Classical Computer Vision: Feature Engineering

Connelly Barnes

With slides from Alexei Efros, James Hays, Antonio Torralba, Jean-Francois Lalonde, Frederic Heger, Steve Seitz, Rick Szeliski, Fredo Durand, Kristin Grauman

Big Problems in Computer Vision

- Find correspondences between the same object in 2 photos

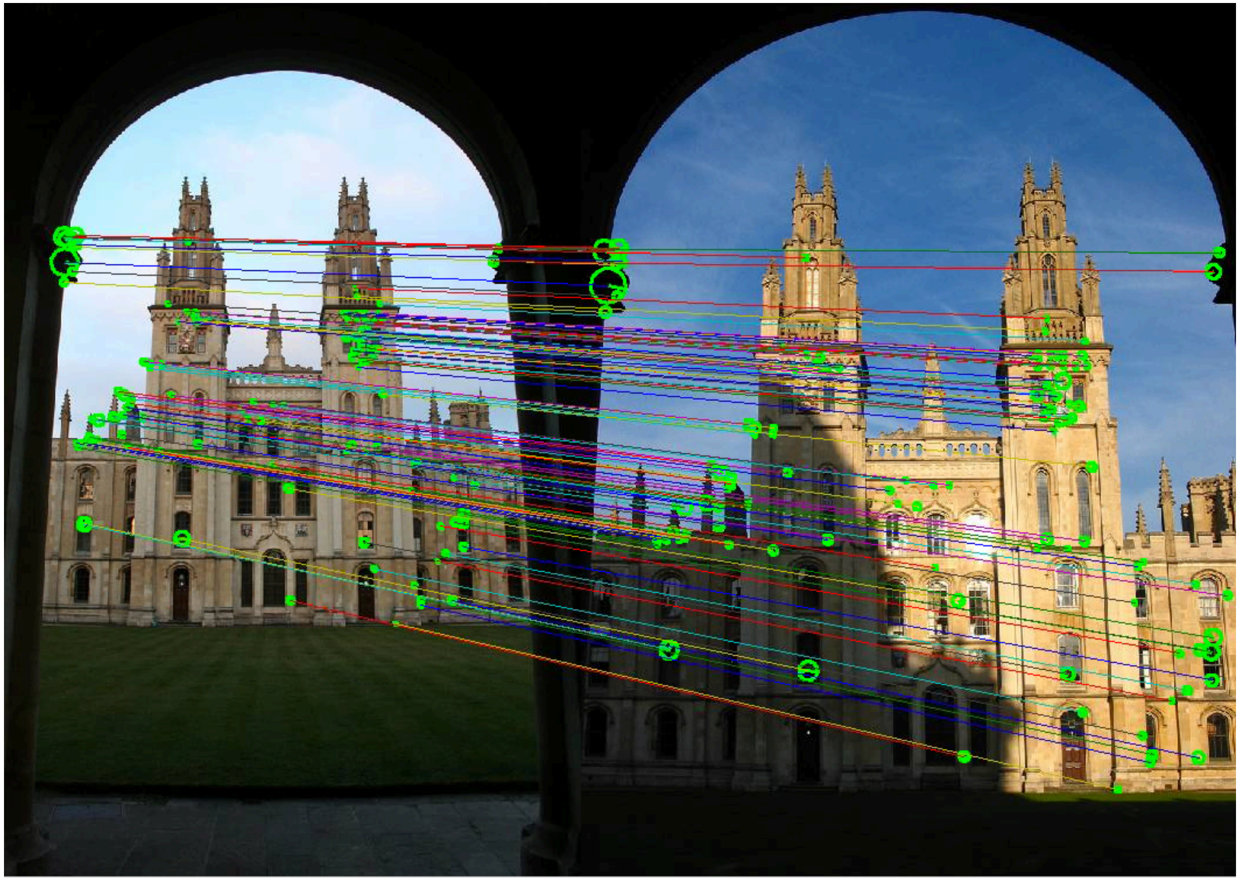


Photo from: [Vedaldi and Zisserman]

Big Problems in Computer Vision

- What category is this image? (classification/recognition)

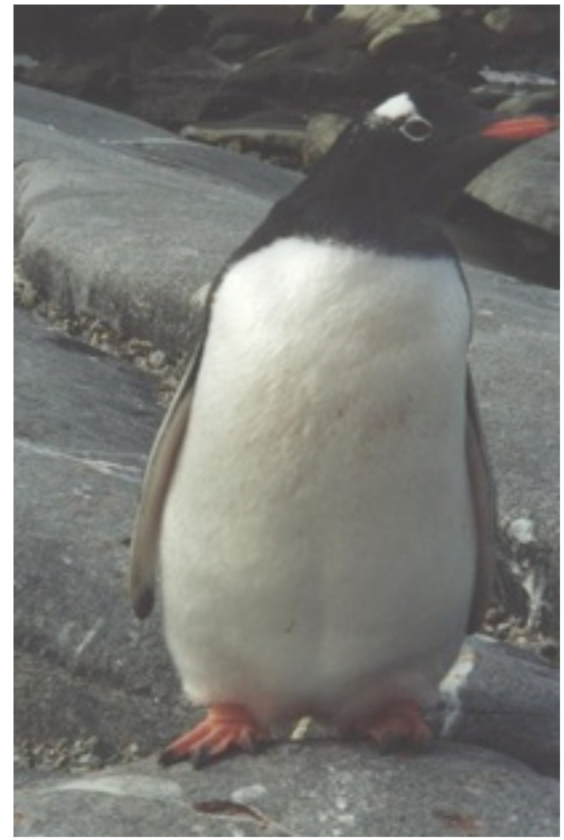
?

Better than human performance reported on ImageNet large-scale challenge.

Big Problems in Computer Vision

- Are two photos the same?

?

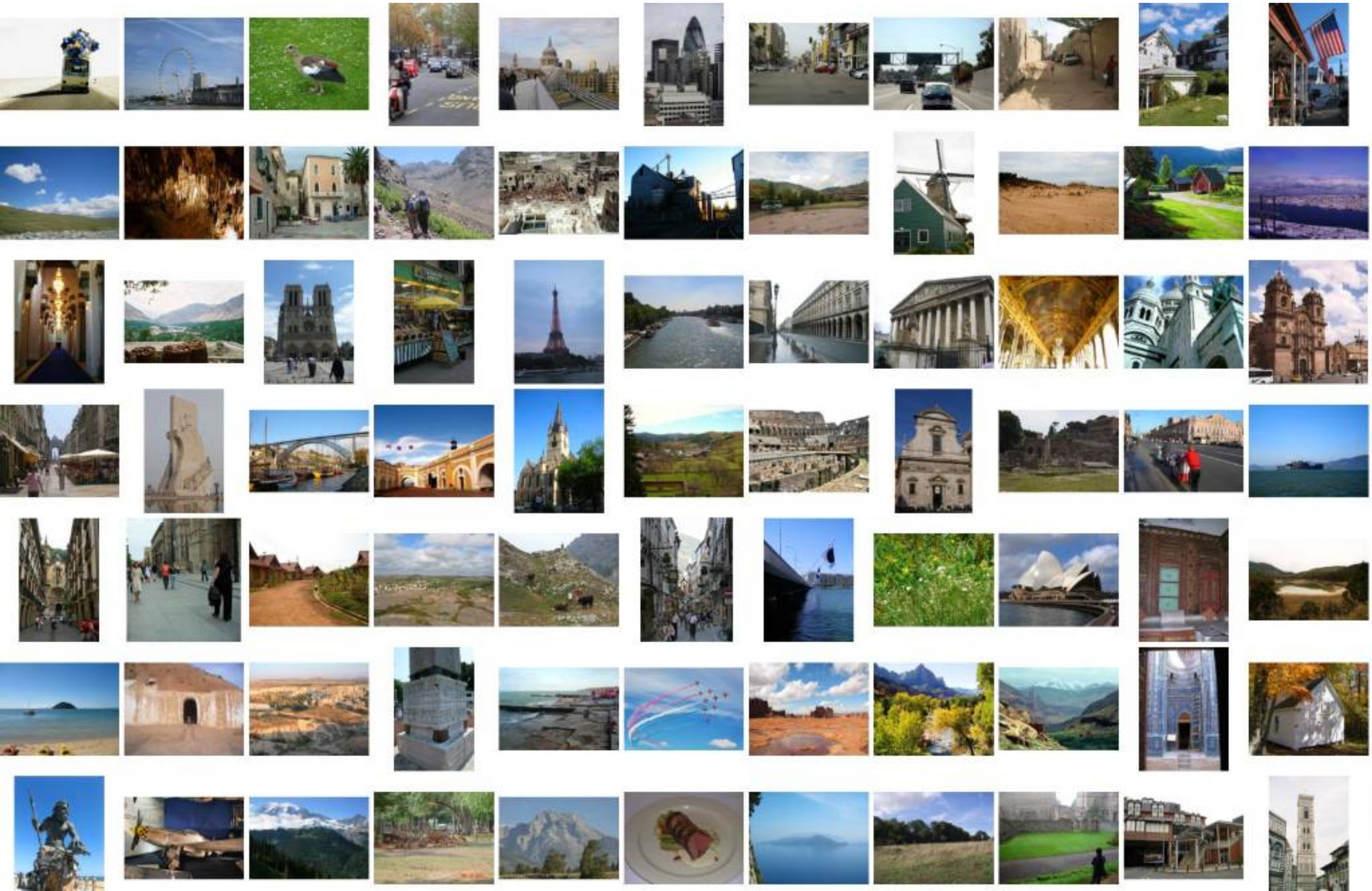


Classical Approach

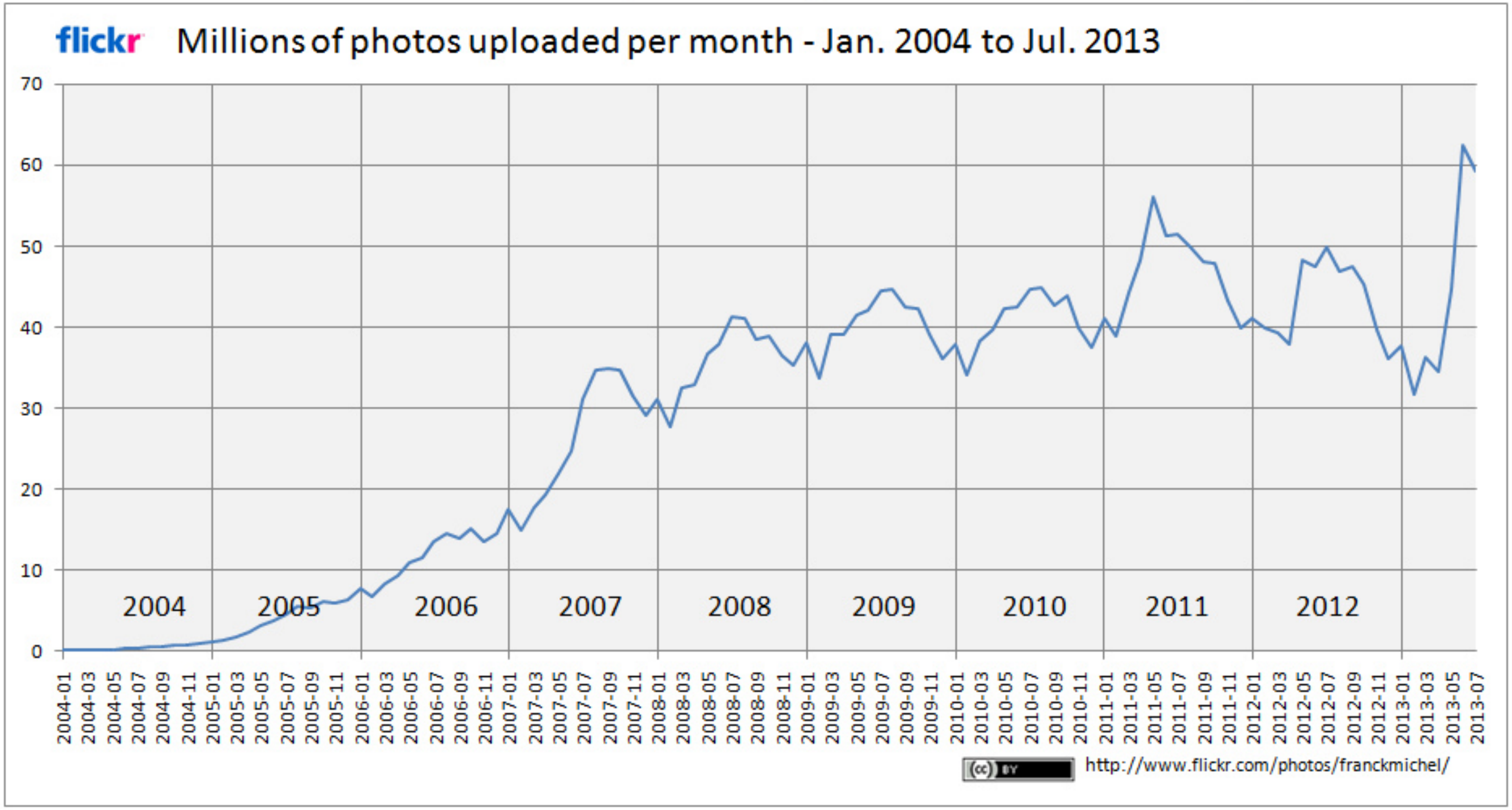
- Manually engineer features to detect and describe different regions of the image.

- A feature is just a vector in $\mathbf{R}^n$.
- It could represent the entire image…
- …Or just a local region
- To find similar features, use a distance metric such as Euclidean distance.

The Visual World



How big is Flickr?



100M photos updated *daily*

6B photos as of August 2011!

- ~3B public photos

Credit: Franck_Michel (http://www.flickr.com/photos/franckmichel/)

How Annotated is Flickr? (tag search)

Party – 23,416,126

Paris – 11,163,625

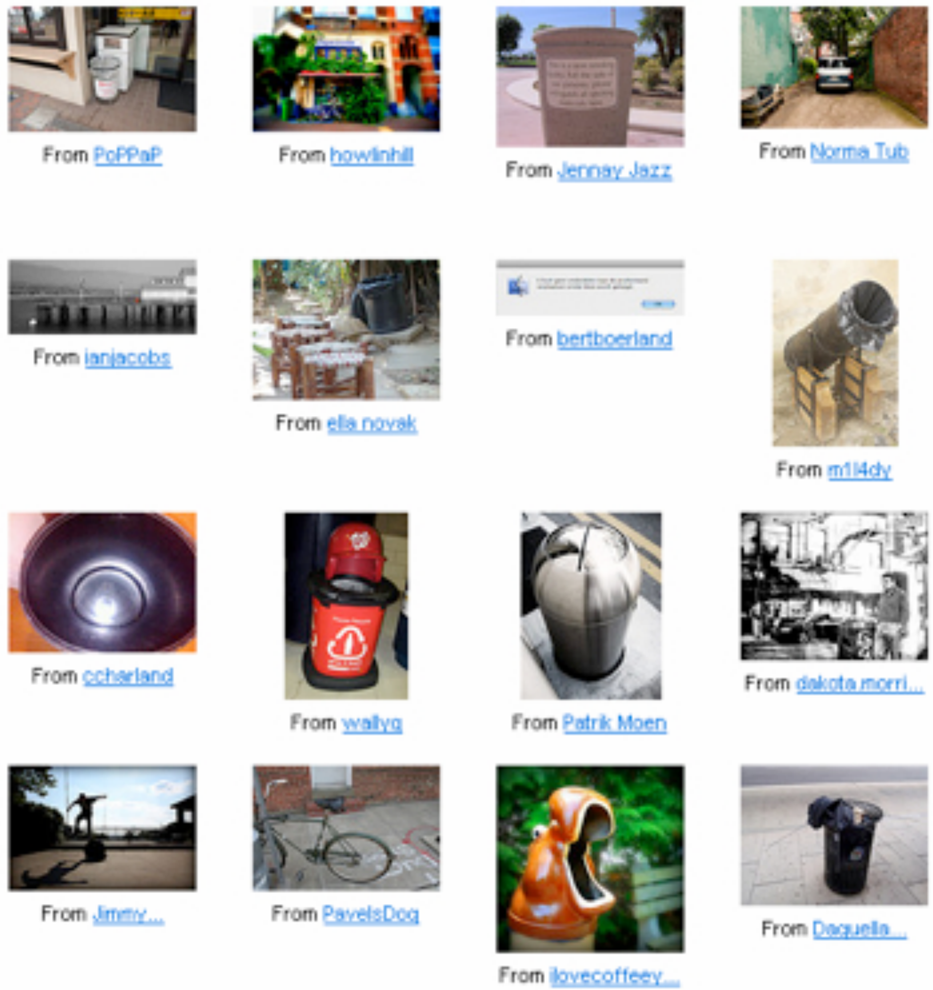
Pittsburgh – 1,152,829

Chair – 1,893,203

Violin – 233,661

Trashcan – 31,200

“Trashcan” Results



- http://www.flickr.com/search/?q=trashcan+NOT+party&m=tags&z=t&page=5

Big Issues

If we could harness all this data, we could use it.

What is out there on the Internet?

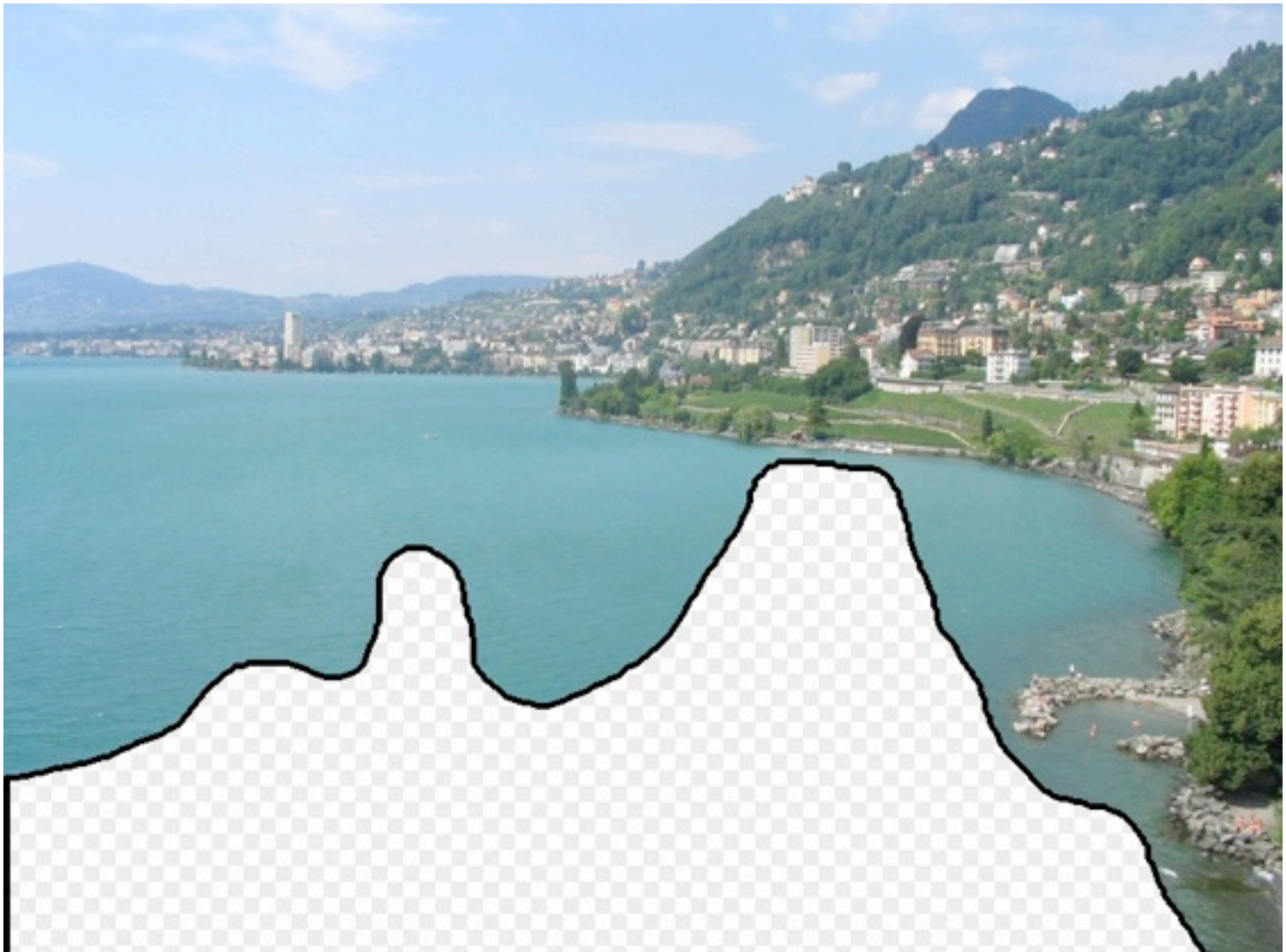
How do we get it?

What can we do with it?

