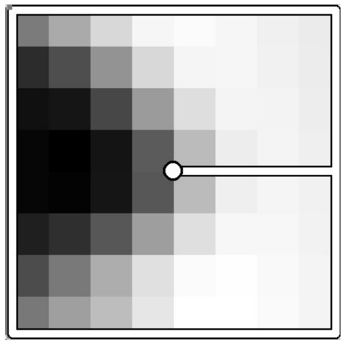


Subtract the mean, divide by standard deviation

(removes bias and gain)



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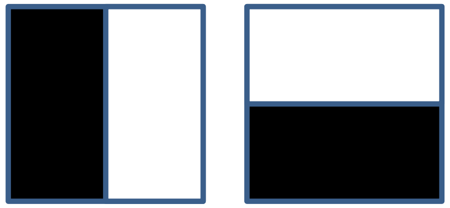

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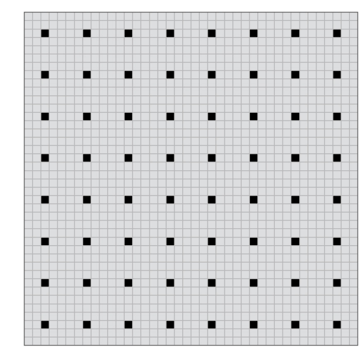

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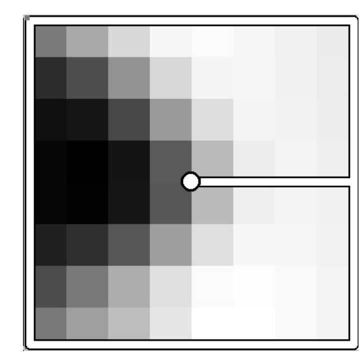
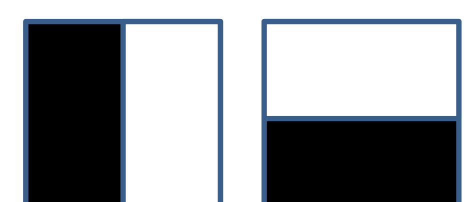


Haar Wavelet Transform

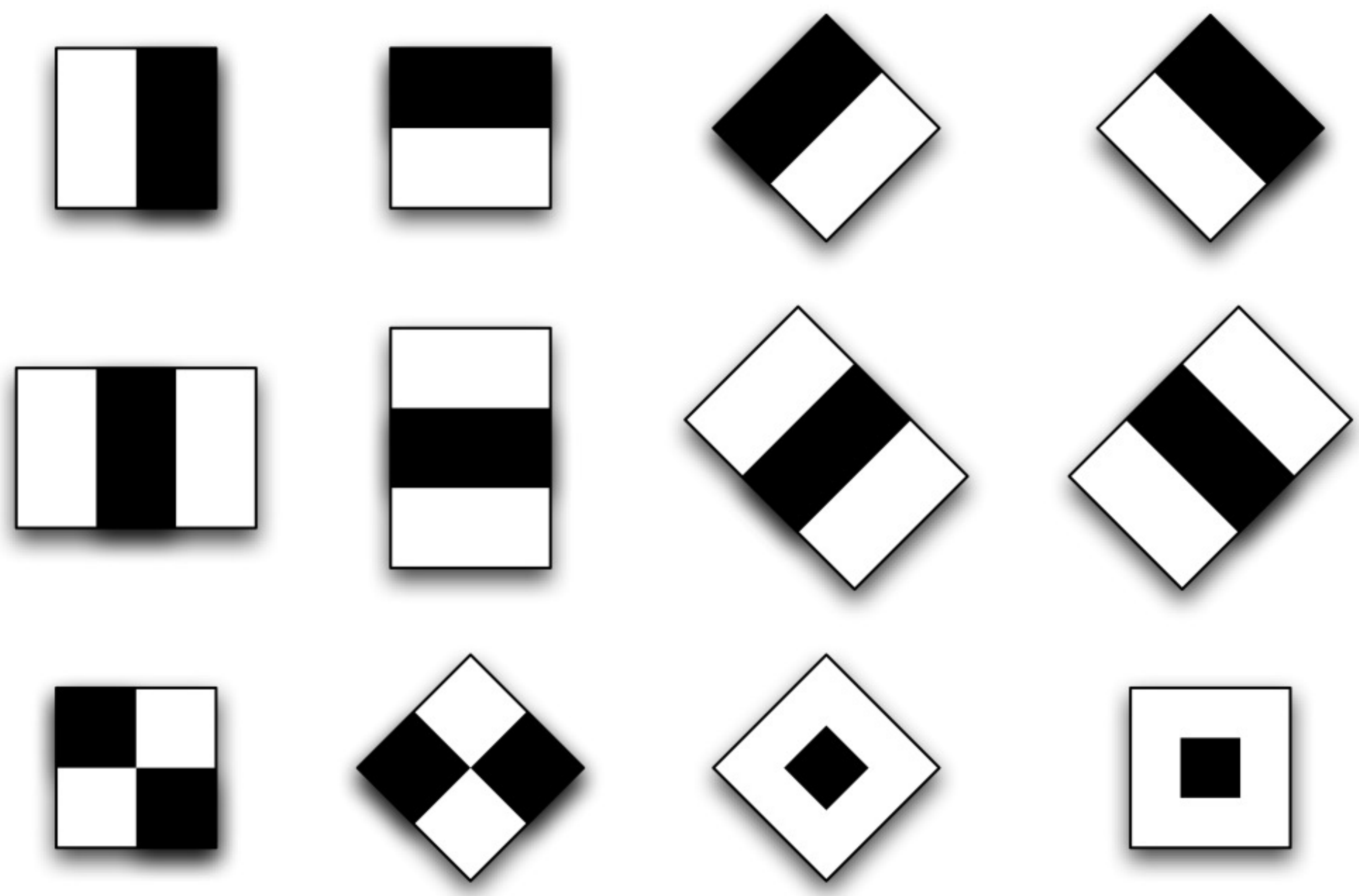
(low frequency projection)



Haar Wavelets

(actually, Haar-like features)

