Reminder: Student survey

Hi everyone,

This is the final reminder to participate in the anonymous mid-semester survey: https://melbourneuni.au1.qualtrics.com/jfe/form/SV_0JaLNfvPK07kIzY

The survey will be active until 5 pm today.

Thanks in advance!

Local features

Semester 2, 2022

Kris Ehinger

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https://www.youtube.com/watch?v=0Pj-jzy6ESE

Outline

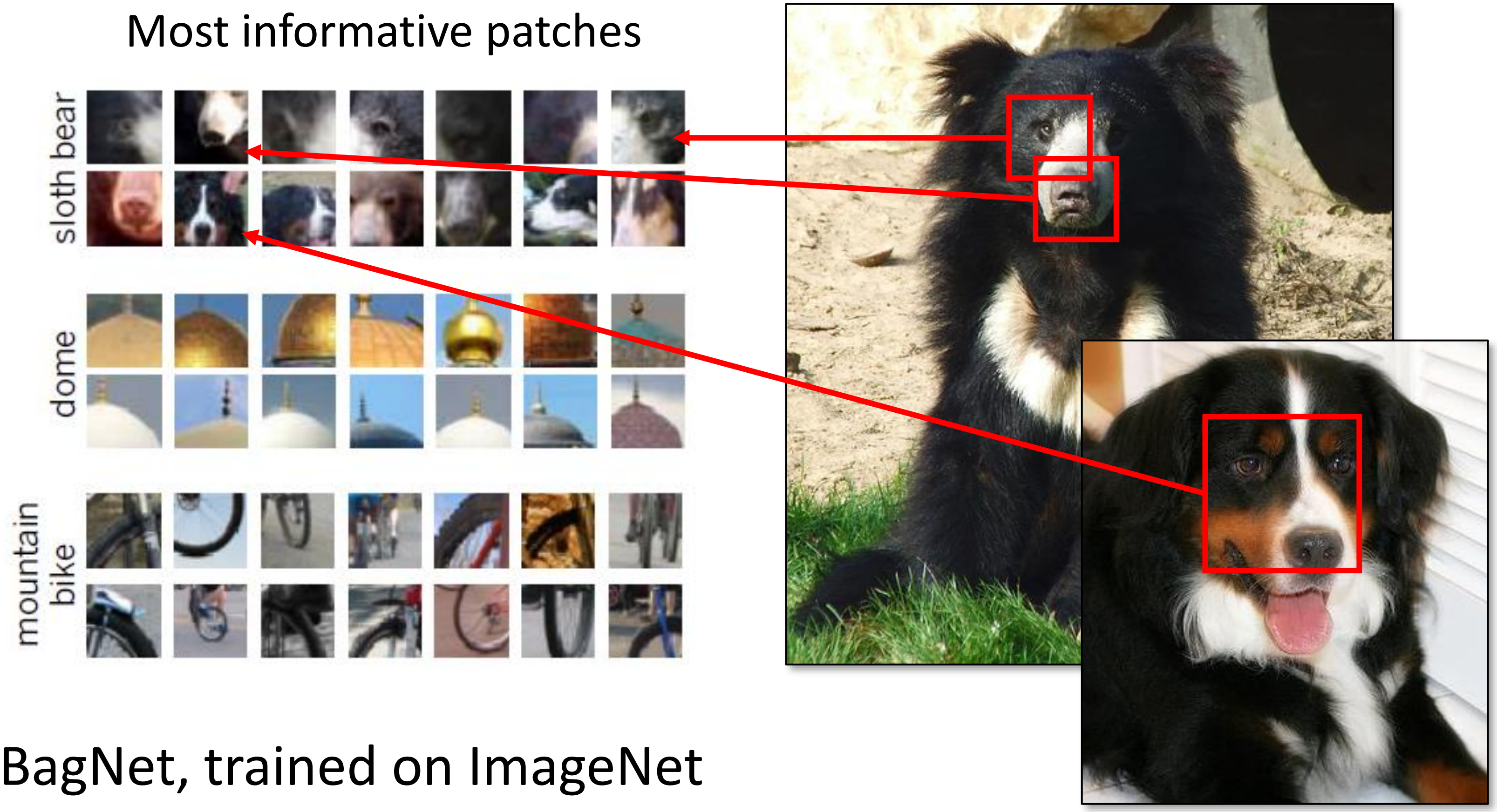
- Recognition from local features
- Feature detection
- Feature descriptors

Learning outcomes

- Explain the differences between bag-of-features and feature-detection-based approaches and their applications
- Implement an algorithm for feature detection (Harris corners)
- Explain the desirable properties of feature descriptors

Approaches to recognition

CNN object recognition



BagNet, trained on ImageNet

Brendel & Bethge (2019)

CNN object recognition

original texturised images

VGG-16, trained on ImageNet

Performance drop:
90% → 79%

Image: Brendel & Bethge (2019)

Classification from local texture

A

B

D

C

E

F

Approaches to recognition

- Detect local features, ignore spatial position
  - Example: bag of words / bag of features
- Local features + weak spatial relations
  - Spatial pyramid models
- Detect local features and model spatial relations between them
  - Deformable-parts models
  - Keypoint tracking / matching

Recognition from local features

Bag of words


frosting
cake
Step
butter
cakes
pan
recipe
minutes
time
batter
make
Kitchen
Test
ingredients
flour
Cake
oven
baking
temperature
texture
speed
recipes
pans
spread
layer
sugar
will
can
eggs
Tip
Using
liquid
chocolate
Add
around
bowl
stand
called
light
beating
medium
fluffy
combined
frost
Bake
food
first
mixture
paper
creamed
crumb
mixer
waxed
dessert
together
step
Ingredients
top
get
keep
sides
parchment
doneness
cup
even
need
different
use
Let
try
flip
dark
way
wire
dry
Dry
knife
Allow
coat
brush
cups
small
cool
special
individually
directions
homemade
teach
higher
angel
crumbs
completely
one
edges
room
covered
Alternate
Pans
easily
Many
takes
knowing
generously
gluten
beat
rack
add
bubbles
steps
chiffon
careful
adding
Start
sure
important
methods
reduce
toothpick
moist
perfect
birthday
choose
specified
makes
overmix
recipe's
prevent
vanilla
wants
letting
layers
requires
Whether
making
require
using
next
bake
start
know
new
flour

Bag of features

Object → **Bag of 'words'**

Image: Li Fei Fei

Bag of features

- Based on the method from NLP – represent a document using a histogram of word frequency
- In an image, “words” are local features

