Lecture 8: Features 2

COMP 590/776: Computer Vision

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Course Website:
Scan Me!

Recap

Why extract features?

- Motivation: panorama stitching
  - We have two images – how do we combine them?

Step 1: extract features
Step 2: match features
Step 3: align images
Step 4: blending images

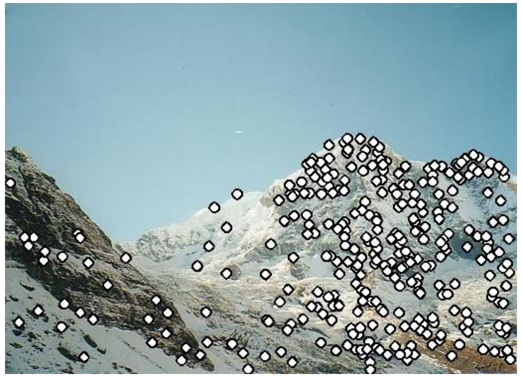
This Week

Next Week

Local features: main components

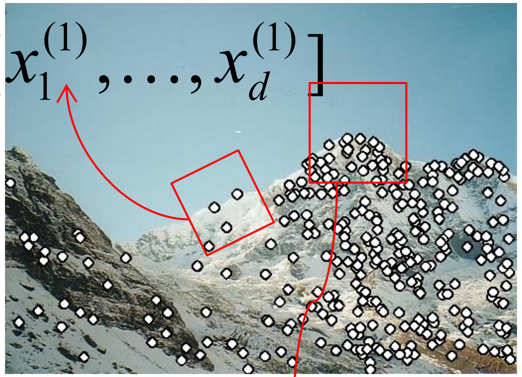
1) **Detection**: Identify the interest points

e.g. corners



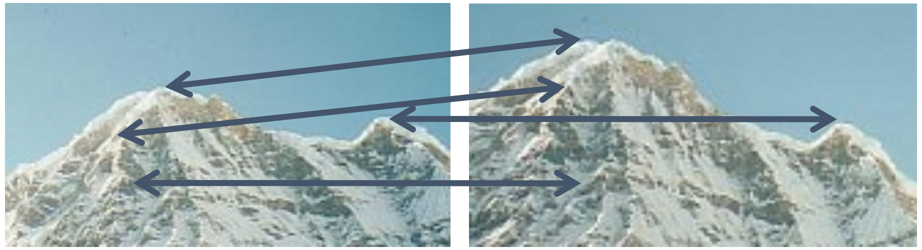
2) **Description**: Extract vector feature descriptor surrounding each interest point

$$\mathbf{x}_1 = [x_1^{(1)}, \ldots, x_d^{(1)}]$$



$$\mathbf{x}_2 = [x_1^{(2)}, \ldots, x_d^{(2)}]$$

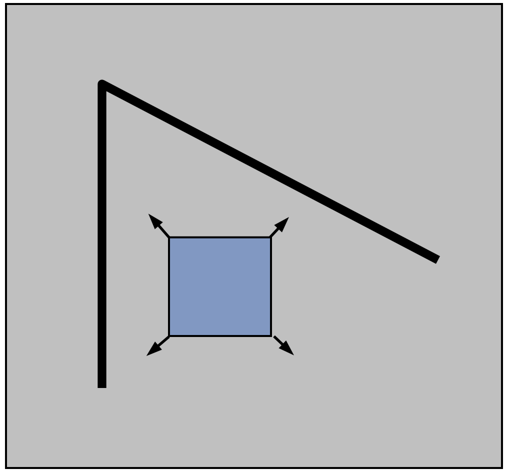
3) **Matching**: Determine correspondence between descriptors in two views



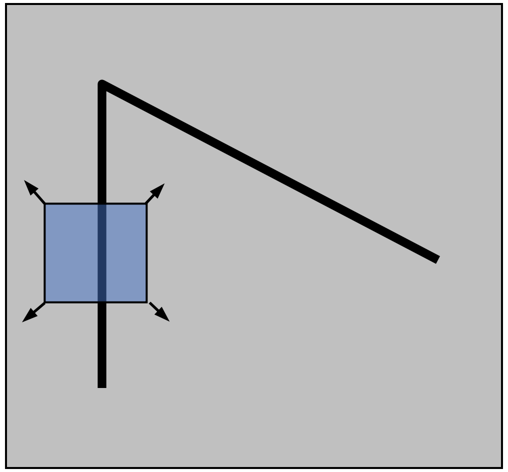
Credit: Kristen Grauman

How do we measure corner?

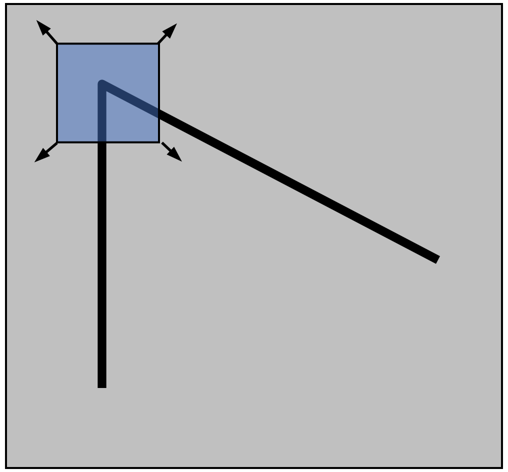
- Take a window W, and shift it in all directions by (u,v) pixels
- Corner = where shifting window in all directions causes significant change.