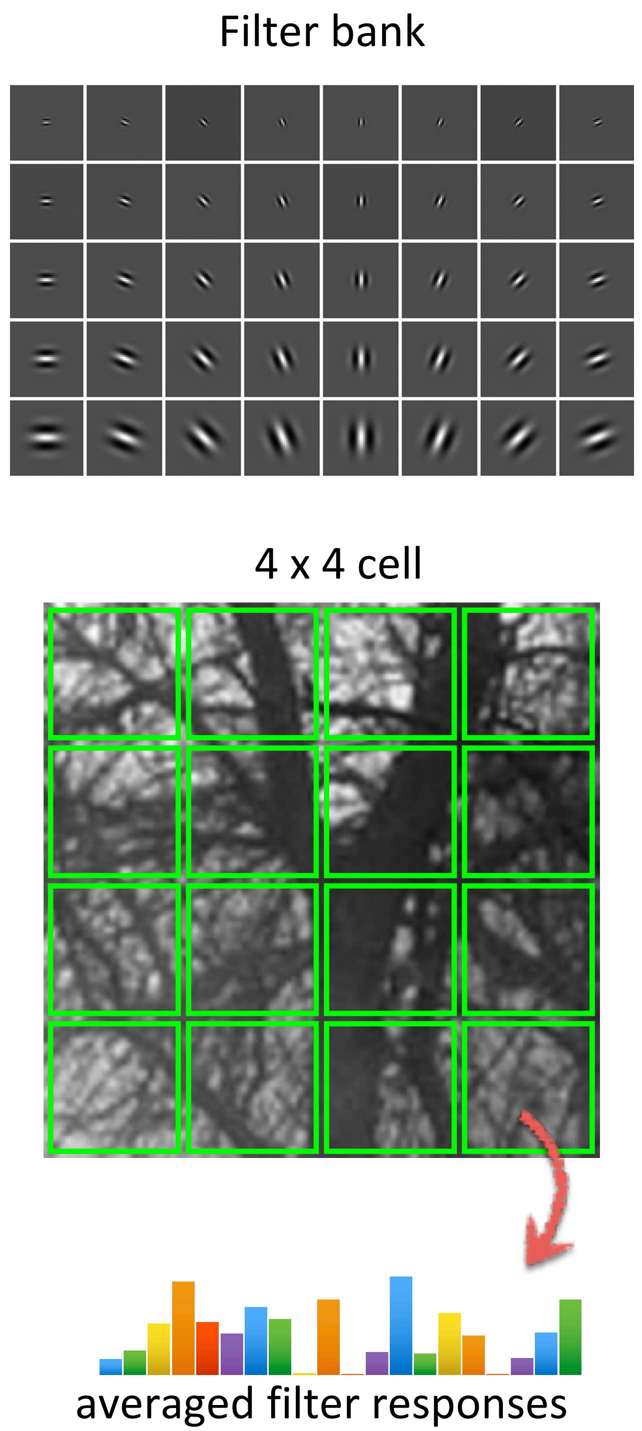
Use responses of a bank of filters as a descriptor



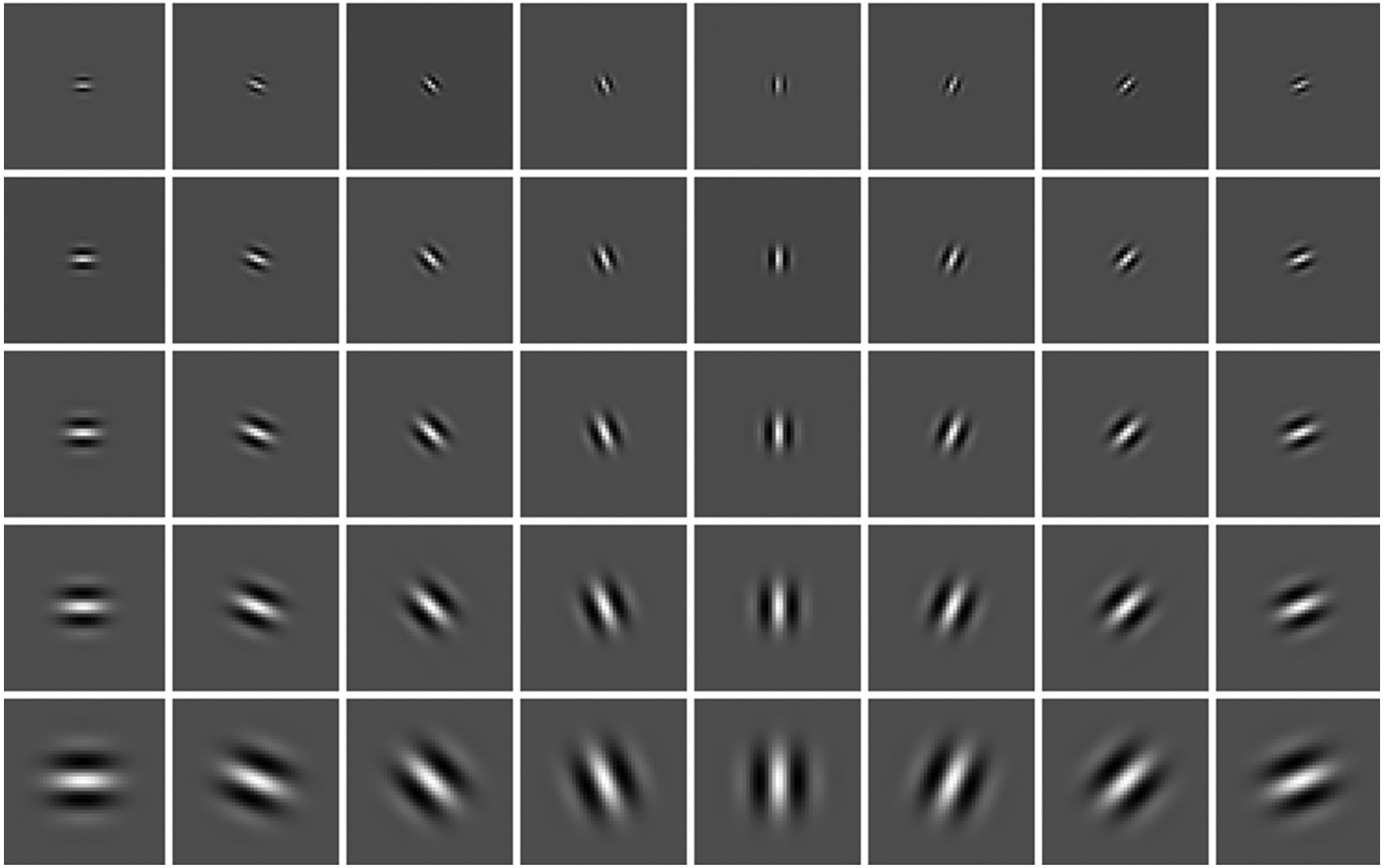
GIST descriptor

GIST

1. Compute filter responses (filter bank of Gabor filters)
2. Divide image patch into 4 x 4 cells
3. Compute filter response averages for each cell
4. Size of descriptor is 4 x 4 x N, where N is the size of the filter bank