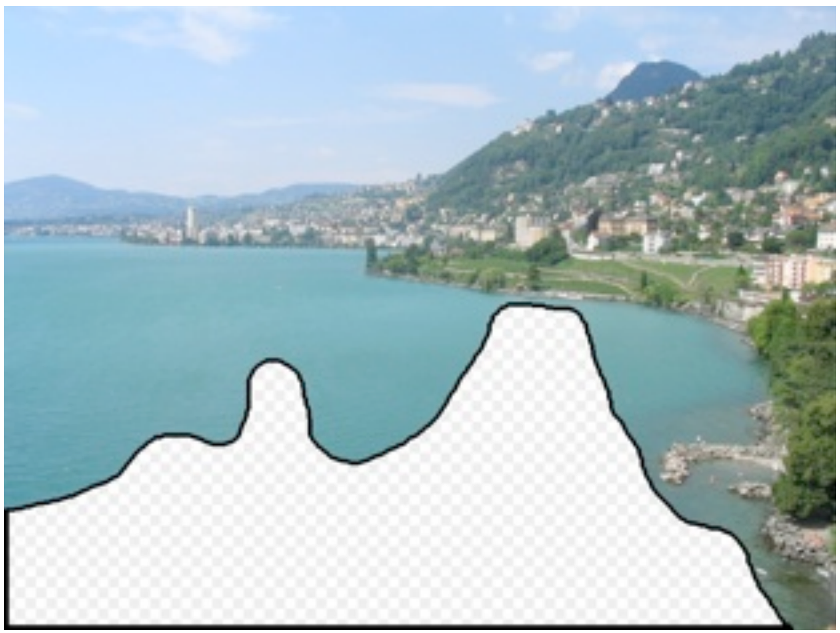
- Let's see a motivating example...

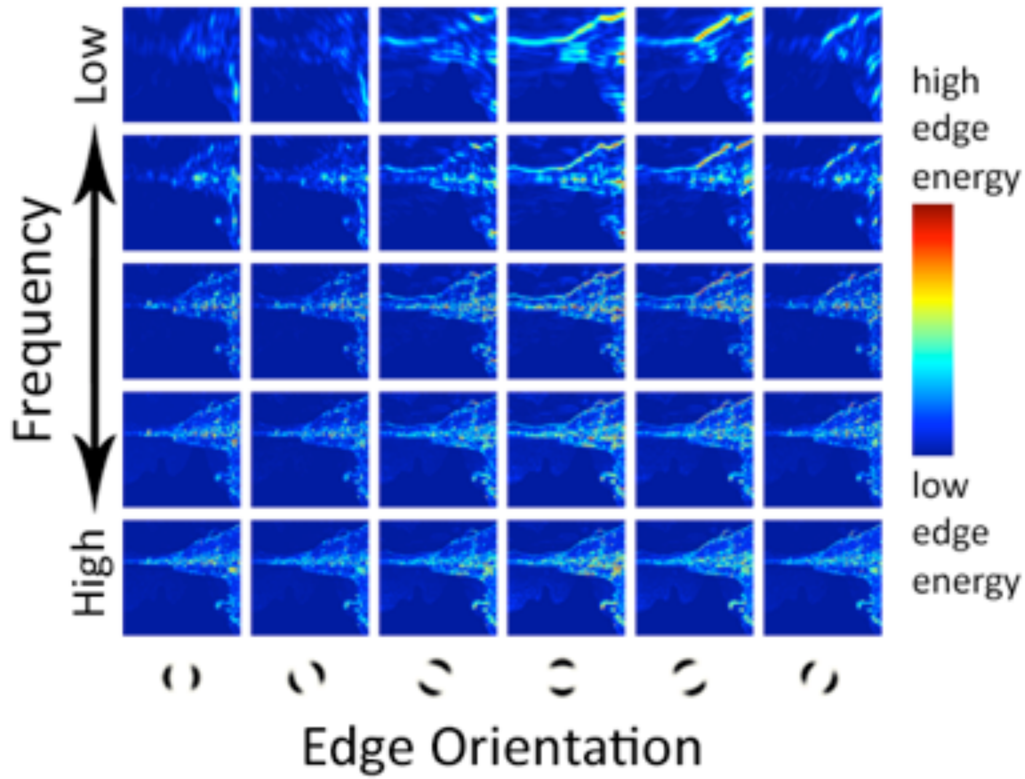
Scene Completion

Scene Matching



Scene Descriptor





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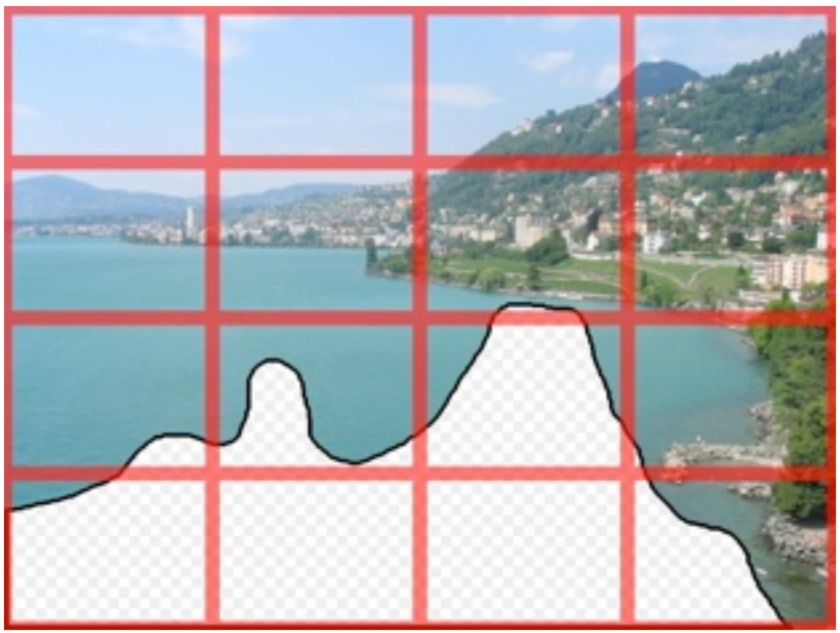
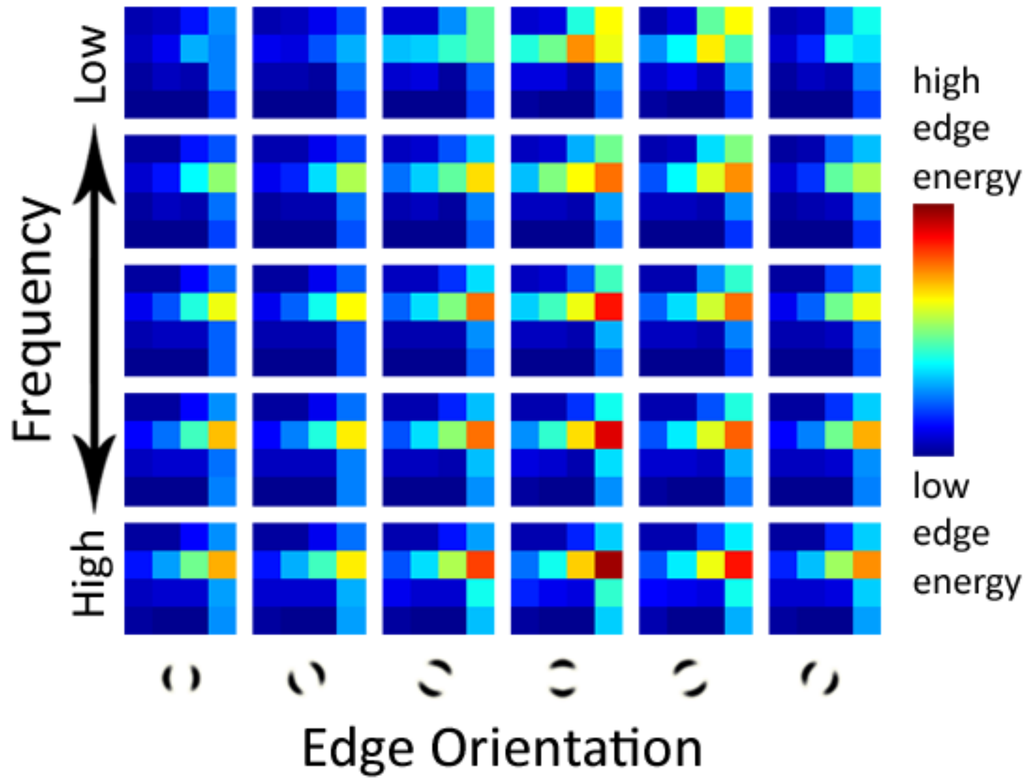
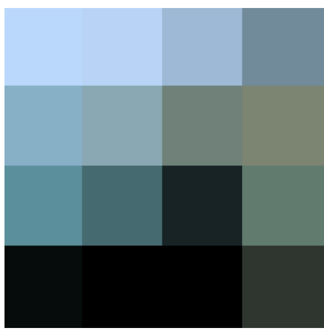


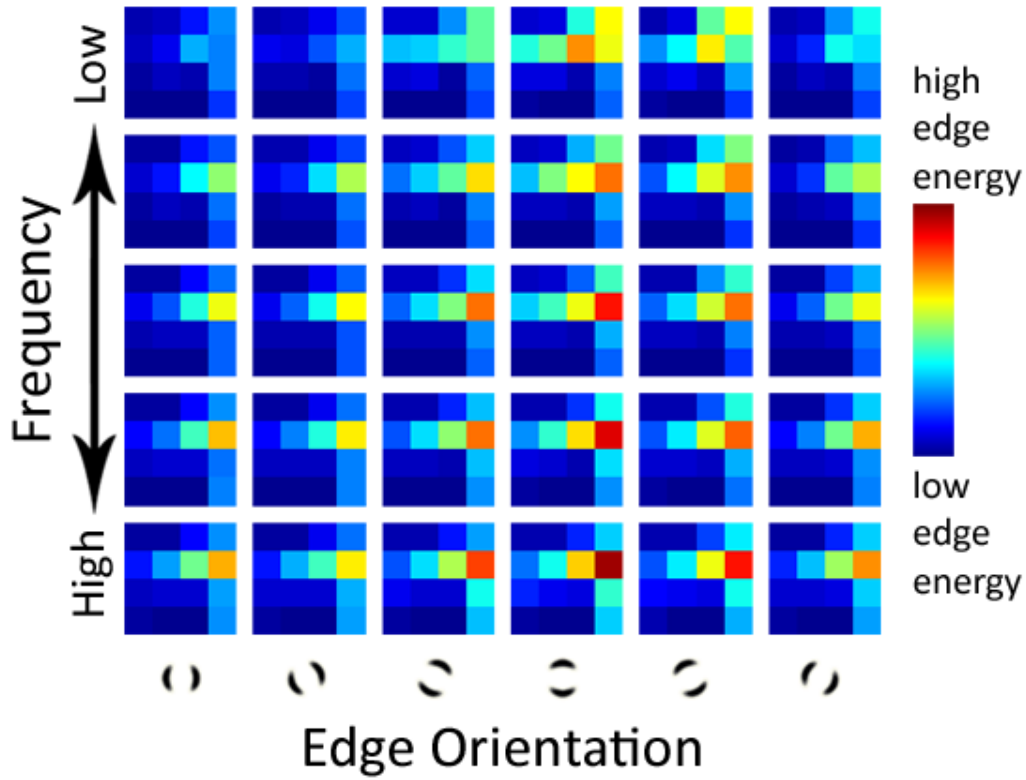


Scene Gist Descriptor
(Oliva and Torralba 2001)

Scene Descriptor



+



Scene Gist Descriptor
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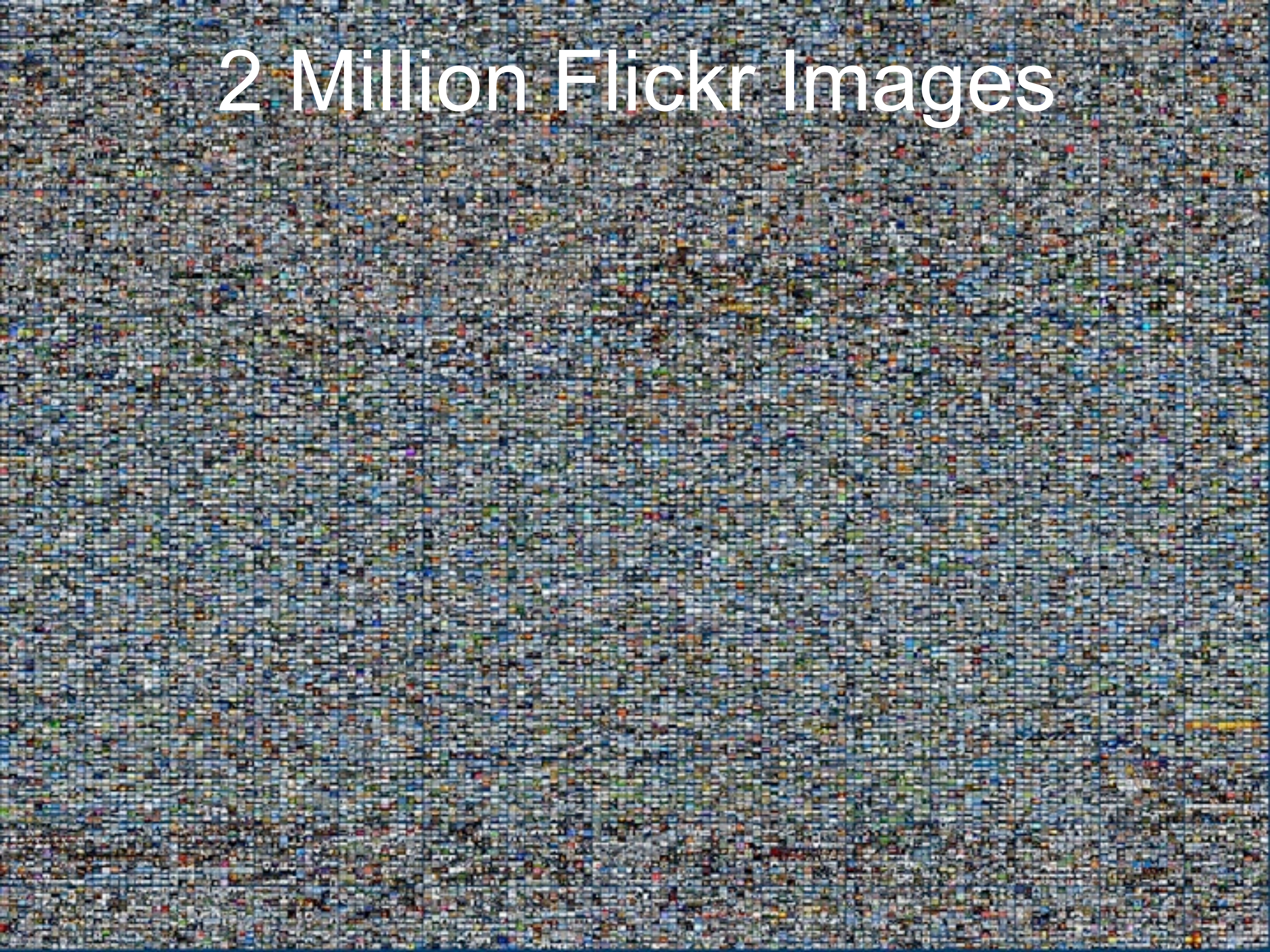
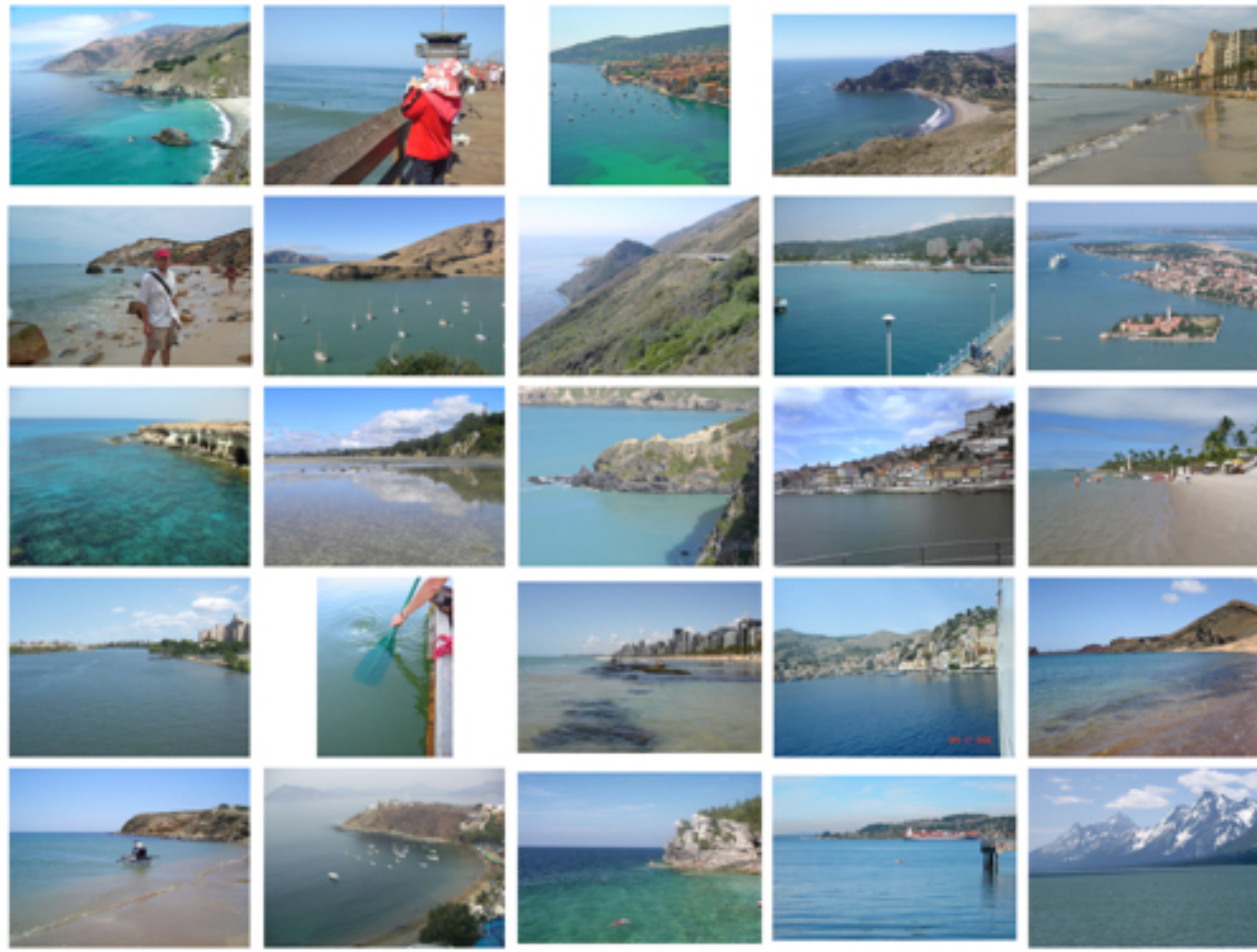
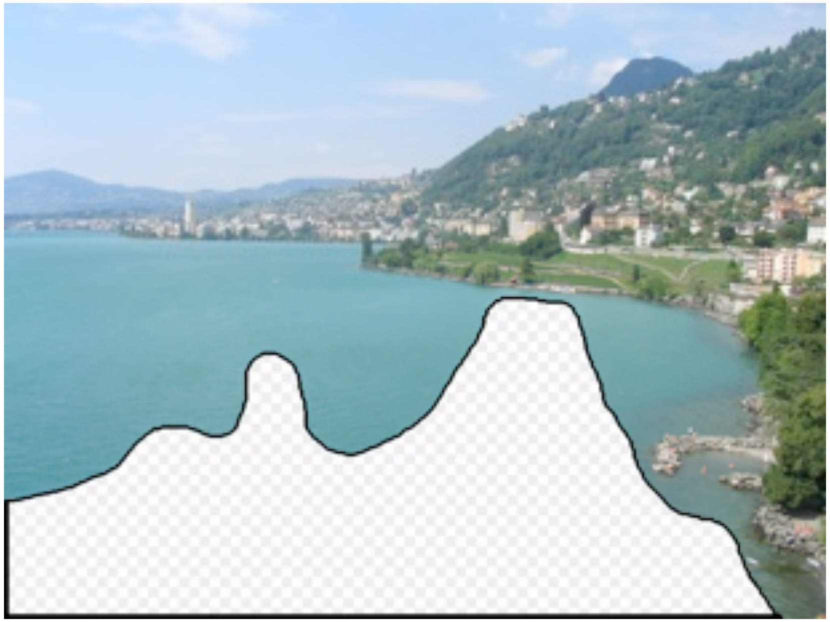
2 Million Flickr Images



