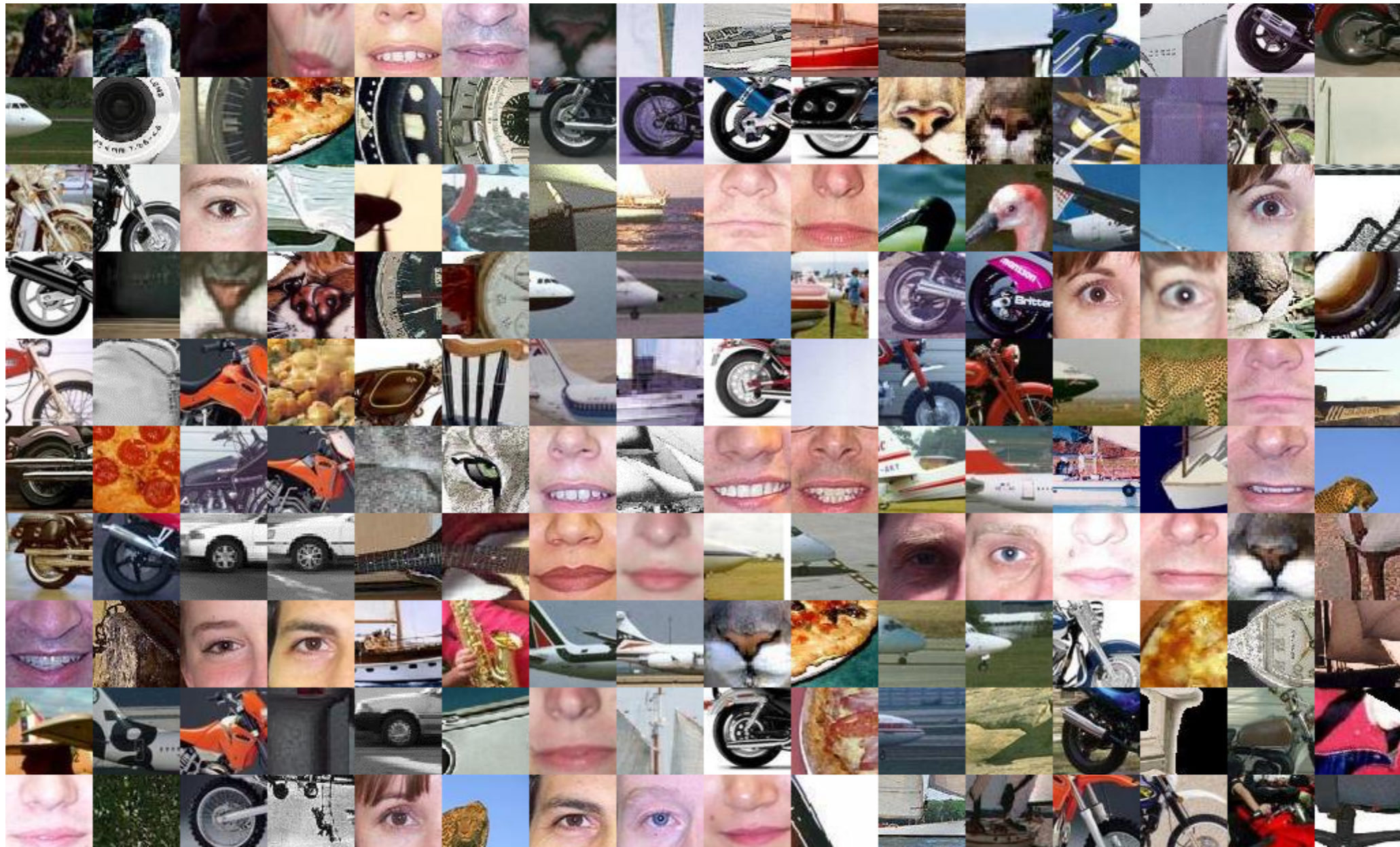# Feature detectors and descriptors

16-385 Computer Vision