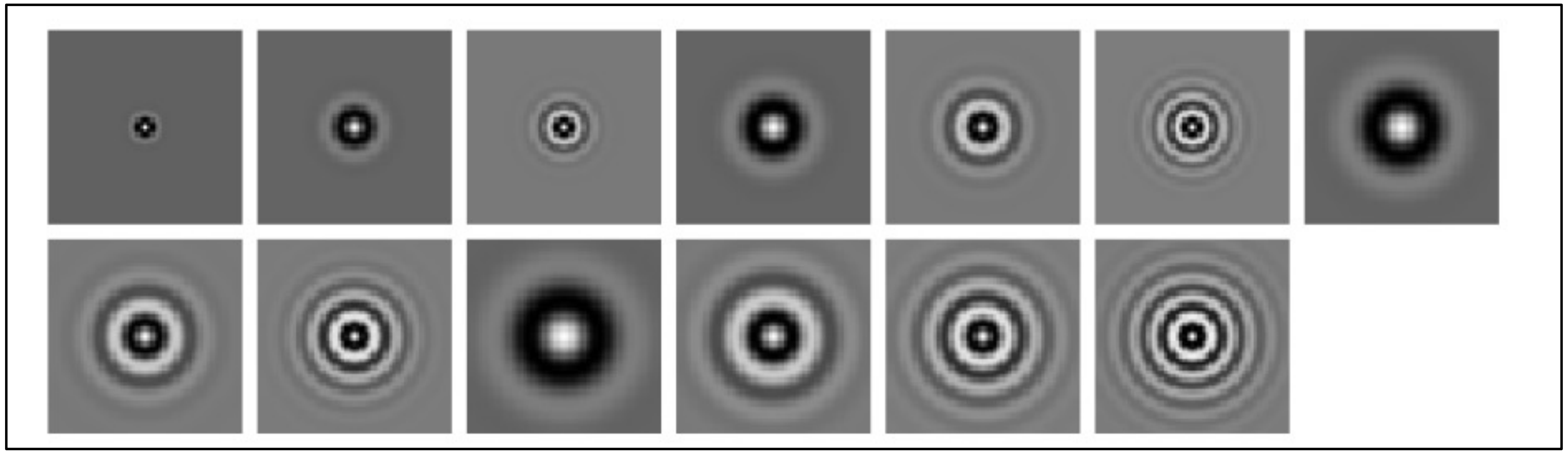


Directional edge detectors



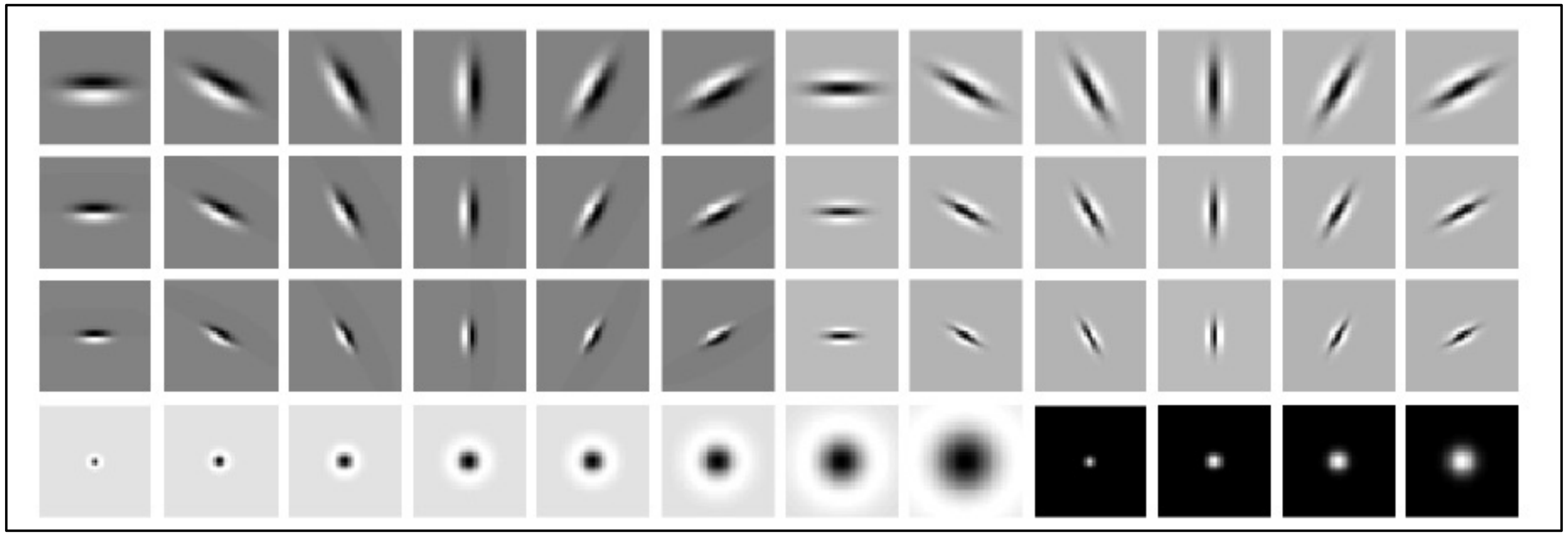
Example of Filter Banks

Isotropic Gabor