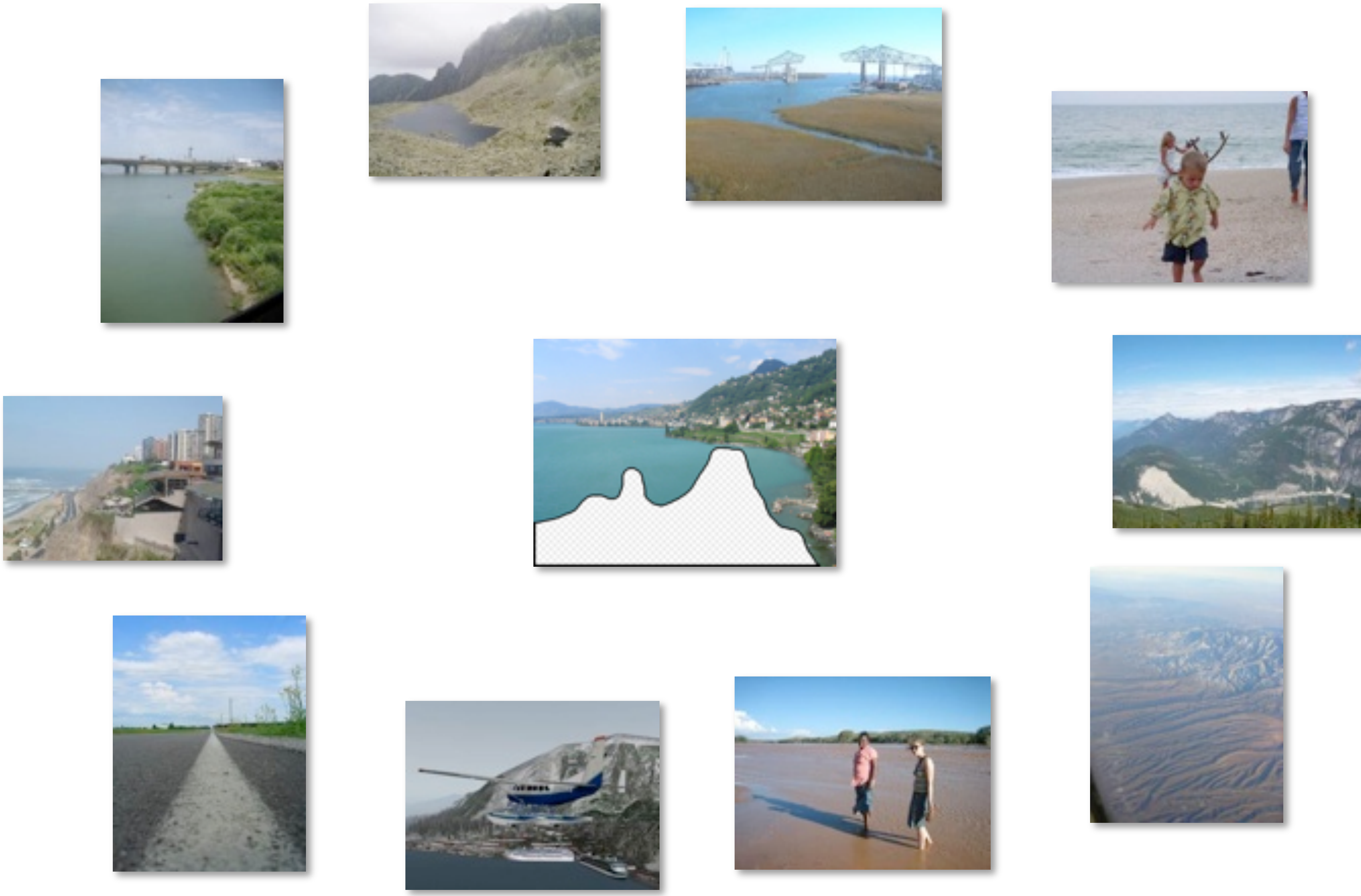


… 200 total

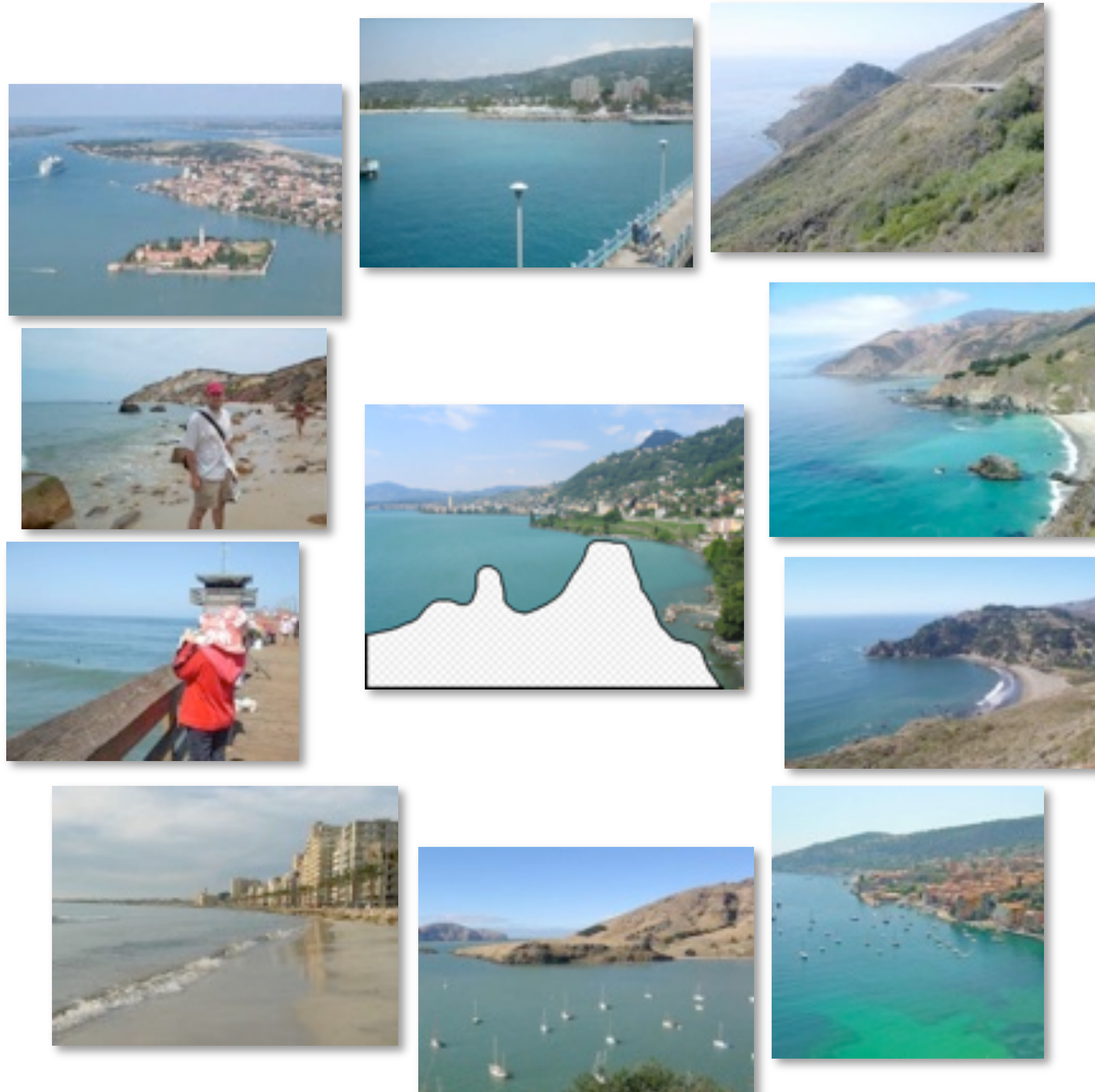
Context Matching




Graph cut + Poisson blending



Nearest neighbors from a
collection of 20 thousand images



Nearest neighbors from a
collection of 2 million images

“Unreasonable Effectiveness of Data”

Parts of our world can be explained by elegant mathematics

- physics, chemistry, astronomy, etc.

But much cannot

- psychology, economics, genetics, etc.

Enter The Data!

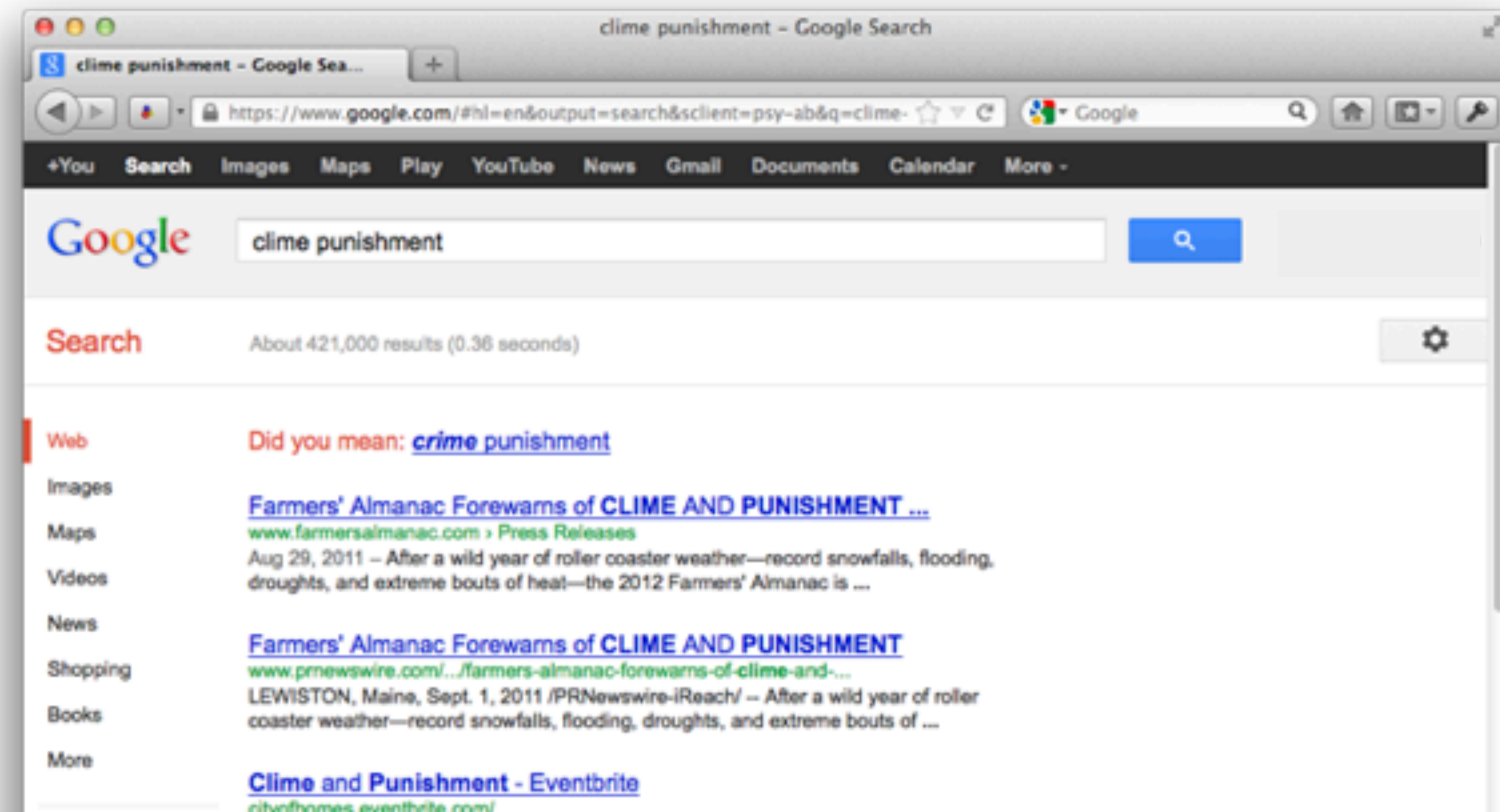
- Great advances in several fields:
  - e.g. speech recognition, machine translation
  - Case study: Google

[Halevy, Norvig, Pereira 2009]

Google

A.I. for the postmodern world:

- all questions have already been answered…many times, in many ways
- Google is dumb, the “intelligence” is in the data



How about *visual* data?

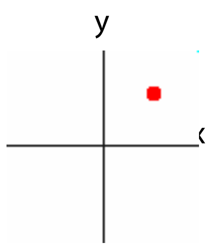
Text is simple:

- clean, segmented, compact, 1D

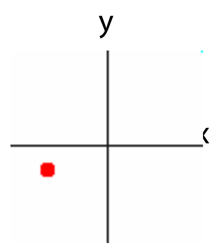
Visual data is much harder:

- Noisy, unsegmented, high entropy, 2D/3D

Distance Metrics



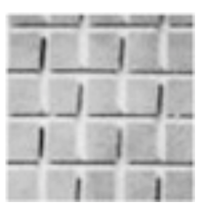
-



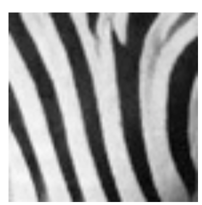
= Euclidian distance of 5 units

-

= Gray value distance of 50 values



-



= ?

SSD says these are not similar

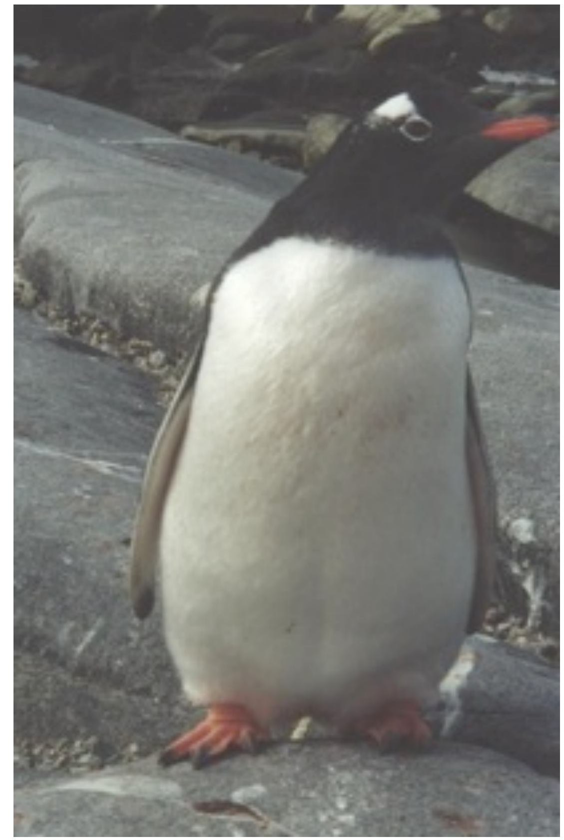


Image Descriptors

- **Blur + SSD**
- **Gist descriptor (average edge response in a coarse spatial grid)**
- Color histograms
- Filter response histograms
- Invariant detectors and descriptors (SIFT)
- Convolutional neural networks (CNNs) – later classes

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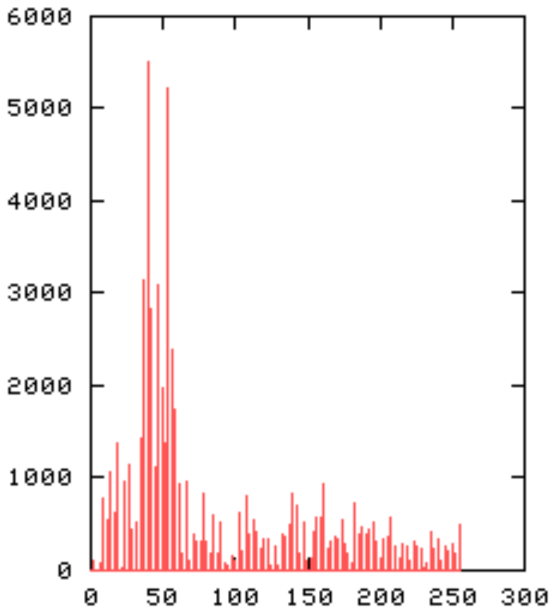
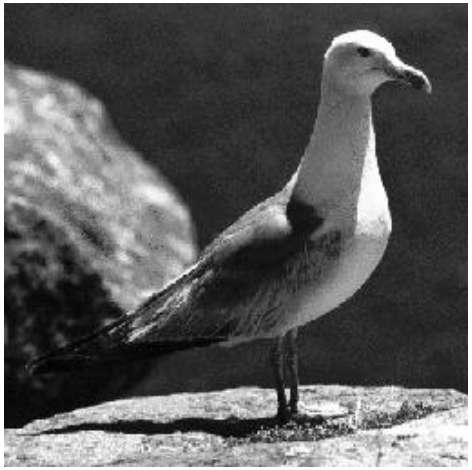
Image Representations: Histograms

Images from Dave Kauchak





global histogram

Represent distribution of features

Color, texture, depth, …

Image Representations: Histograms

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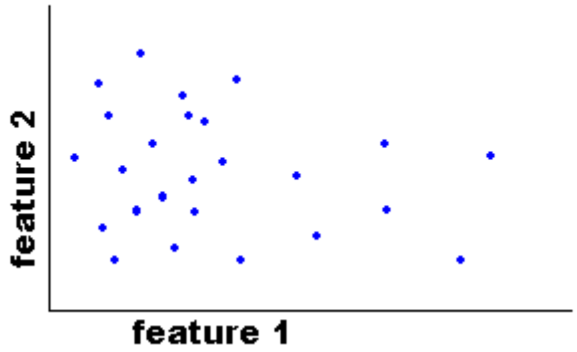

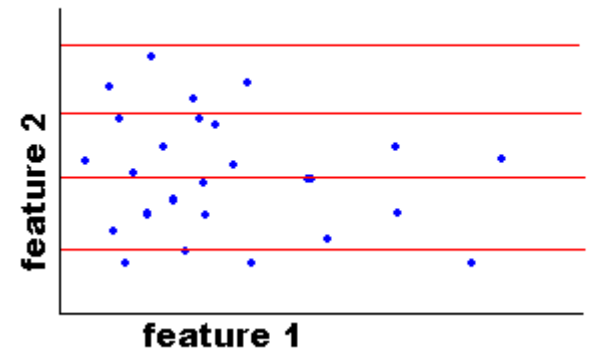

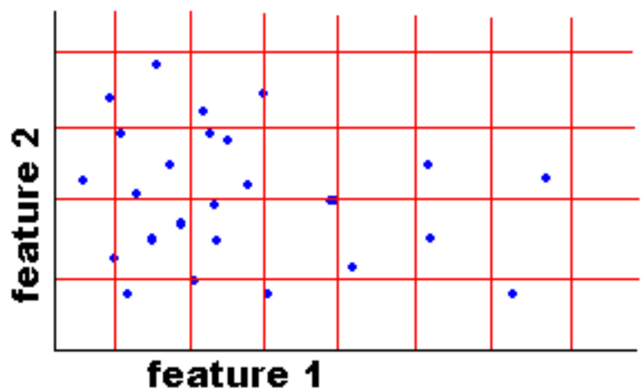

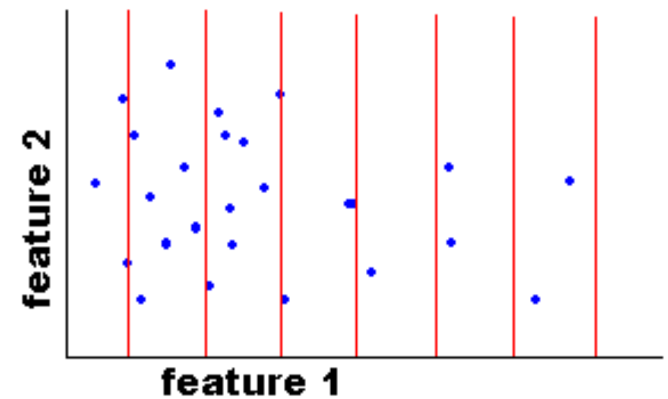

Joint histogram

- Requires lots of data
- Loss of resolution to avoid empty bins

Marginal histogram

- Requires independent features
- More data/bin than joint histogram

Image Representations: Histograms

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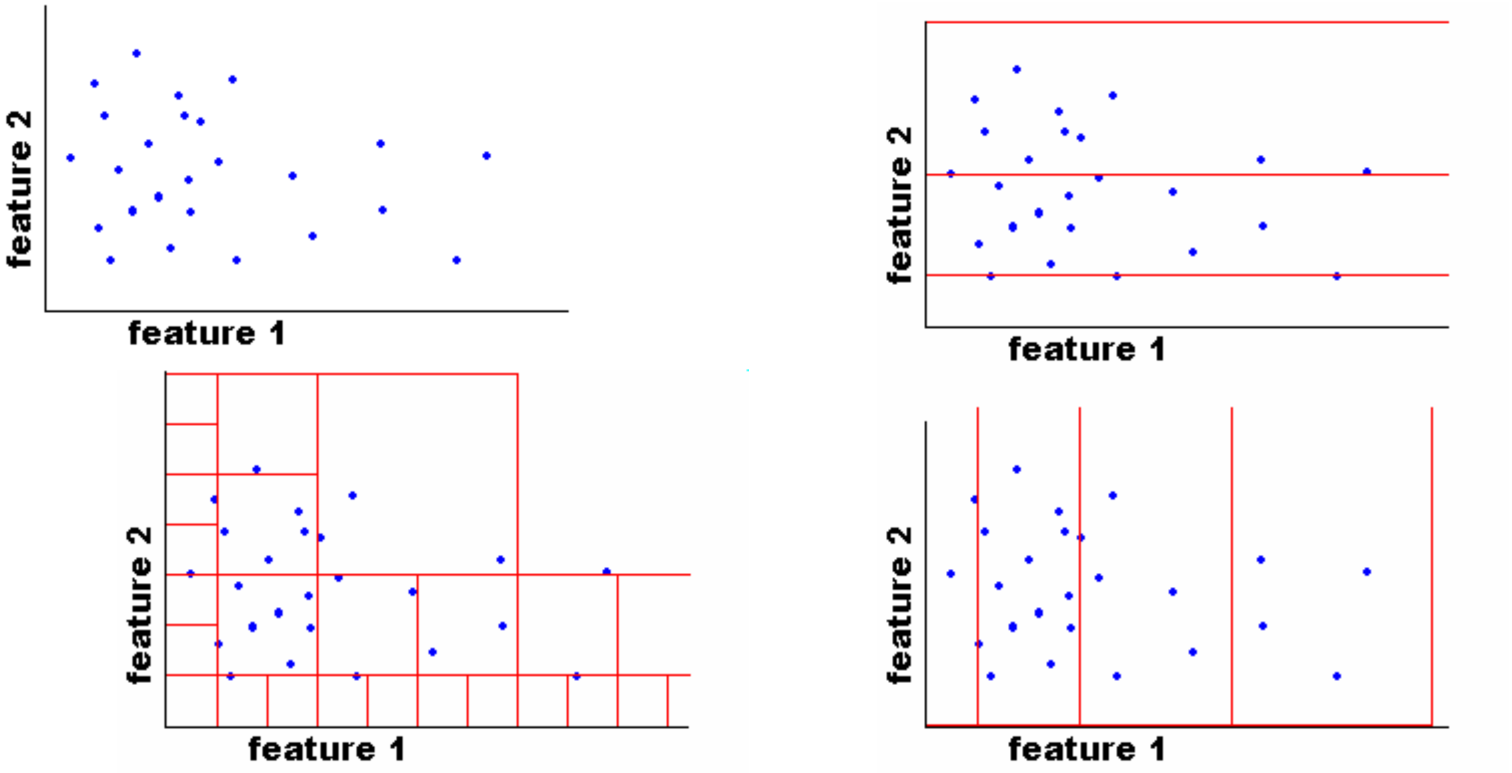

