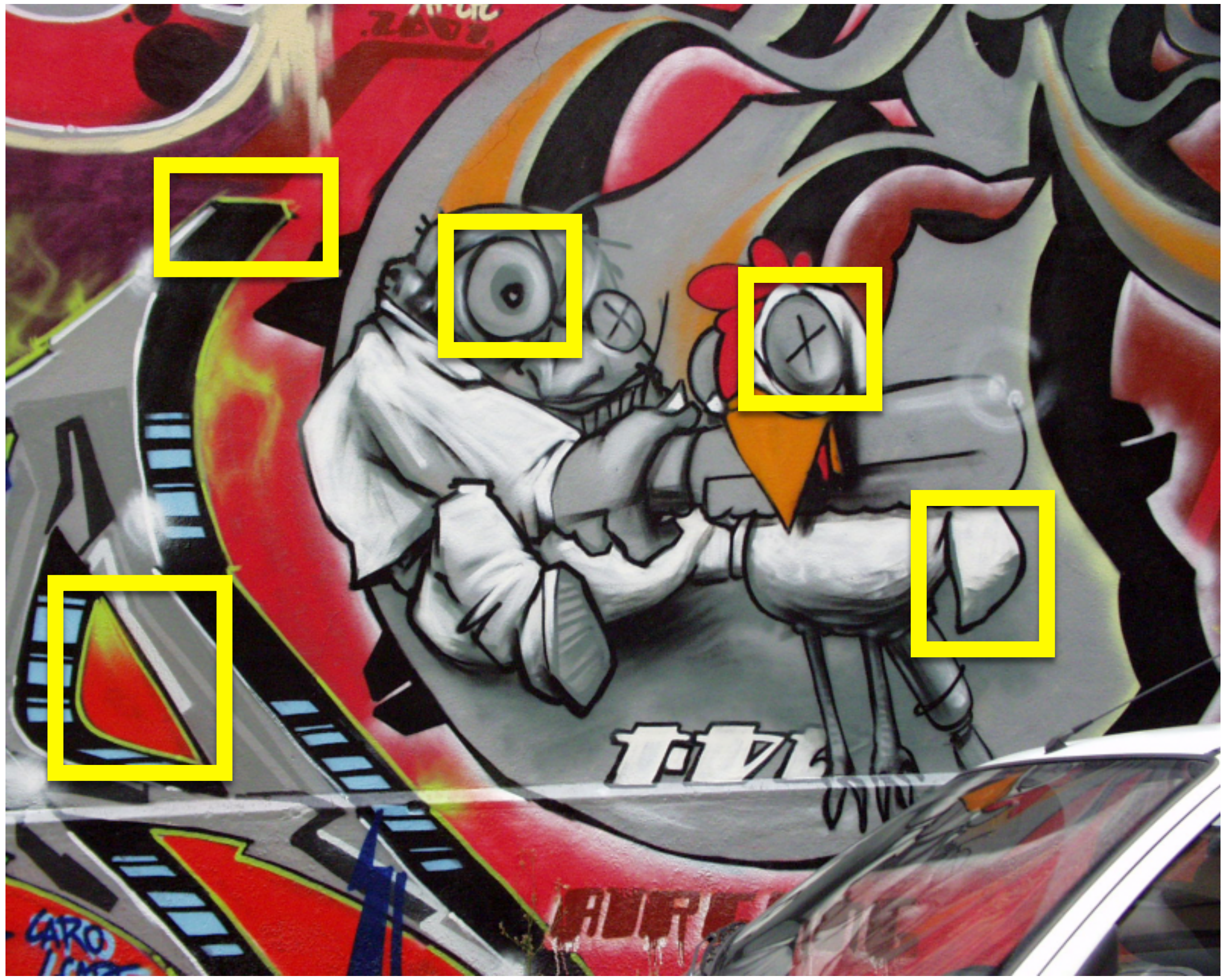
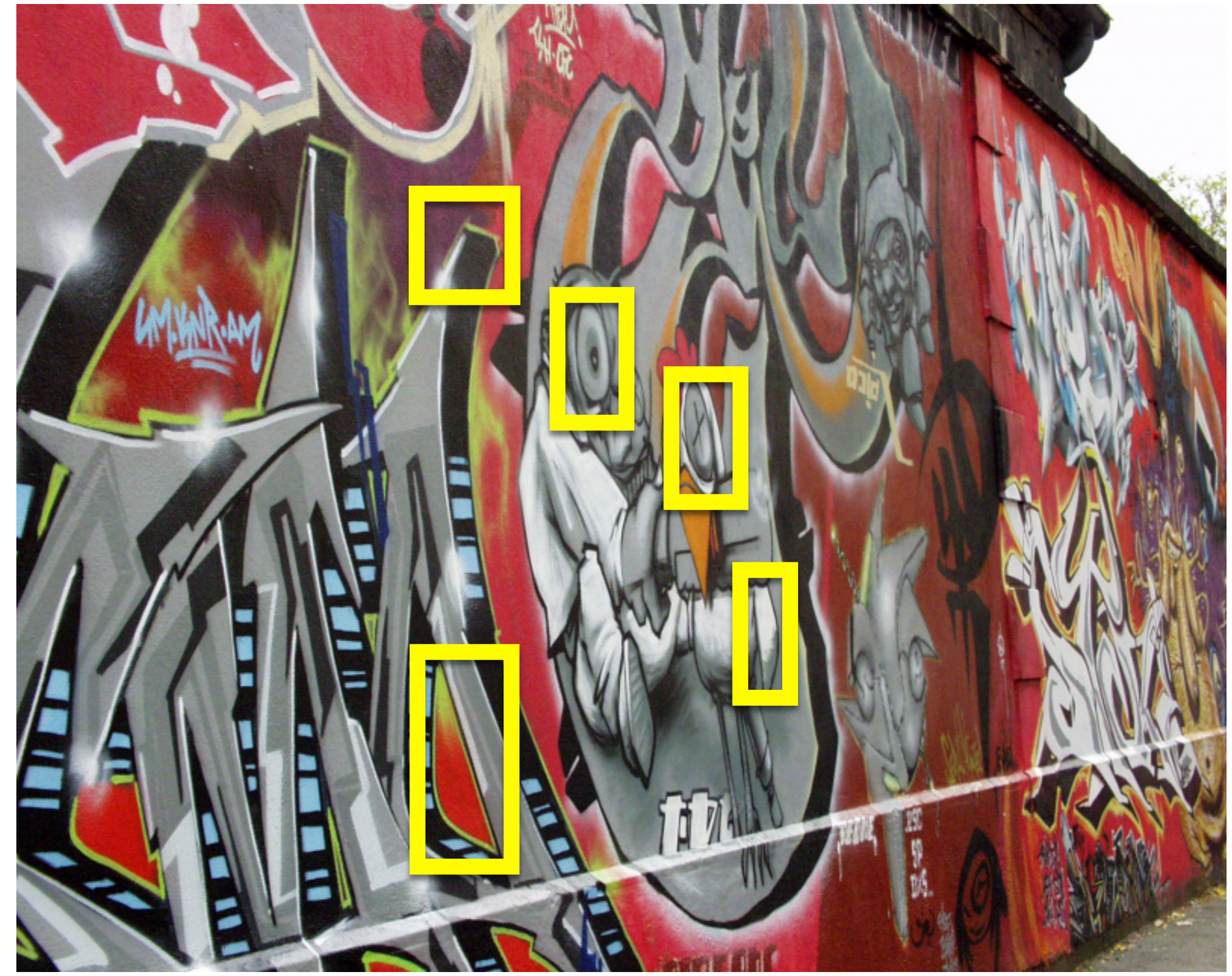
Why do we need feature descriptors?