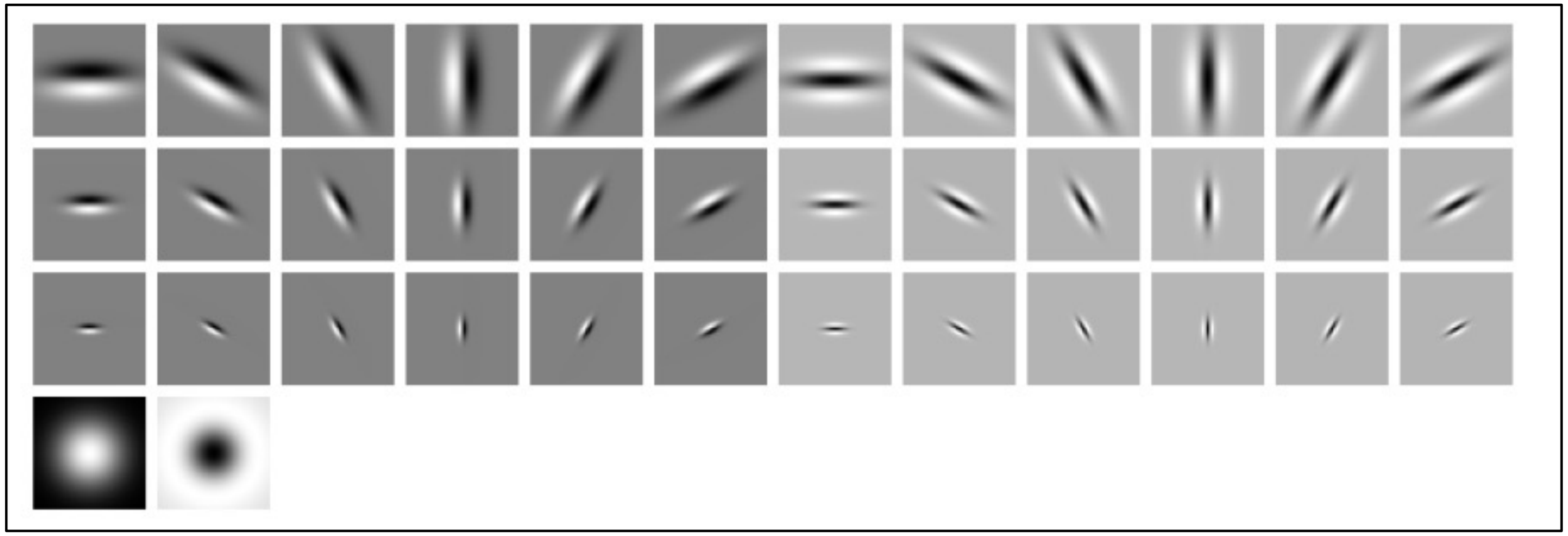


'S'

Gaussian derivatives at different scales and orientations

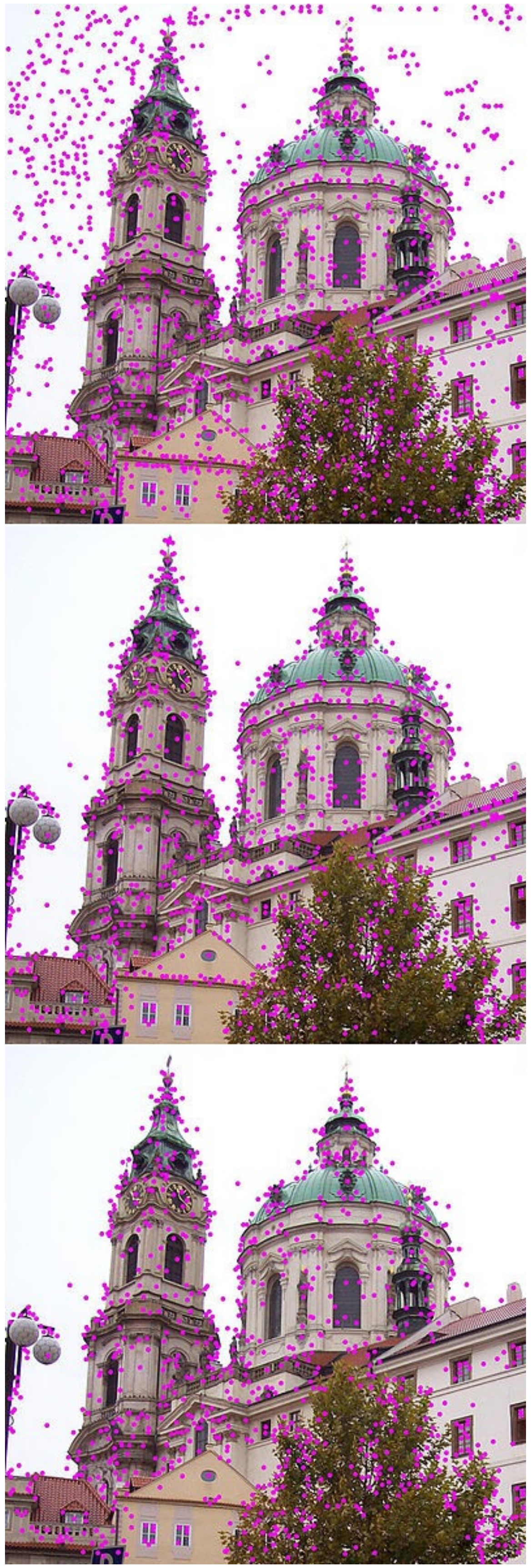


'LM'



'MR8'