Adaptive binning

- Better data/bin distribution, fewer empty bins
- Can adapt available resolution to relative feature importance

Image Representations: Histograms

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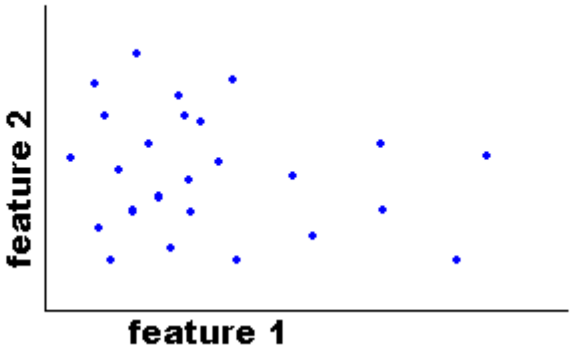
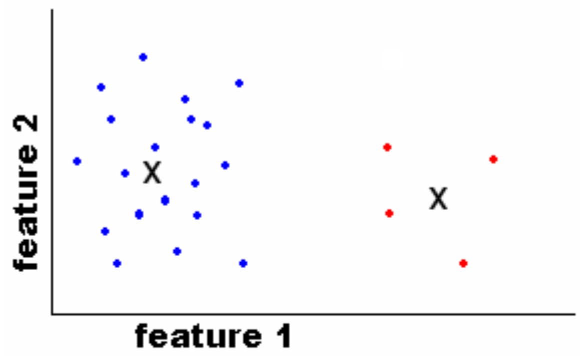
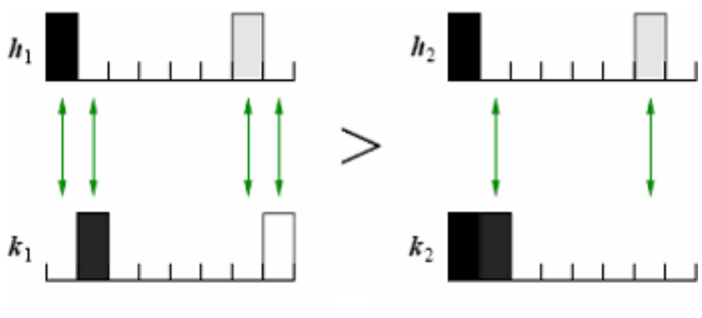


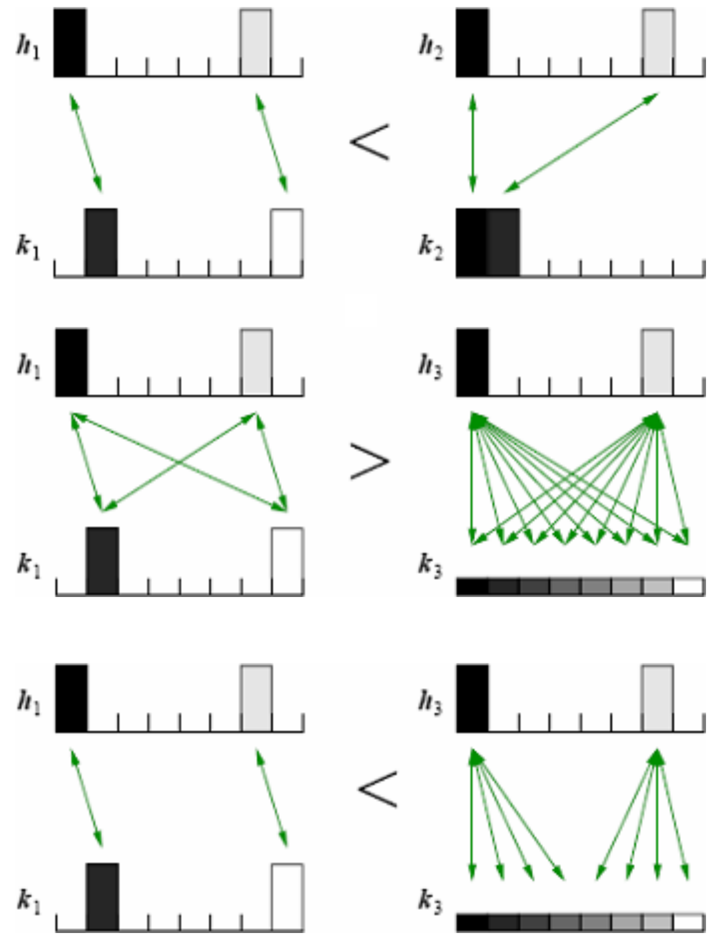


Clusters / Signatures

- “super-adaptive” binning
- Does not require discretization along any fixed axis

Issue: How to Compare Histograms?





Bin-by-bin comparison

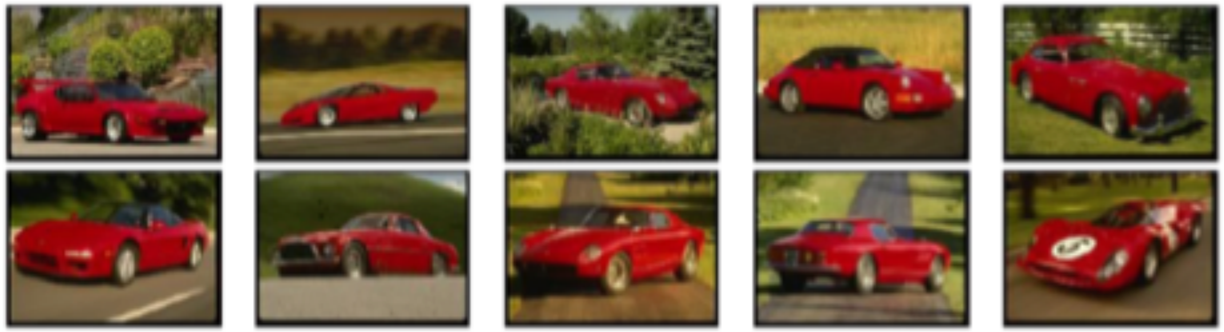
Sensitive to bin size.

Could use wider bins …
… but at a loss of resolution

Cross-bin comparison

How much cross-bin influence is necessary/sufficient?

Red Car Retrievals (Color histograms)



$$\chi^2(h_i, h_j) = \frac{1}{2}\sum_{m=1}^{K}\frac{[h_i(m) - h_j(m)]^2}{h_i(m) + h_j(m)}$$

Histogram matching distance

Image Descriptors

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Capturing the "essence" of texture

…for real images

We don't want an actual texture realization, we want a texture invariant

What are the tools for capturing statistical properties of some signal?

But first…

How to filter an image?

Convolution

Convolution takes a windowed average of an image *F* with a filter *H*, where the filter is flipped horizontally and vertically before being applied:

$$G[i,j] = \sum_{u=-k}^{k} \sum_{v=-k}^{k} H[u,v]F[i-u,j-v]$$

$$G = H \star F$$

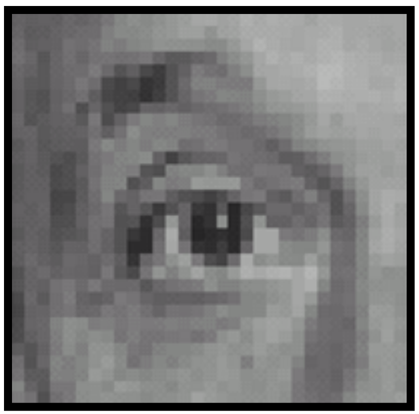
Slide by Steve Seitz

Convolution is nice!

- Notation: $b = c \star a$
- Convolution is a multiplication-like operation
  - commutative $a \star b = b \star a$
  - associative $a \star (b \star c) = (a \star b) \star c$
  - distributes over addition $a \star (b + c) = a \star b + a \star c$
  - scalars factor out $\alpha a \star b = a \star \alpha b = \alpha(a \star b)$
  - identity: unit impulse e = [..., 0, 0, 1, 0, 0, ...]

    $a \star e = a$
- Conceptually no distinction between filter and signal
- Usefulness of associativity
  - often apply several filters one after another: $(((a * b_1) * b_2) * b_3)$
  - this is equivalent to applying one filter: a * $(b_1 * b_2 * b_3)$

Practice with linear filters



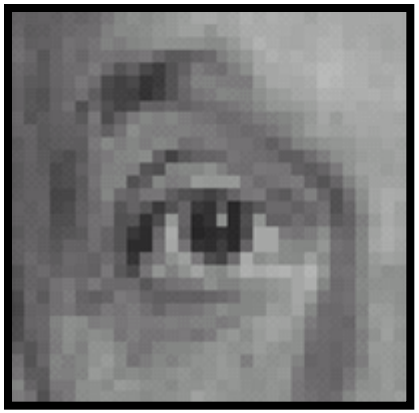
Original

0	0	0
0	1	0
0	0	0

?

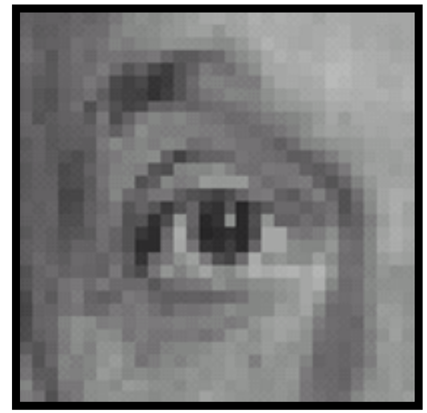
Source: D. Lowe

Practice with linear filters



Original

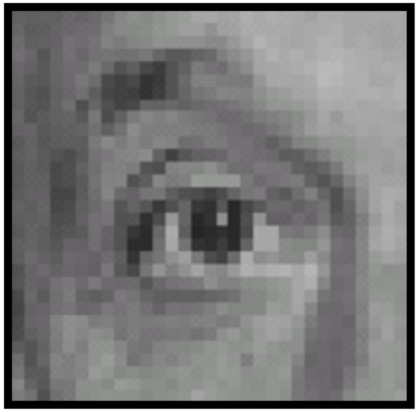
0	0	0
0	1	0
0	0	0



Filtered
(no change)

Source: D. Lowe

Practice with linear filters



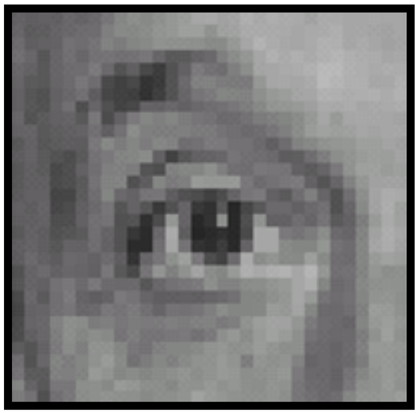
Original

0	0	0
0	0	1
0	0	0

?

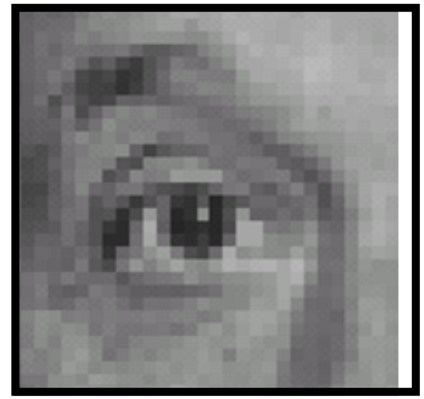
Source: D. Lowe

Practice with linear filters



Original

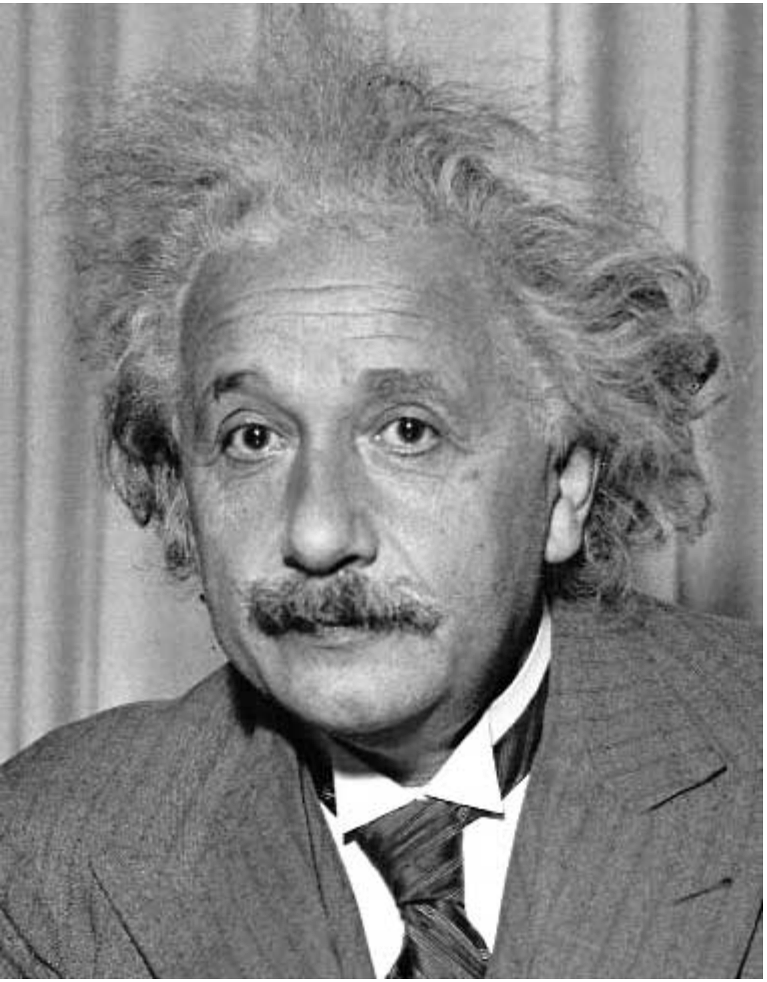
0	0	0
0	0	1
0	0	0



Shifted left
By 1 pixel

Source: D. Lowe

Other filters



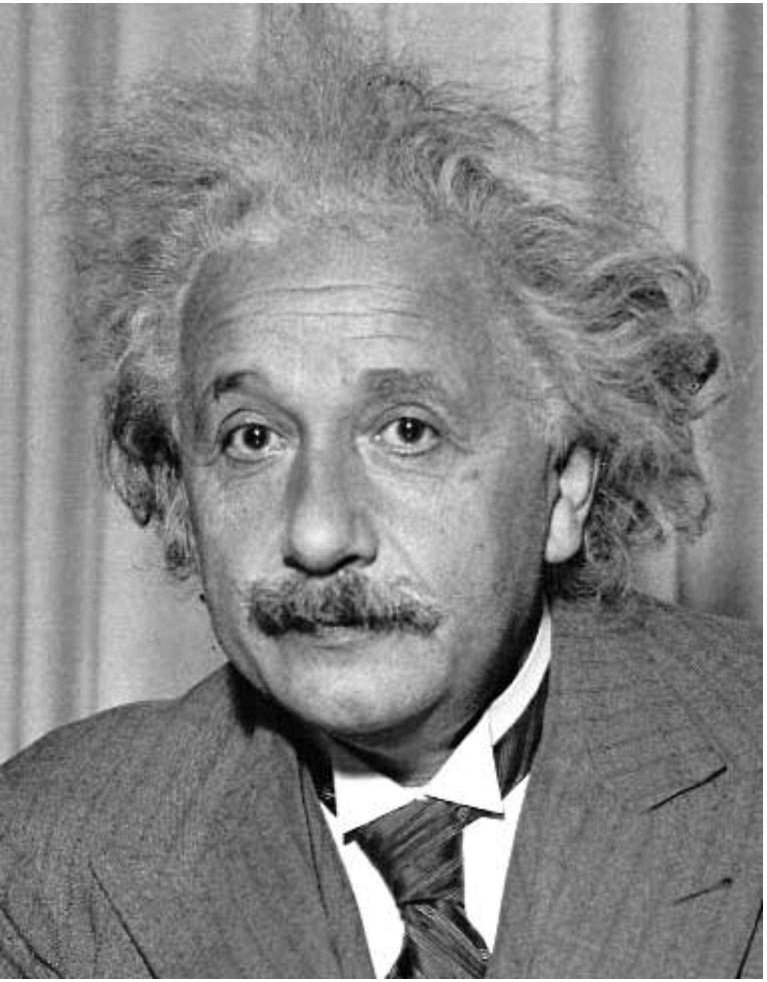
1	0	-1
2	0	-2
1	0	-1

Sobel

?

Separable (show on board)

Other filters

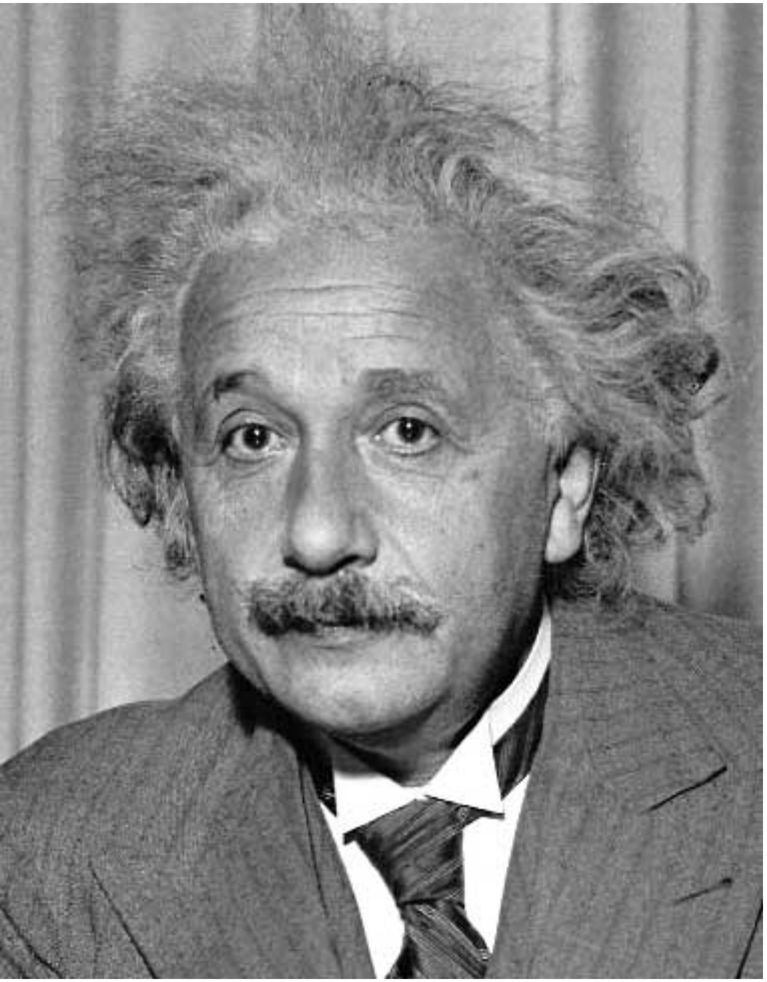


1	0	-1
2	0	-2
1	0	-1

Sobel

Vertical Edge
(absolute value)

Other filters



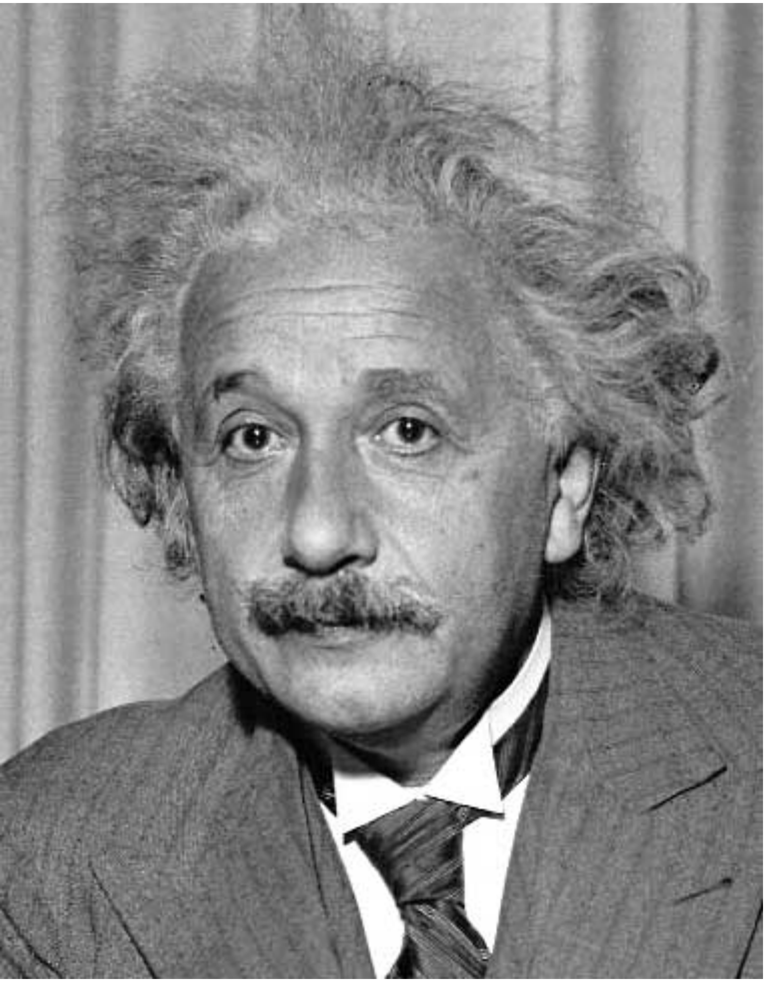
1	2	1
0	0	0
-1	-2	-1

Sobel

?