Slide Credits

Kris Kitani
Ioannis Gkiolekas

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

Object instance recognition

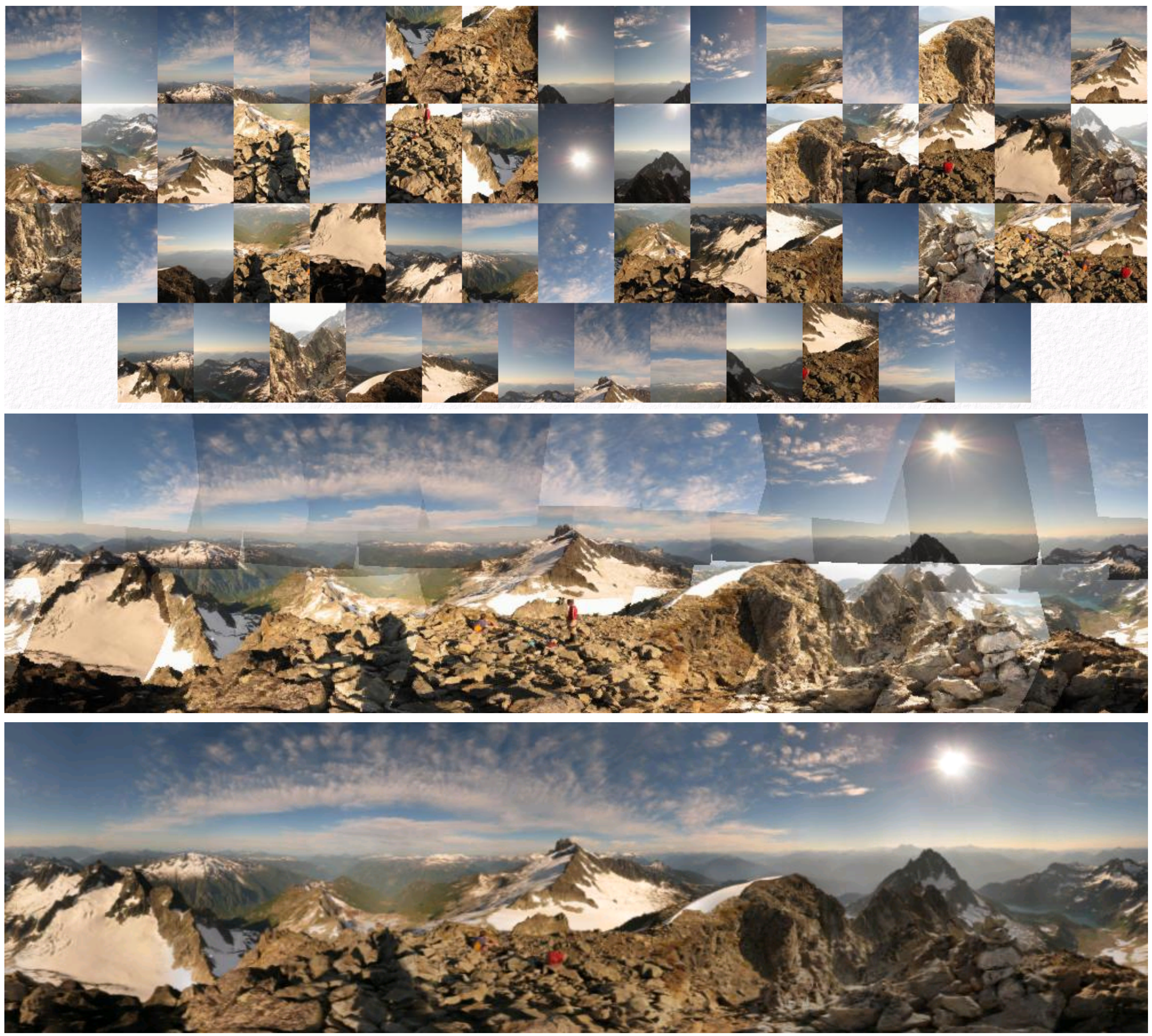
Schmid and Mohr 1997

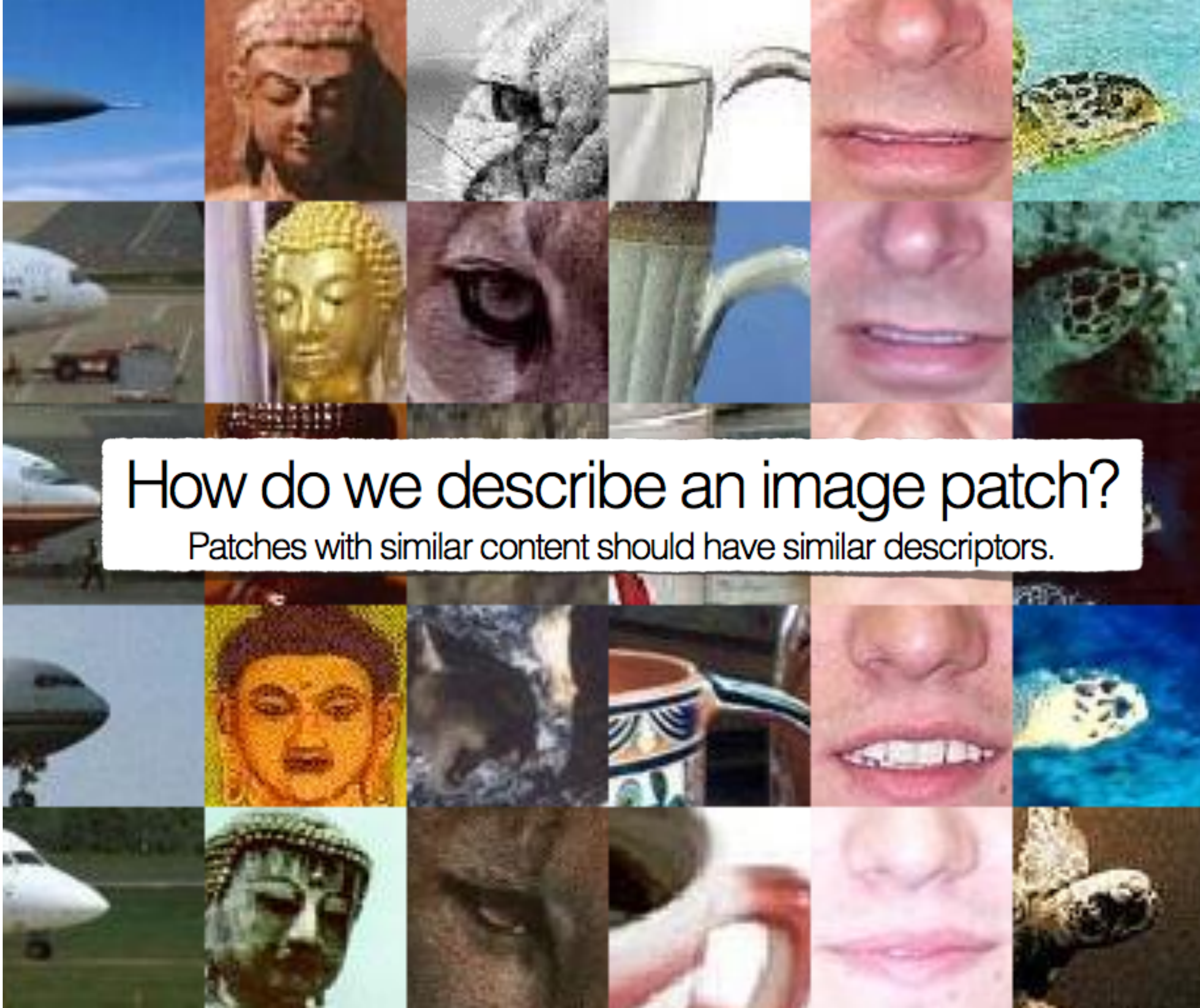
Sivic and Zisserman, 2003

Rothganger et al. 2003

Lowe 2002

Image mosaicing



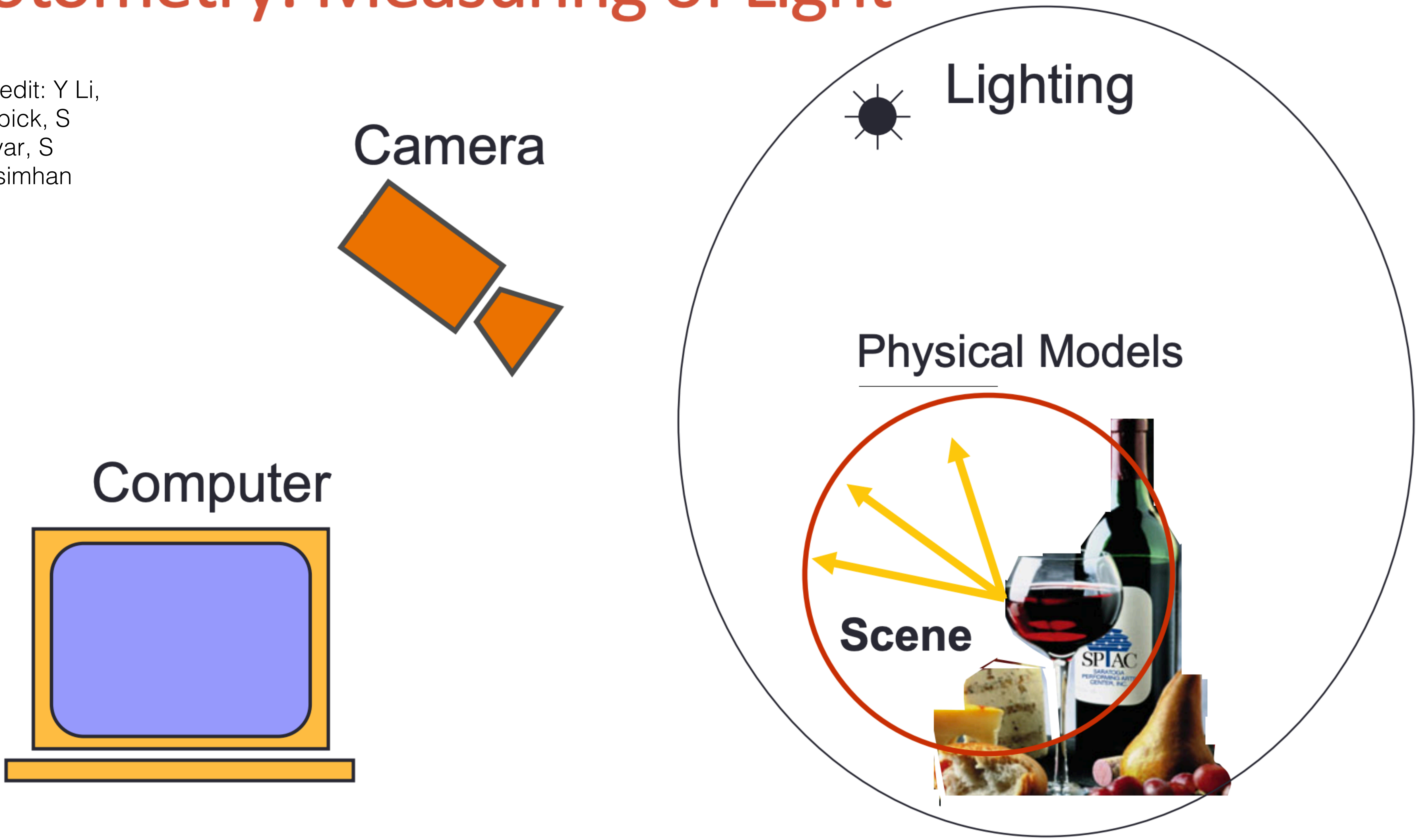

How do we describe an image patch?
Patches with similar content should have similar descriptors.