"flat" region:
no change in all directions



"edge":
no change along the edge direction



"corner":
significant change in all directions

Credit: S. Seitz, D. Frolova, D. Simakov

Harris Corner Recap

- 2^{nd} moment matrix *H* characterizes how intensities change in the neighborhood of a point.

- Max eigenvector (x_{max})-> minor axis of ellipse; Min eigenvector (x_{min}) -> major axis of ellipse. Max eigenvalue (λ_{max})-> length of minor axis; Min eigenvector (λ_{min})-> length of major axis. (From ellipse equation)

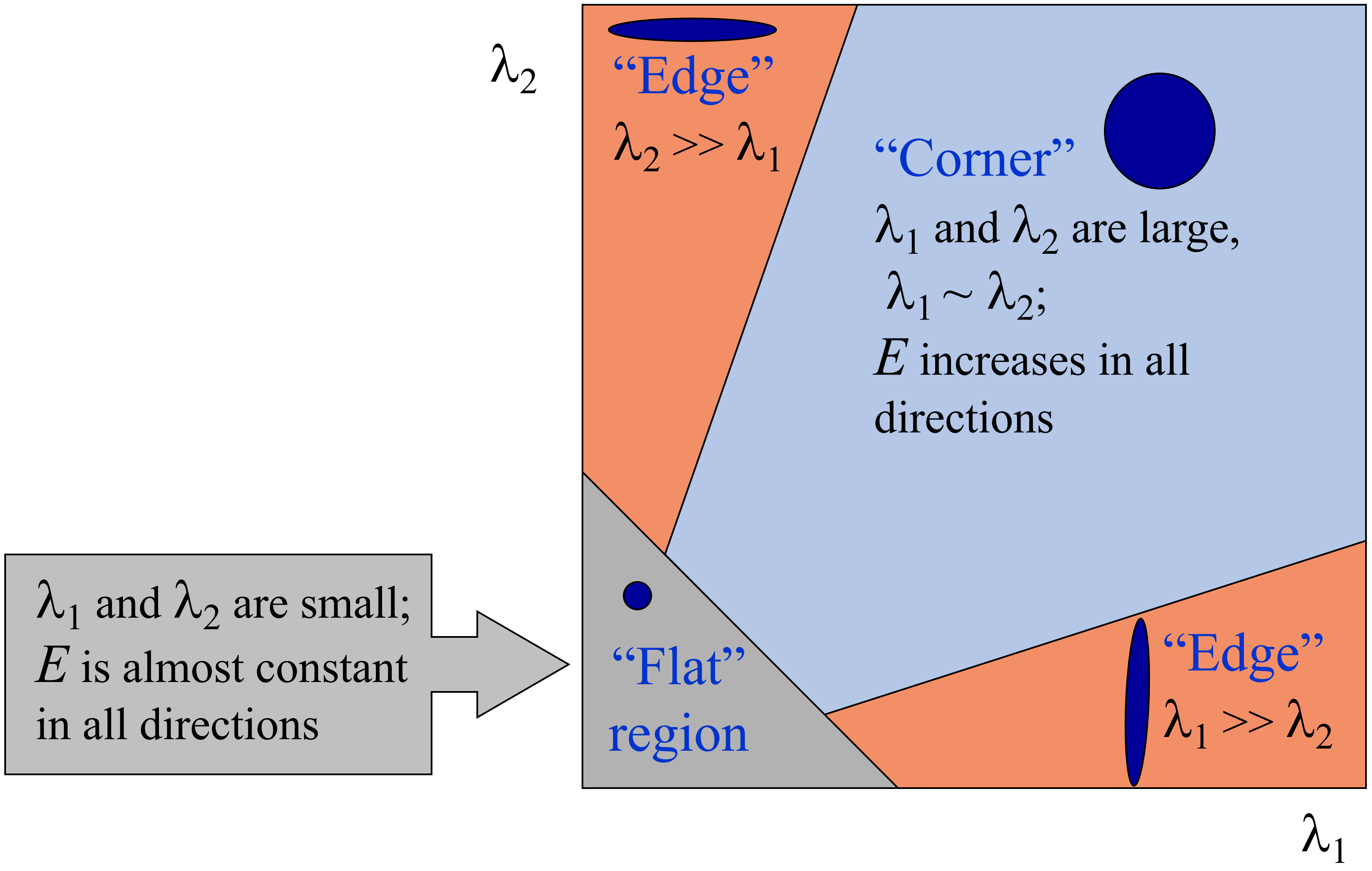
- Max eigenvector (x_{max}) -> direction of max change; Min eigenvector -> direction of min change. (What eigenvectors of image gradient's 2^{nd} moment matrix means)

- For an edge, Major axis of the ellipse -> parallel to the direction of the edge; Minor axis of the ellipse -> perpendicular to the edge.
  - Note: major axis of ellipse means direction of slowest change!

- For corner, both major and minor eigenvalues are large, indicating roughly equal change in any direction, and the ellipse becomes more like a circle.