SIFT



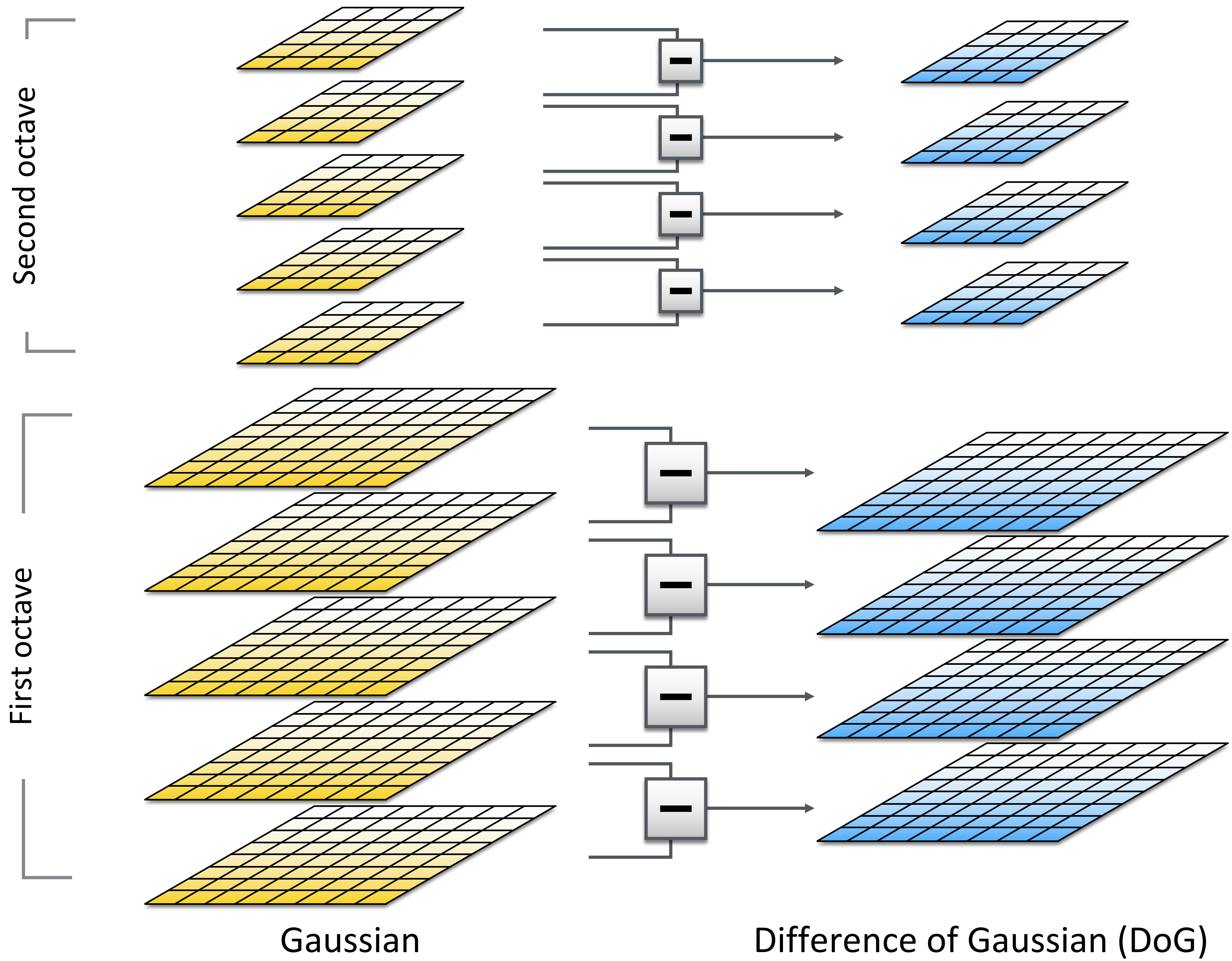
SIFT

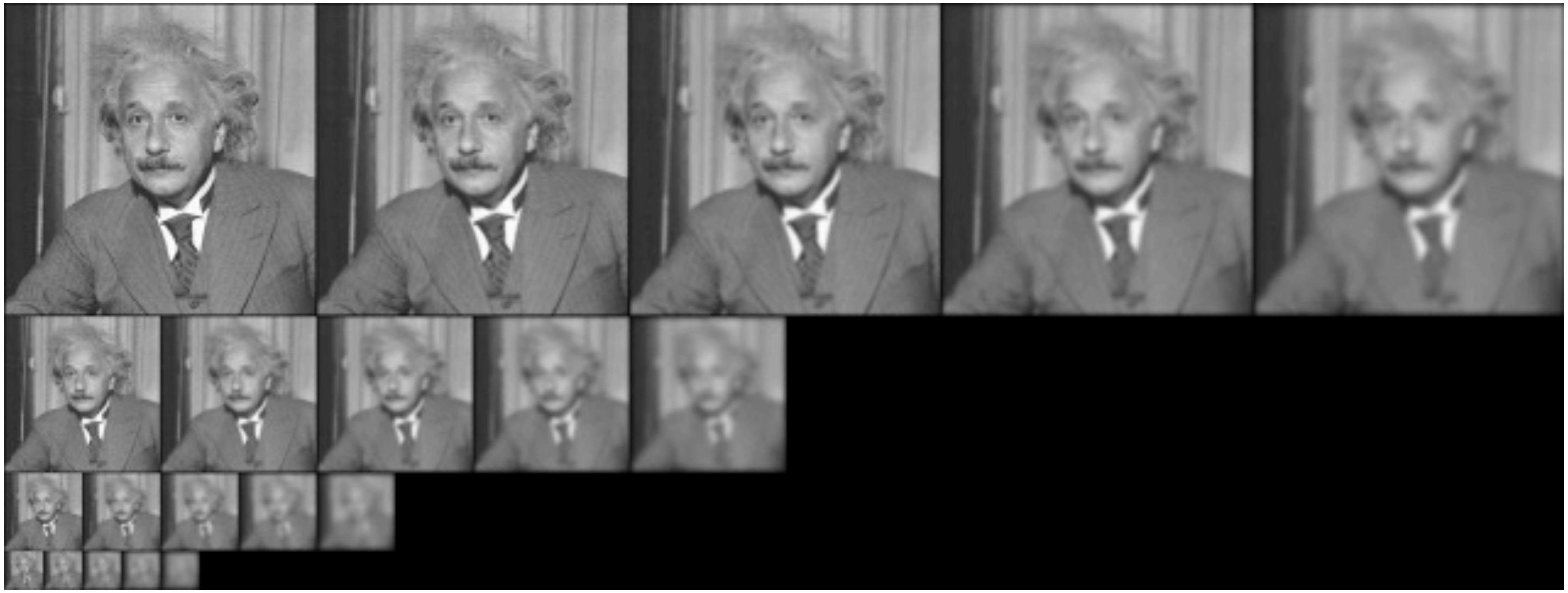
(Scale Invariant Feature Transform)