Designing feature descriptors

Photometric transformations

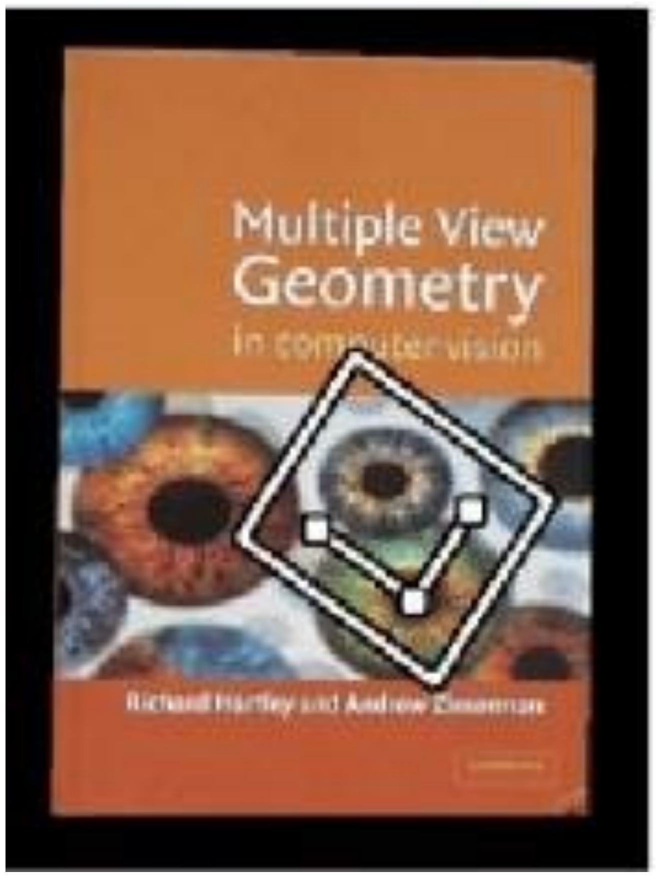
Photometry: Measuring of Light

Slide Credit: Y Li, A Bobick, S Nayar, S Narasimhan



We need to understand the relation between the lighting, surface reflectance and medium and the image of the scene.

Geometric transformations

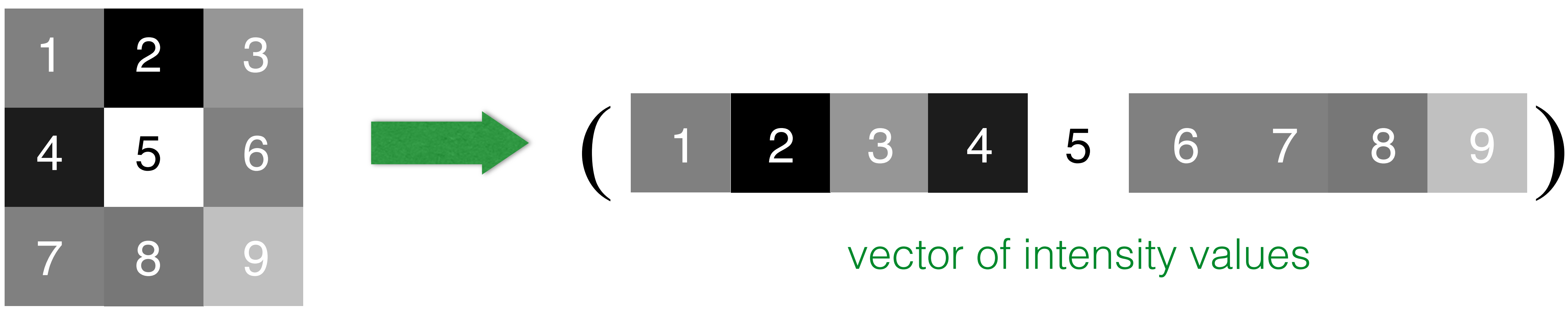


objects will appear at different scales,
translation and rotation

What is the best descriptor for an image feature?

Image patch

Just use the pixel values of the patch



Perfectly fine if geometry and appearance is unchanged

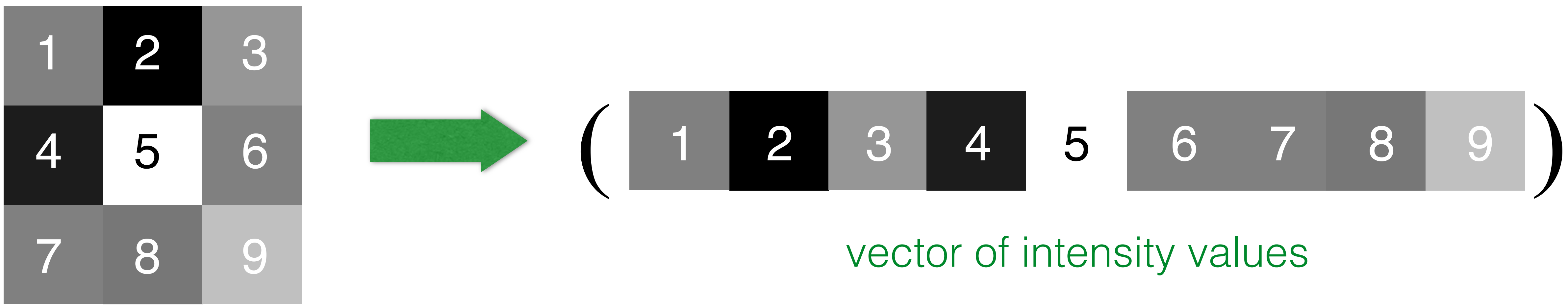
(a.k.a. template matching)

Tiny Images

Just down-sample it!
Simple, fast, robust to small affine transforms.

Image patch

Just use the pixel values of the patch

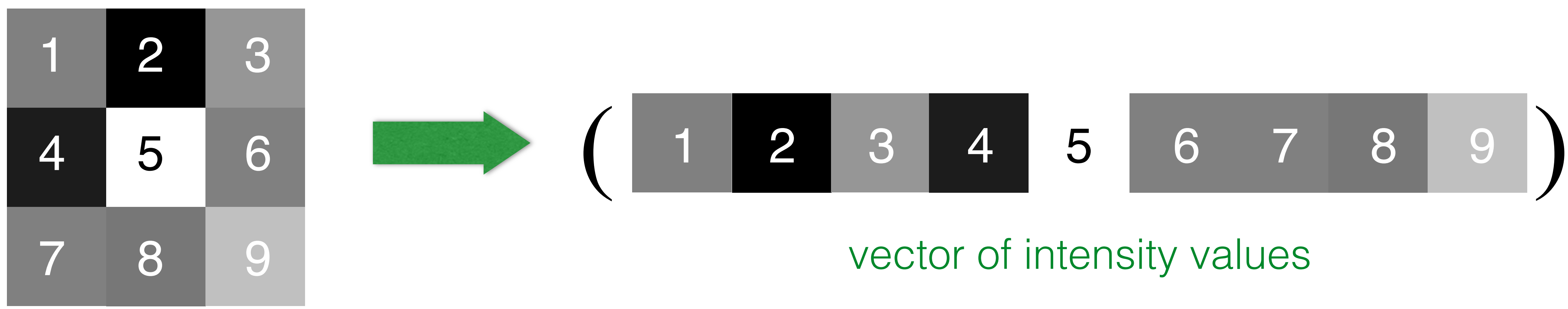


Perfectly fine if geometry and appearance is unchanged
(a.k.a. template matching)

What are the problems?

Image patch

Just use the pixel values of the patch



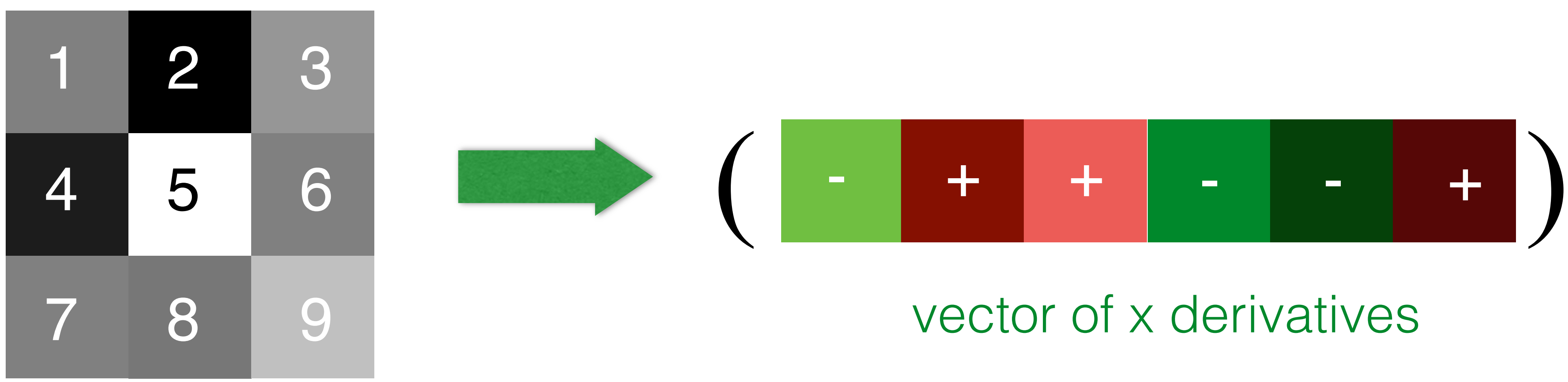
Perfectly fine if geometry and appearance is unchanged
(a.k.a. template matching)

What are the problems?