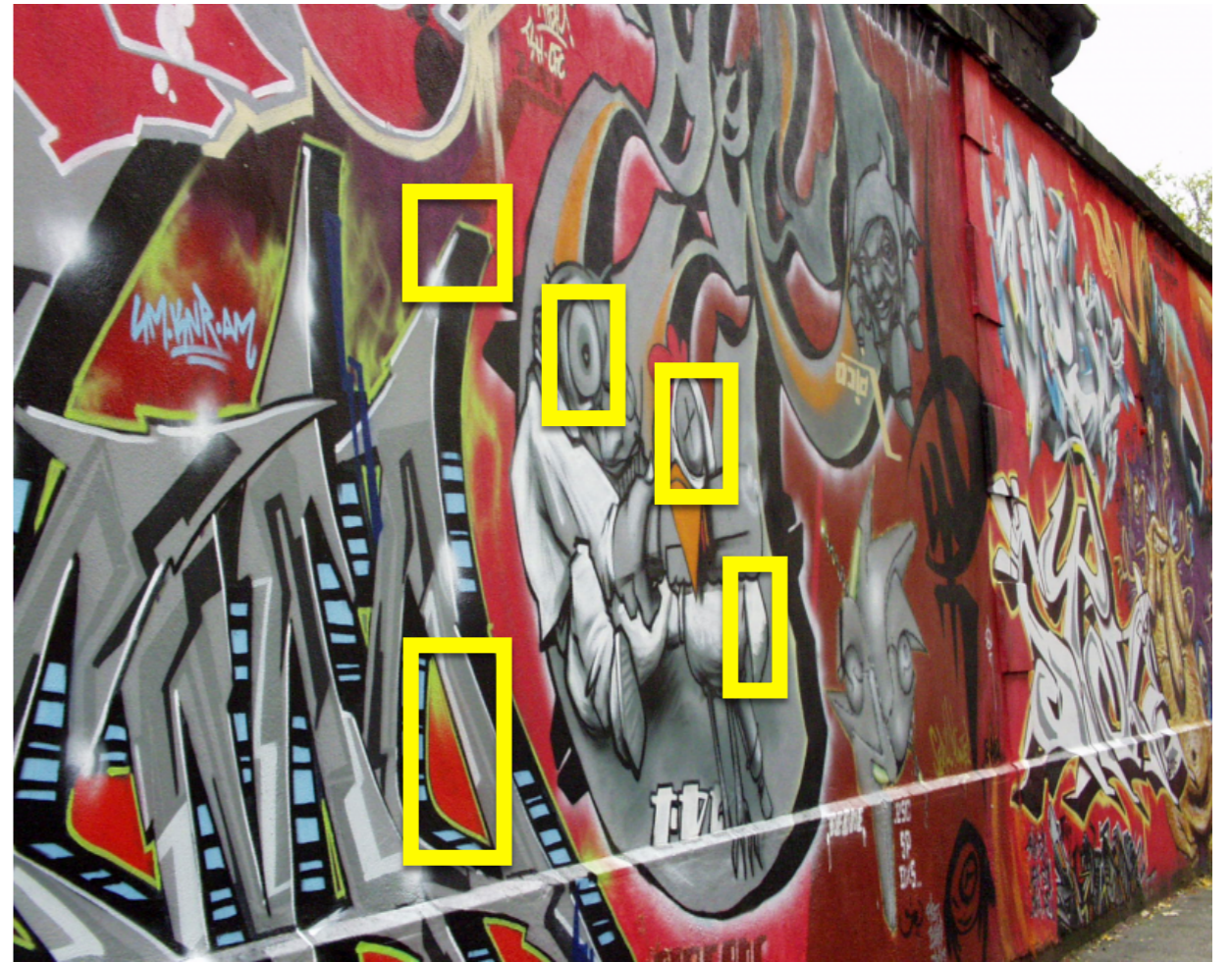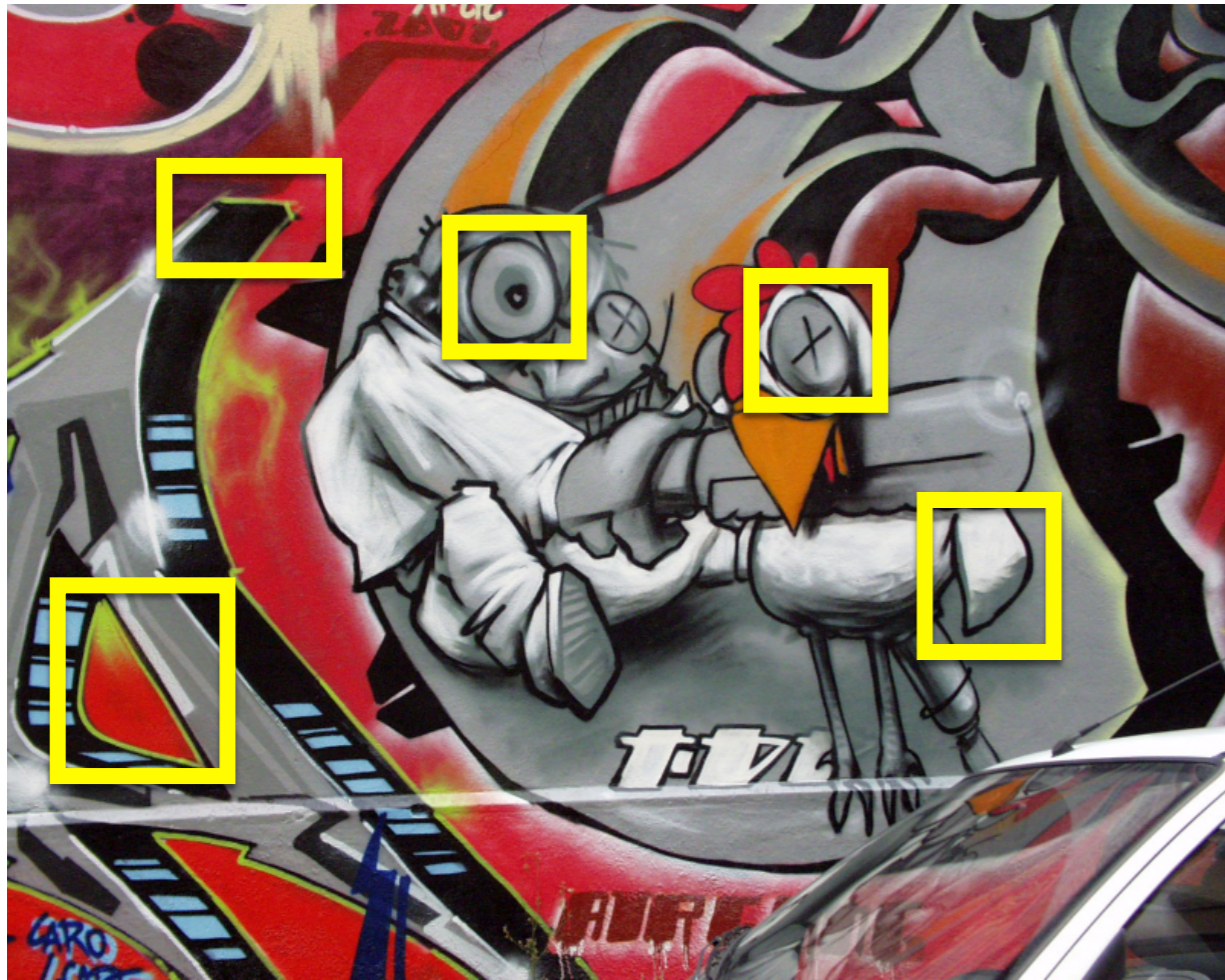Spring 2021, Lecture 6