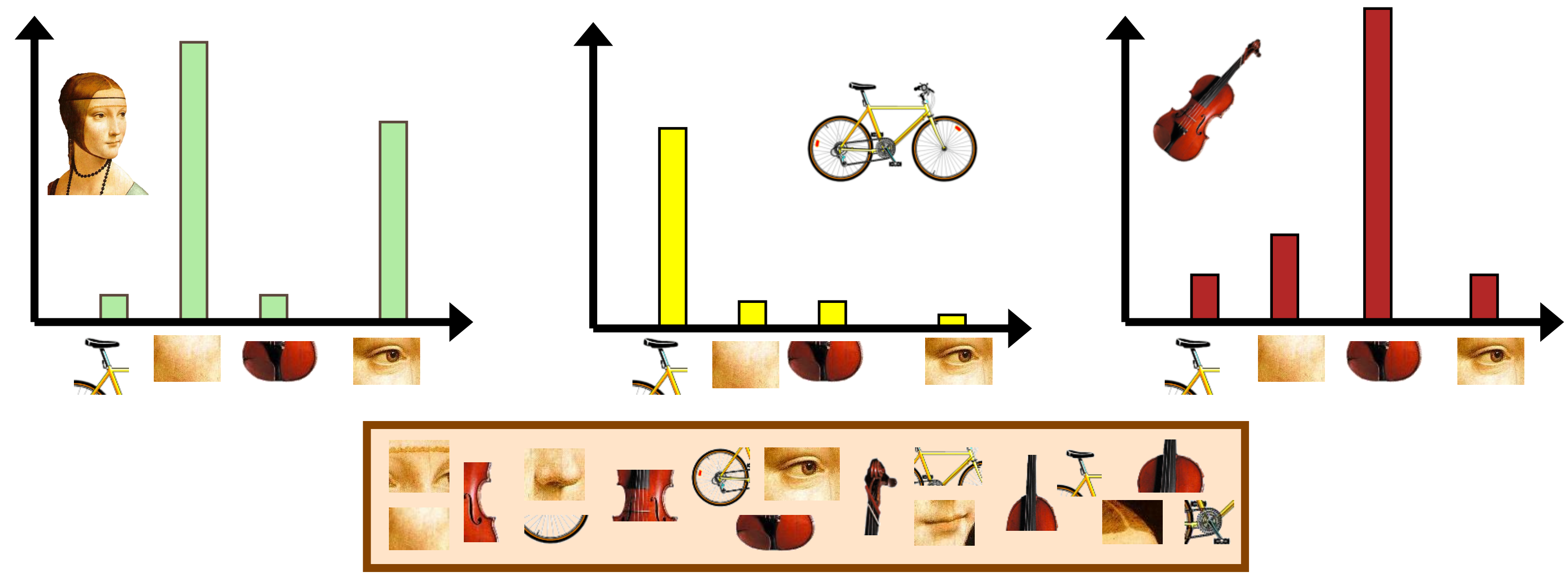
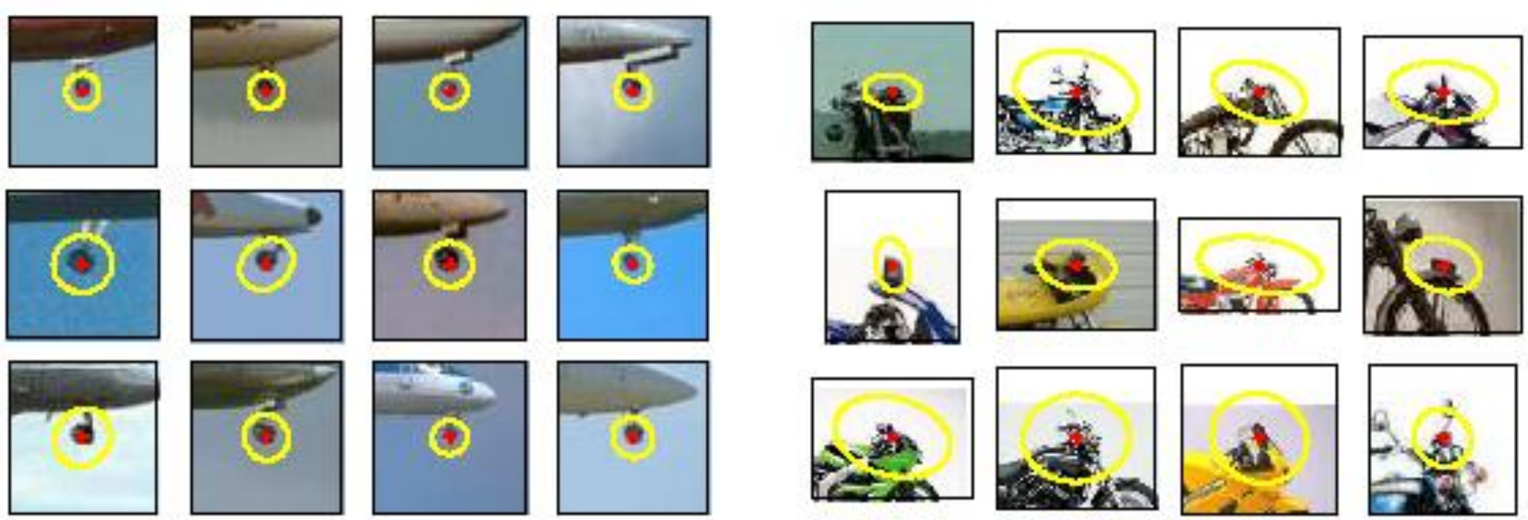


Image: Li Fei Fei

Words -> features

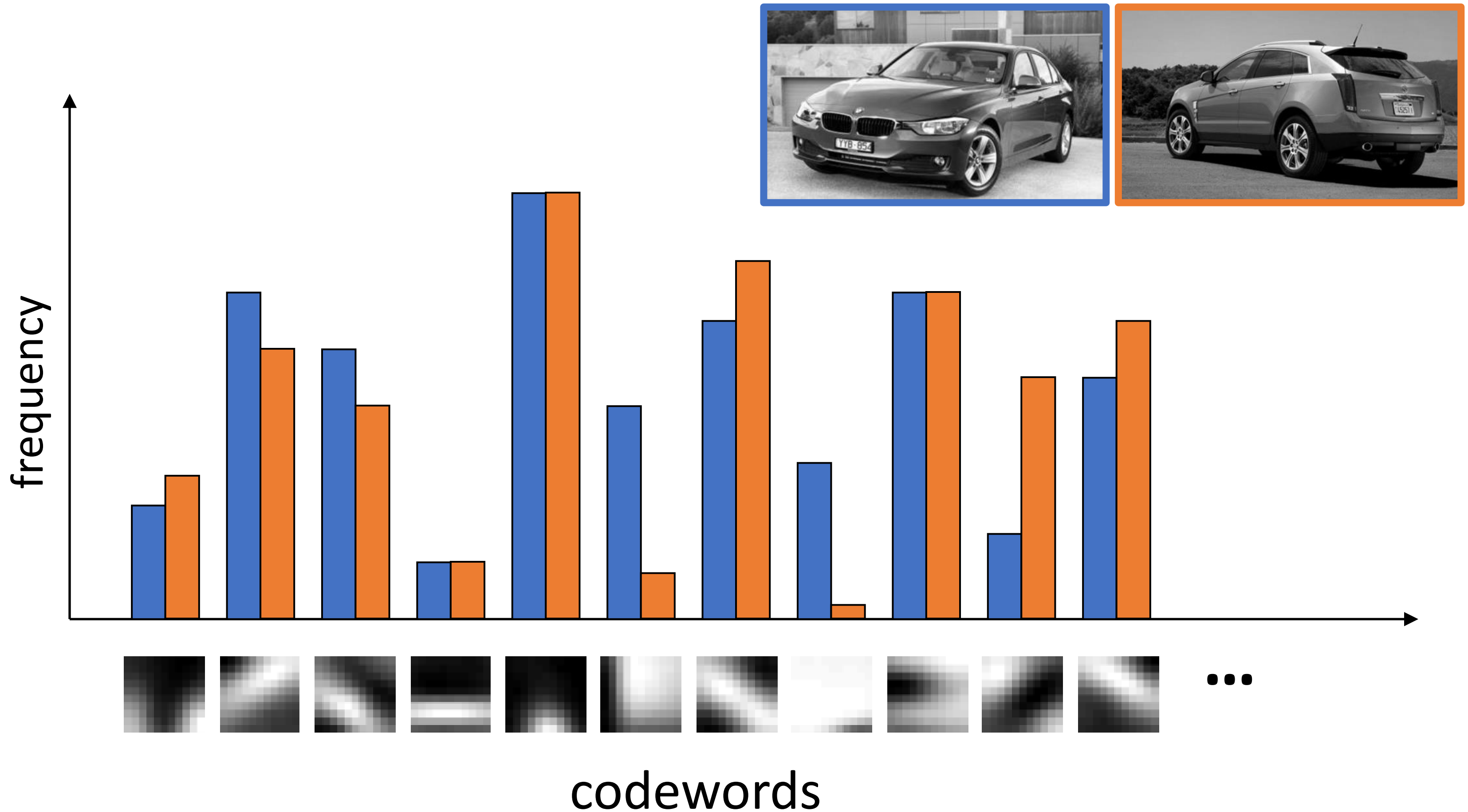
- Problem: in images, the same "word" can have many appearances