Interpreting the eigenvalues of H

Classification of image points using eigenvalues of *M*:



Harris Corner detector: Steps

1. Compute Gaussian derivatives at each pixel
2. Compute second moment matrix *H* in a Gaussian window around each pixel
3. Compute corner response function *f* or *R*

$$R = \lambda_1 \lambda_2 - k \cdot (\lambda_1 + \lambda_2)^2 = \det(M) - k \cdot \mathrm{tr}(M)^2$$

$$f = \frac{\lambda_1 \lambda_2}{\lambda_1 + \lambda_2} = \frac{determinant(H)}{trace(H)}$$

4. Threshold *f* or *R*
5. Find local maxima of response function (nonmaximum suppression)

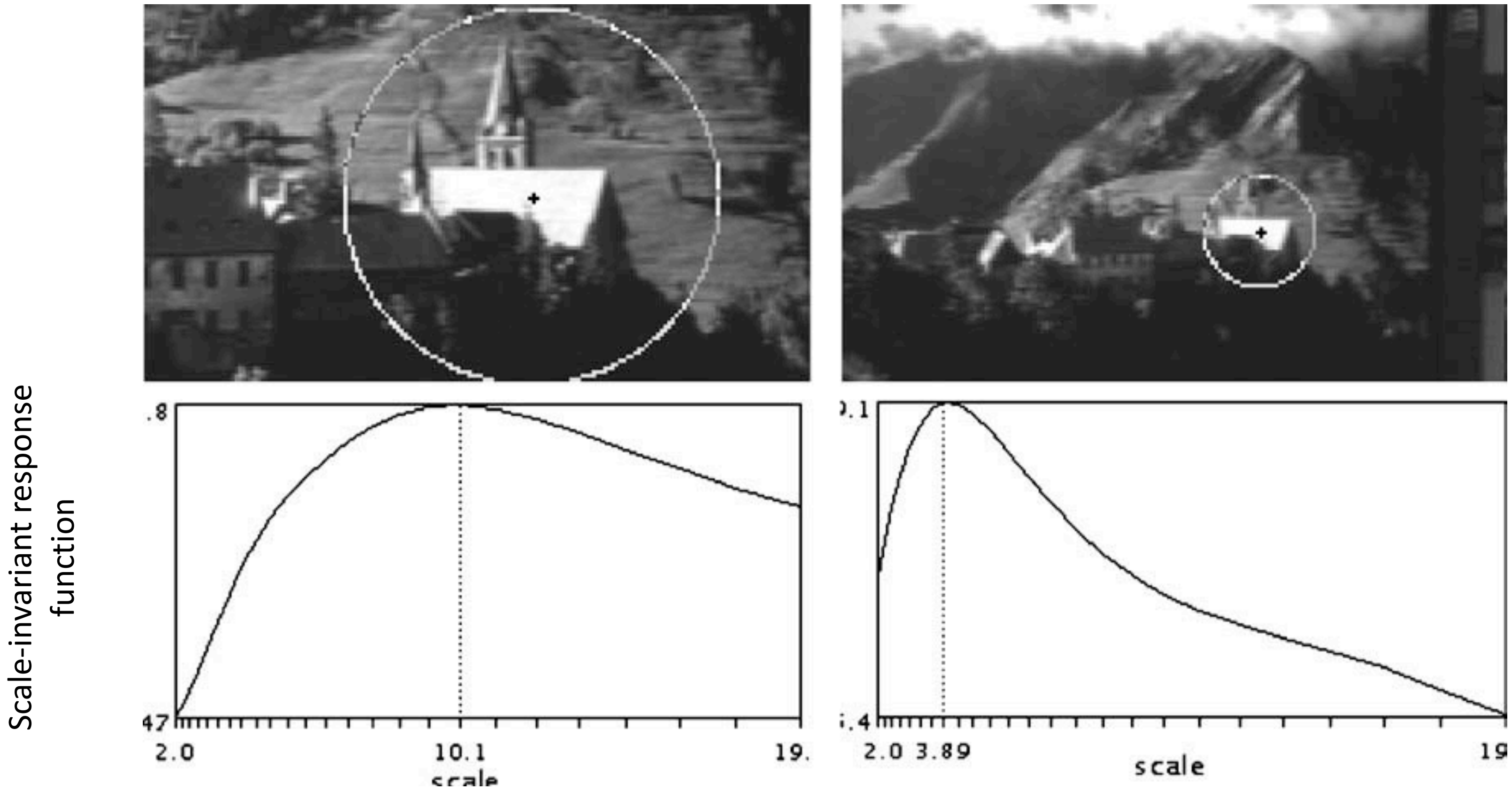
C.Harris and M.Stephens. "A Combined Corner and Edge Detector." *Proceedings of the 4th Alvey Vision Conference*: pages 147—151, 1988.

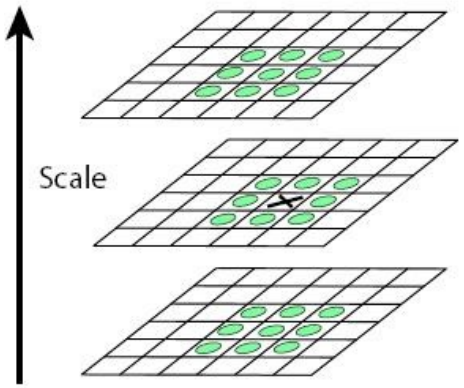
Properties of Harris: Invariance and equivariance

- We want corner locations to be *invariant* to photometric transformations and *equivariant* to geometric transformations
  - **Invariance:** image is transformed and corner locations do not change
  - **Equivariance:** if we have two transformed versions of the same image, features should be detected in corresponding locations

- Harris detector is equivariant to translation and rotation.
- Harris detector is somewhat invariant to intensity change (I' =a*I +b).
- Harris detector is NOT equivariant to scaling.

Keypoint detection with scale selection





"scale space"

Characteristic scale = scale at which the Harris operator *f*/R is maximum.

Approach: compute a *scale-invariant* response function over neighborhoods centered at each location (x, y) and a range of scales (σ), find *scale-space locations* (x, y, σ) where this function reaches a local maximum.