# 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 <u>good</u> features are, how do we <u>match</u> them?*
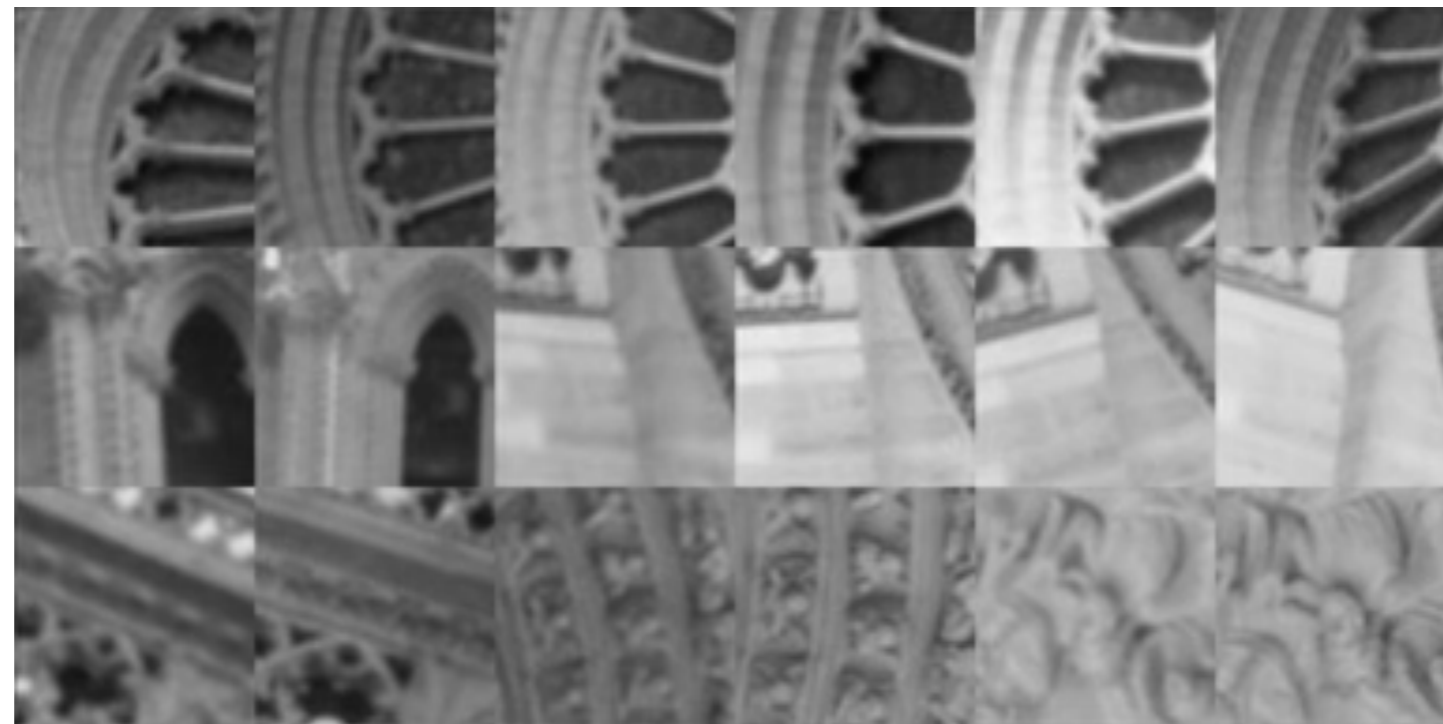
How do we describe an image patch?
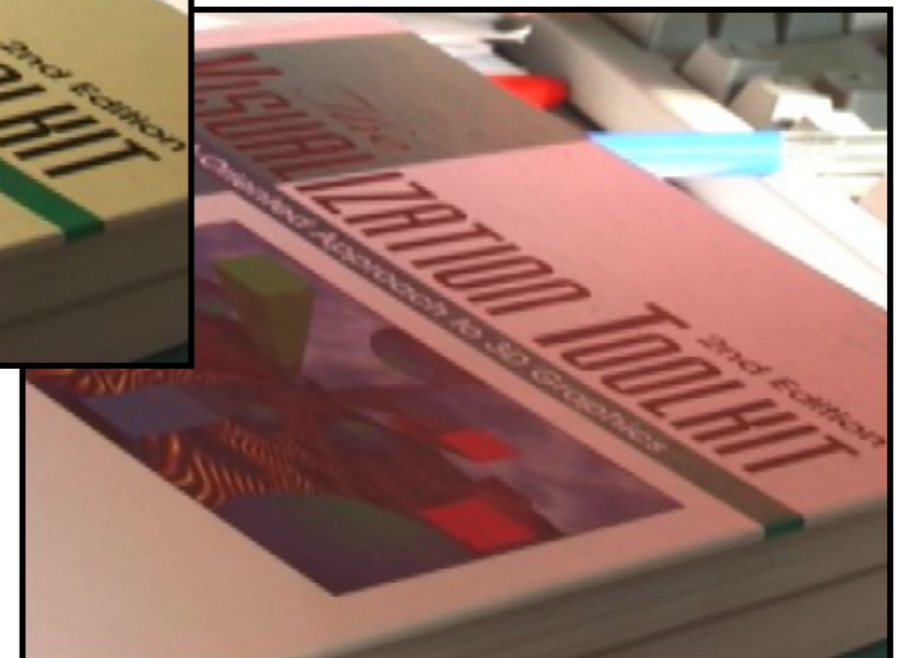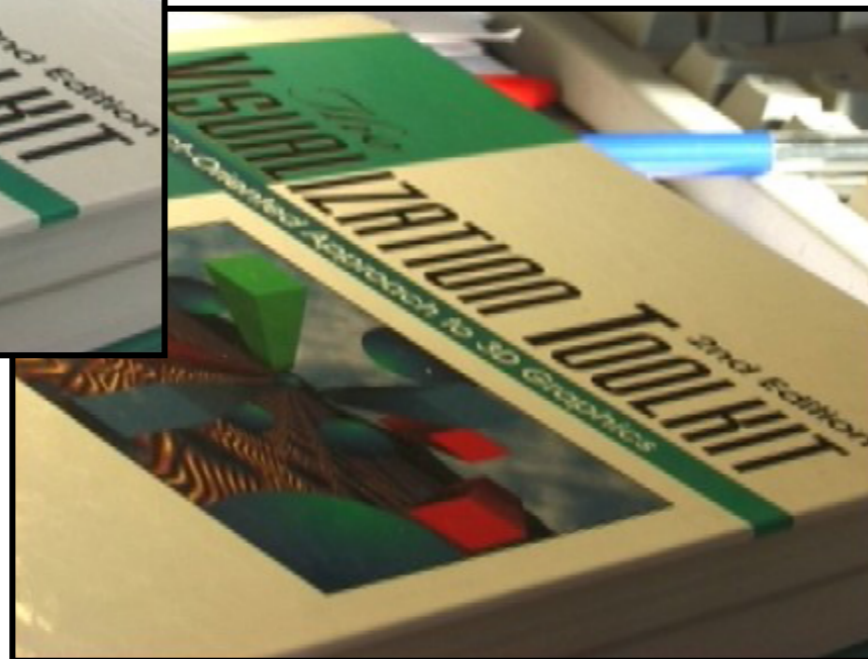Patches with similar content should have similar descriptors.
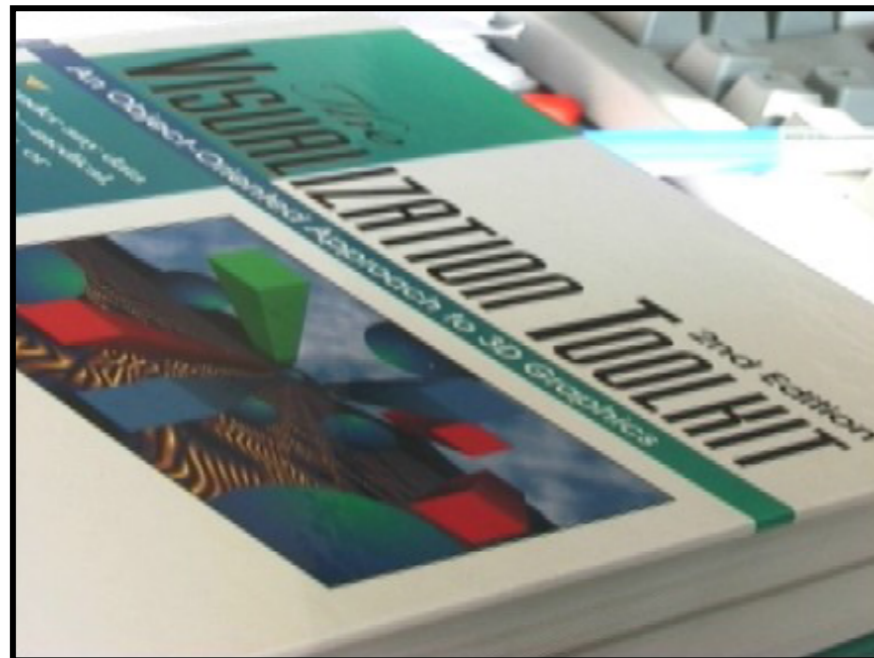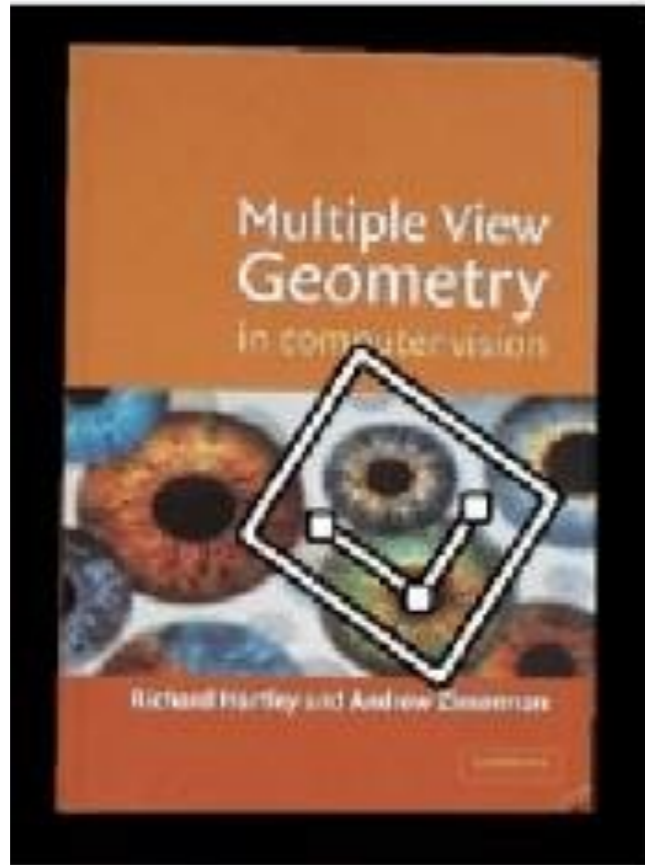
# Designing feature descriptors