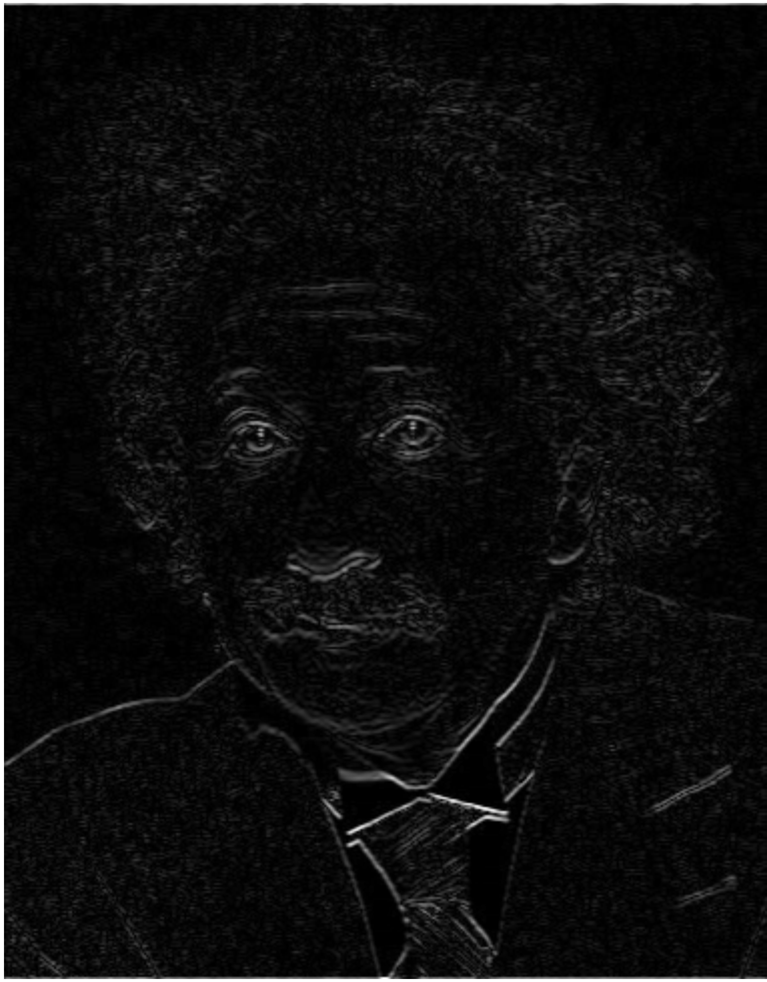
Separable (show on board)

Other filters



1	2	1
0	0	0
-1	-2	-1

Sobel



Separable (show on board)

Horizontal Edge
(absolute value)

How to use filters to describe texture?

Representing textures

Subelement ->

Textures are made up of quite stylised subelements, repeated in meaningful ways

Representation:

- find the subelements, and represent their statistics

But what are the subelements, and how do we find them?

- find subelements by applying filters, looking at the magnitude of the response

What filters?

- experience suggests spots and oriented bars at a variety of different scales

What statistics?

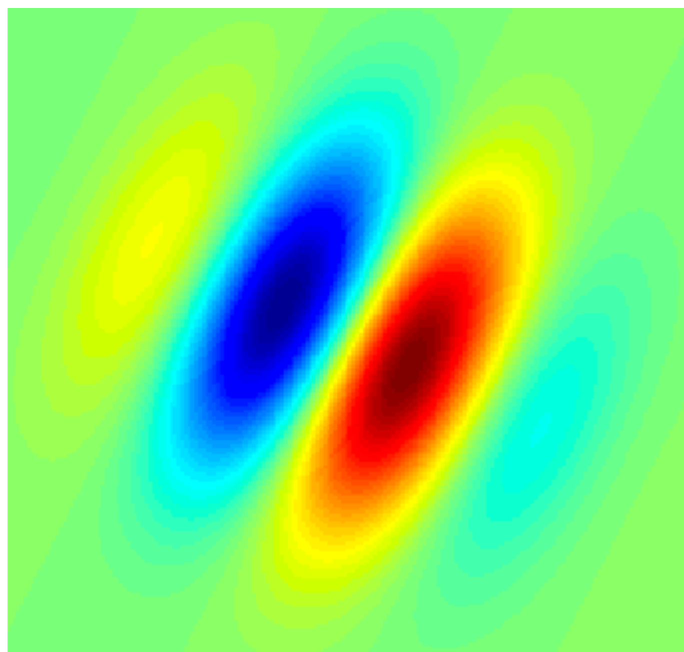
- within reason, the more the merrier.
- At least, mean and standard deviation
- better, various conditional histograms.

Gabor Filter

- Rotated Gaussian filter times cosine wave.

Real

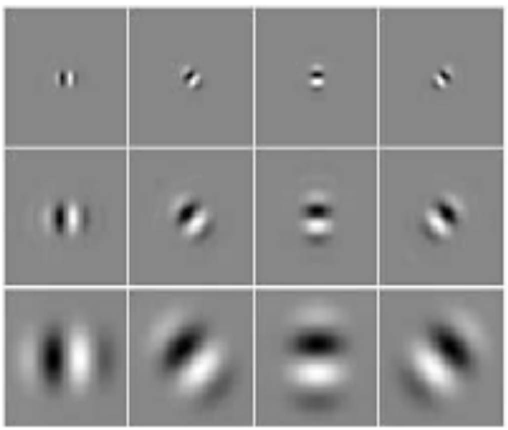
$$g(x, y; \lambda, \theta, \psi, \sigma, \gamma) = \exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right)\cos\left(2\pi\frac{x'}{\lambda} + \psi\right)$$