Today’s class

- SIFT detector
- SIFT descriptor
- Feature Matching
- Evaluating Results

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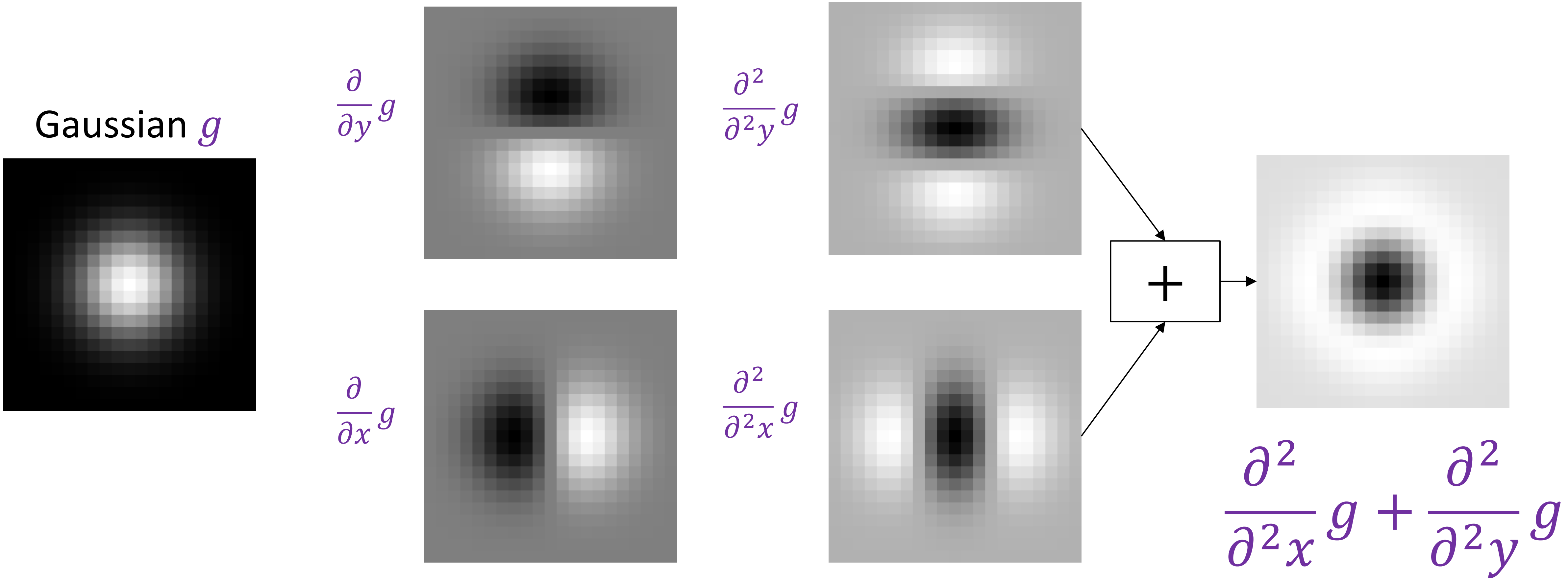
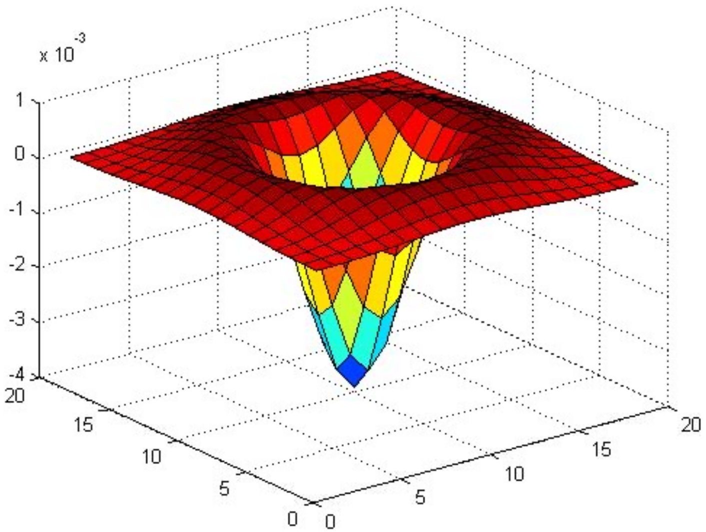
Laplacian of Gaussian

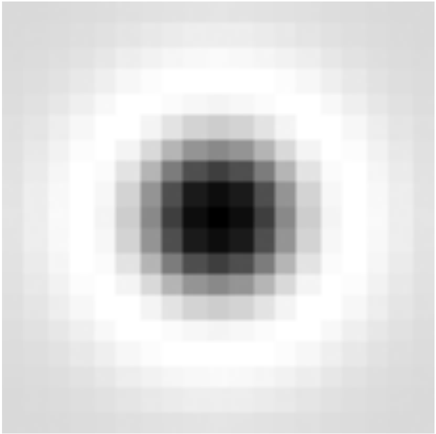


Source: [J. Johnson and D. Fouhey]