**What is the best descriptor for an image feature?**

# Photometric transformations

# Geometric transformations



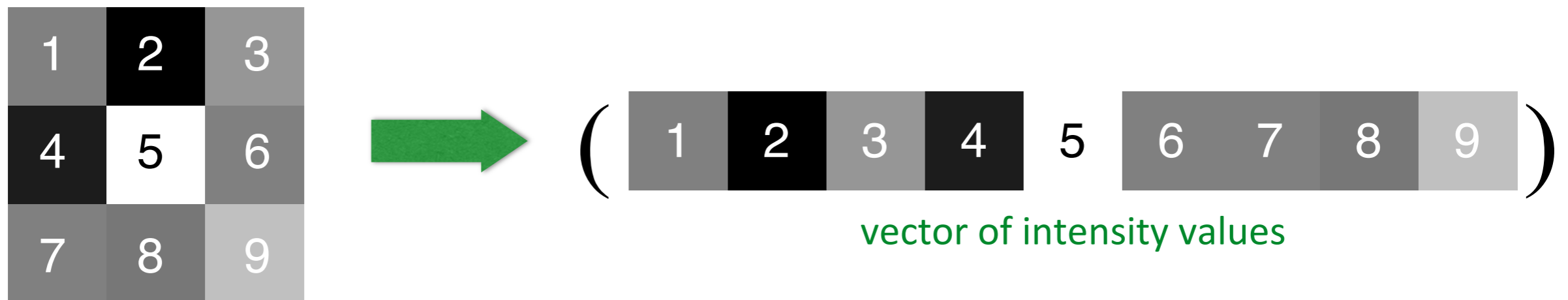objects will appear at different scales,
translation and rotation

# Image patch

Just use the pixel values of the patch!



vector of intensity values

Perfectly fine if geometry and appearance is unchanged

(a.k.a. template matching)

# Image patch

Just use the pixel values of the patch!
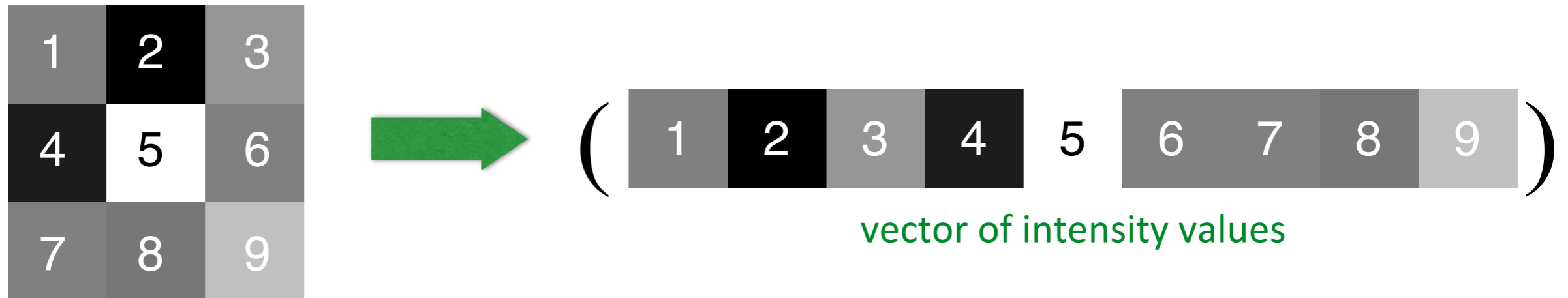


vector of intensity values

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!



vector of intensity values

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



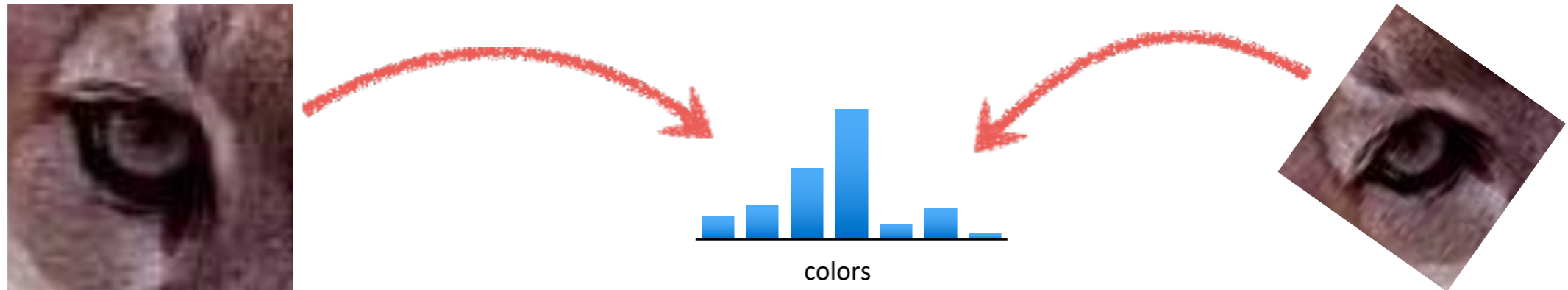vector of x derivatives

'binary descriptor'

Feature is invariant to absolute intensity values

*What are the problems?*

*How can you be less sensitive to deformations?*

# Color histogram

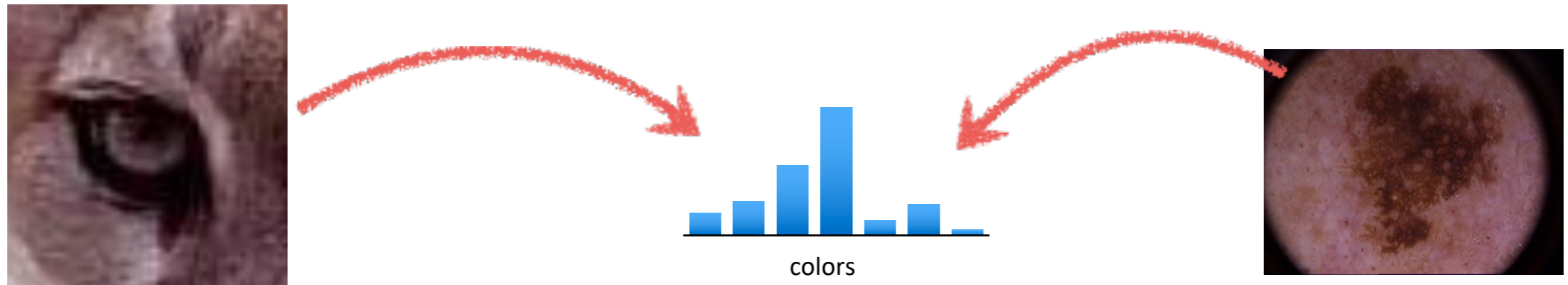Count the colors in the image using a histogram
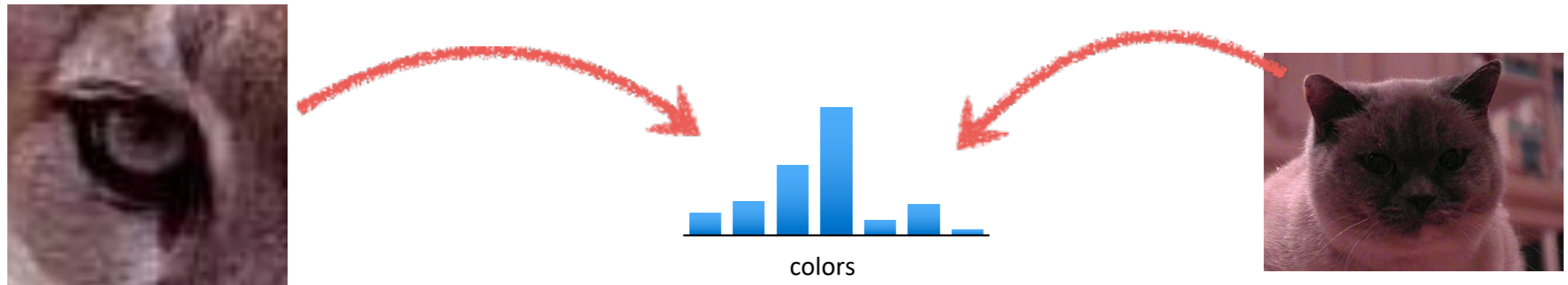