SIFT describes both a **detector** and **descriptor**

1. Multi-scale extrema detection
2. Keypoint localization
3. Orientation assignment
4. Keypoint descriptor

1. Multi-scale extrema detection

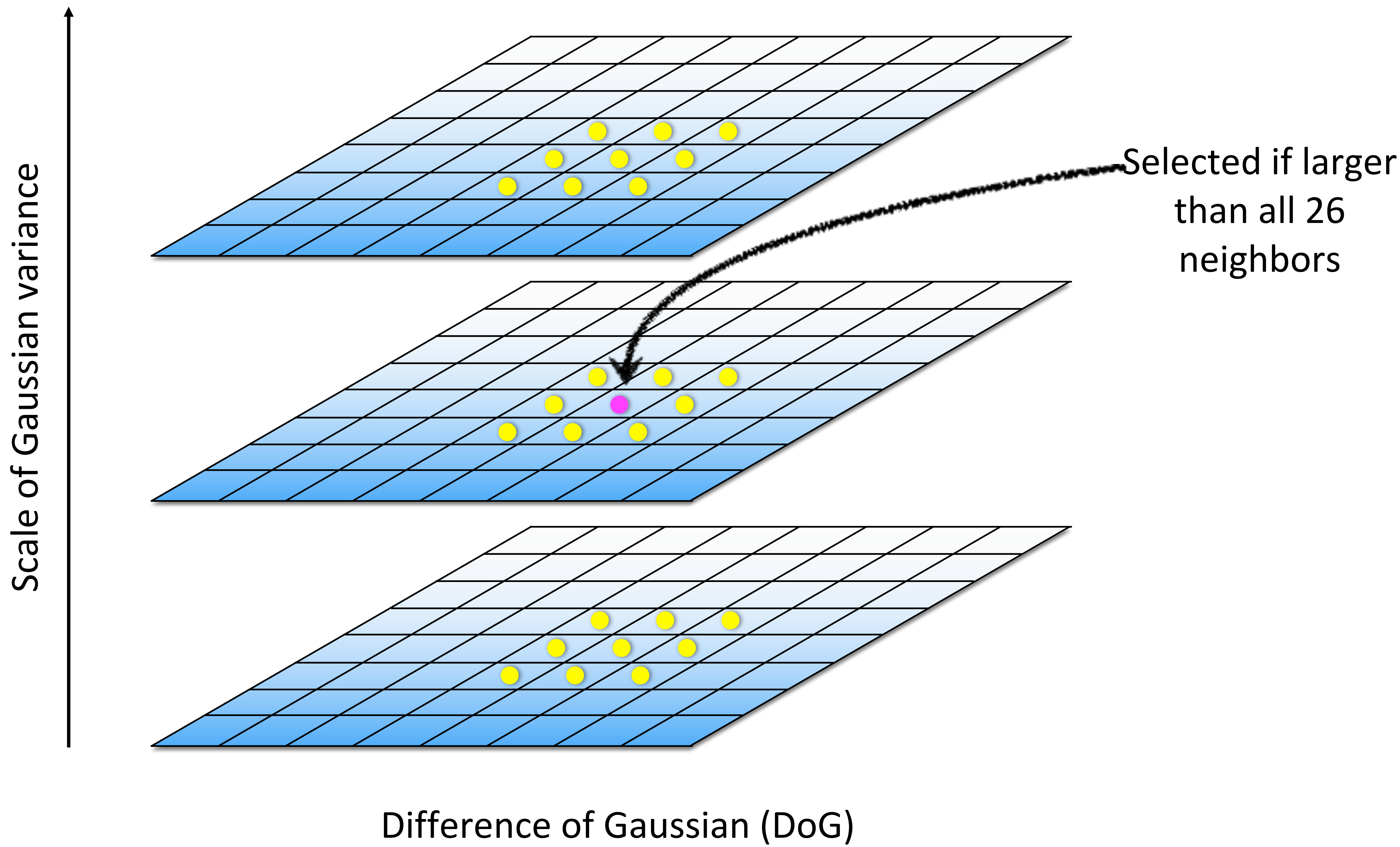




Gaussian

Laplacian

Scale-space extrema



2. Keypoint localization

2nd order Taylor series approximation of DoG scale-space

$$f(\mathbf{x}) = f + \frac{\partial f}{\partial \mathbf{x}}^T \mathbf{x} + \frac{1}{2}\mathbf{x}^T \frac{\partial^2 f}{\partial \mathbf{x}^2}\mathbf{x}$$

$$\mathbf{x} = \{x, y, \sigma\}$$

Take the derivative and solve for extrema

$$\mathbf{x}_m = -\frac{\partial^2 f}{\partial \mathbf{x}^2}^{-1} \frac{\partial f}{\partial \mathbf{x}}$$

Additional tests to retain only strong features

3. Orientation assignment

For a keypoint, **L** is the **Gaussian-smoothed** image with the closest scale,

$$m(x,y) = \sqrt{\underbrace{(L(x+1,y) - L(x-1,y))^2}_{\text{x-derivative}} + \underbrace{(L(x,y+1) - L(x,y-1))^2}_{\text{y-derivative}}}$$