Scale-normalized Laplacian

- You need to multiply the LoG by σ^2 to make responses comparable across scales

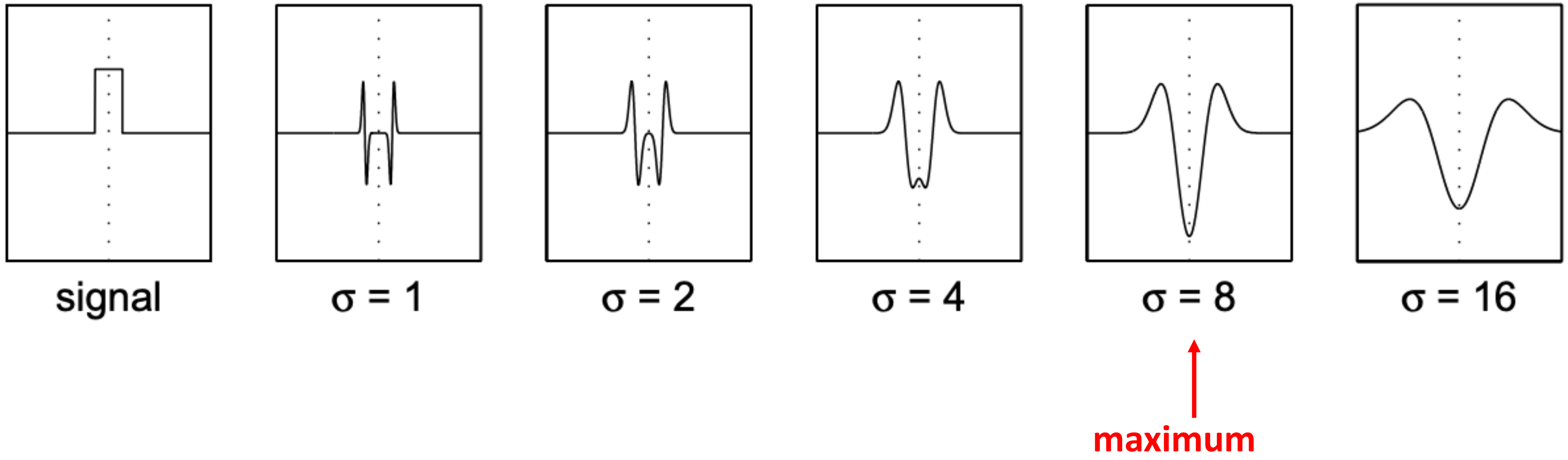




$$\nabla^2_{\text{norm}} = \sigma^2 \left(\frac{\partial^2}{\partial x^2} g + \frac{\partial^2}{\partial^2 y} g \right)$$

Scale selection: Characteristic Scale

- We can find the *characteristic scale* of the blob by convolving it with *scale-normalized* Laplacians at several scales (σ) and looking for the maximum response