colors

Invariant to changes in scale and rotation

*What are the problems?*

# Color histogram

Count the colors in the image using a histogram



colors

Invariant to changes in scale and rotation

*What are the problems?*

# Color histogram

Count the colors in the image using a histogram
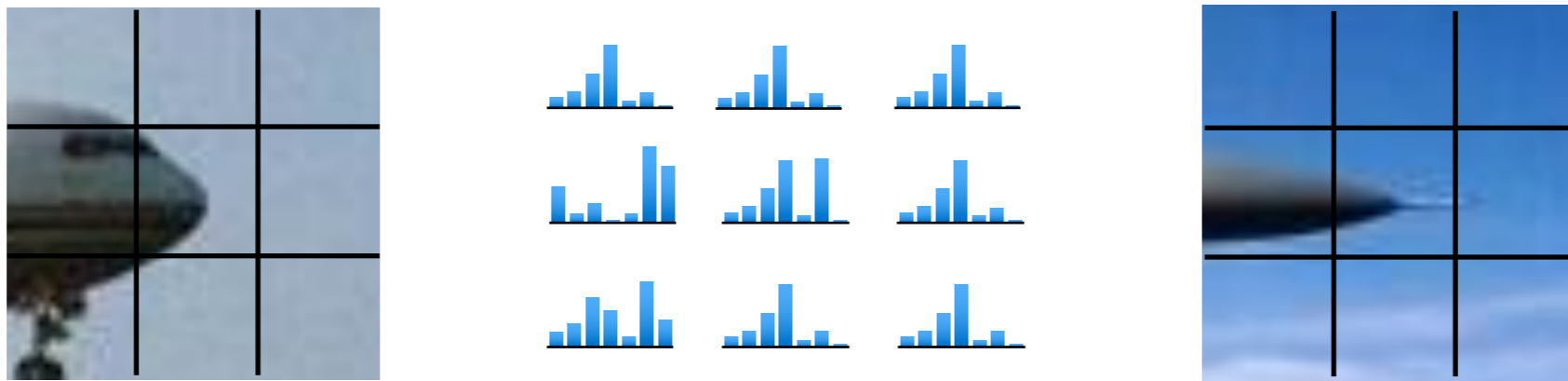


colors

Invariant to changes in scale and rotation

*What are the problems?*

*How can you be more sensitive to spatial layout?*

# Spatial histograms
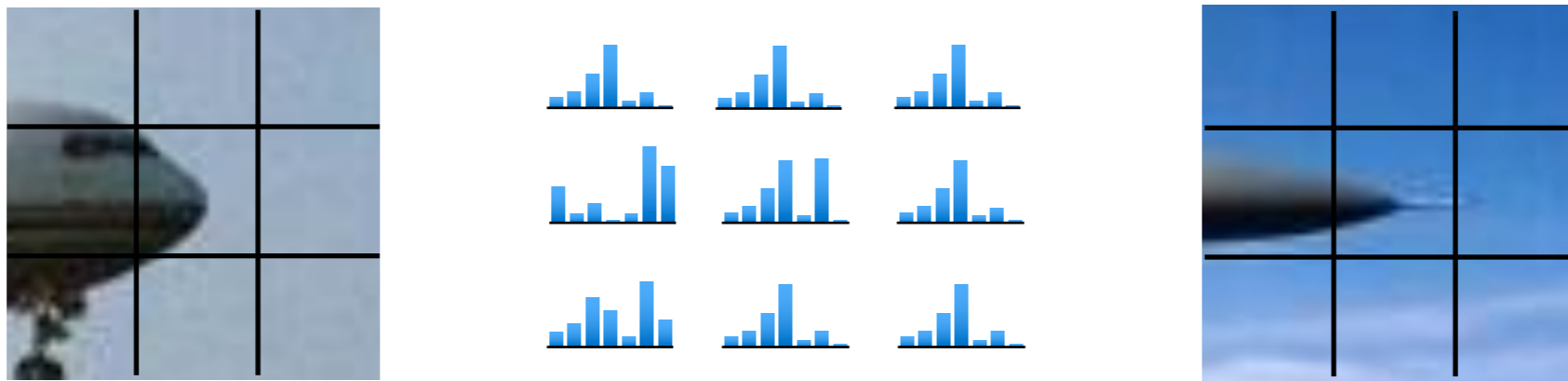
Compute histograms over spatial 'cells'



Retains rough spatial layout
Some invariance to deformations

*What are the problems?*

# Spatial histograms
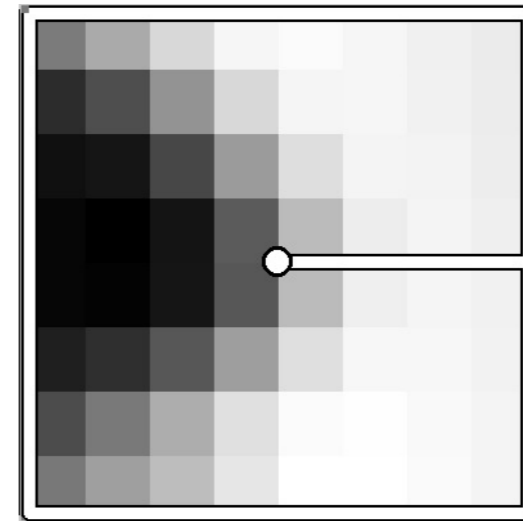
Compute histograms over spatial 'cells'



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 $\theta$ 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
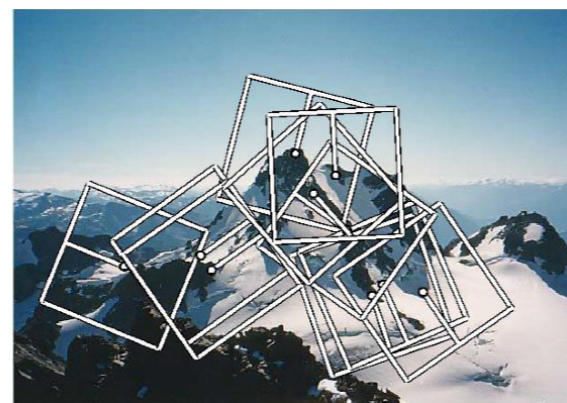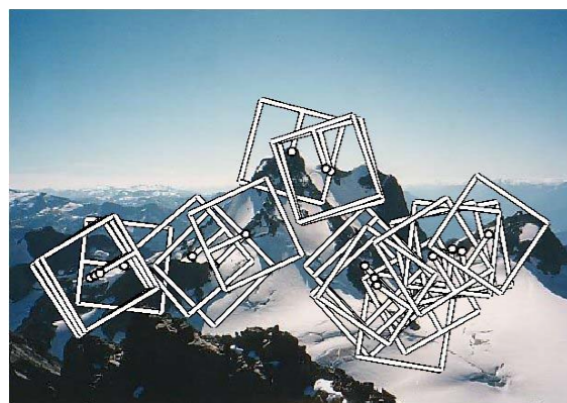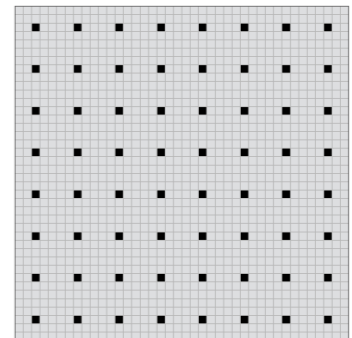
# Multi-Scale Oriented Patches (MOPS)