- Solution: combine similar local features, e.g., with k-means clustering

Image: Sivic et al. (2005)

Histogram comparison

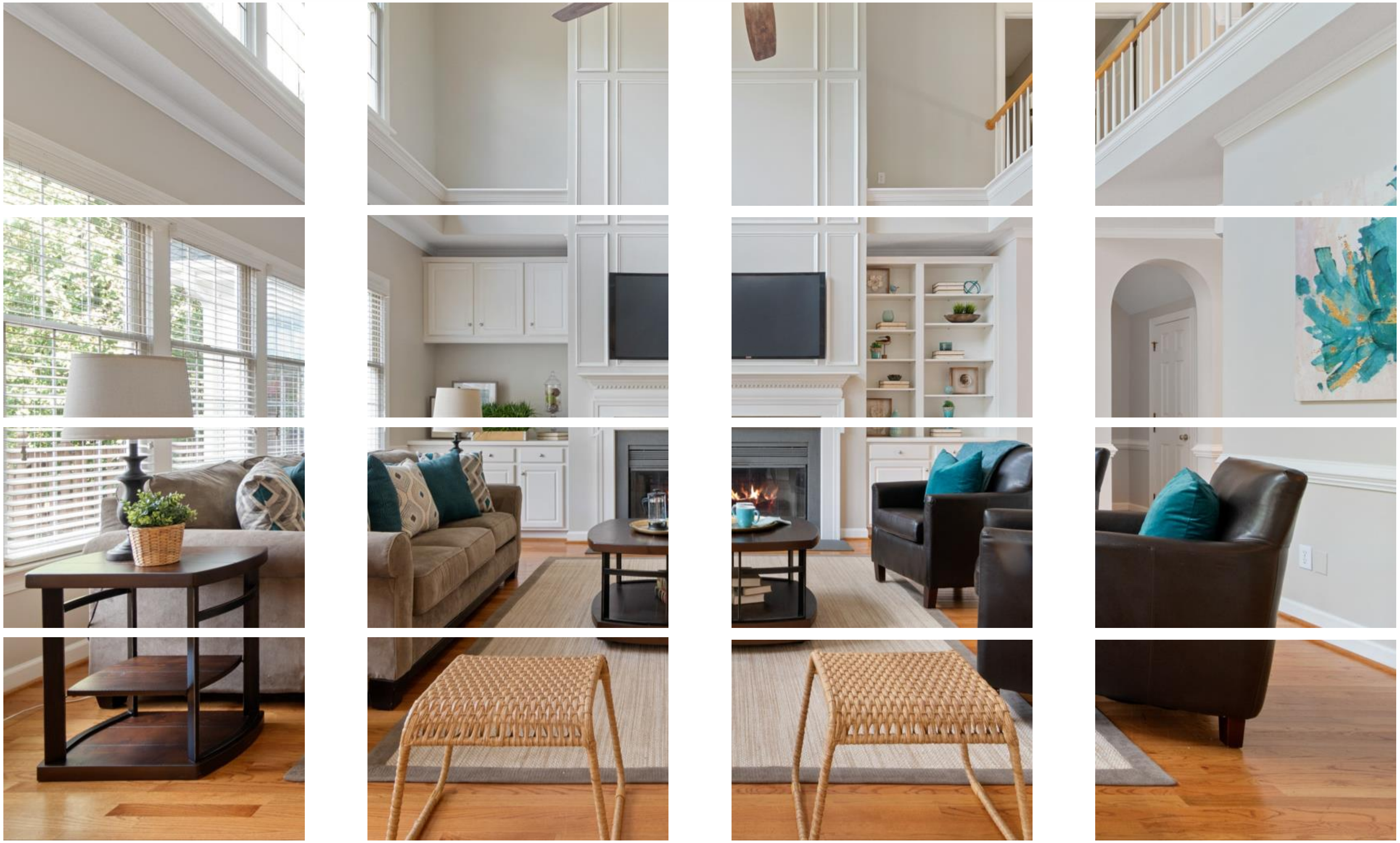


Adapted from: Li Fei Fei

Spatial pyramids

Spatial pyramids

Spatial pyramids



Spatial pyramids

- Main idea: run bag of features at multiple scales
- Note that there's a difference between:
  - Detecting features at one scale and pooling at multiple scales
  - Detecting features at multiple scales

Multiscale pooling

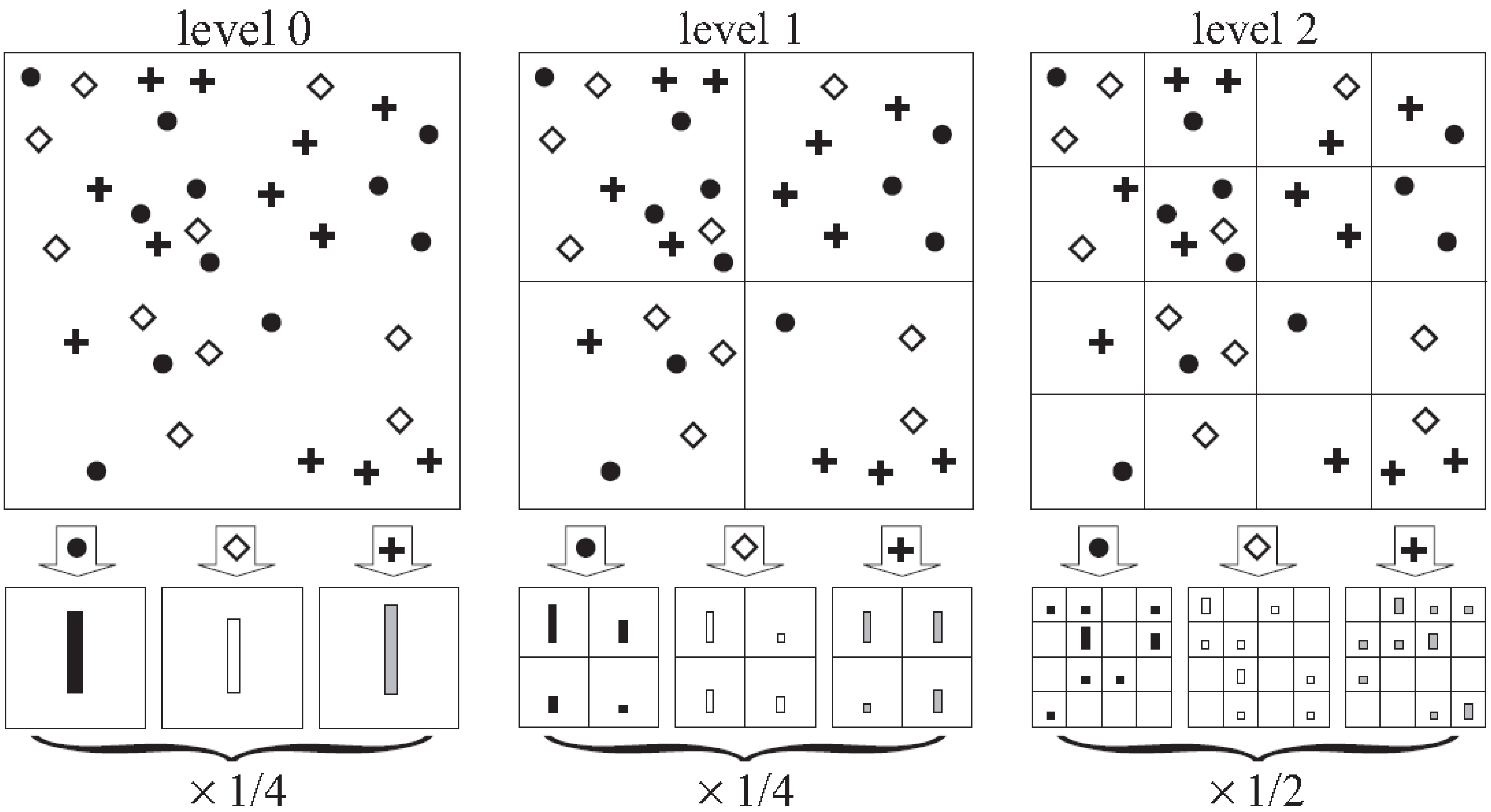


Figure: Lazebnik, Schmidt, & Ponce (2006)