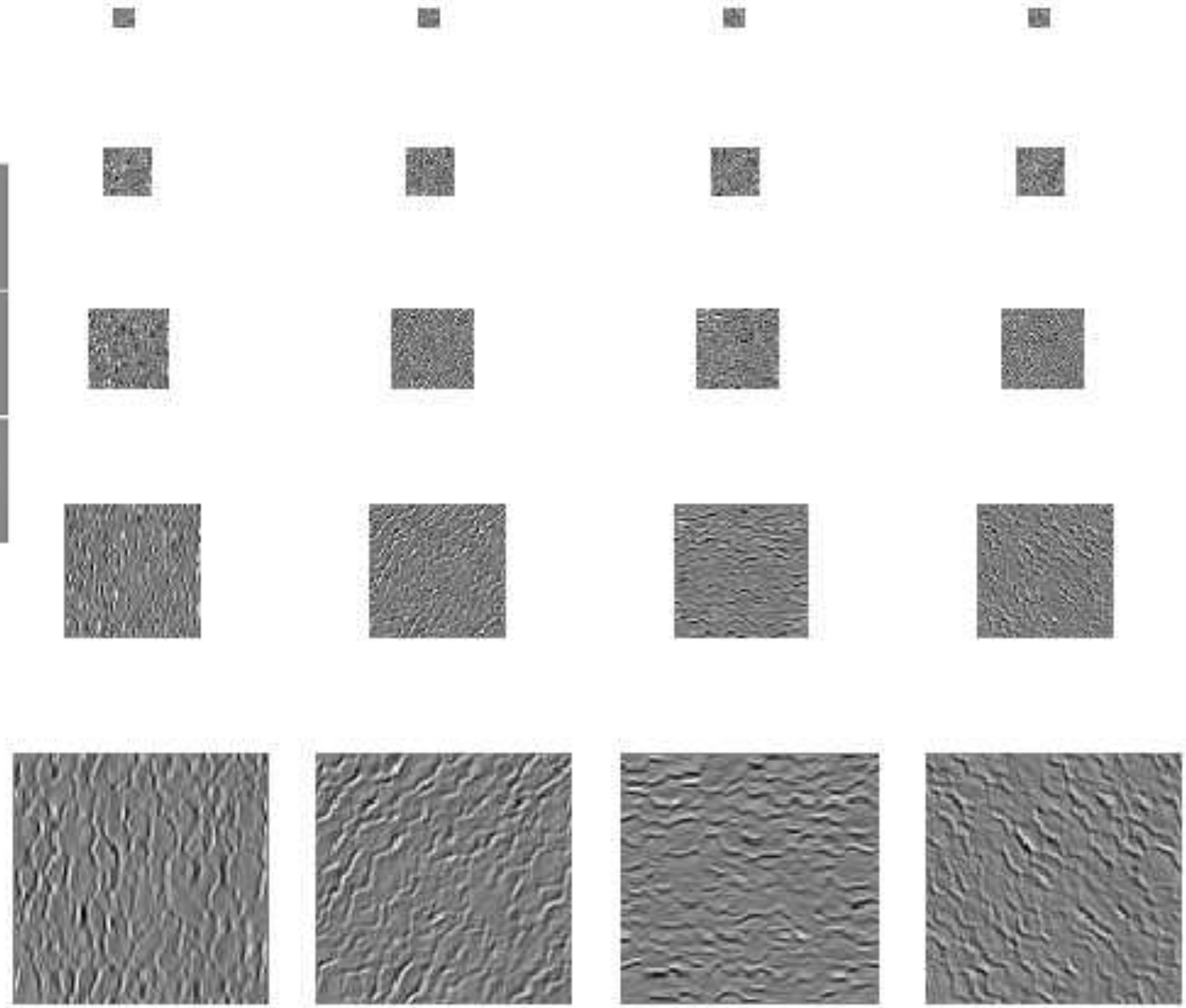


Wikipedia: Gabor Filter

Multi-scale filter decomposition

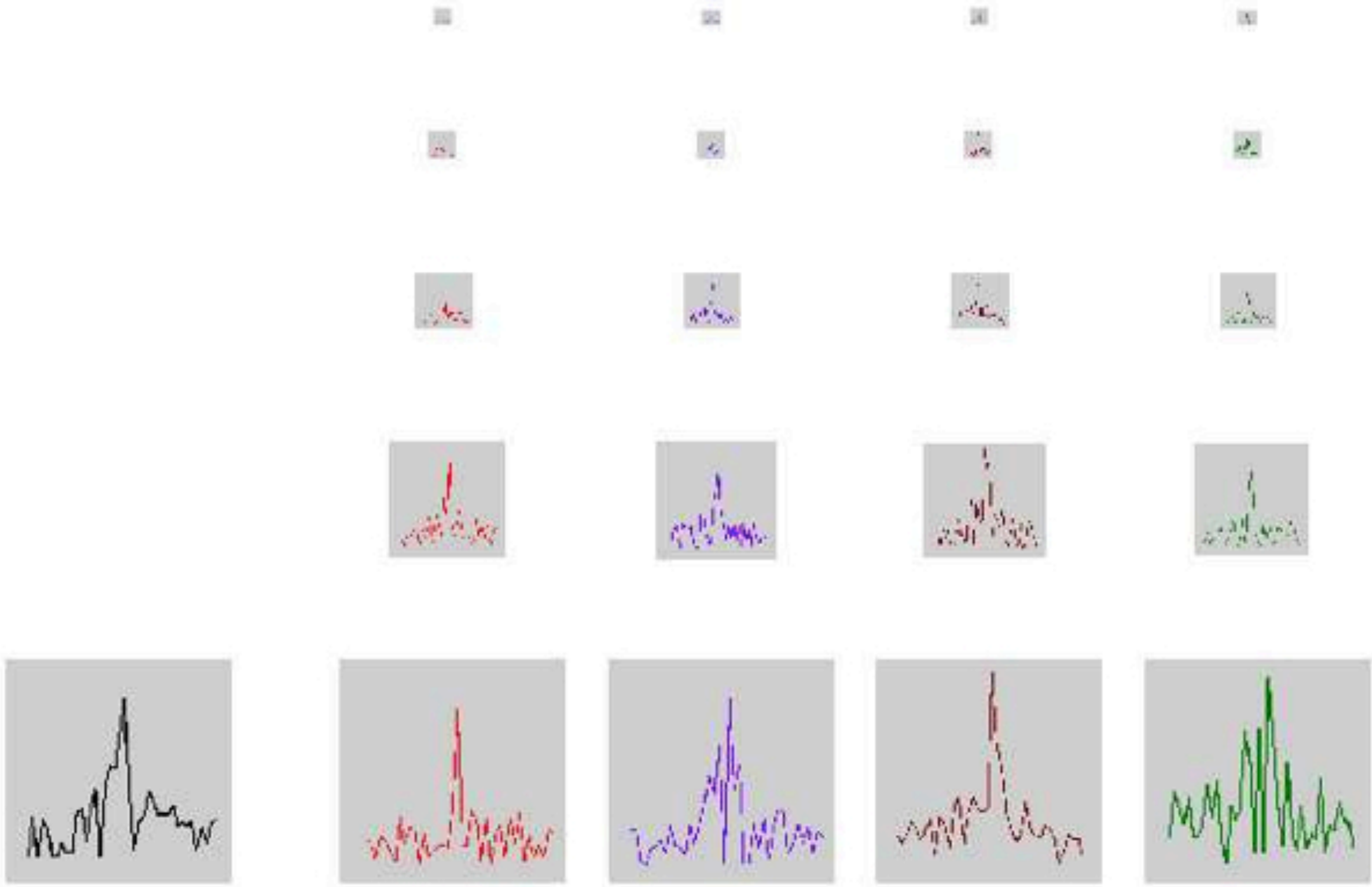
Gabor Filter
bank

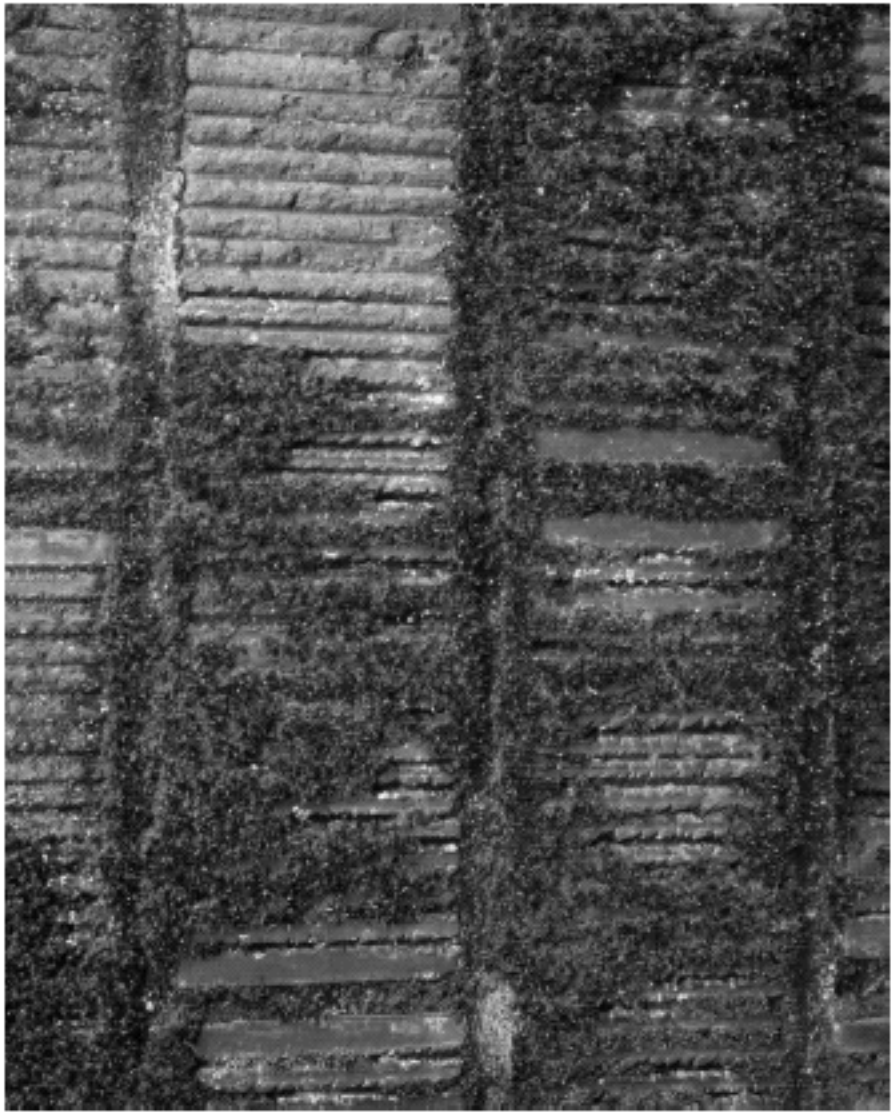


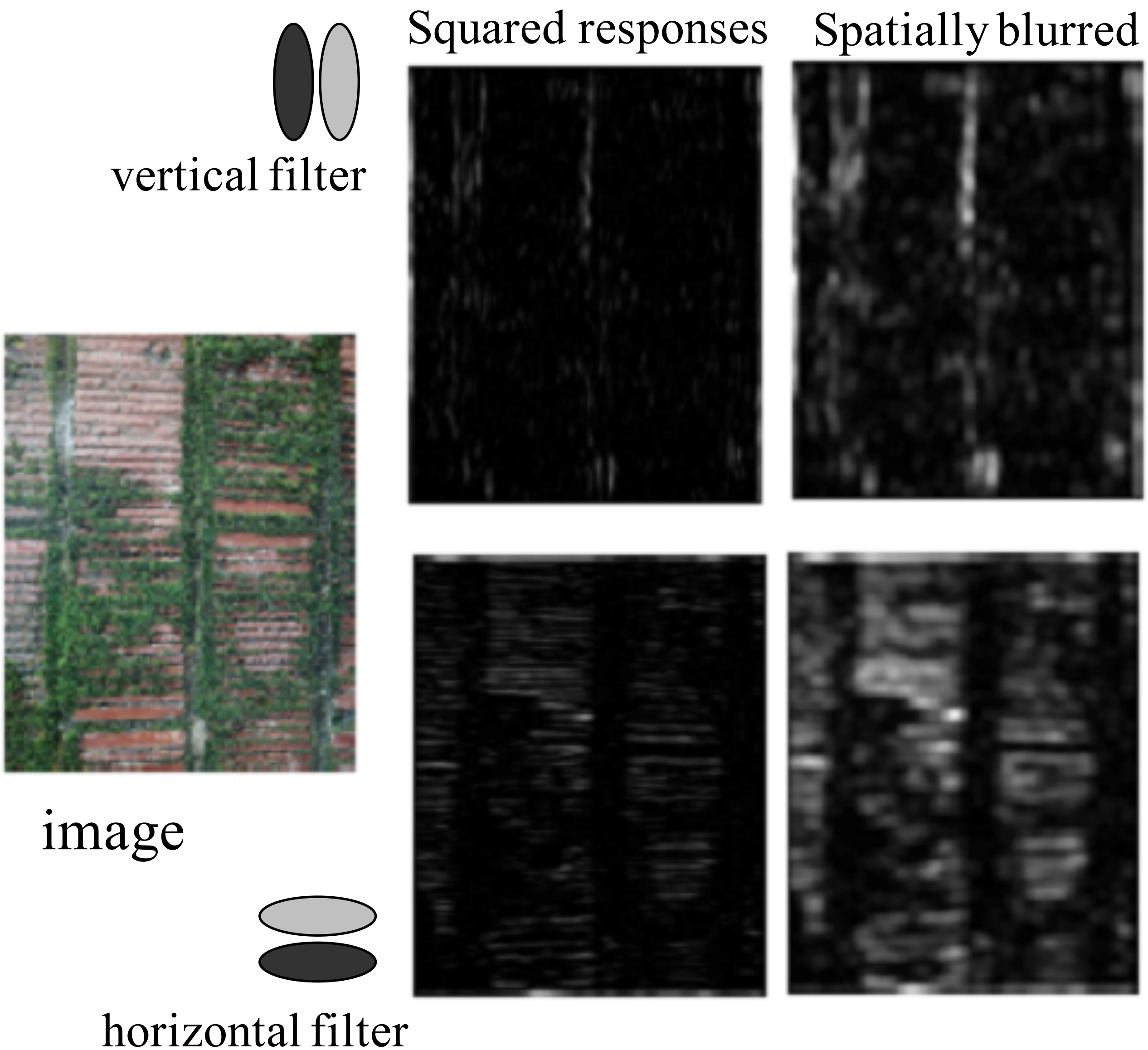


Input image

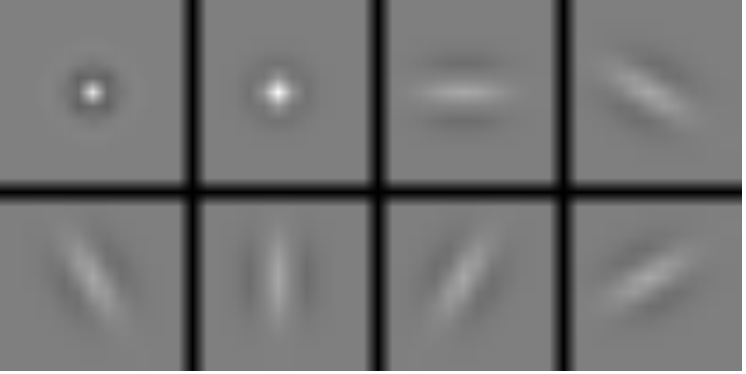
Filter response histograms

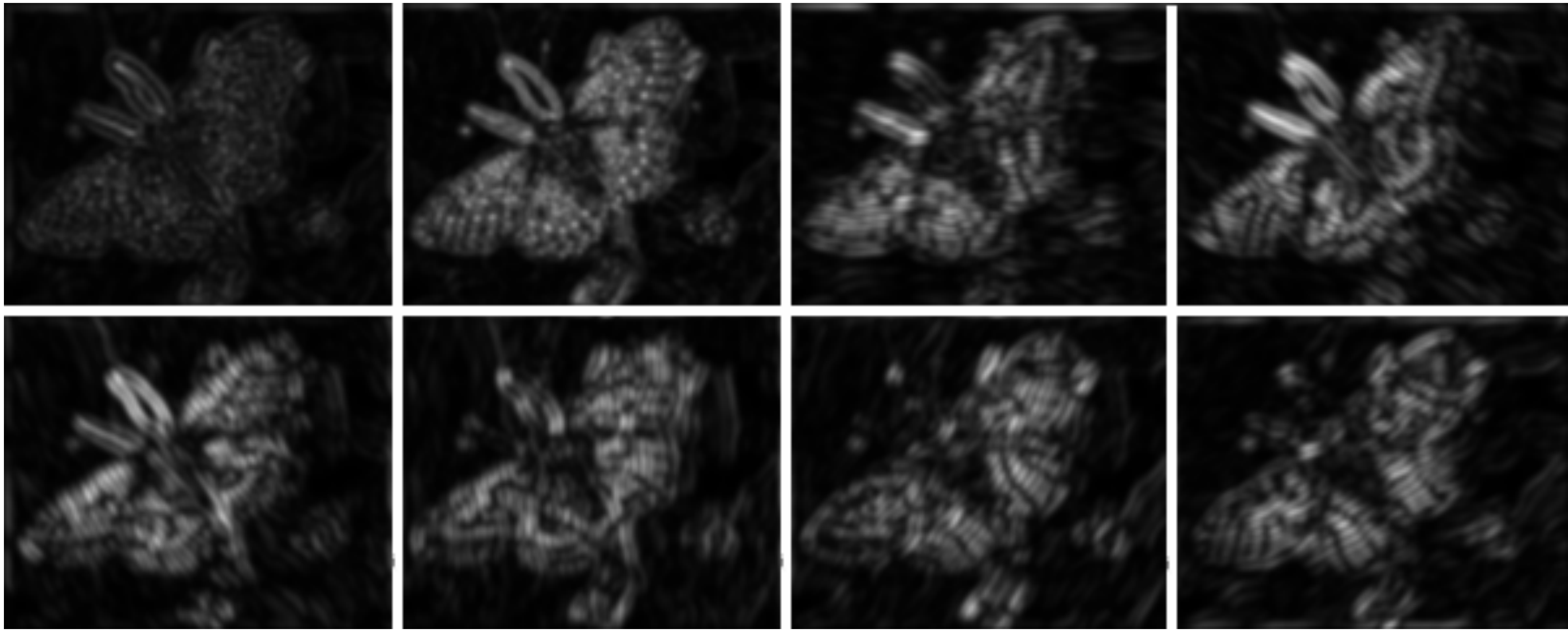


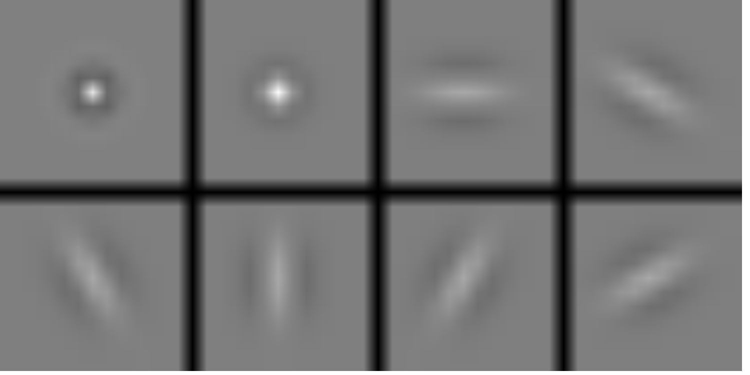


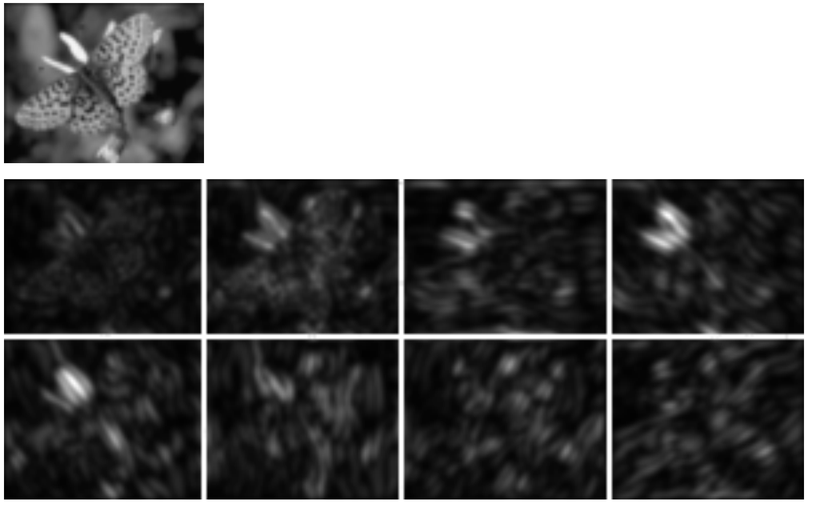


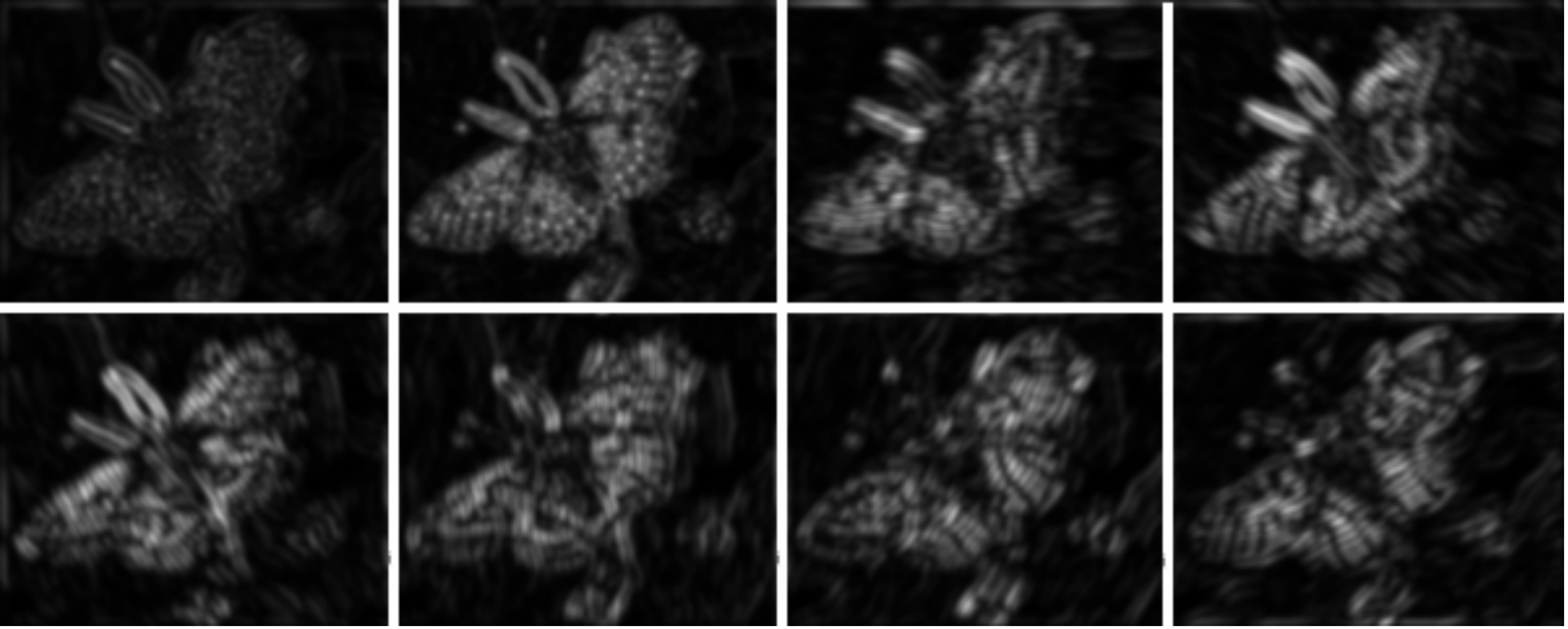
Threshold squared, blurred responses, then categorize texture based on those two bits

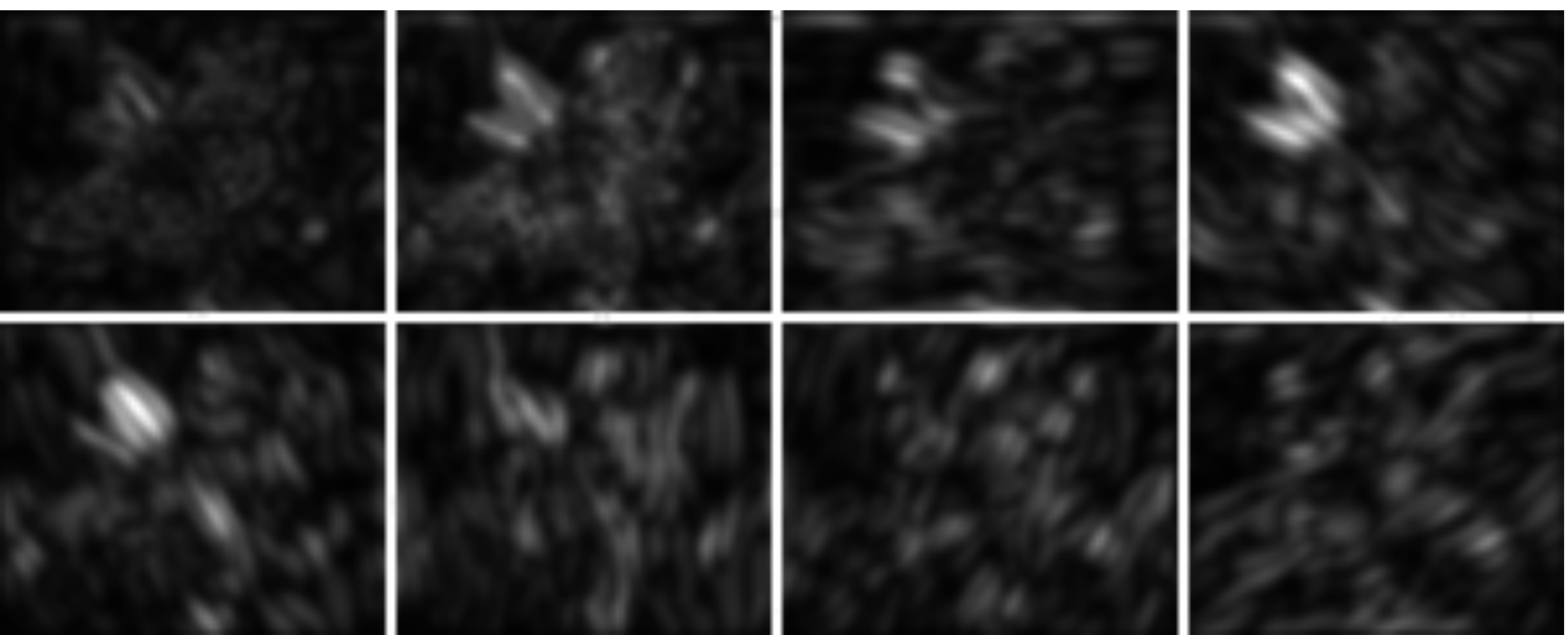










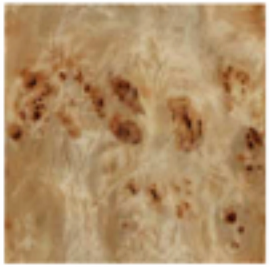


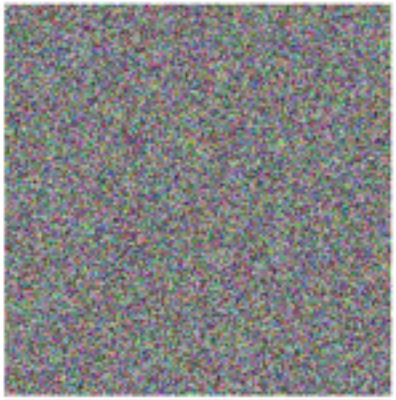
Heeger & Bergen '95

Start with a noise image as output

Main loop:

- Match *pixel* histogram of output image to input
- Decompose input and output images using multi-scale filter bank (Steerable Pyramid)
- Match sub-band histograms of input and output pyramids
- Reconstruct input and output images (collapse the pyramids)





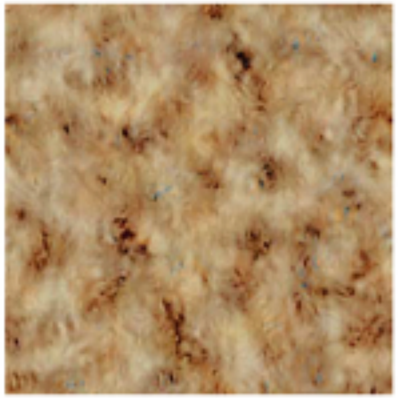
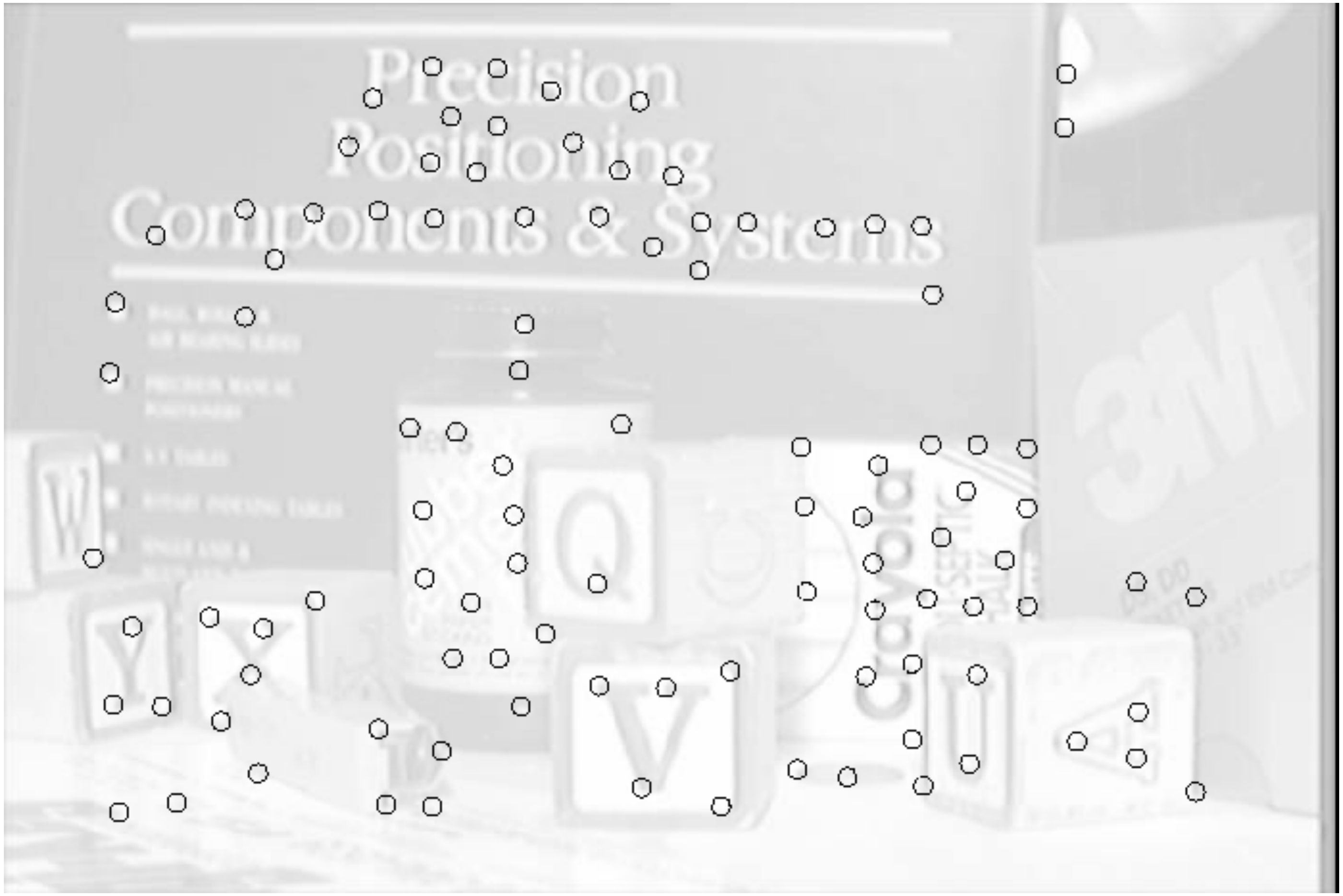


Image Descriptors

- Blur + SSD
- Gist descriptor (average edge response in a coarse spatial grid)
- Color histograms
- Filter response histograms
- **Invariant detectors and descriptors (SIFT)**
- Convolutional neural networks (CNNs) – later classes

Feature Detection



Feature Matching

How do we match the features between the images?