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 $(x, y, s, \theta)$

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

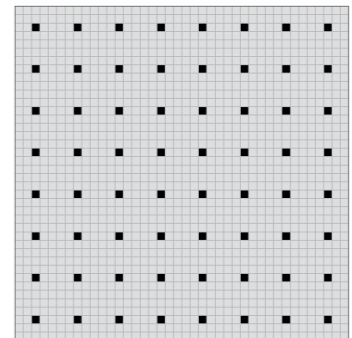(*what's the purpose of this step?*)

# Multi-Scale Oriented Patches (MOPS)

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

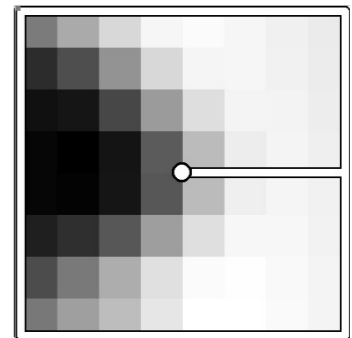Given a feature $(x, y, s, \theta)$

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

(low frequency filtering, absorbs localization errors)

Subtract the mean, divide by standard deviation

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

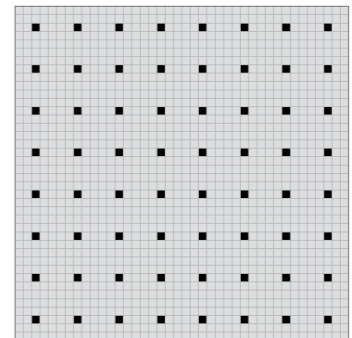Haar Wavelet Transform

(*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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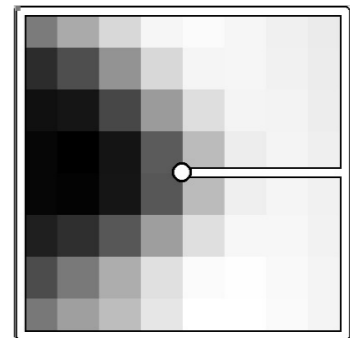Given a feature $(x, y, s, \theta)$

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

(low frequency filtering, absorbs localization errors)

Subtract the mean, divide by standard deviation

(removes bias and gain)

Haar Wavelet Transform

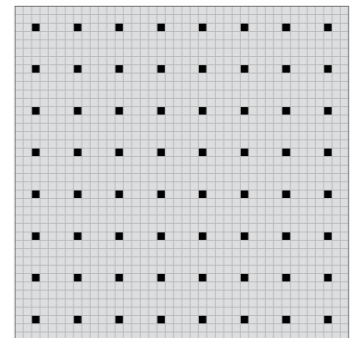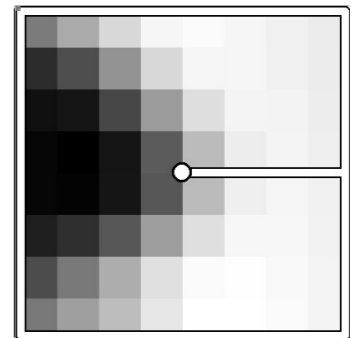(*what's the purpose of this step?*)

# Multi-Scale Oriented Patches (MOPS)

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Given a feature $(x, y, s, \theta)$

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

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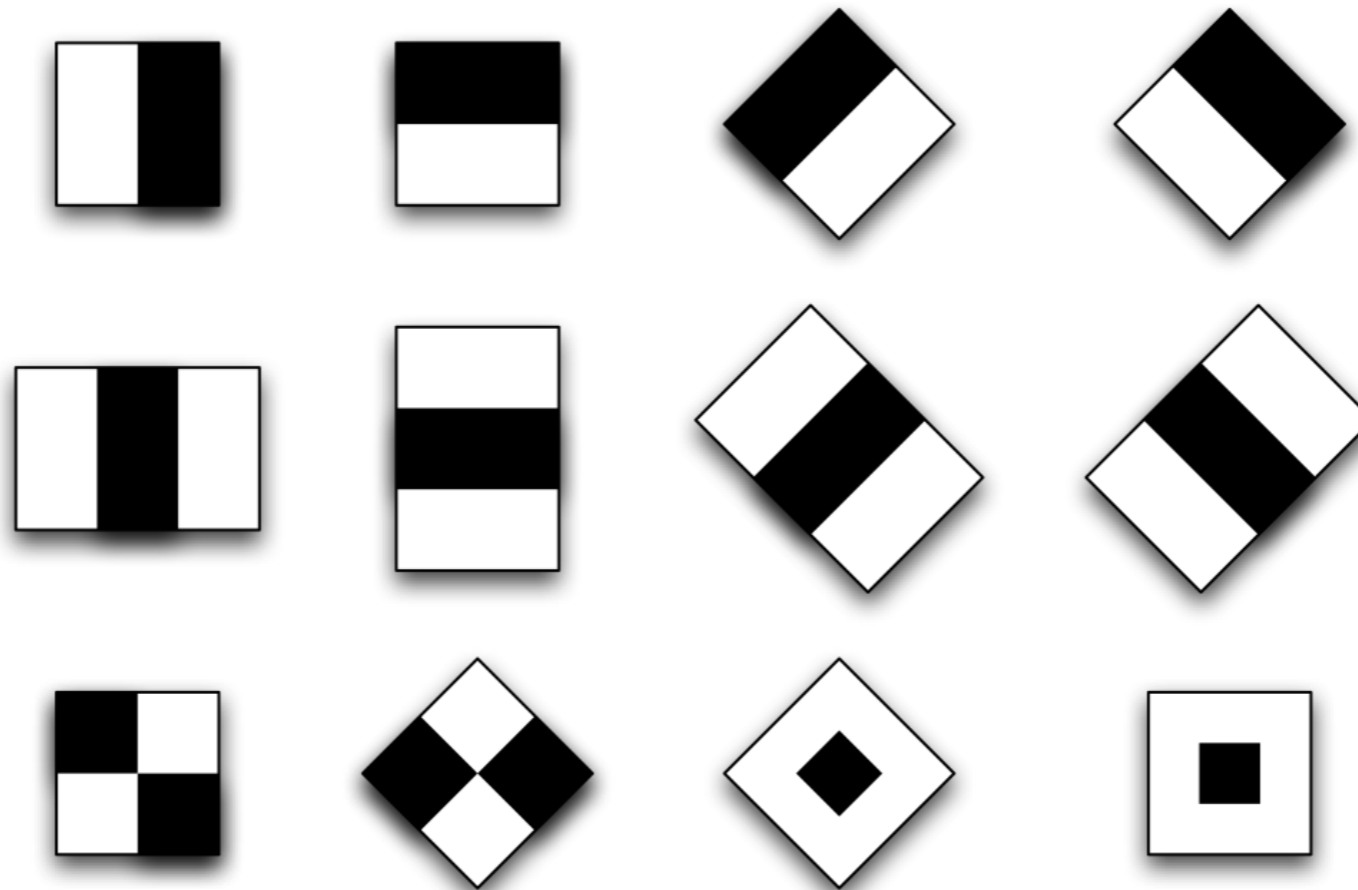
(removes bias and gain)

Haar Wavelet Transform

(low frequency projection)

# Haar Wavelets

(actually, Haar-like features)