How can you be less sensitive to absolute intensity values?

Image gradients

Use pixel differences



vector of x derivatives

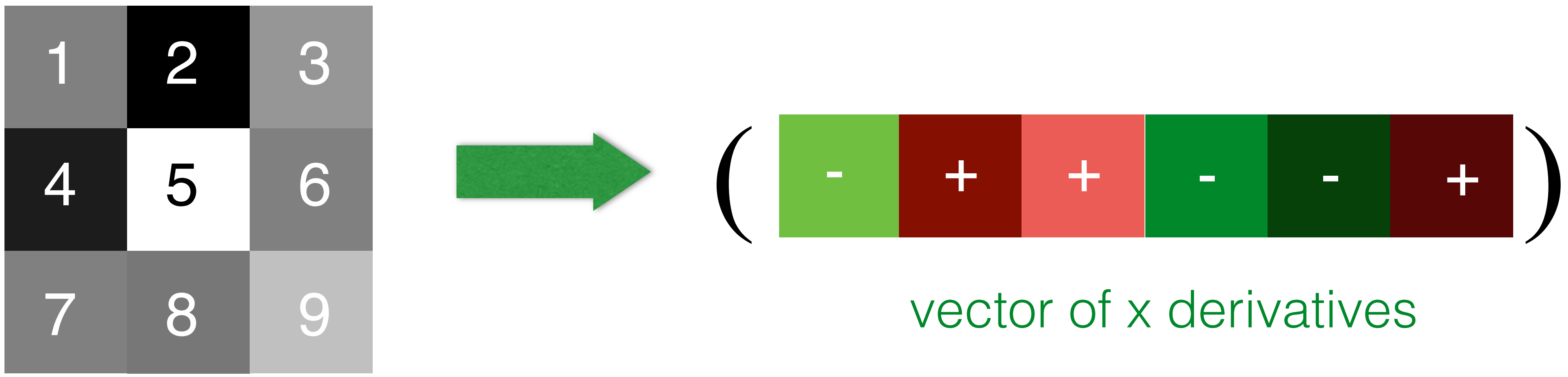
‘binary descriptor’

Feature is invariant to absolute intensity values

What are the problems?

Image gradients

Use pixel differences



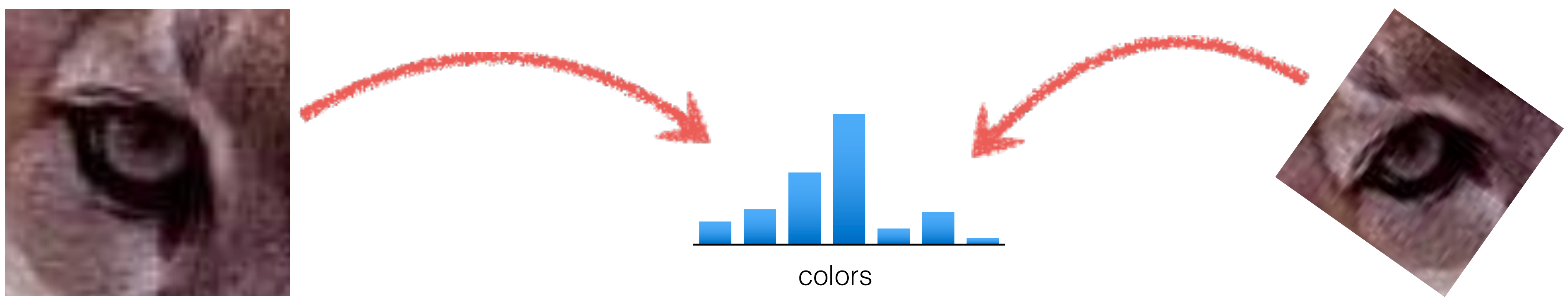
Feature is invariant to absolute intensity values

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

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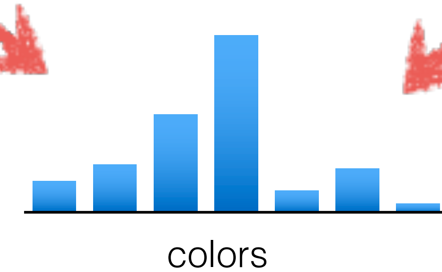

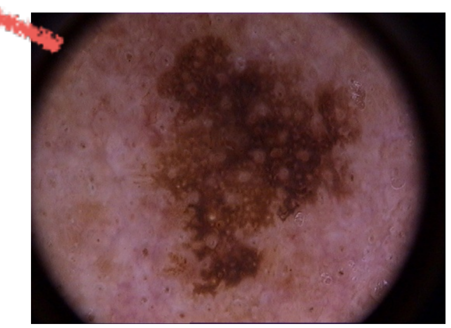

Invariant to changes in scale and rotation

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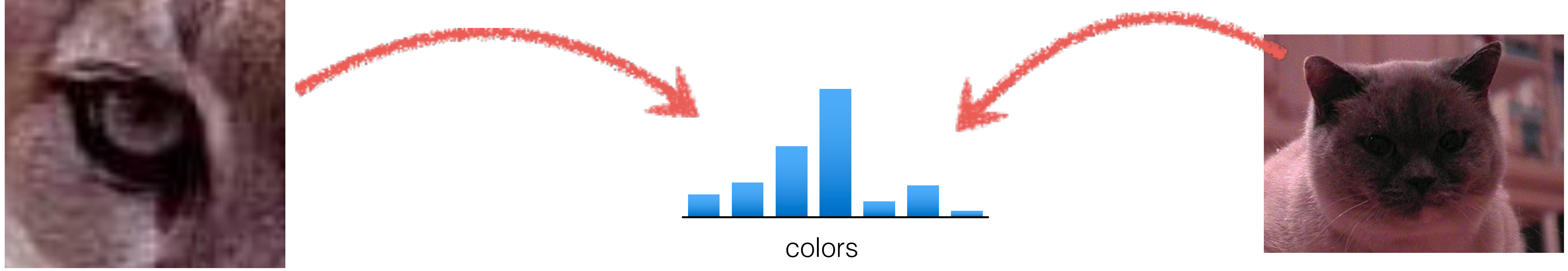


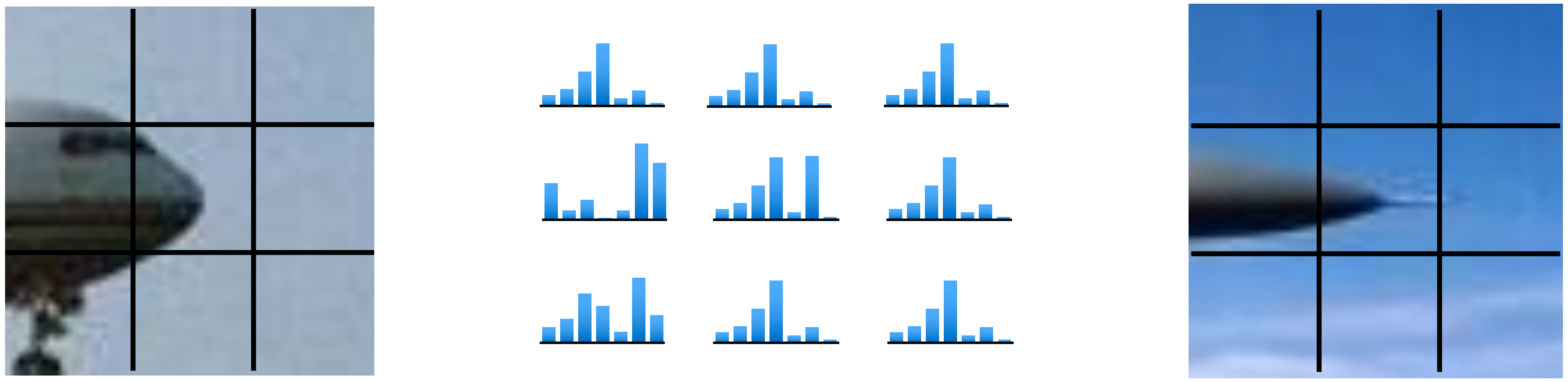
Invariant to changes in scale and rotation

What are the problems?

How can you be more sensitive to spatial layout?

Spatial histograms

Compute histograms over spatial ‘cells’



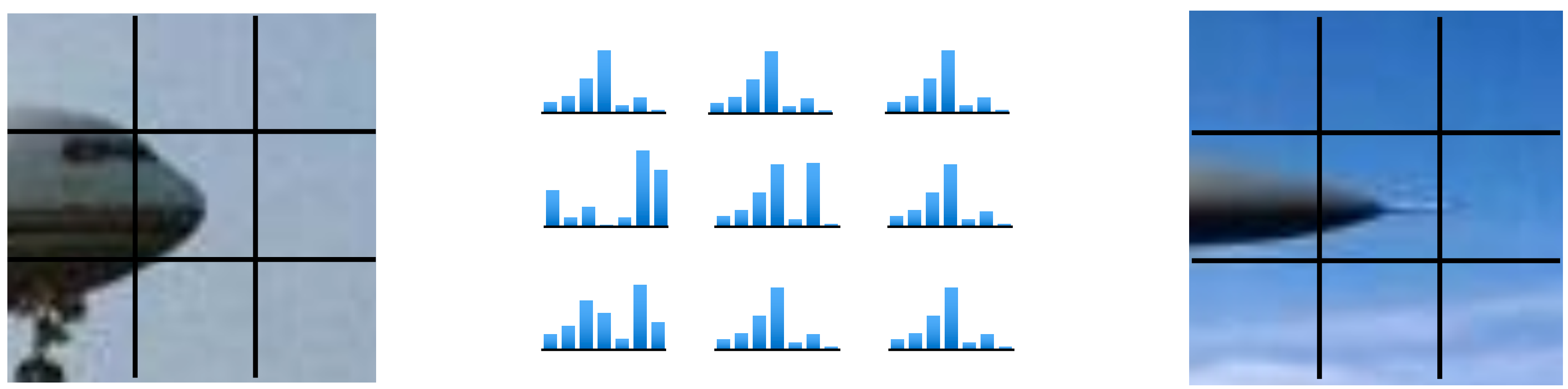
Retains rough spatial layout

Some invariance to deformations

What are the problems?