- Need a way to <u>describe</u> a region around each feature
  - e.g. image patch around each feature
- Use successful matches to estimate models of objects/scene
  - Need to do something to get rid of outliers

Issues:

- What if the image patches for several interest points look similar?
  - Make patch size bigger
- What if the image patches for the same feature look different due to scale, rotation, exposure etc.
  - Need an invariant descriptor

Invariant Feature Descriptors

Schmid & Mohr 1997, Lowe 1999, Baumberg 2000, Tuytelaars & Van Gool 2000, Mikolajczyk & Schmid 2001, Brown & Lowe 2002, Matas et. al. 2002, Schaffalitzky & Zisserman 2002

Applications

Feature points are used for:

- Image alignment (homography, fundamental matrix)
- 3D reconstruction
- Motion tracking
- Object recognition
- Scene categorization
- Indexing and database retrieval
- Robot navigation
- … other

Feature Detectors and Descriptors

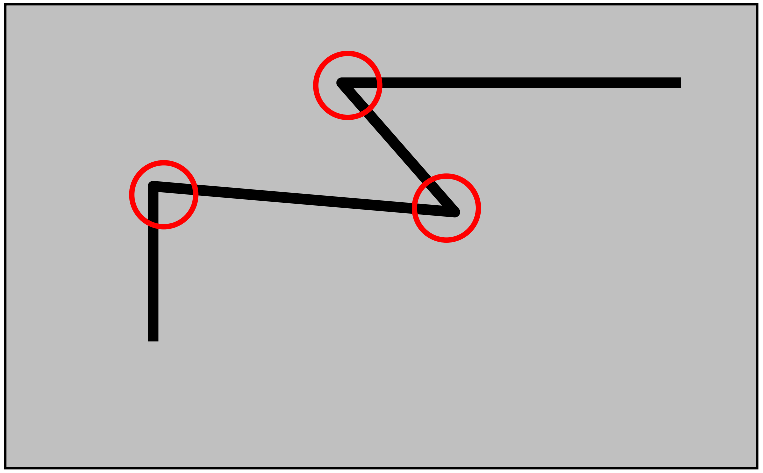
- Feature detector
    - scale invariant Harris corners
- Feature descriptor
    - patches, oriented patches

Reading:

David Lowe 2004,
Distinctive Image Features from Scale-Invariant Keypoints

Harris corner detector

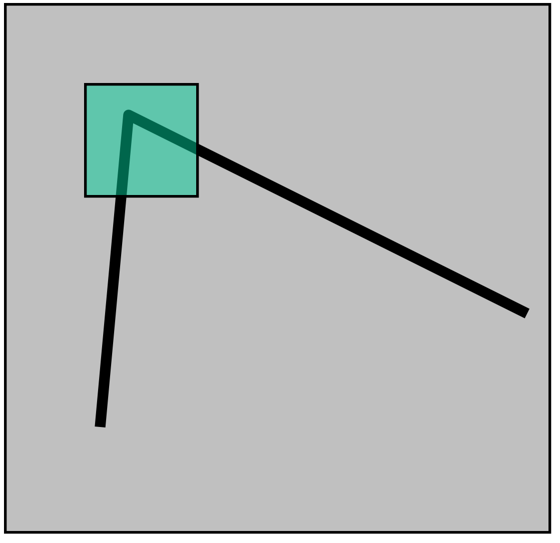
C.Harris, M.Stephens. "A Combined Corner and Edge Detector". 1988



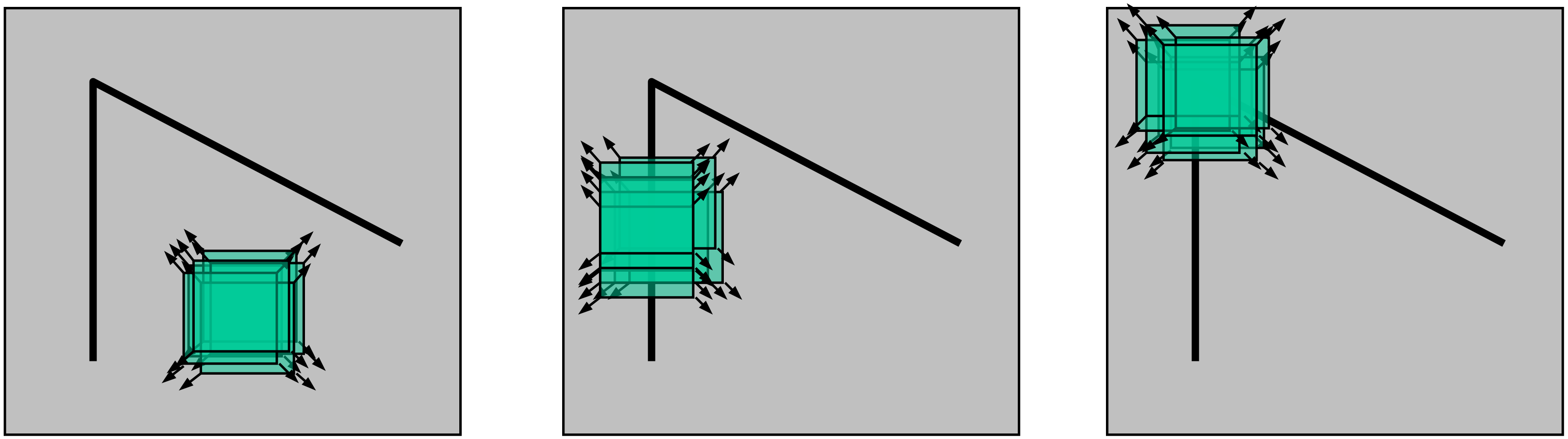
The Basic Idea

We should easily recognize the point by looking through a small window

Shifting a window in *any direction* should give *a large change* in intensity



Harris Detector: Basic Idea



"flat" region:
no change in
all directions

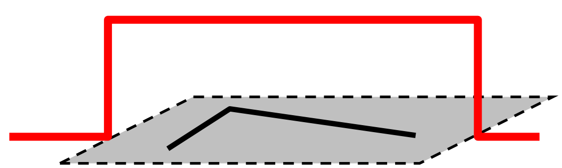
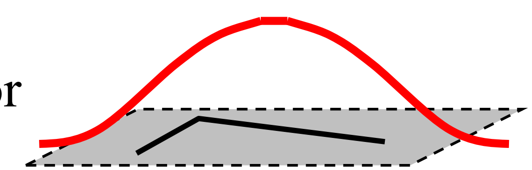
"edge":
no change along
the edge direction

"corner":
significant change
in all directions

Harris Detector: Mathematics

Change of intensity for the shift $[u,v]$:

$$E(u,v) = \sum_{x,y} \underbrace{w(x,y)}_{\text{Window function}} \big[\underbrace{I(x+u, y+v)}_{\text{Shifted intensity}} - \underbrace{I(x,y)}_{\text{Intensity}} \big]^2$$

Window function $w(x,y) =$  or 

1 in window, 0 outside — Gaussian

Harris Detector: Mathematics

For small shifts $[u, v]$ we have a *bilinear* approximation:

$$E(u,v) \cong [u, v] \; M \begin{bmatrix} u \\ v \end{bmatrix}$$

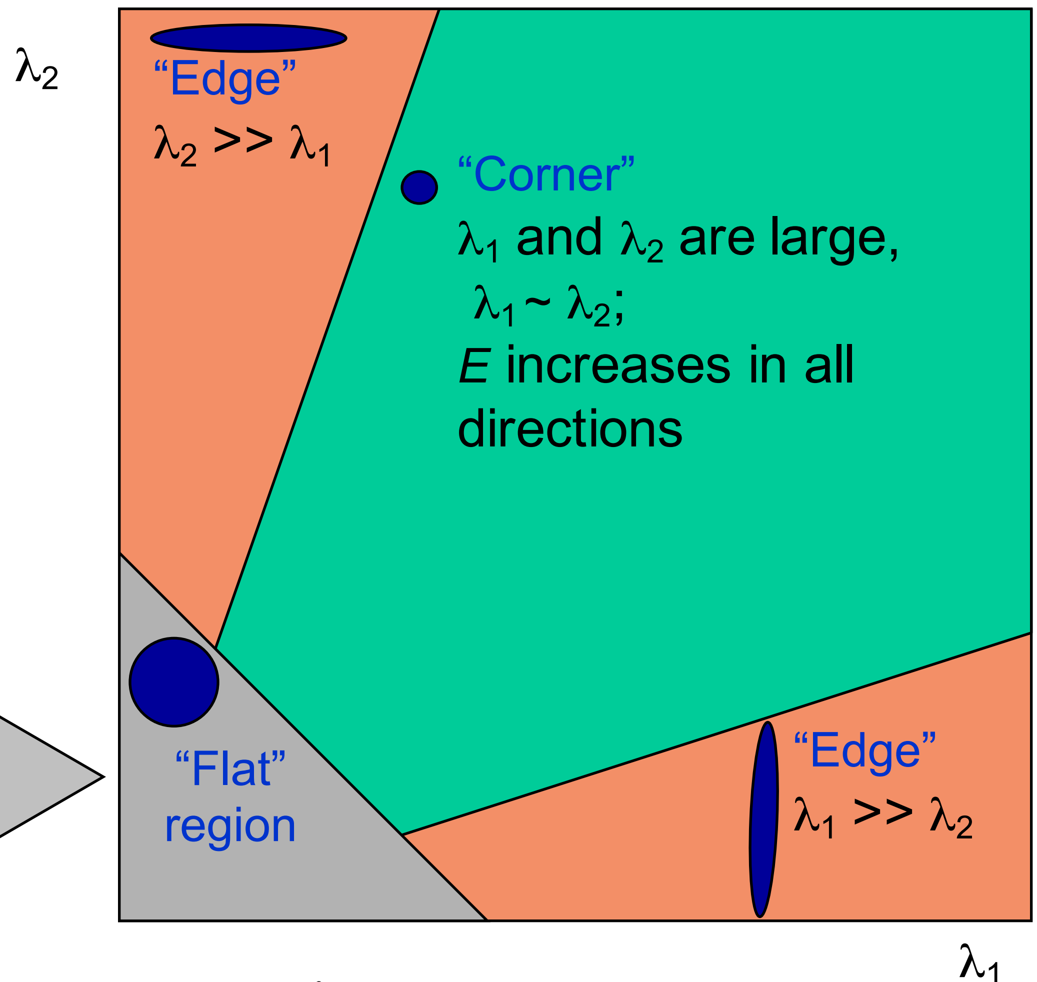
where M is a 2×2 matrix computed from image derivatives:

$$M = \sum_{x,y} w(x,y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

$$A^T A = \begin{bmatrix} \sum I_x I_x & \sum I_x I_y \\ \sum I_x I_y & \sum I_y I_y \end{bmatrix} = \sum \begin{bmatrix} I_x \\ I_y \end{bmatrix} [I_x \; I_y] = \sum \nabla I (\nabla I)^T$$

Harris Detector: Mathematics

Classification of image points using eigenvalues of M:



λ_1 and λ_2 are small;
E is almost constant in all directions

But eigenvalues are expensive to compute

Harris Detector: Mathematics

Measure of corner response:

$$R = \frac{\det M}{\operatorname{Trace} M}$$

$$\det M = \lambda_1 \lambda_2$$
$$\operatorname{trace} M = \lambda_1 + \lambda_2$$

Algorithm: collect local maxima of R (above a threshold).

DoG Feature Detector (“Blob detection”)

Idea: Find blob regions, scale invariant

Approach:

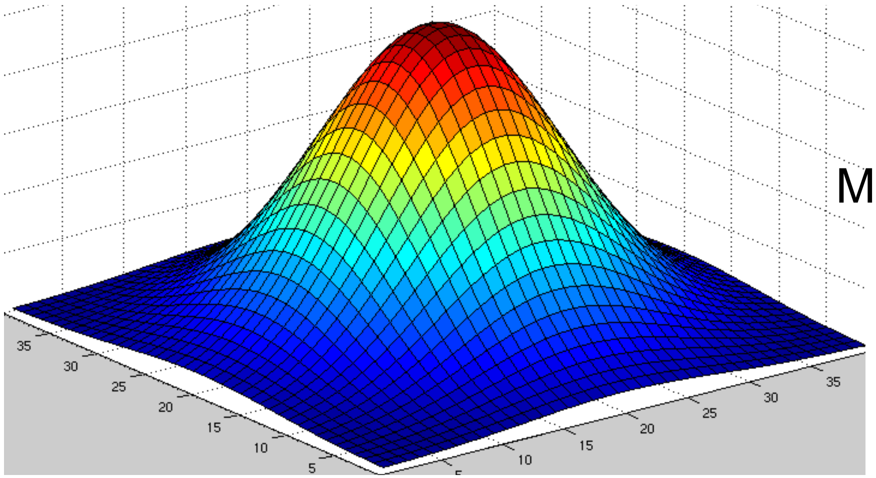
Run linear filter (Difference of Gaussians)

At different resolutions of image

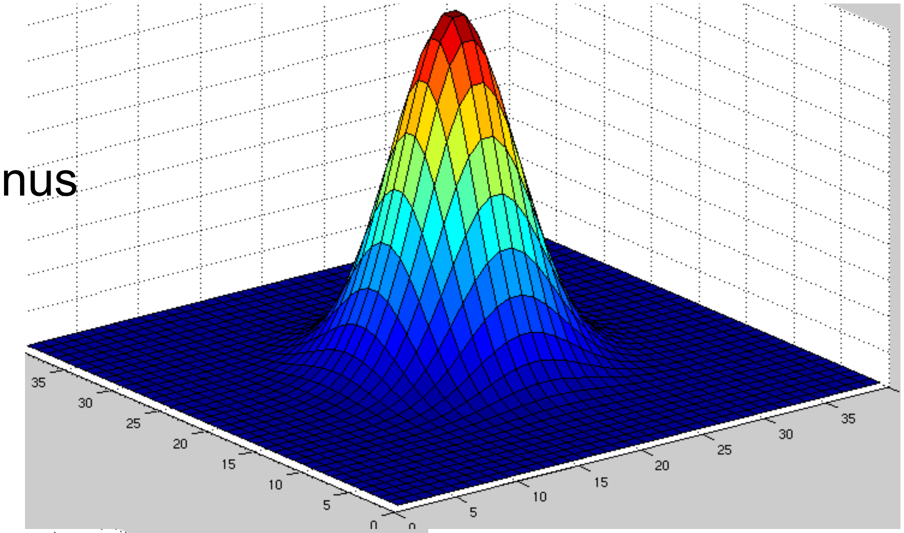
Often used for computing SIFT.

“SIFT” = DoG detector + SIFT descriptor

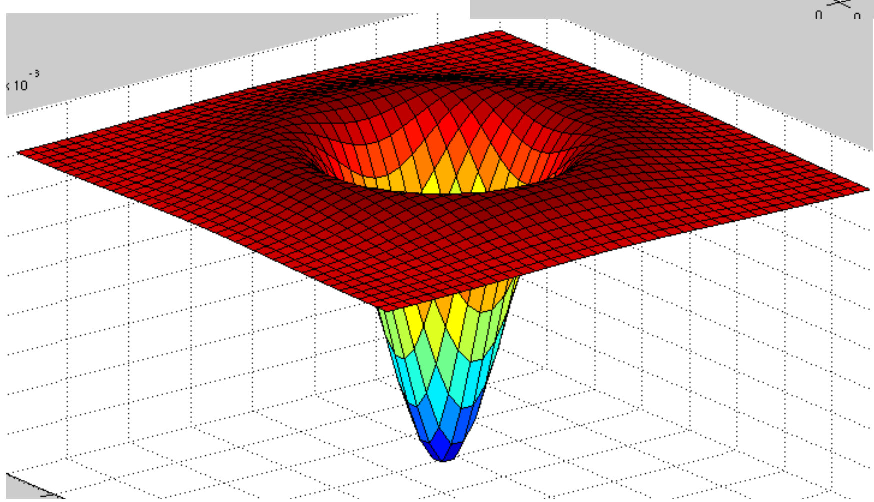
Difference of Gaussians



Minus

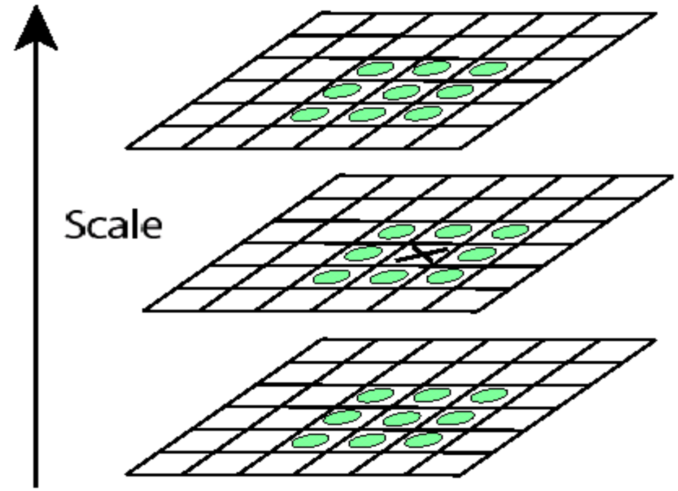


Equals

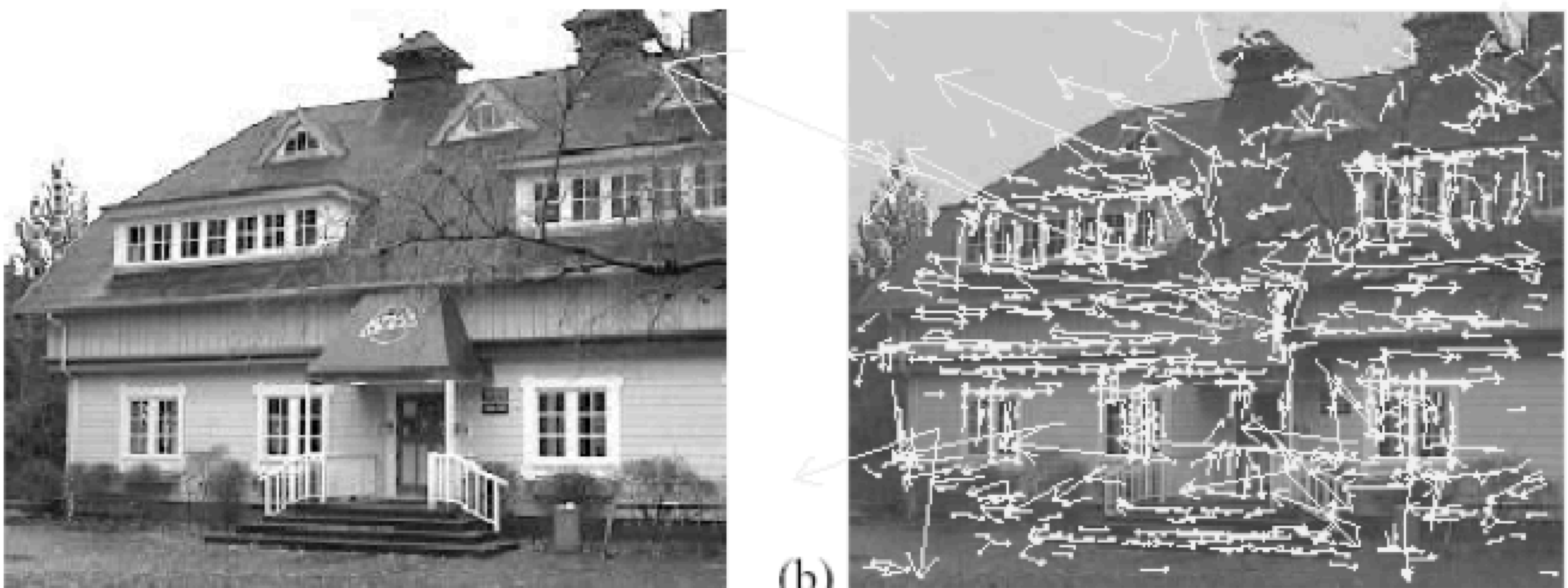


Key point localization

Detect maxima and minima of difference-of-Gaussian in scale space



Example of keypoint detection

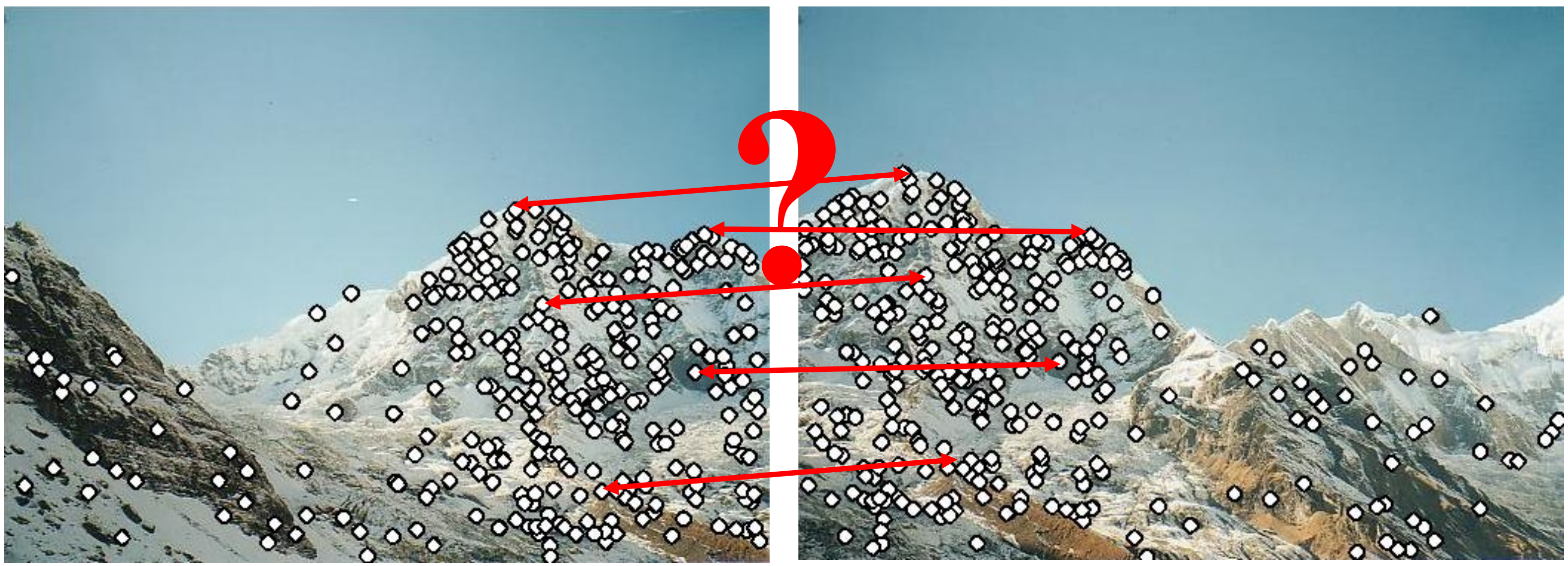


(a) (b)

(a) 233x189 image
(b) 832 DOG extrema

Feature descriptors

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

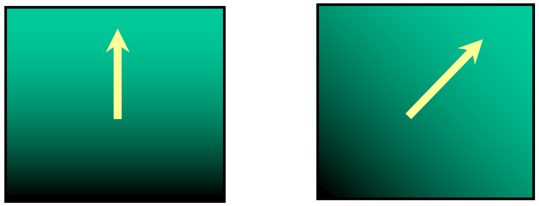


Point descriptor should be:
1. Invariant
2. Distinctive

Descriptors Invariant to Rotation

Find local orientation

Dominant direction of gradient



- Extract image patches relative to this orientation

Descriptor Vector

Orientation = dominant gradient direction

Rotation Invariant Frame

- Scale-space position (x, y, s) + orientation (θ)