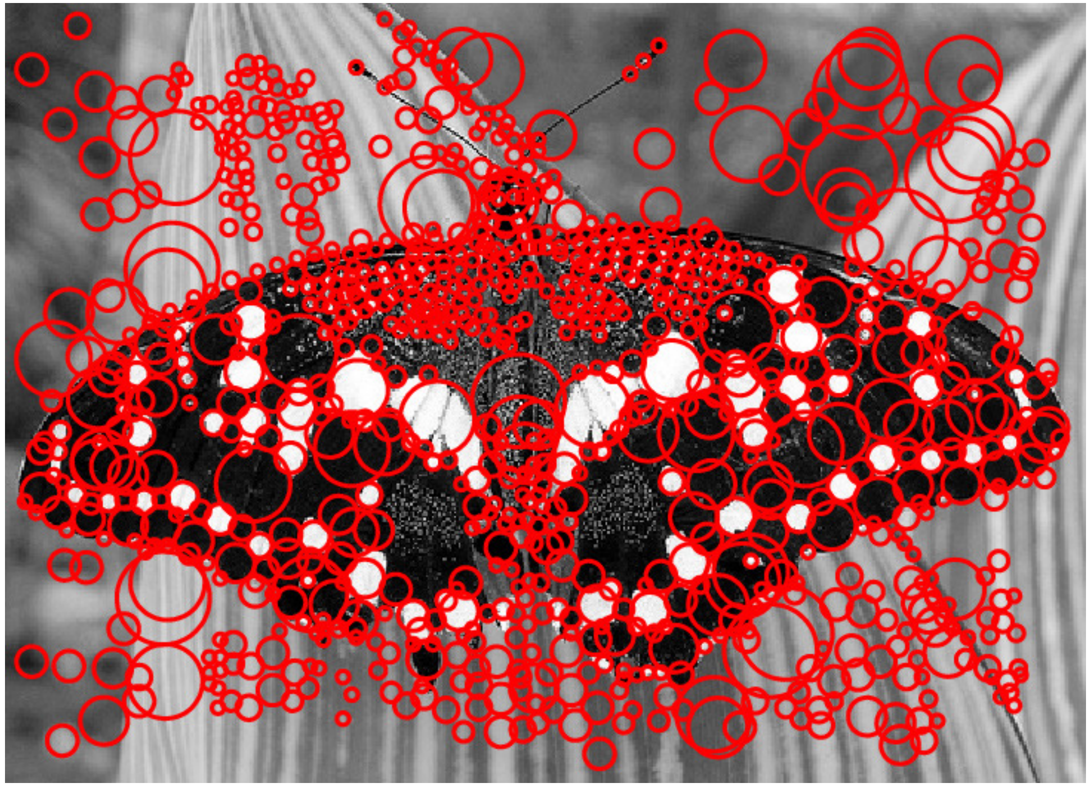


Scale-space blob detector: Example

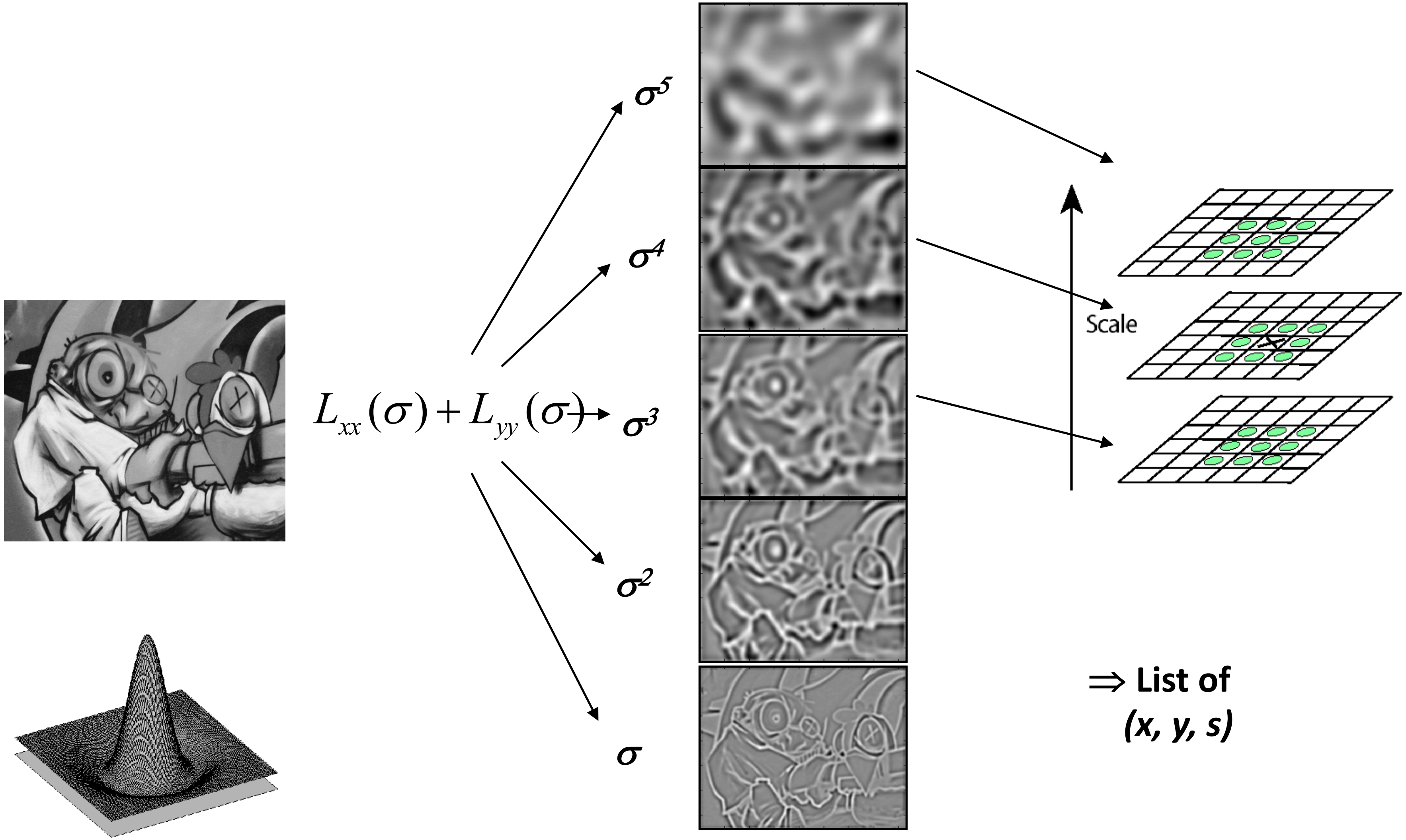
Scale-space blob detector: Example

sigma = 11.9912

Scale-space blob detector: Example



Find local maxima in 3D position-scale space



$\Rightarrow$ **List of *(x, y, s)***

Approximating Laplacian of Gaussian

- Functions for determining scale $f = \text{Kernel} * \text{Image}$

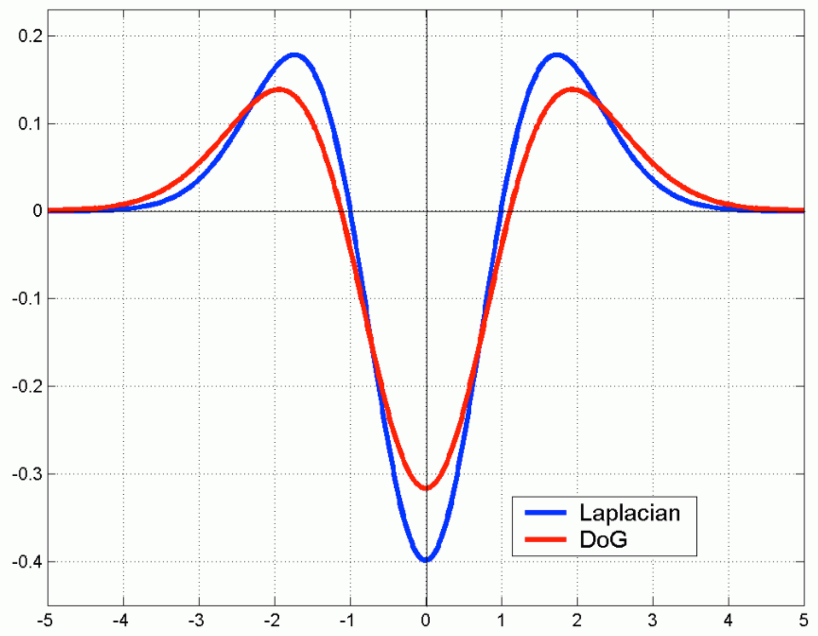
Kernels:

$$L = \sigma^2 \left(G_{xx}(x, y, \sigma) + G_{yy}(x, y, \sigma) \right)$$

(Laplacian)

$$DoG = G(x, y, k\sigma) - G(x, y, \sigma)$$

(Difference of Gaussians)