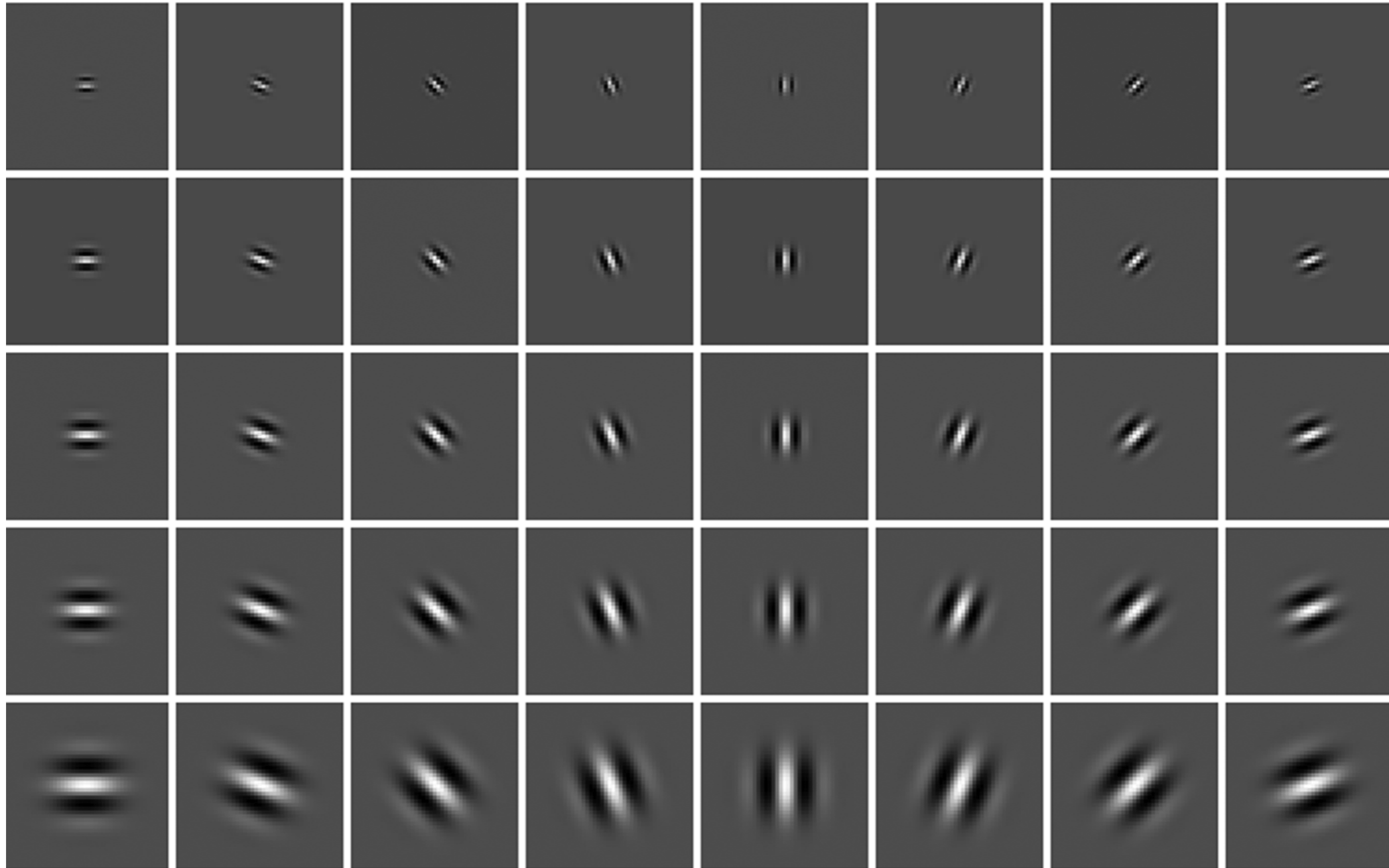Use responses of a bank of filters as a descriptor
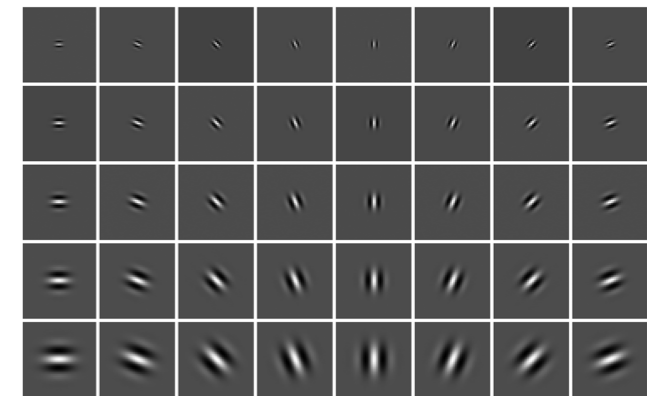
# GIST descriptor

# 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

Filter bank

4 x 4 cell

averaged filter responses
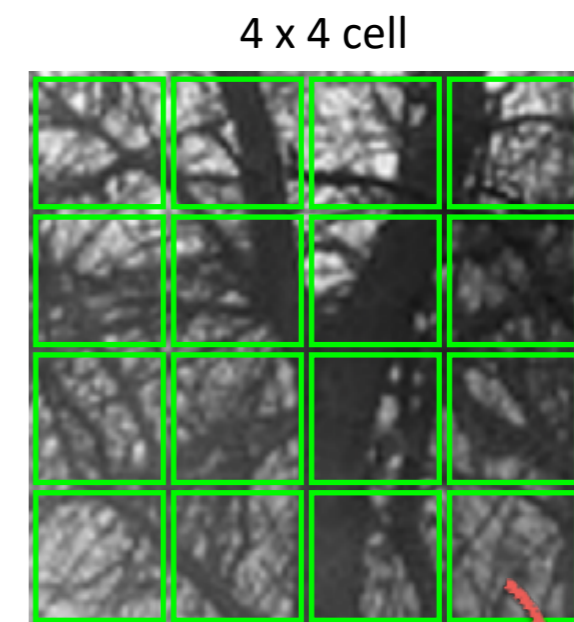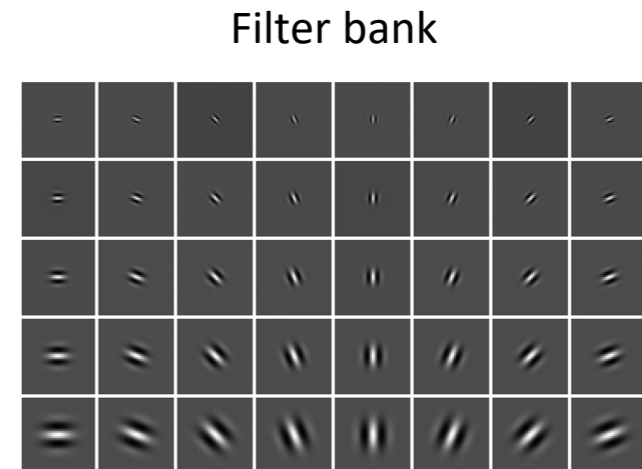
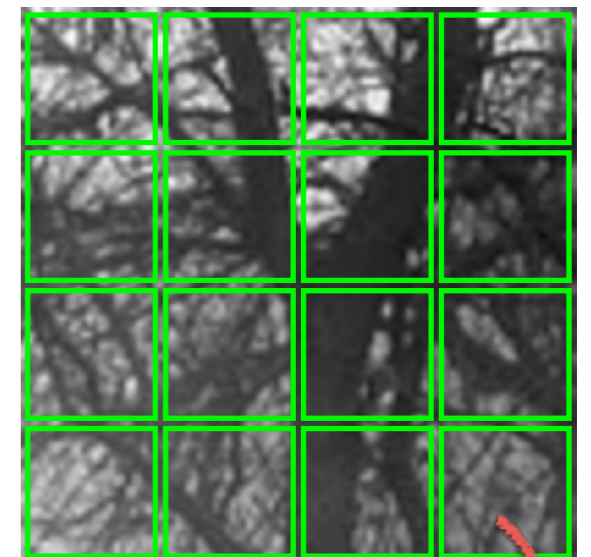# Directional edge detectors