SIFT vector formation

Thresholded image gradients are sampled over 16x16 array of locations in scale space

Create array of orientation histograms

8 orientations x 4x4 histogram array = 128

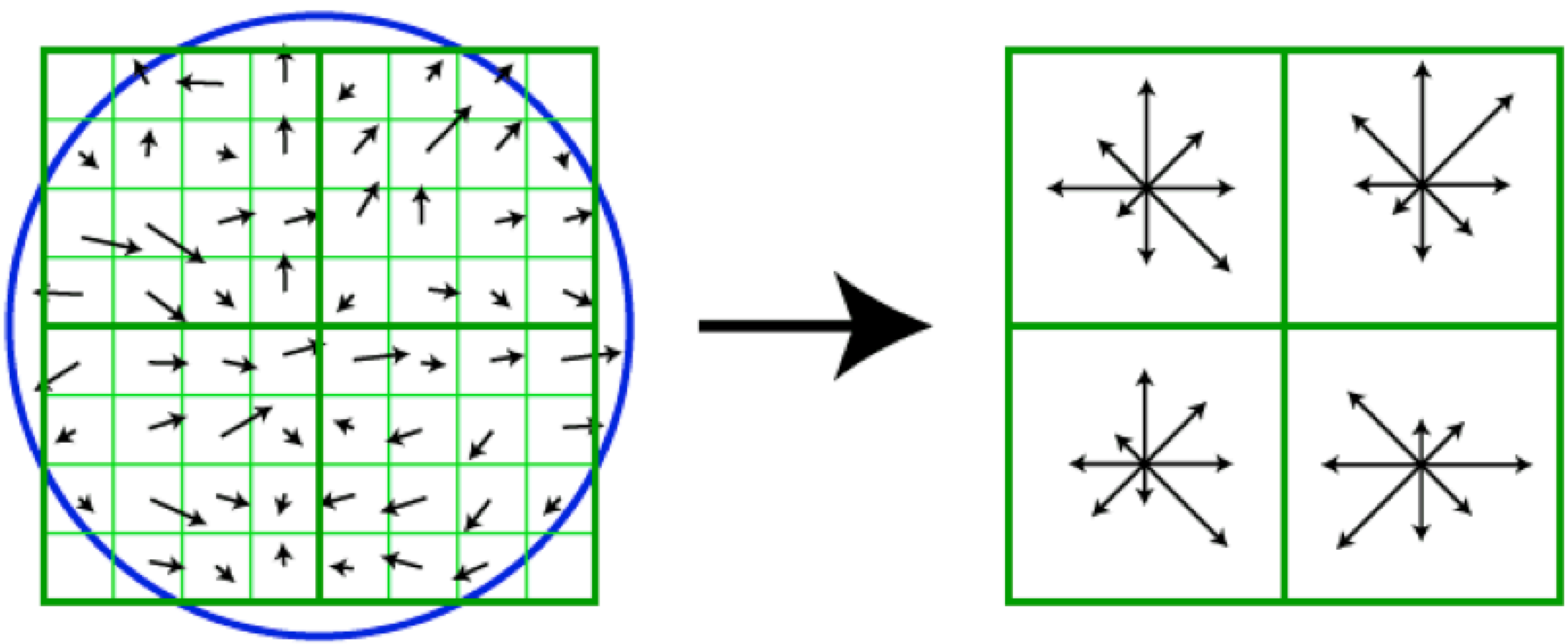
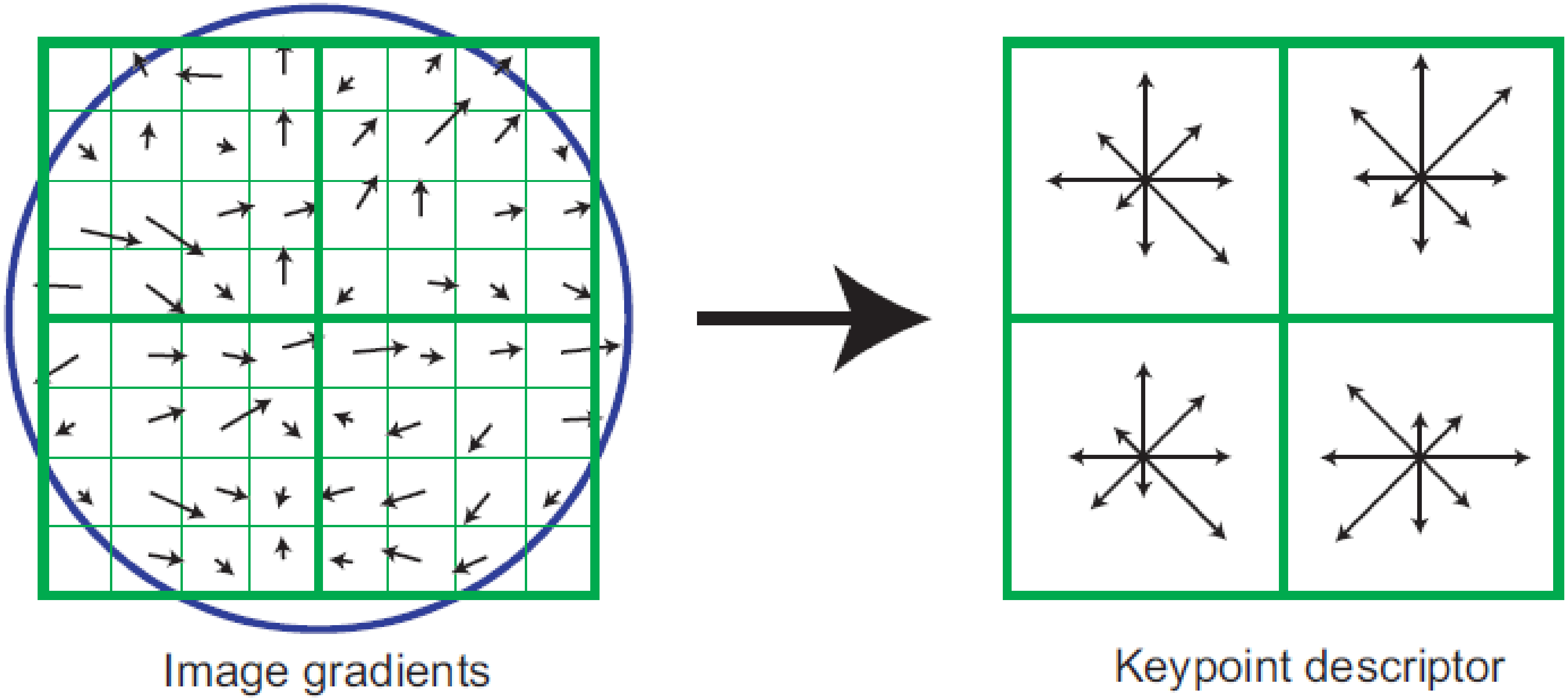


Image gradients

Keypoint descriptor

SIFT local feature descriptor



Based on 16*16 patches

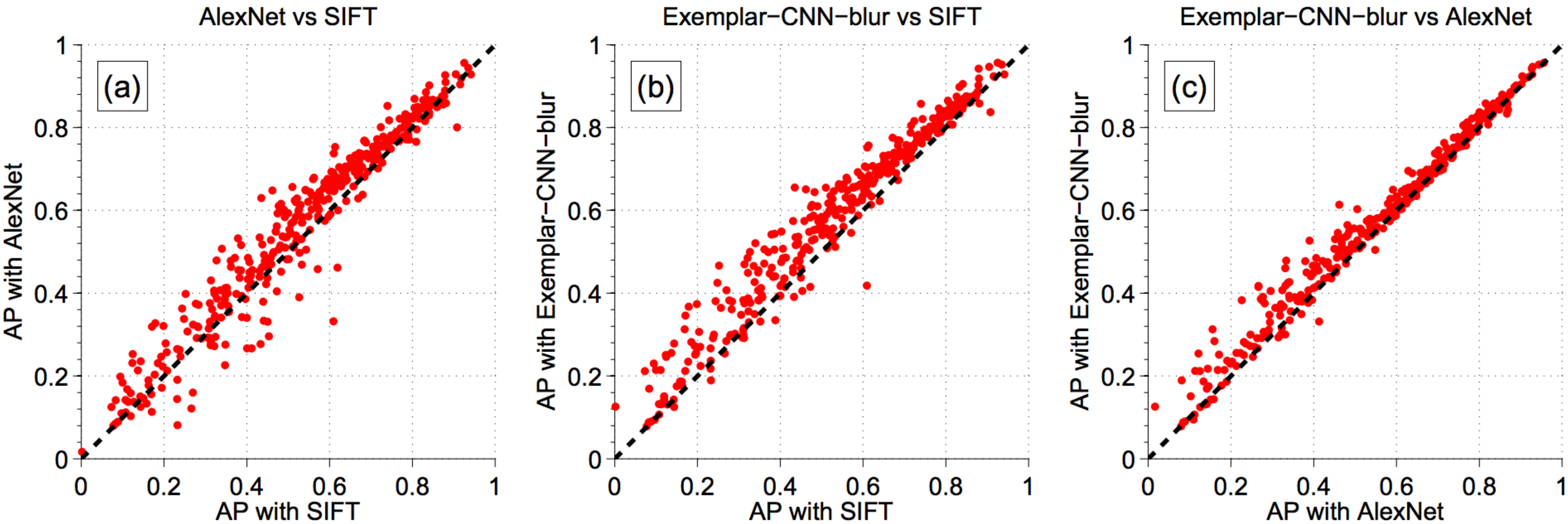
4*4 subregions

8 bins in each subregion

4*4*8=128 dimensions in total

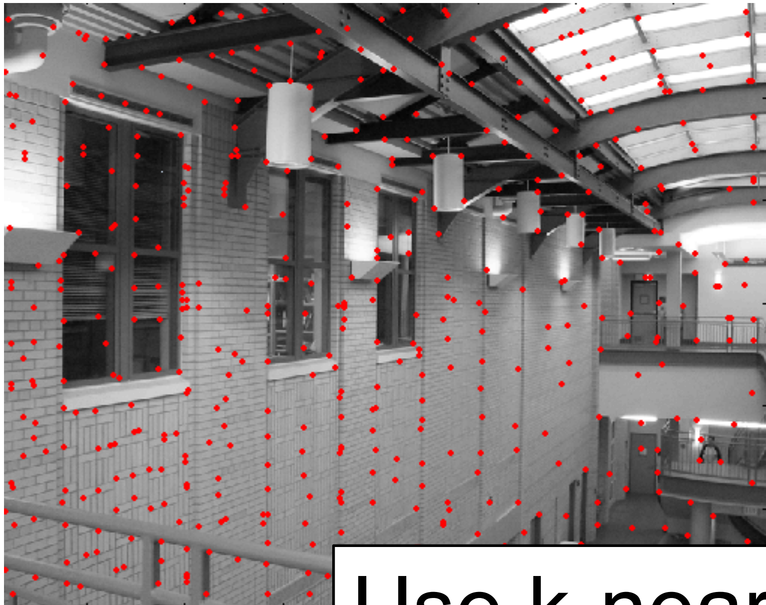
SIFT vs CNNs

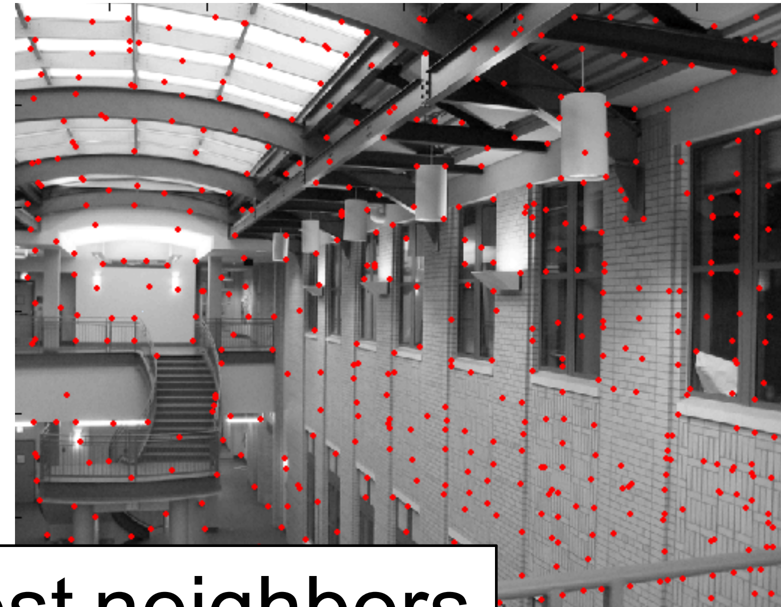
SIFT descriptor is outperformed by CNN features.



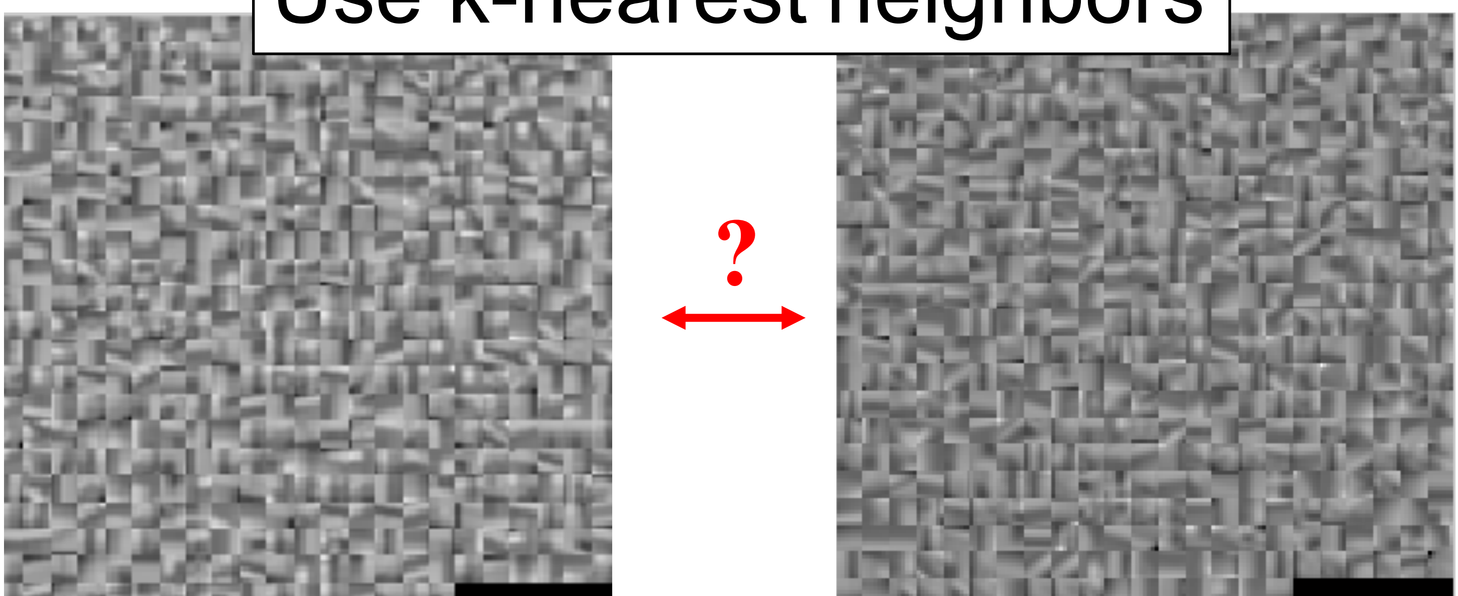
[Discriminative Unsupervised Feature Learning... 2015]

Feature matching

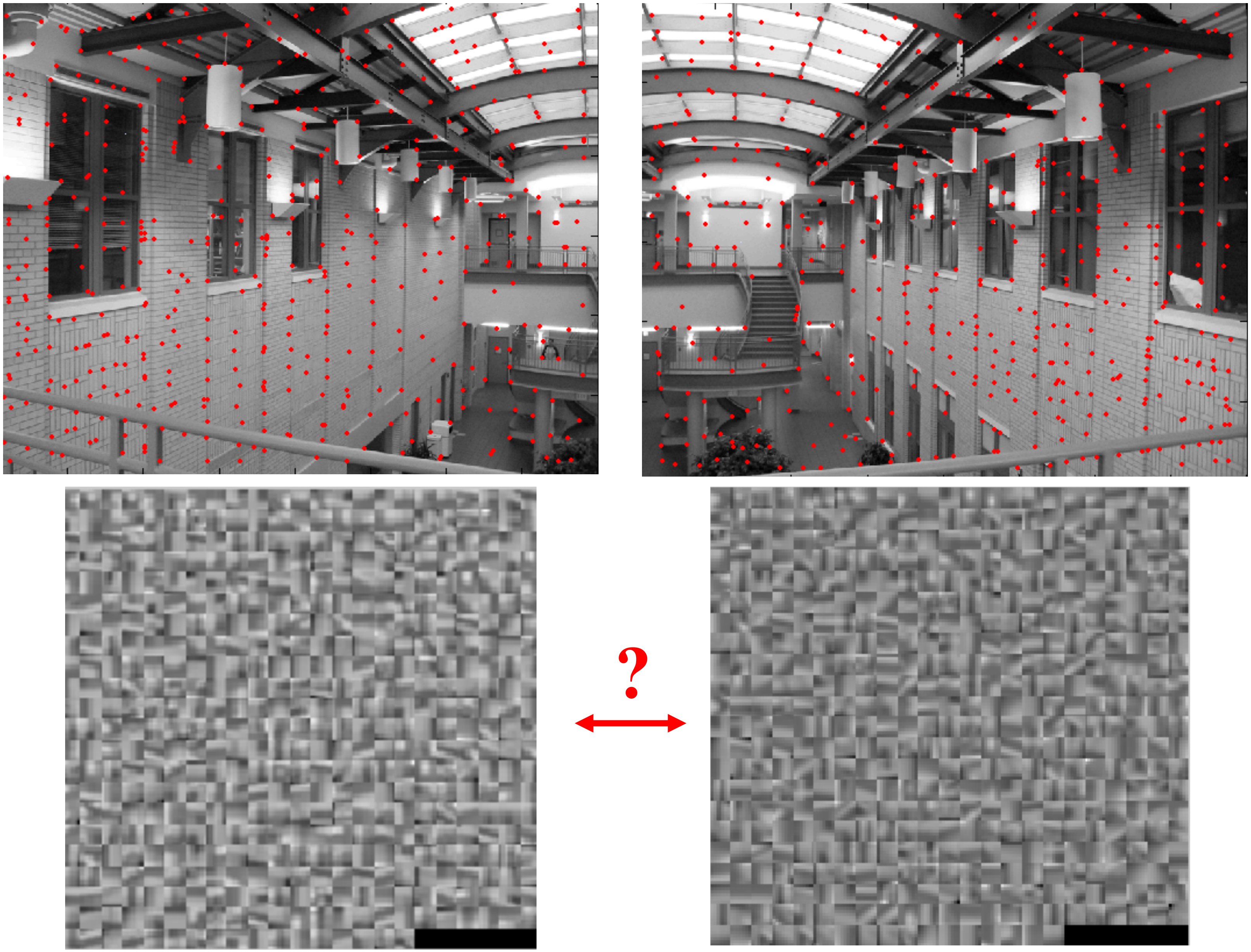




Use k-nearest neighbors

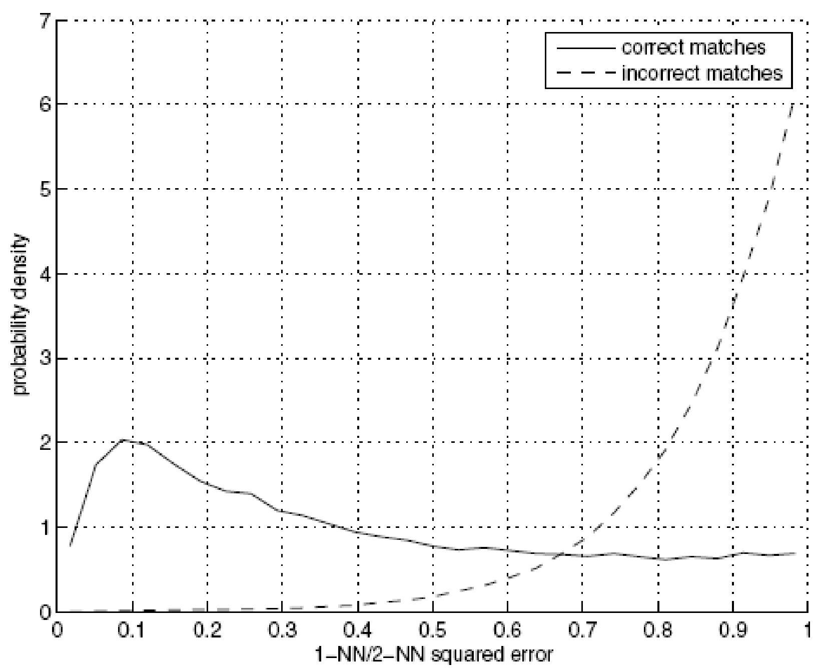


What about outliers?



Feature-space outlier rejection

- 1-NN: SSD of the closest match
- 2-NN: SSD of the <u>second-closest</u> match
- Look at how much better 1-NN is than 2-NN, e.g. 1-NN/2-NN
- That is, is our best match so much better than the rest?



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