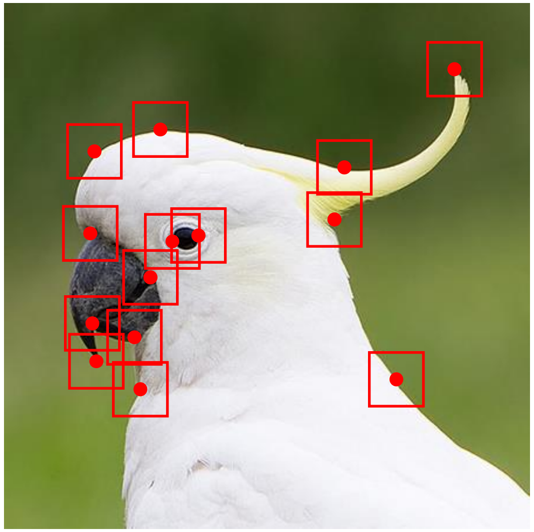
Summary

- Bag of words/features = detect local features anywhere in the image, ignore location and spatial relations
- Spatial pyramids add weak spatial relation information to the “bag of features” approach
- Generally works well for category-level recognition – high invariance to object translation and pose

Feature detection

Dense vs. sparse features

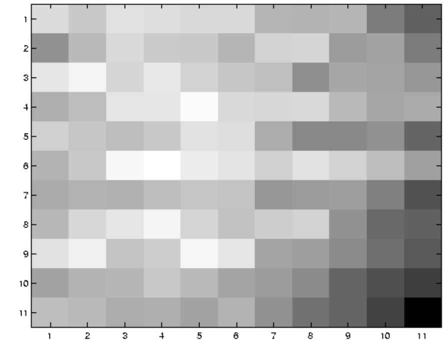
- Dense feature representation: compute local features everywhere
- Sparse feature representation : compute local features only at a few “important” points



Definitions

- **Feature detection:** finding "important" points (interest points or keypoints) in images
  - What's important?
  - Generally, points that can be detected reliably across image transformations
- **Feature descriptor:** a short code or set of numbers to represent a point in an image

What makes a good keypoint?



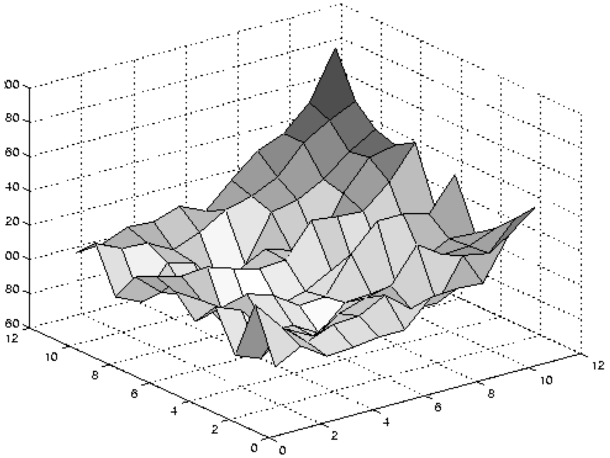
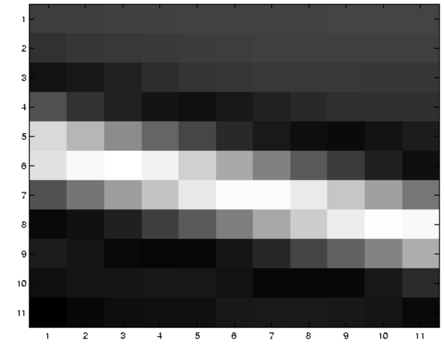


Figure: R. Szeliski

What makes a good keypoint?



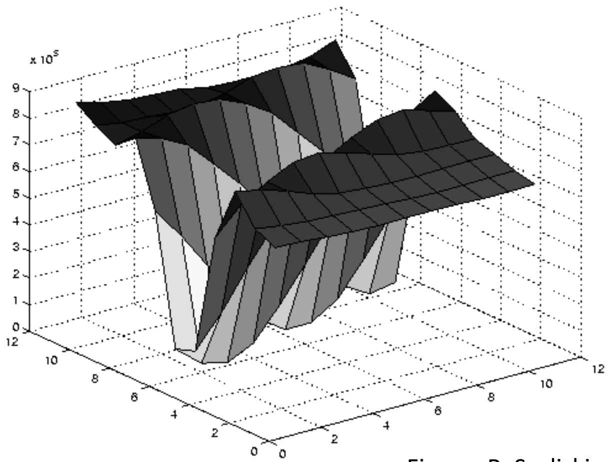
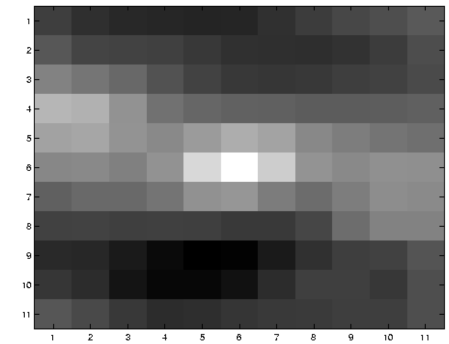
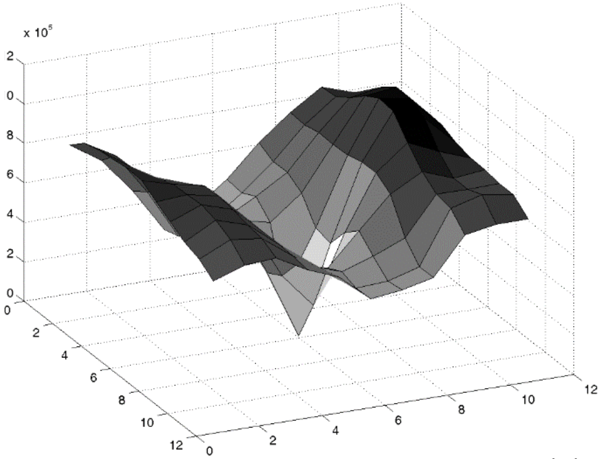


Figure: R. Szeliski

What makes a good keypoint?