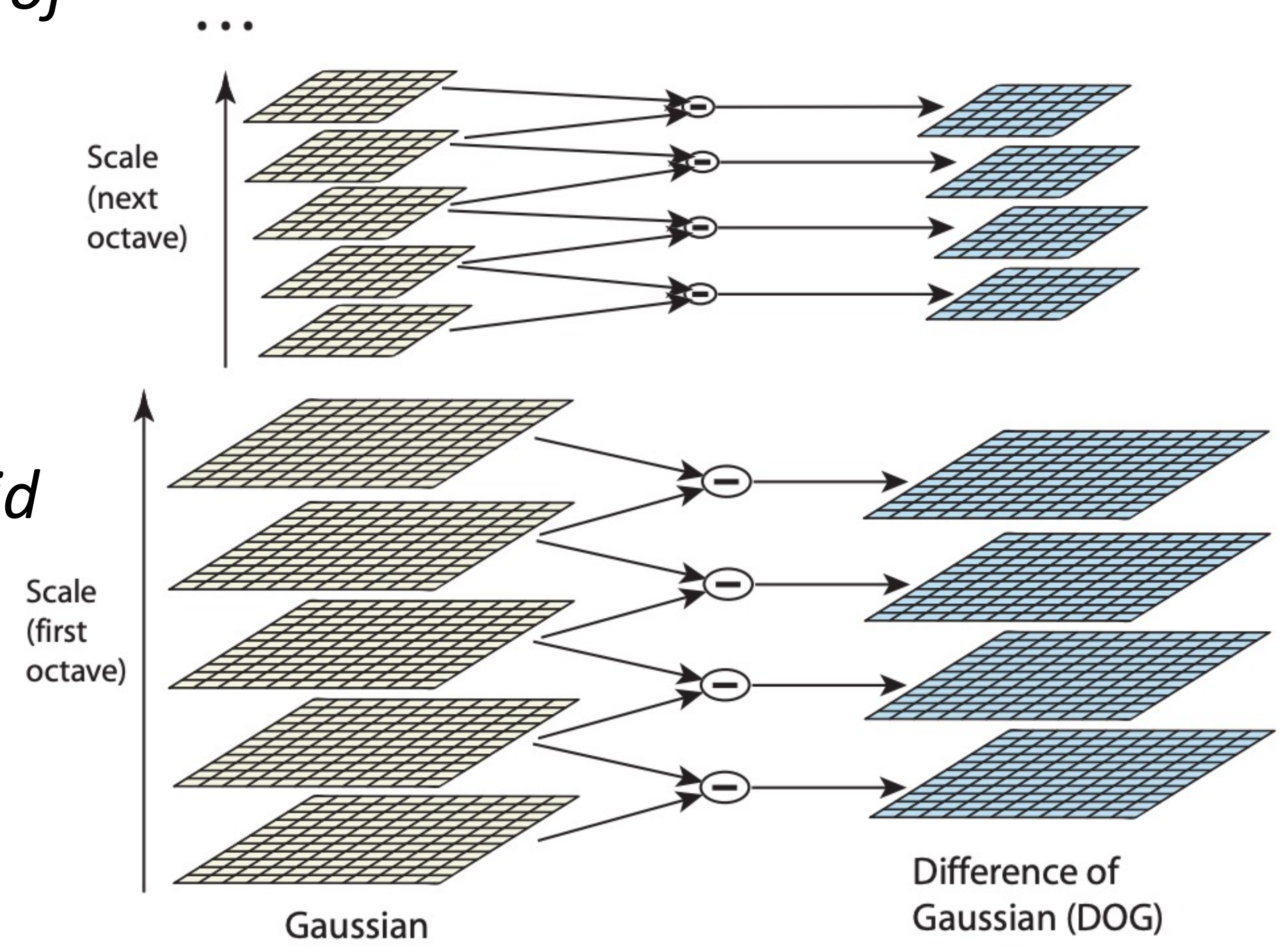
where Gaussian

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Note: The LoG and DoG operators are both rotation equivariant

SIFT detector

- Approximate LoG with a *difference of Gaussians* (DoG)
  - Laplacian:
  - $\sigma^2\left(G_{xx}(x,y,\sigma)+G_{yy}(x,y,\sigma)\right)$
  - DoG:
  - $G(x,y,k\sigma)-G(x,y,\sigma)$
- Compute DoG via an *image pyramid*



- In each Octave you progressively blur the image
- To go to next Octave you downsample the image by x2

SIFT: Scale-invariant feature transform

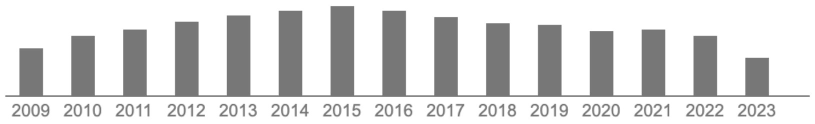
D. Lowe. Object recognition from local scale-invariant features. ICCV 1999

D. Lowe. Distinctive image features from scale-invariant keypoints. *IJCV* 60 (2), pp. 91-110, 2004

David Lowe

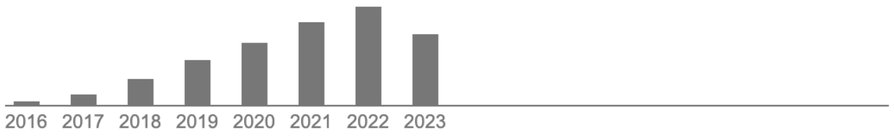
Distinctive image features from scale-invariant keypoints