Spatial histograms

Compute histograms over spatial ‘cells’



Retains rough spatial layout

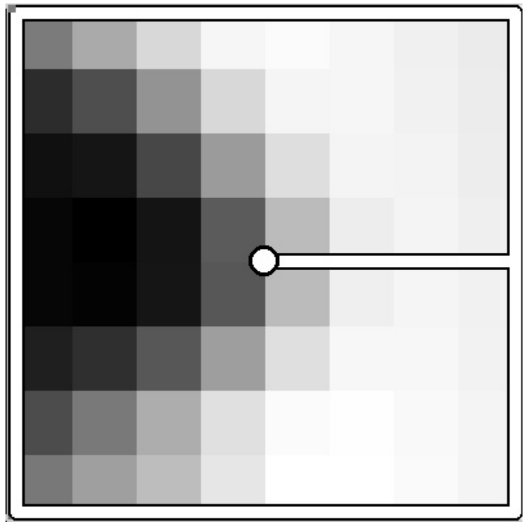
Some invariance to deformations

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



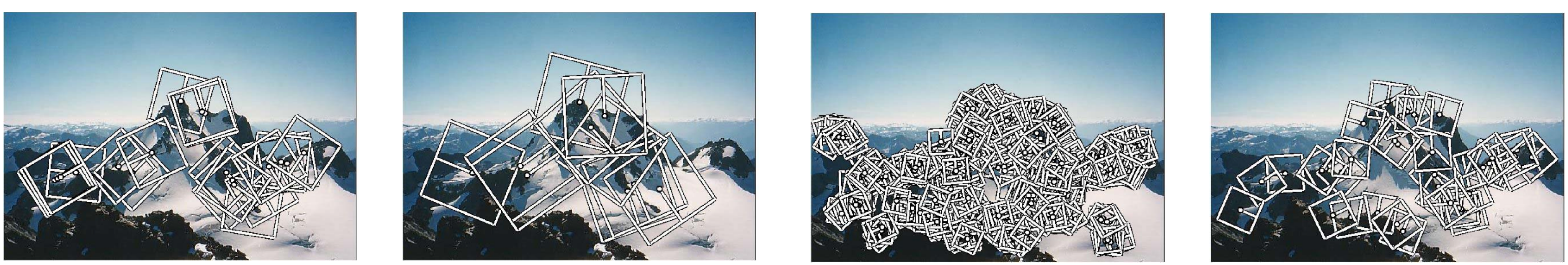
save the orientation angle θ along with (x, y, s)

What are the problems?

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

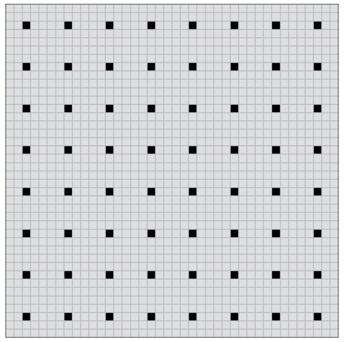


Multi-Scale Oriented Patches (MOPS)

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
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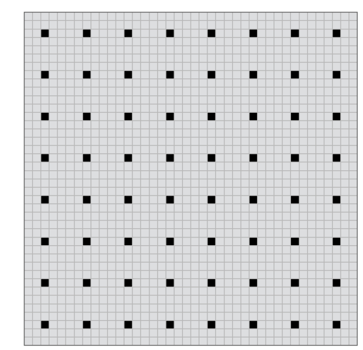
Given a feature (x, y, s, θ)

Get 40 x 40 image patch, subsample every 5th pixel
(low frequency filtering, absorbs localization errors)



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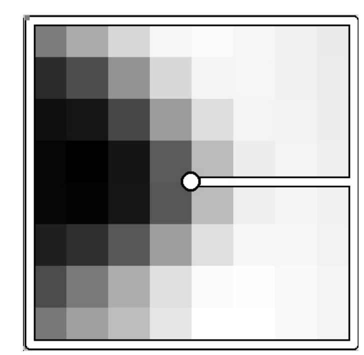

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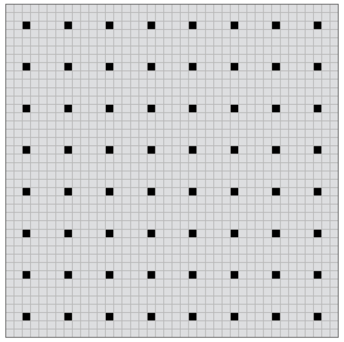
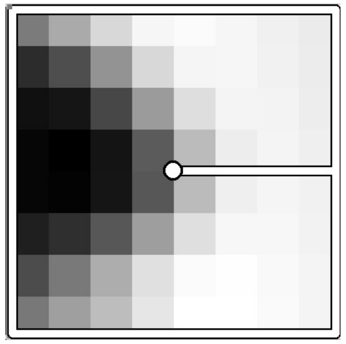


Subtract the mean, divide by standard deviation
(removes bias and gain)



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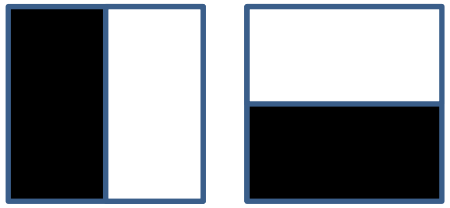

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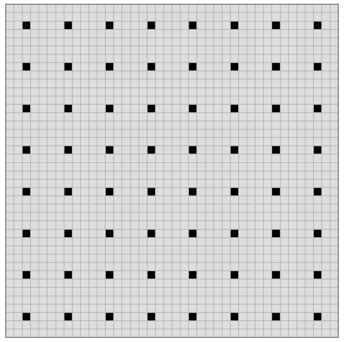

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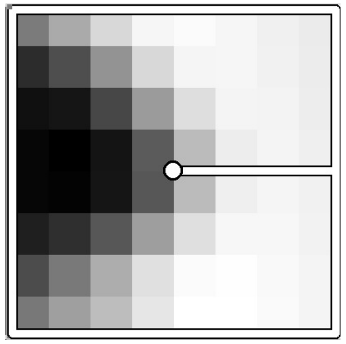
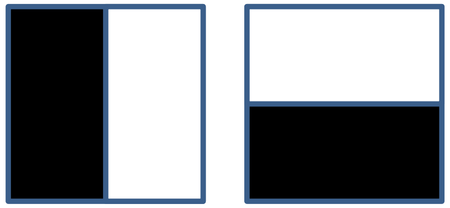


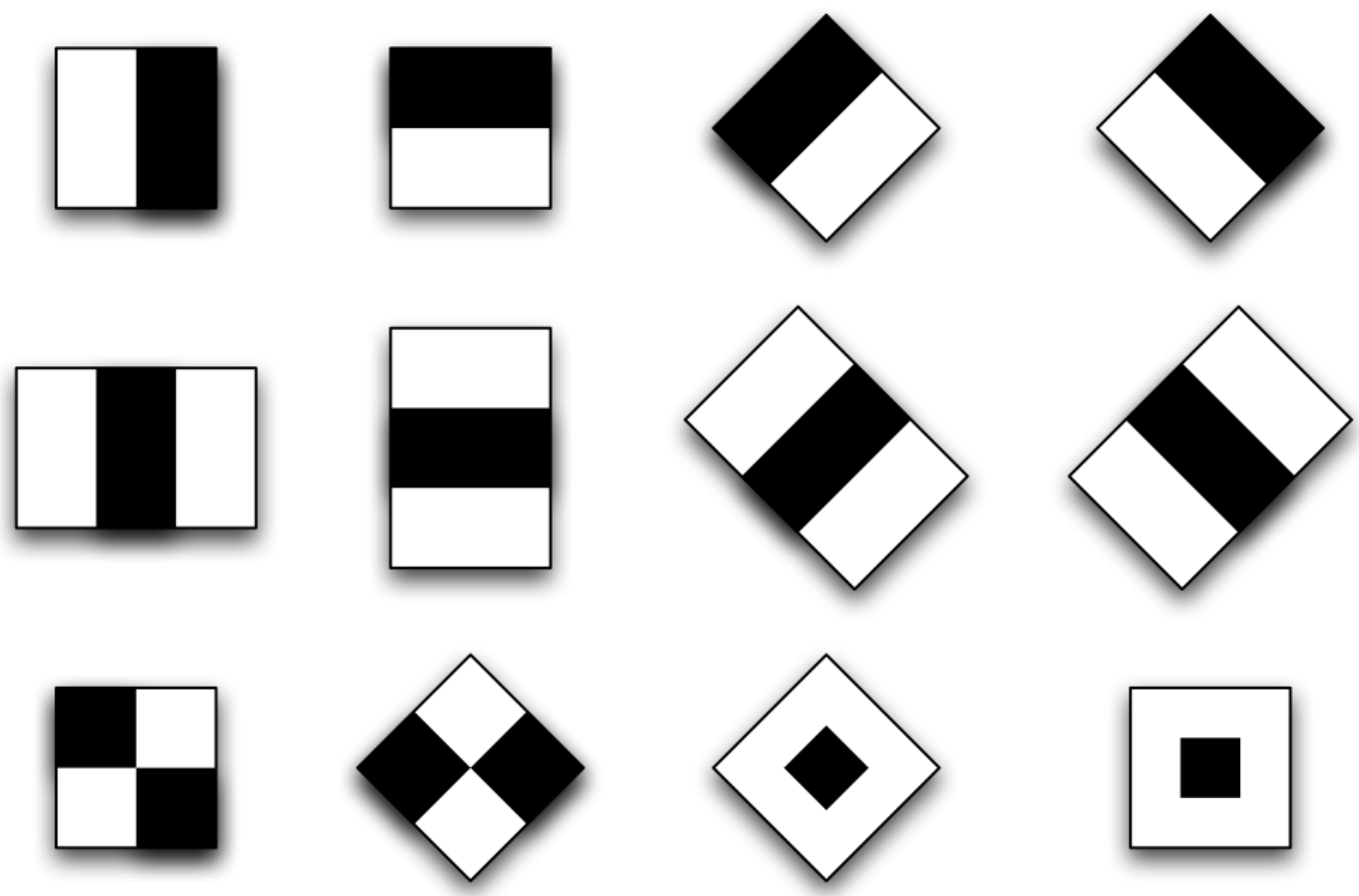
Haar Wavelet Transform
(low frequency projection)