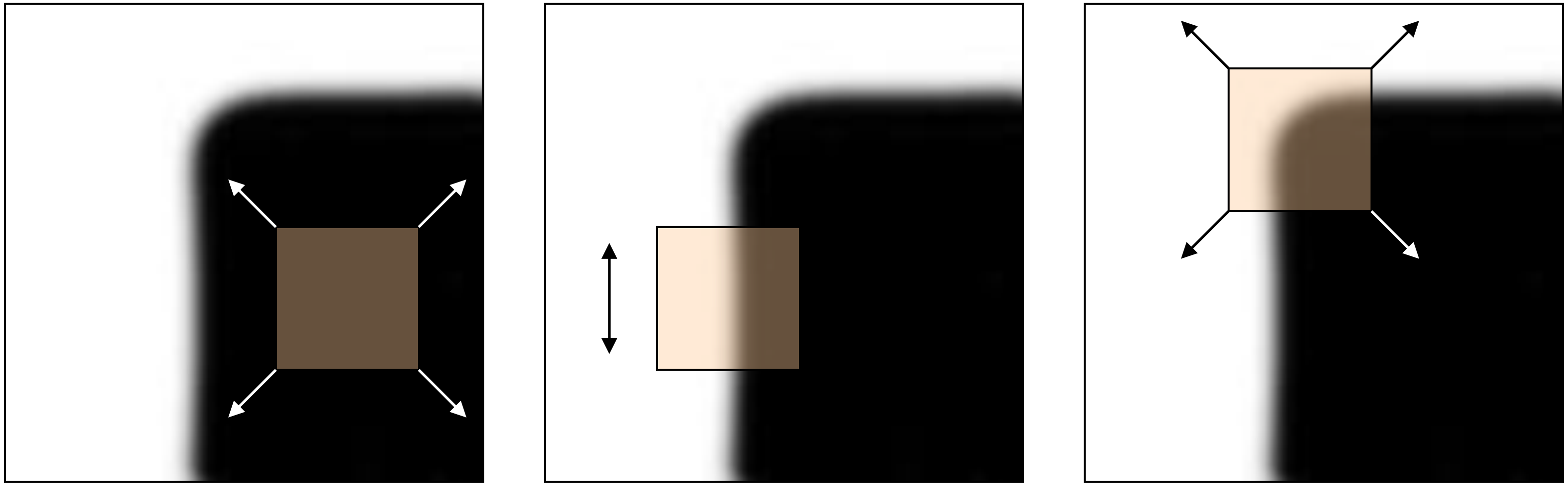


pollev.com/krisehinger432

Figure: R. Szeliski

Selecting good keypoints

- Should be easy to recognize in a small window
- Shifting the window in any direction should produce a large change in intensity



Uniform = no change in any direction

Edge = no change along edge direction

Corner = change in all directions

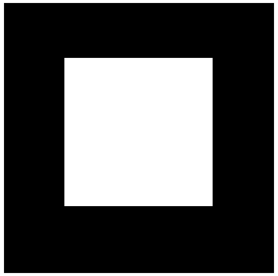
Slide: K. Grauman

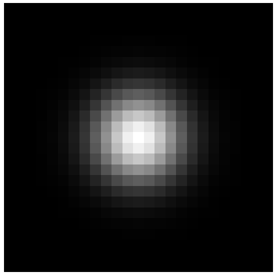
Corner detection

- Change in appearance of window w(x,y) for the shift [u,v]:

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

Common window functions:
square, Gaussian



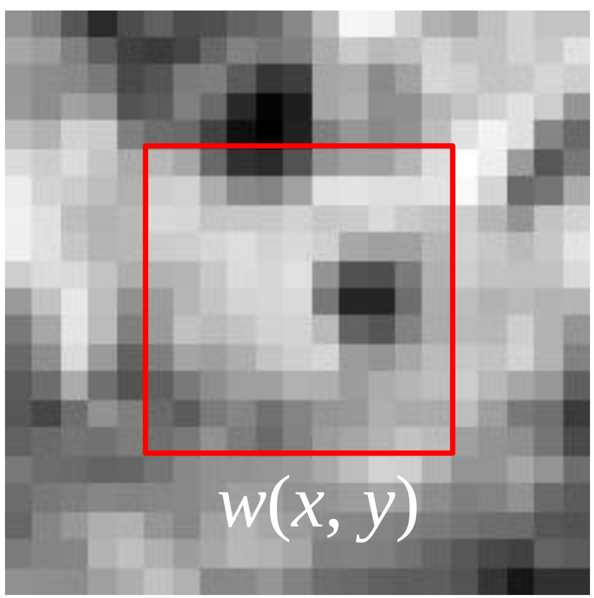


Corner detection

- Change in appearance of window w(x,y) for the shift [u,v]:

$$E(u,v) = \sum_{x,y} w(x,y)\left[I(x+u,y+v) - I(x,y)\right]^2$$

$I(x, y)$



$E(u, v)$

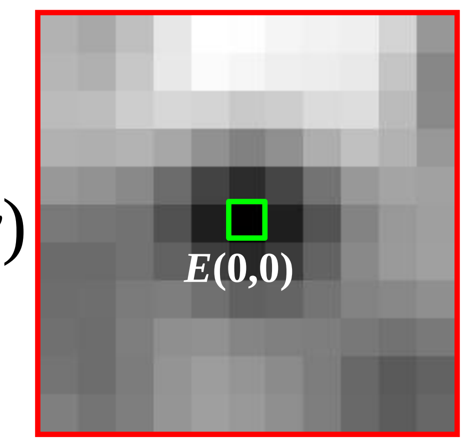


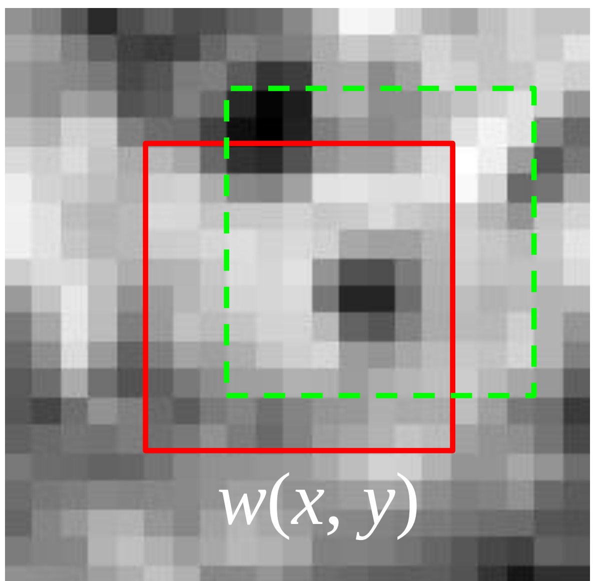
Figure: R. Szeliski

Corner detection

- Change in appearance of window w(x,y) for the shift [u,v]:

$$E(u,v)=\sum_{x,y} w(x,y)\left[I(x+u,y+v)-I(x,y)\right]^2$$

$I(x, y)$



$E(u, v)$

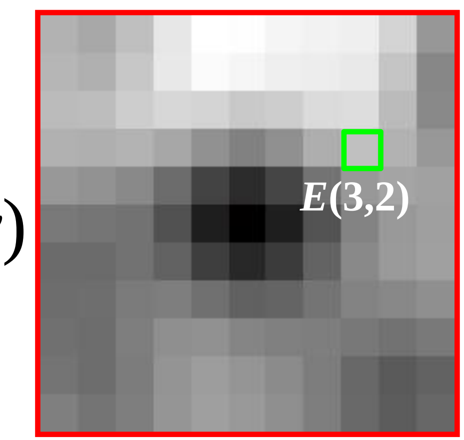
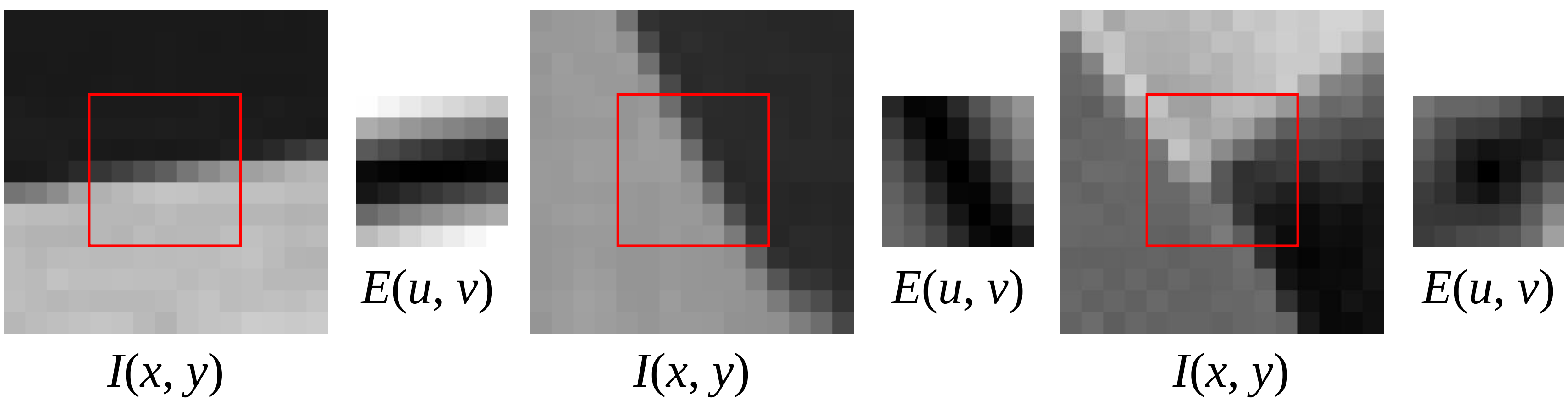