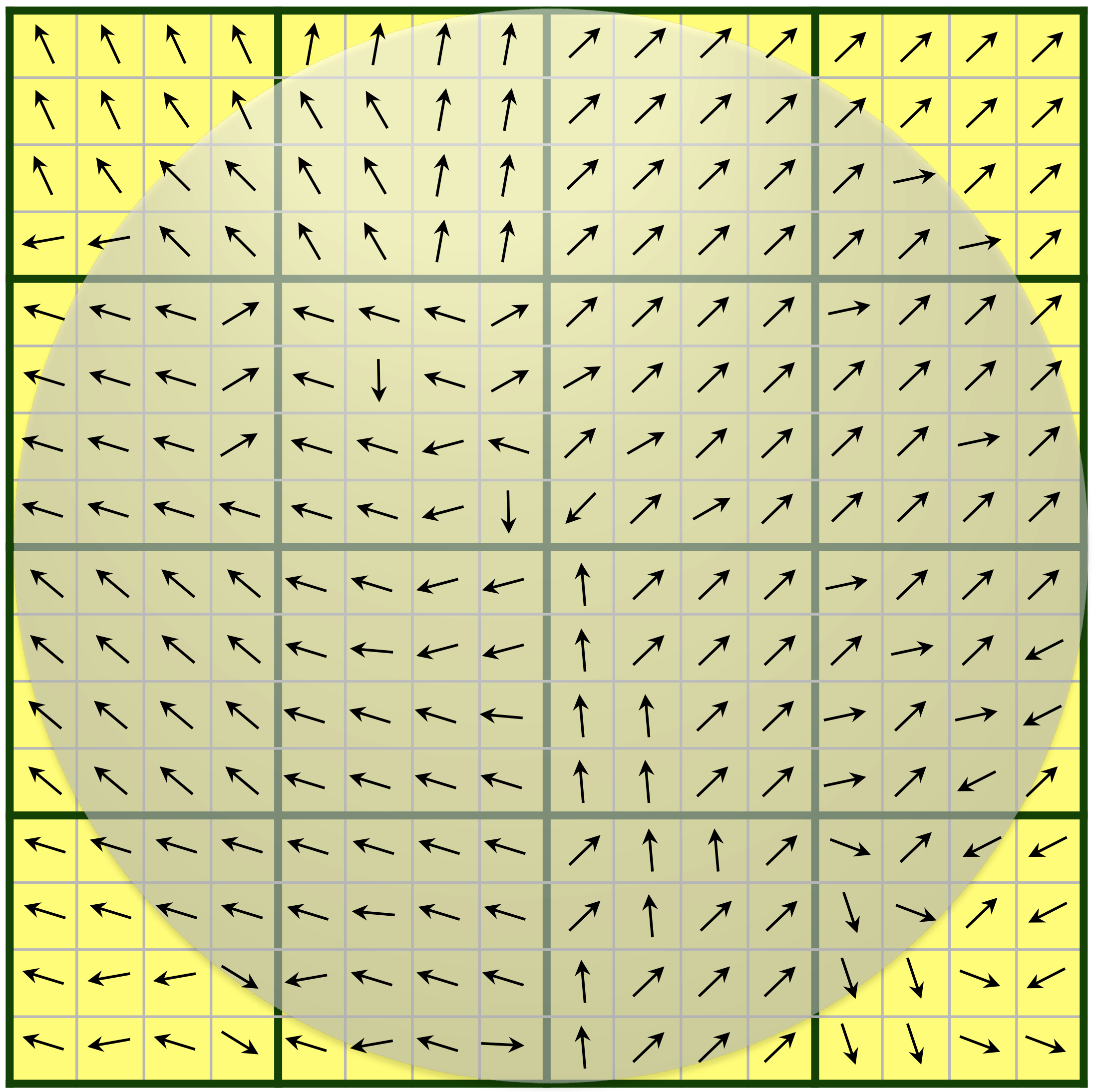
$$\theta(x,y) = \tan^{-1}((L(x,y+1) - L(x,y-1))/(L(x+1,y) - L(x-1,y)))$$