Haar Wavelets

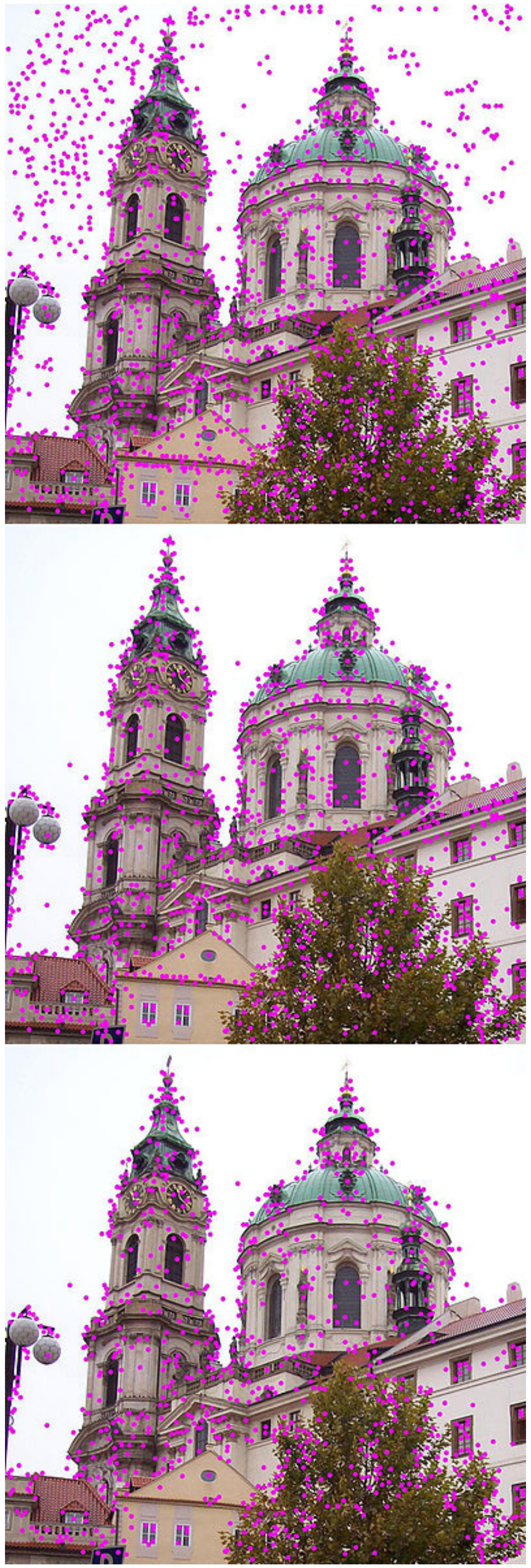
(actually, Haar-like features)

Use responses of a bank of filters as a descriptor



We will see later in class how to compute Haar wavelet responses **efficiently** (in constant time) with integral images