Figure: R. Szeliski

Corner detection

- Change in appearance of window w(x,y) for the shift [u,v]:

$$E(u,v)=\sum_{x,y} w(x,y)\left[I(x+u,y+v)-I(x,y)\right]^2$$



Corner detection mathematics

- Approximate shifted intensity using Taylor series:

$$E(u,v)=\sum_{x,y} w(x,y)\left[I(x+u,y+v)-I(x,y)\right]^2$$

$$E(u,v)\approx\sum_{x,y} w(x,y)[I(x,y)+u\underbrace{I_x}_{\frac{\partial I}{\partial x}}+v\underbrace{I_y}_{\frac{\partial I}{\partial y}}-I(x,y)]^2$$

$$=\sum_{x,y} w(x,y)[uI_x+vI_y]^2$$

$$=\sum_{x,y} w(x,y)\begin{pmatrix}u & v\end{pmatrix}\begin{bmatrix}I_xI_x & I_xI_y\\ I_xI_y & I_yI_y\end{bmatrix}\begin{pmatrix}u\\ v\end{pmatrix}$$

Corner detection mathematics

- Change in appearance of window w(x,y) for the shift [u,v]:

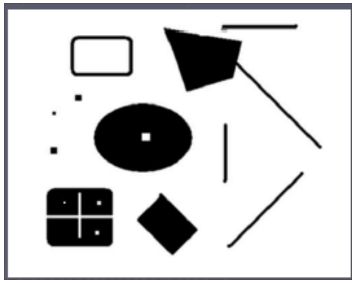
$$E(u,v) = \sum_{x,y} w(x,y)\left[I(x+u, y+v) - I(x,y)\right]^2$$

- Simplifies to: $E(u,v) \approx [u \;\; v] \; M \begin{bmatrix} u \\ v \end{bmatrix}$

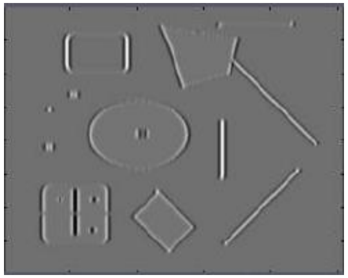
$$M = \sum_{x,y} w(x,y) \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix}$$

Values of M

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

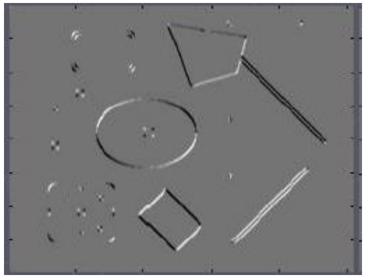


Image



$$I_x = \frac{\partial I}{\partial x}$$

$$I_y = \frac{\partial I}{\partial y}$$



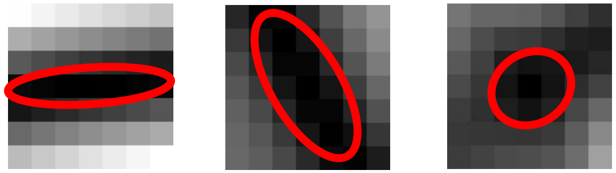
$$I_x I_y = \frac{\partial I}{\partial x}\frac{\partial I}{\partial y}$$