# 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

*What is the GIST descriptor encoding?*

Filter bank



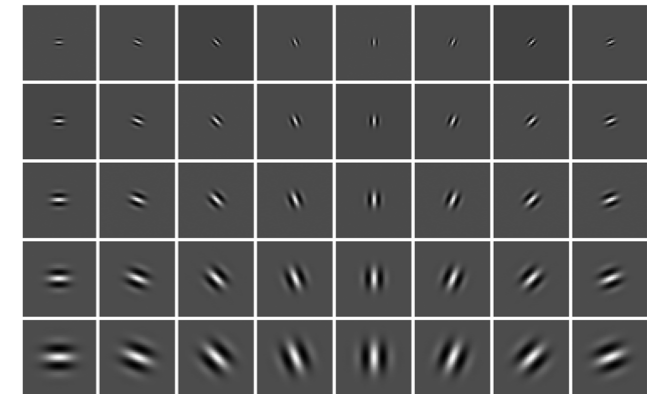4 x 4 cell



averaged filter responses

# 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
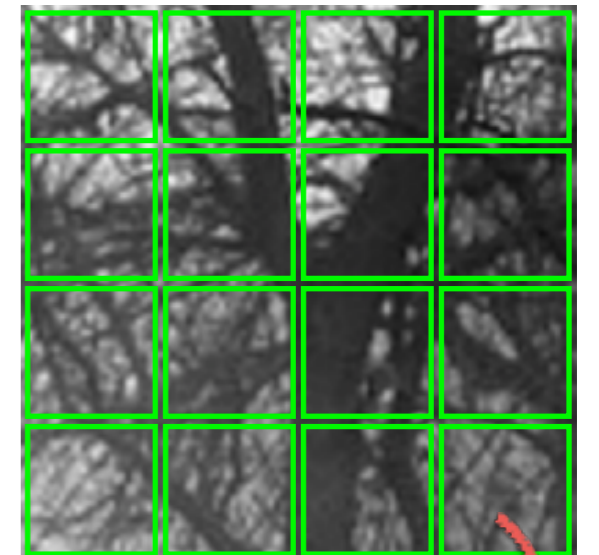
*What is the GIST descriptor encoding?*
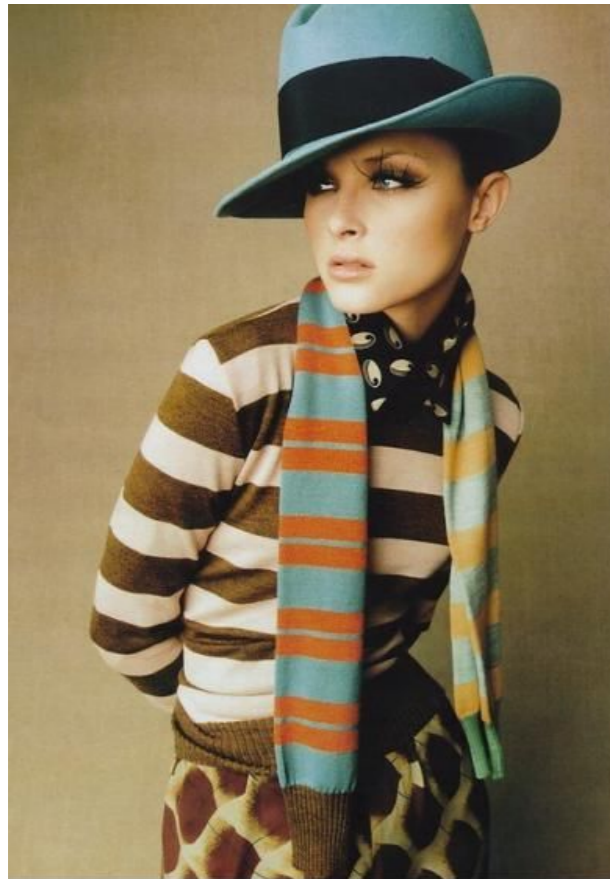
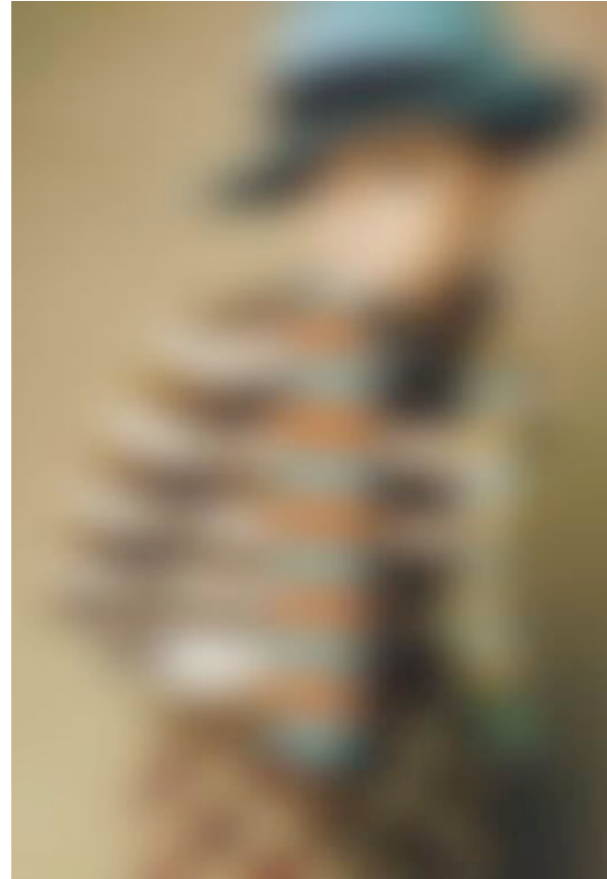Rough spatial distribution of image gradients

Filter bank

4 x 4 cell

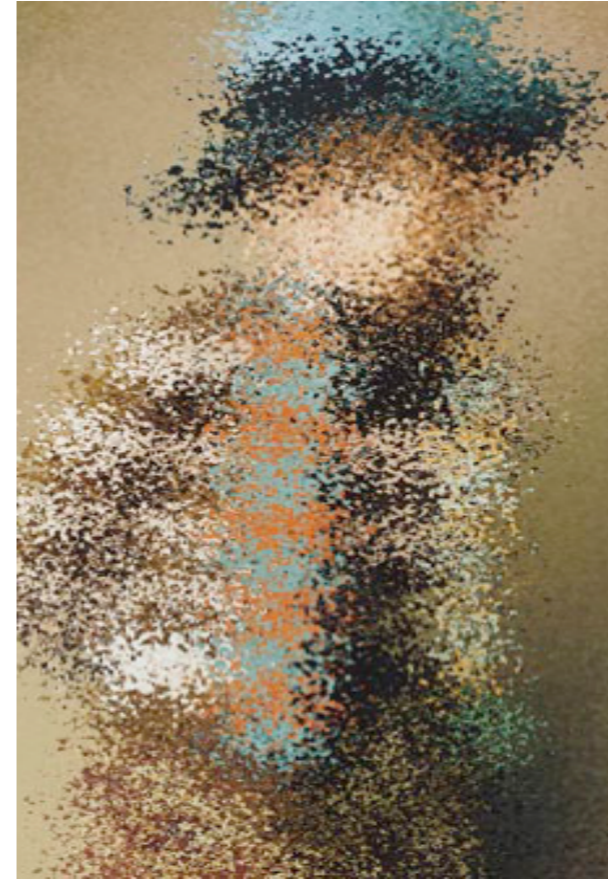averaged filter responses

# Discriminative power



Raw pixels · Sampled · Locally orderless · Global histogram

# Generalization power