SIFT



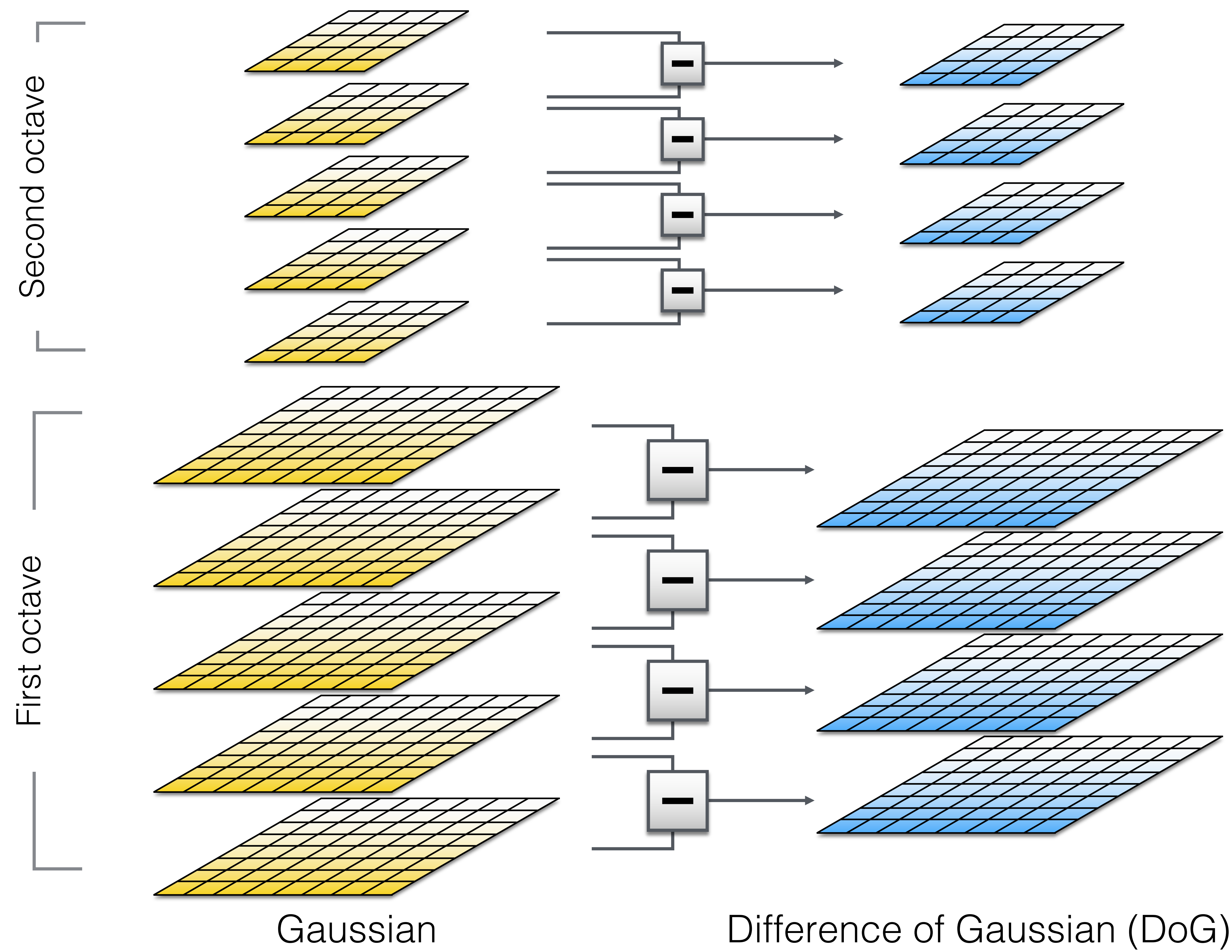
SIFT

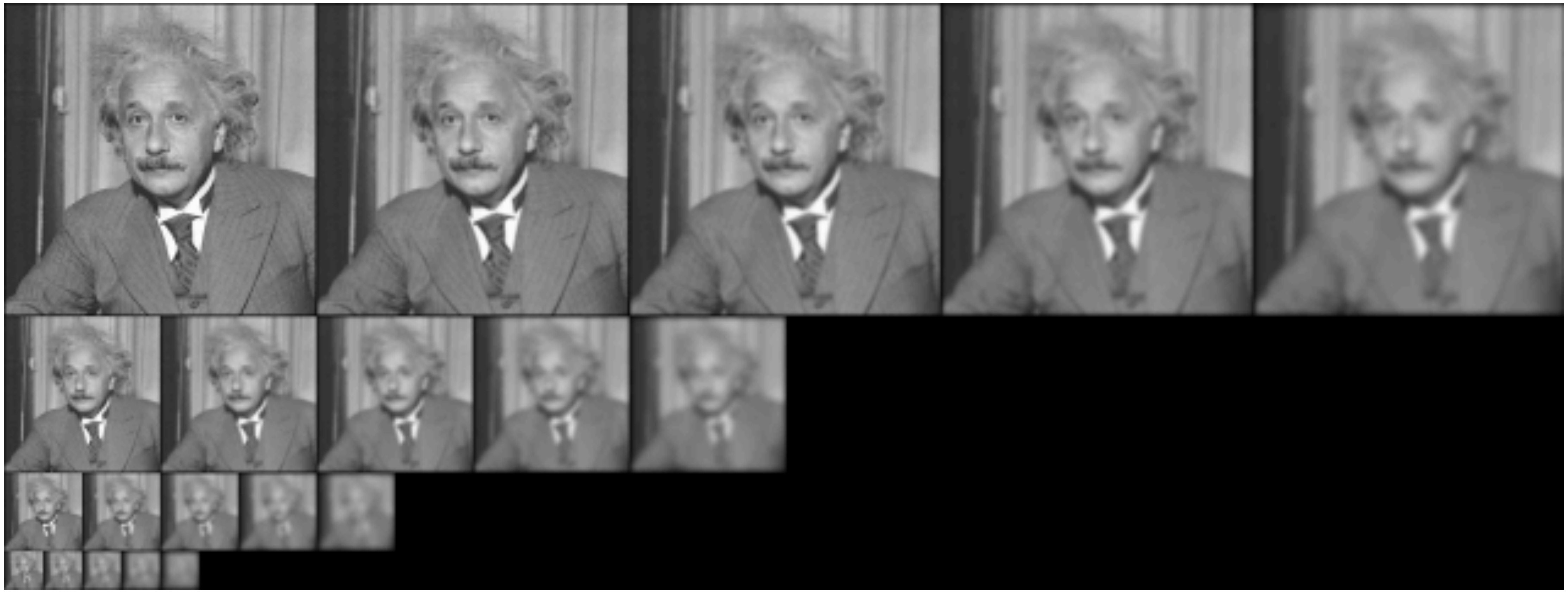
(Scale Invariant Feature Transform)