Slide: K. Grauman

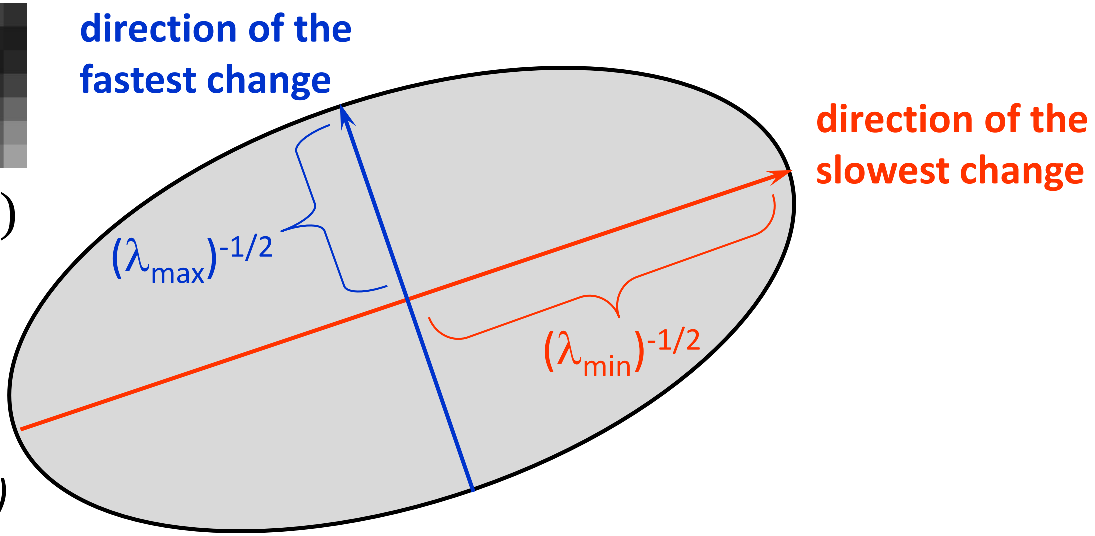
Corner response function

- Detect corners using eigenvalues λ_1, λ_2 of M

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



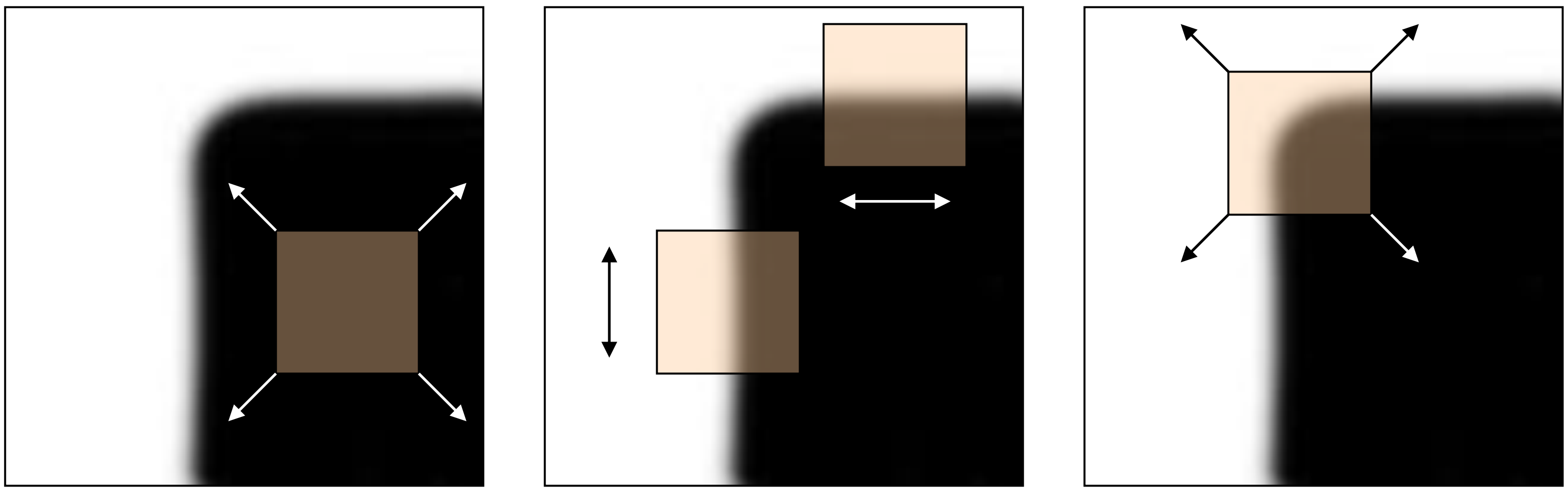
$E(u,v)$ $E(u,v)$ $E(u,v)$



Iso-intensity contour of *E(u,v)*

Figure: R. Szeliski

Corner response function



Uniform: λ_1 and λ_2 are small

Edge: $\lambda_1 >> \lambda_2$
$\lambda_2 >> \lambda_1$

Corner: λ_1 and λ_2 are large

To find corners, look for points where $\lambda_1 \lambda_2$ is high, and $\lambda_1 + \lambda_2$ is low

Figure: K. Grauman

Harris corners

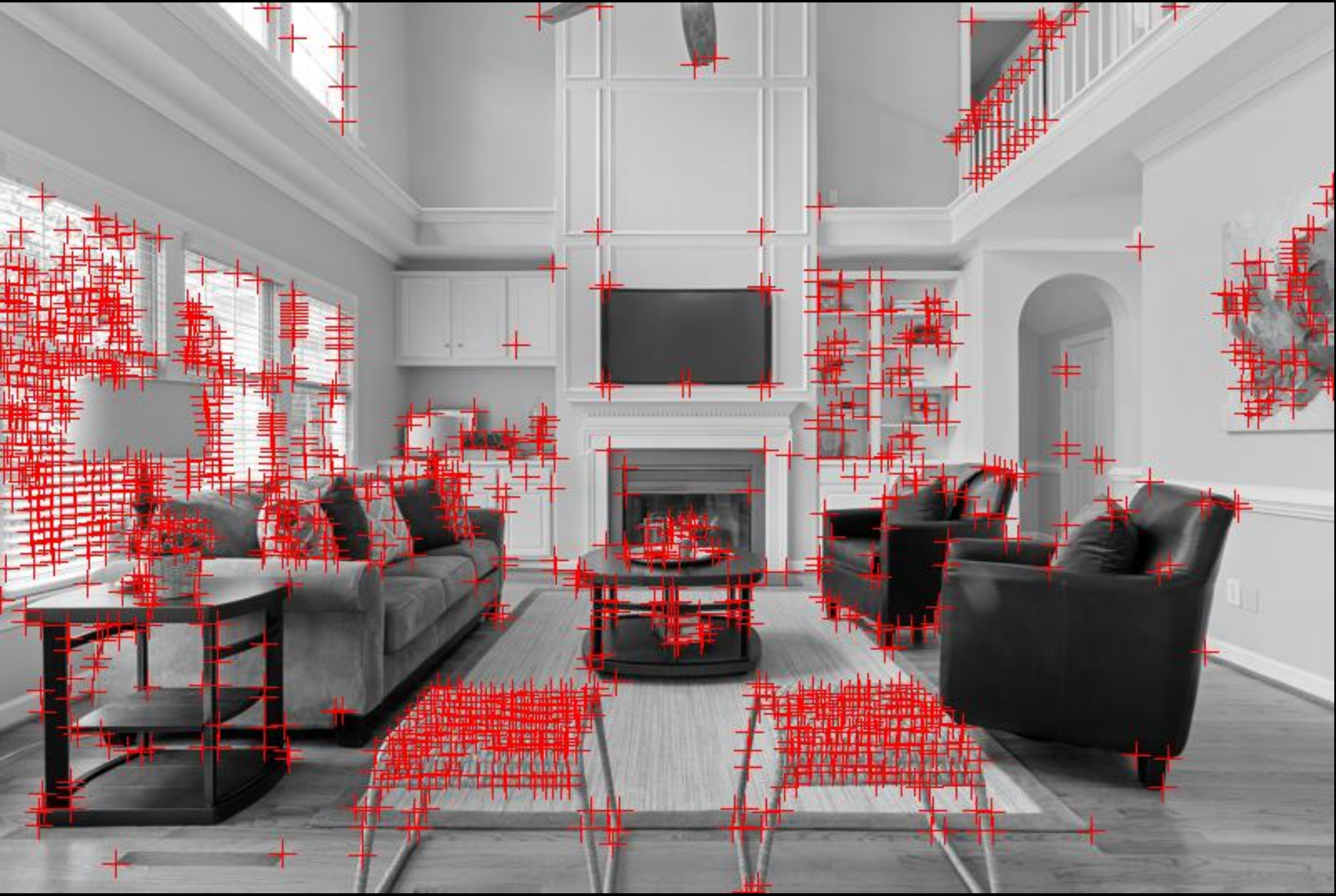
- $\lambda_1\lambda_2$ and $\lambda_1 + \lambda_2$ are the determinant and trace of matrix M:
  - det = np.linalg.det(m) $\quad \det(M) = \lambda_1\lambda_2$
  - trace = m.trace() $\quad \mathrm{tr}(M) = \lambda_1 + \lambda_2$

- Harris corner response: $R = \det(M) - k(\mathrm{tr}(M))^2$

k determined empirically,
around 0.04-0.06

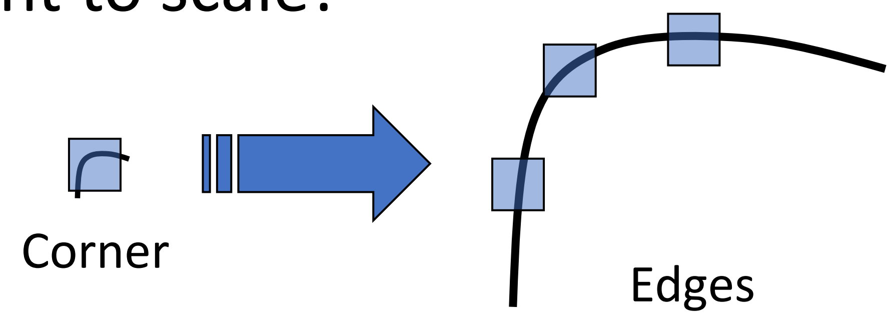
Harris corner response = $\det(M)-k(\mathrm{tr}(M))^2$

Harris corners



Invariance / tolerance

- Corner detection is based on the image gradient (edges), so it's
  - Invariant to translation
  - Tolerant to changes in lighting
- Because the corner response is based on eigenvalues, it is invariant to image-plane rotation
- Not invariant to scale!