Detection process returns

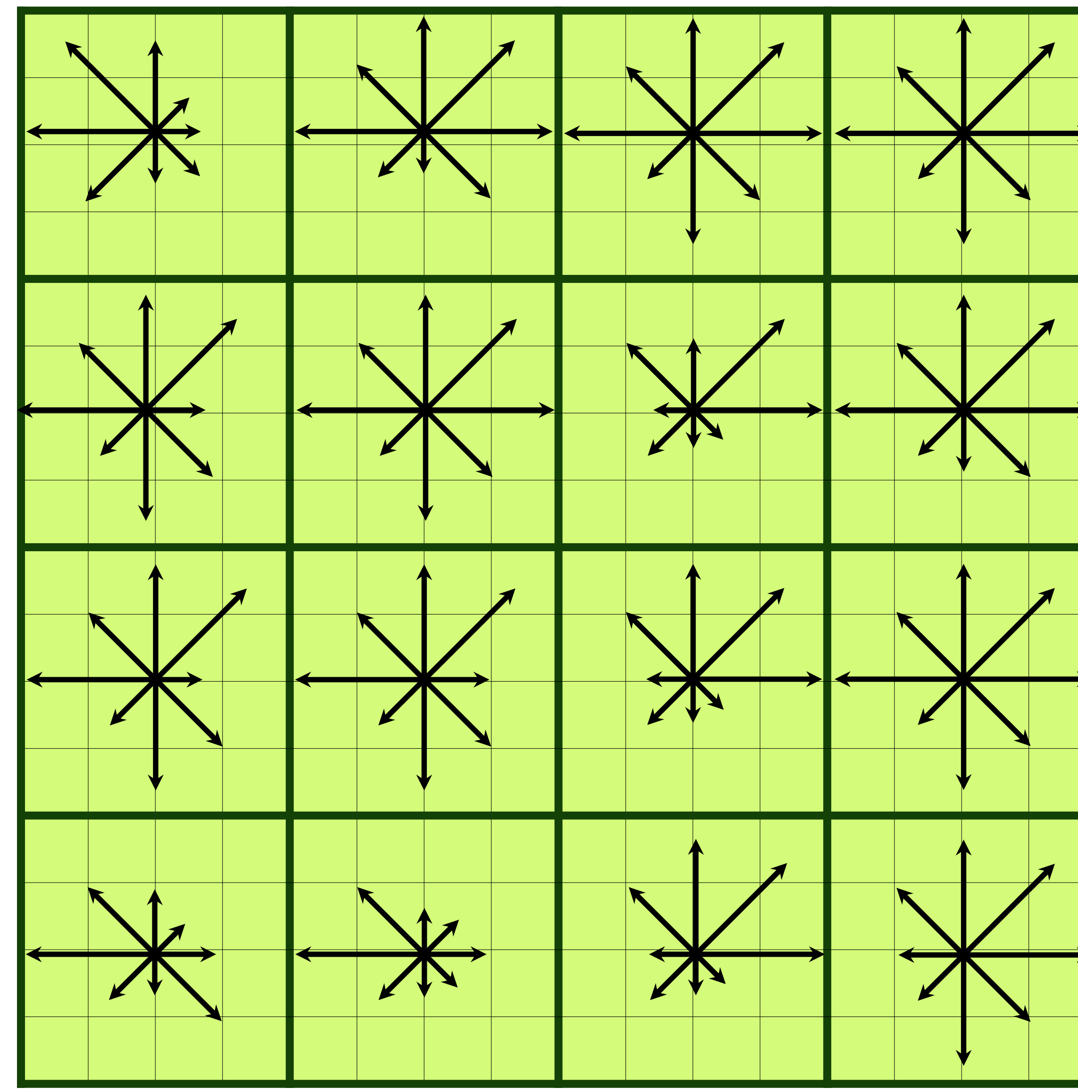
$$\{x, y, \sigma, \theta\}$$

location scale orientation

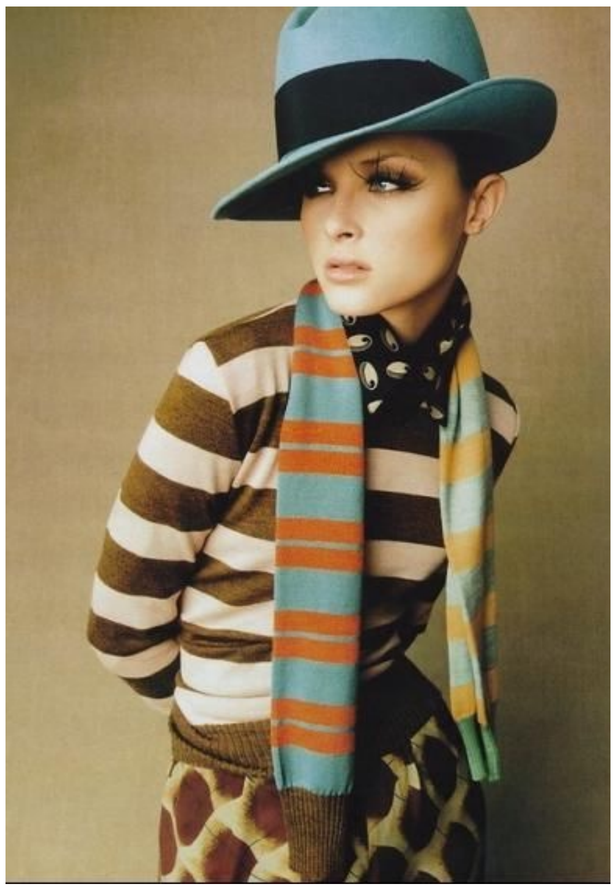
4. Keypoint descriptor

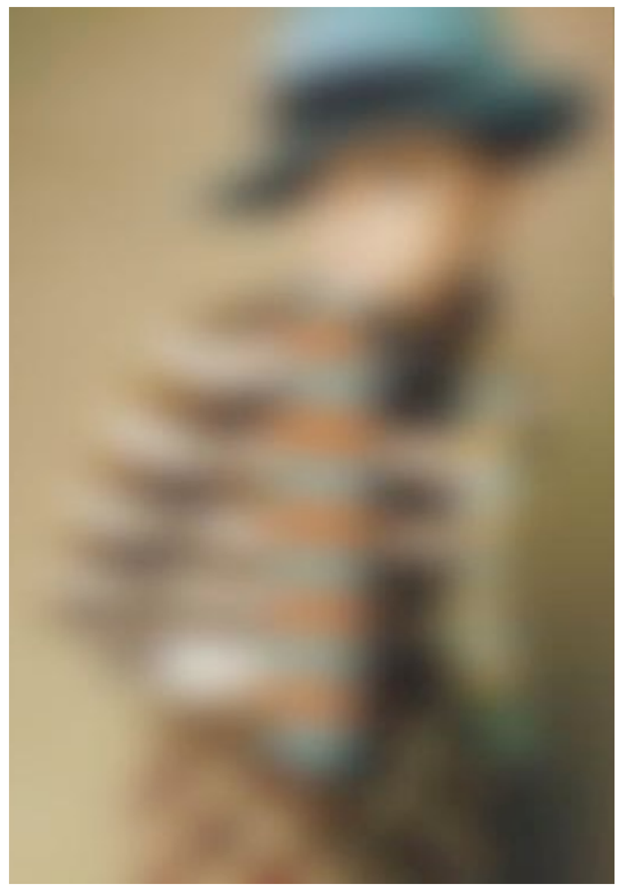


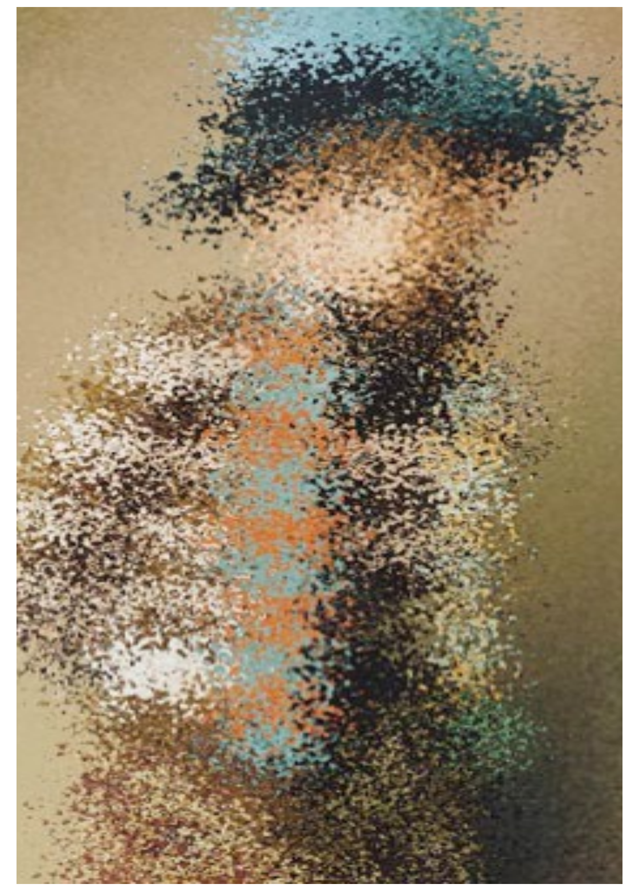
Gaussian weighting
(sigma = half width)



Discriminative power


Raw pixels


Sampled


Locally orderless


Global histogram

Generalization power