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

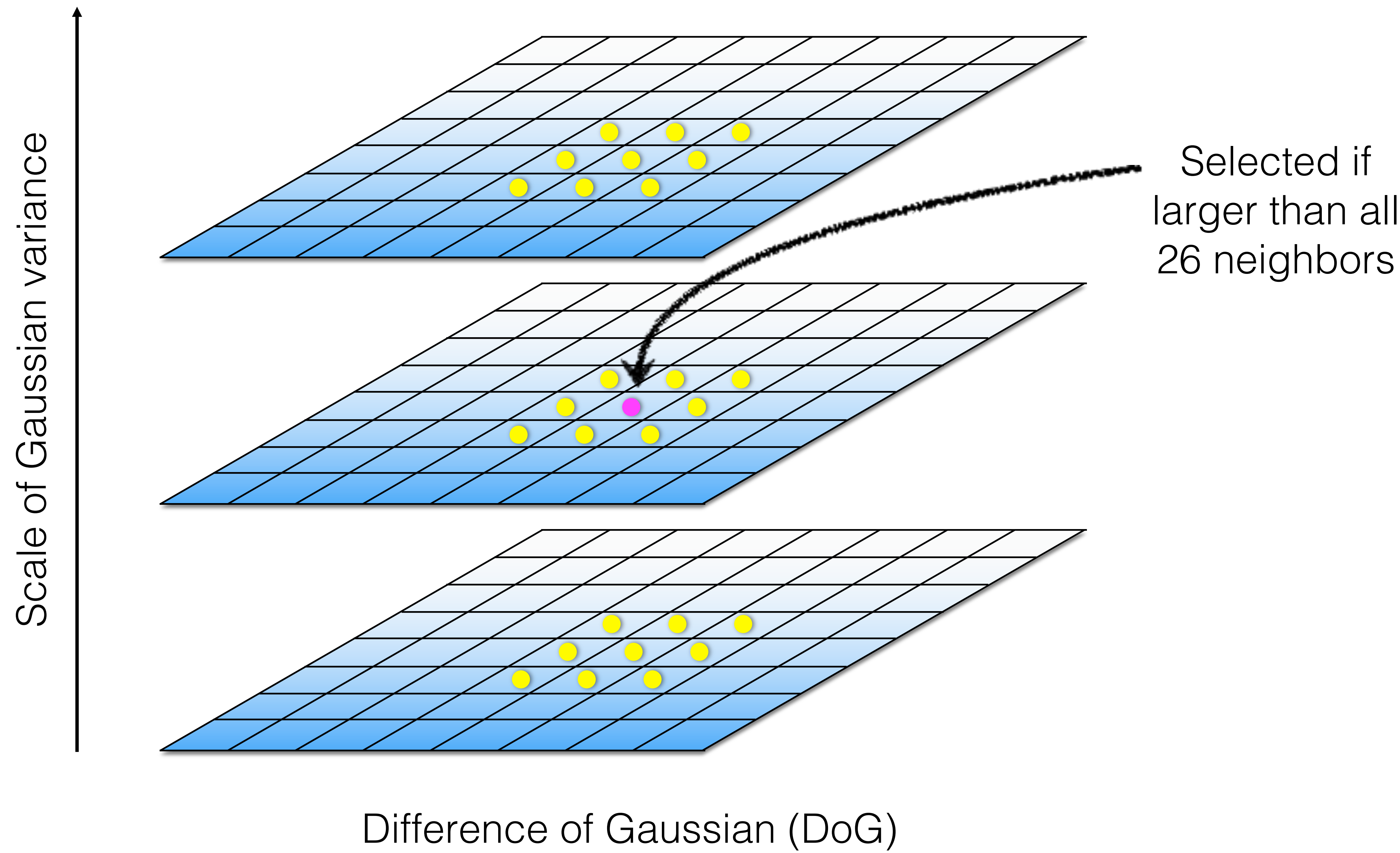




Gaussian

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

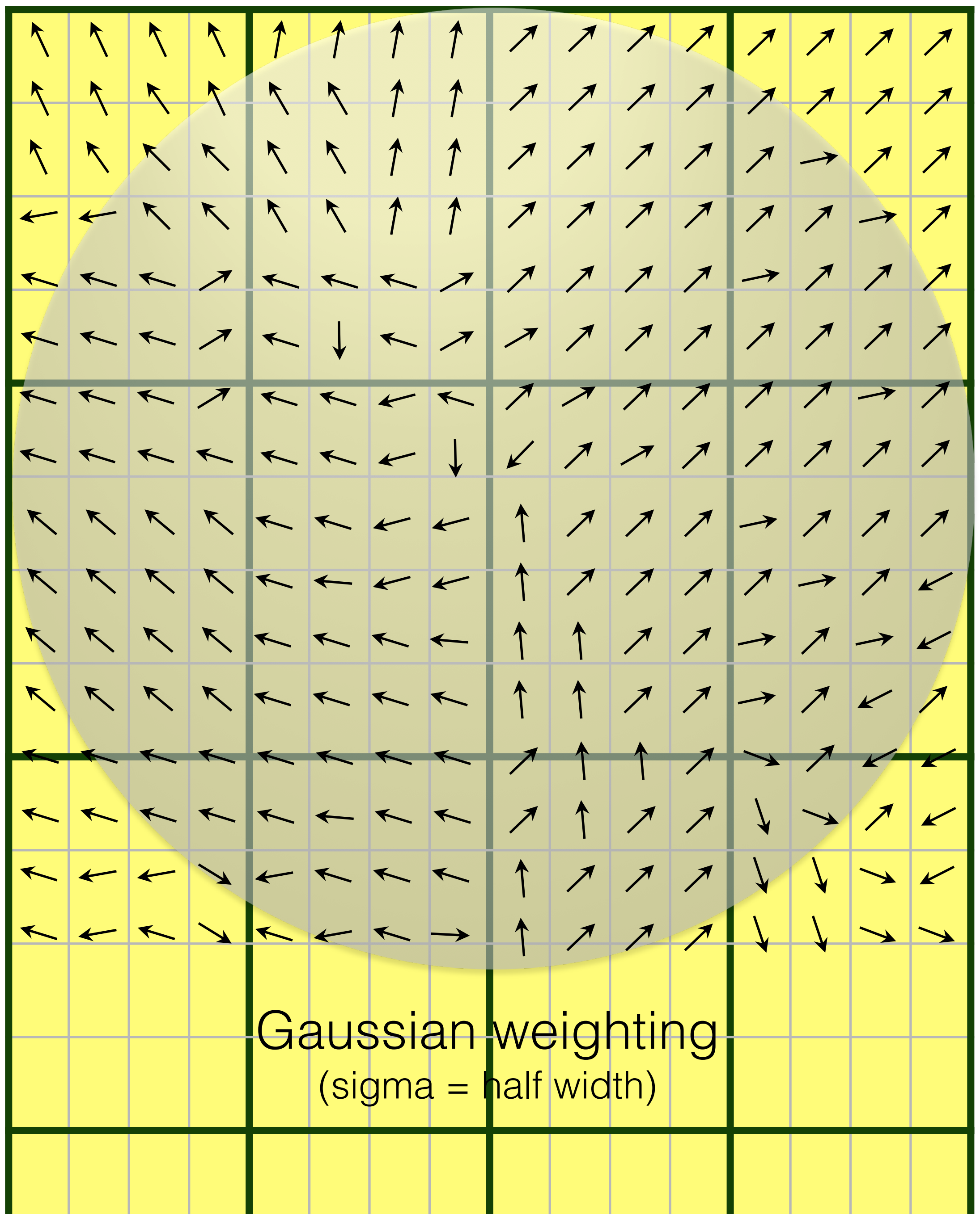
$$\{x, y, \sigma, \theta\}$$

location scale orientation

4. Keypoint descriptor

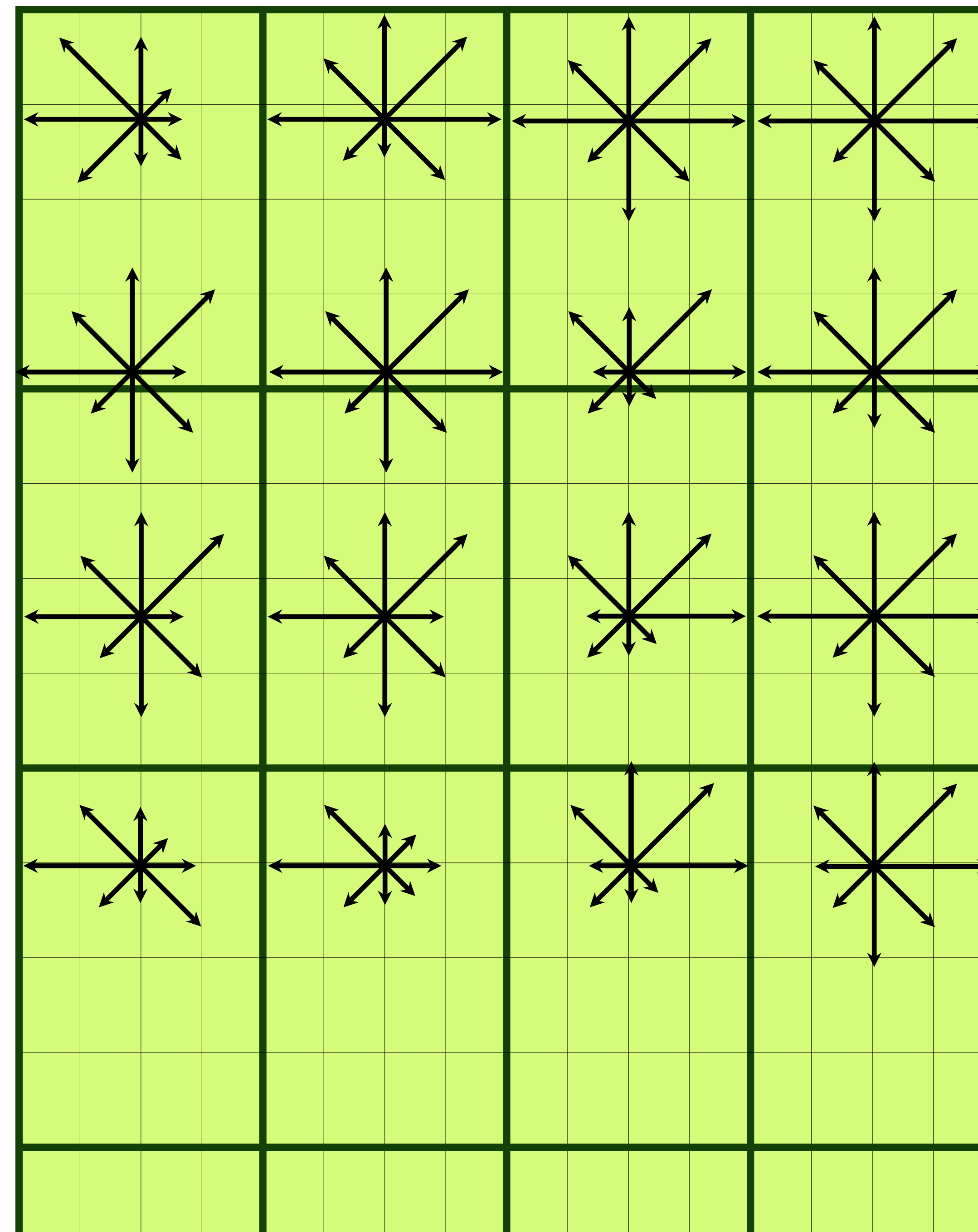
Image Gradients

(4 x 4 pixel per cell, 4 x 4 cells)

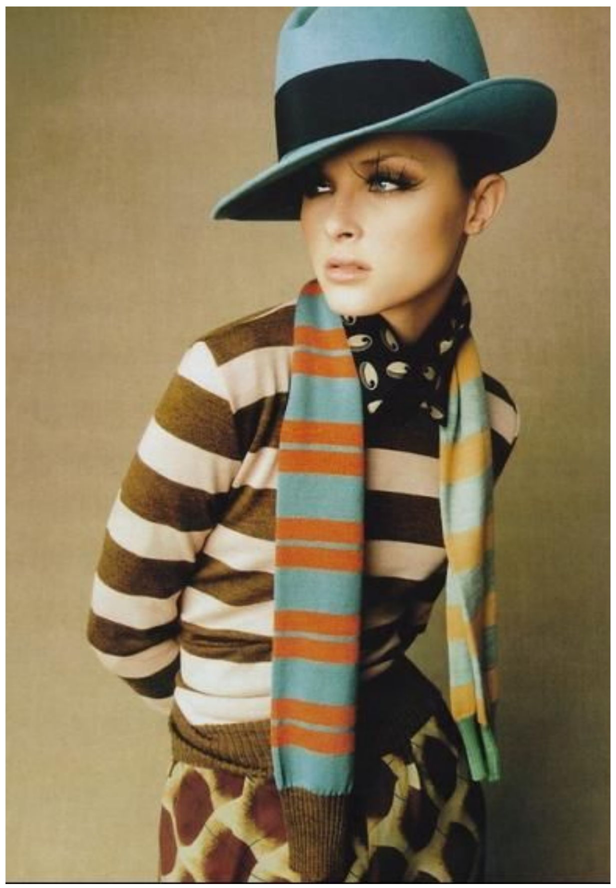


SIFT descriptor

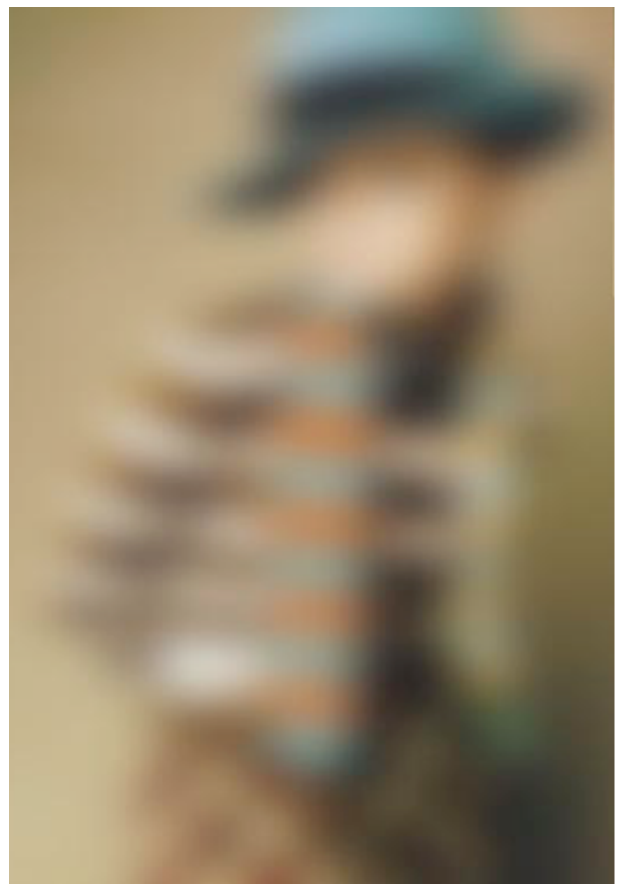
(16 cells x 8 directions = 128 dims)



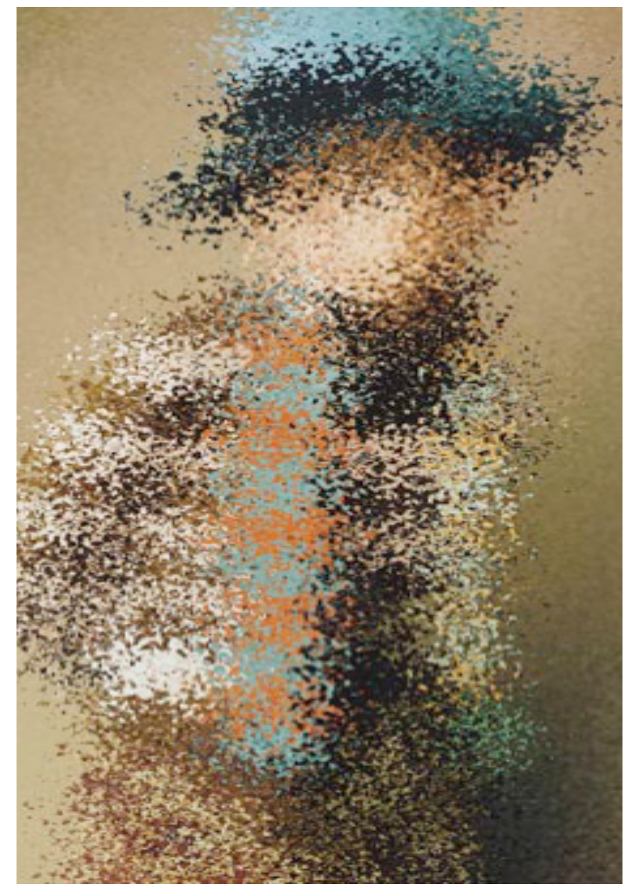
Discriminative power



Raw pixels



Sampled



Locally orderless

Global histogram

Generalization power