Alternatives to Harris corners

- Alternative corner response functions:
  - Shi-Tomasi (1994): $\min(\lambda_1, \lambda_2)$
  - Brown, Szeliski, & Winder (2005): $\frac{\det M}{\operatorname{tr} M}$
- Alternatives to corner detectors:
  - Blob detectors
  - Machine-learning-based detectors

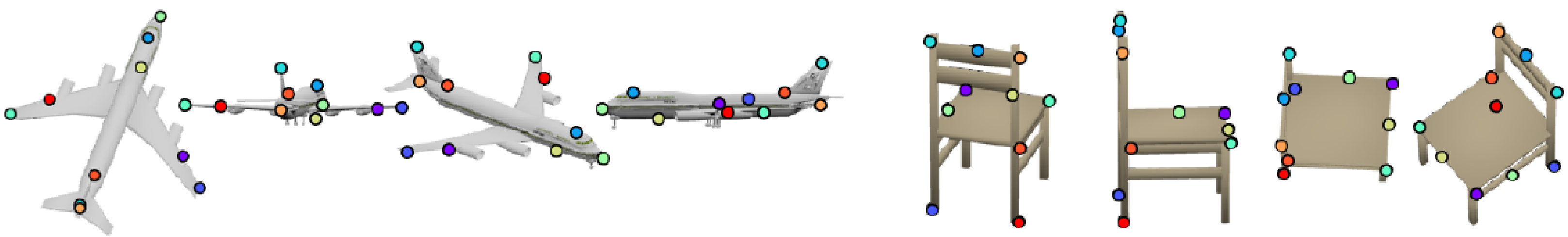


Image: Suwajanakorn, Snavely, Tompson, & Norouzi (2018)

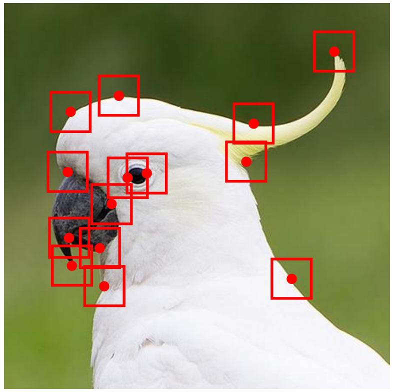
Summary

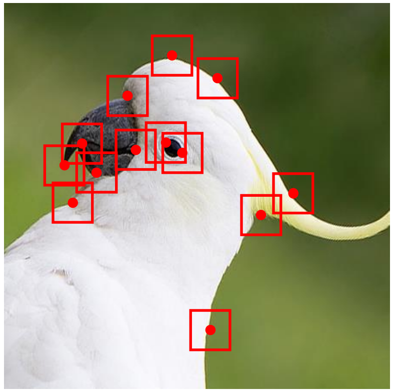
- Rather than detecting local features everywhere, feature detectors can be used to find “important” points (interest points or keypoints)
- Common type of interest point = corners
- Corners can be detected from local gradients

Feature descriptors

Feature descriptors

- Having found keypoints in an image, we need a way to represent them
- Options:
  - Image patch
  - Handcrafted descriptors
    - SIFT
    - GLOH
    - BRIEF
    - BRISK
    - ORB
  - Machine-learned descriptors
    - DeTone, Malisiewicz, & Rabinovich (2018)





Scale-Invariant Feature Transform (SIFT)

- Compute gradient, take histograms in a grid of pixels around interest point
- Weight gradient magnitudes based on distance from centre of patch
- Normalise histograms to sum to 1

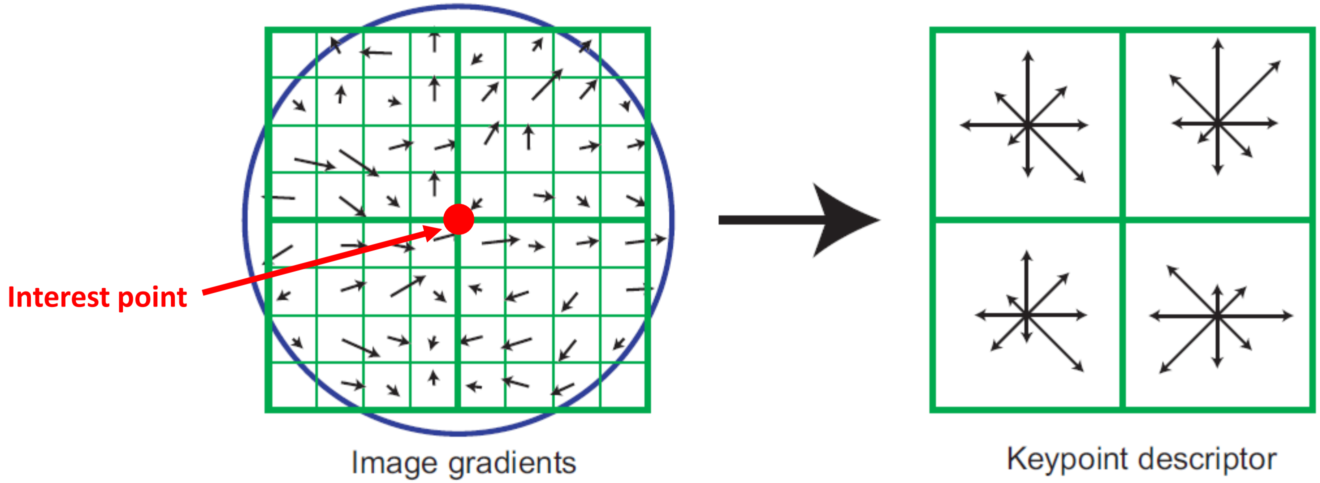


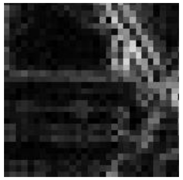
Image: D. Lowe

Scale-Invariant Feature Transform (SIFT)

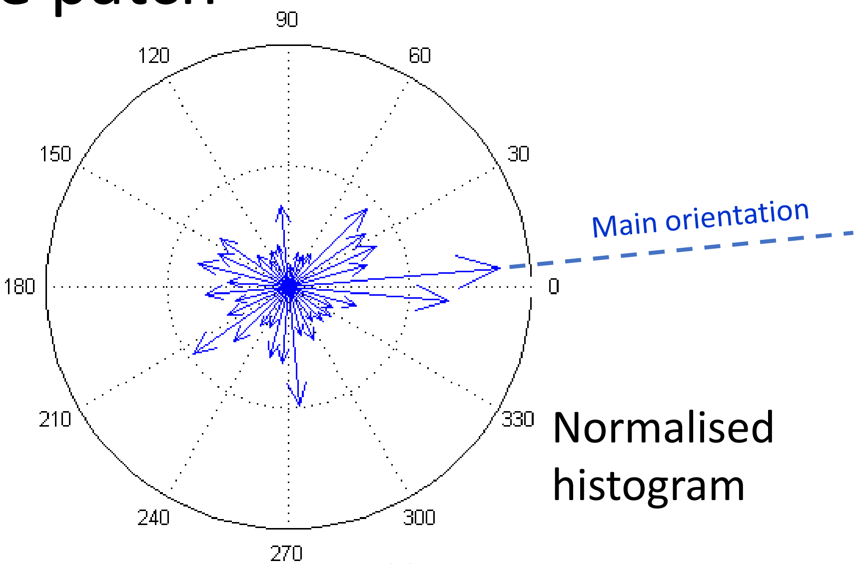
- SIFT implementation details:
  - Patch size = 16 x 16 pixels
  - Grid = 4 x 4 cells
  - Histogram bins = 8 orientations
  - Gaussian weighting from centre of patch
  - Two-step normalisation: normalise to sum to 1, truncate values to 0.2, normalise to sum to 1
- Descriptor length = 4 x 4 x 8 = 128

Scale-Invariant Feature Transform (SIFT)

- Interest points (blobs) are detected at multiple scales; descriptor is based on the scale with maximum response
- Histograms are encoded relative to the main orientation in the patch



Patch



Normalised histogram

Summary

- Feature descriptor = a code to represent a local patch or interest point in an image
- Many handcrafted feature descriptors, with different:
  - Encoding method
  - Speed
  - Descriptor size
  - Feature detection method
- Goal of feature descriptors is invariance, so points can be matched reliably across image transforms

Summary

- Most recognition approaches are based on local features, but differ in how they represent spatial relations between features:
  - Bag-of-features methods: no spatial information
  - Feature detection methods: precise spatial information
- Choice of approach depends on task
  - Spatial information is probably not needed for category-level recognition
  - Spatial information is useful for tasks that require matching structures across images (next lectures!)