Authors	David G Lowe
Publication date	2004/11/1
Journal	International journal of computer vision
Volume	60
Issue	2
Pages	91-110
Publisher	Springer Netherlands
Description	This paper presents a method for extracting distinctive invariant features from images that can be used to perform reliable matching between different views of an object or scene. The features are invariant to image scale and rotation, and are shown to provide robust matching across a substantial range of affine distortion, change in 3D viewpoint, addition of noise, and change in illumination. The features are highly distinctive, in the sense that a single feature can be correctly matched with high probability against a large database of features from many images. This paper also describes an approach to using these features for object recognition. The recognition proceeds by matching individual features to a database of features from known objects using a fast nearest-neighbor algorithm, followed by a Hough transform to identify clusters belonging to a single object, and finally performing verification through …
Total citations	Cited by 71971



Deep Residual Learning for Image Recognition

Authors	Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun
Publication date	2016
Conference	Computer Vision and Pattern Recognition (CVPR), 2016
Description	Deeper neural networks are more difficult to train. We present a residual learning framework to ease the training of networks that are substantially deeper than those used previously. We explicitly reformulate the layers as learning residual functions with reference to the layer inputs, instead of learning unreferenced functions. We provide comprehensive empirical evidence showing that these residual networks are easier to optimize, and can gain accuracy from considerably increased depth. On the ImageNet dataset we evaluate residual nets with a depth of up to 152 layers---8x deeper than VGG nets but still having lower complexity. An ensemble of these residual nets achieves 3.57% error on the ImageNet test set. This result won the 1st place on the ILSVRC 2015 classification task. We also present analysis on CIFAR-10 with 100 and 1000 layers. The depth of representations is of central importance for many visual recognition tasks. Solely due to our extremely deep representations, we obtain a 28% relative improvement on the COCO object detection dataset. Deep residual nets are foundations of our submissions to ILSVRC & COCO 2015 competitions, where we also won the 1st places on the tasks of ImageNet detection, ImageNet localization, COCO detection, and COCO segmentation.
Total citations	Cited by 185084

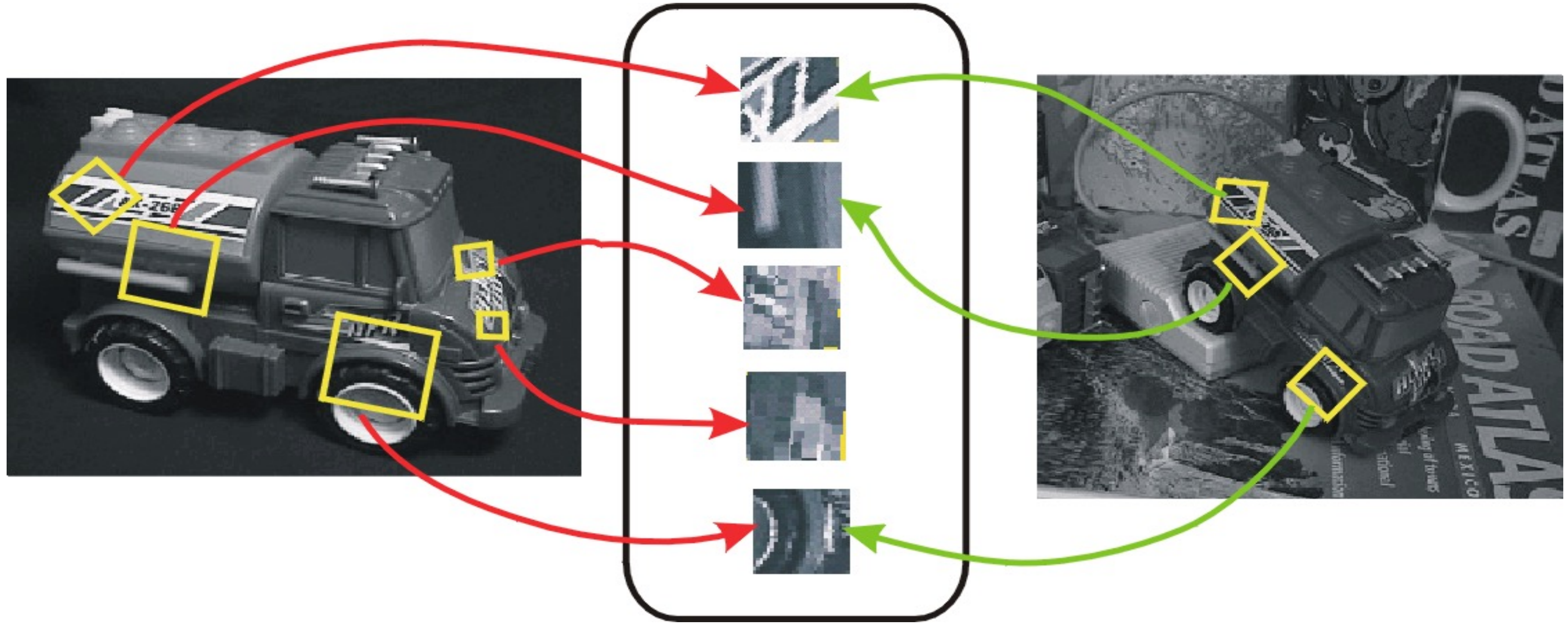


Today's class

- SIFT detector
- SIFT descriptor
- Feature Matching
- Evaluating Results

SIFT for matching

- The main goal of SIFT is to enable image matching in the presence of significant transformations
  - To recognize the same keypoint in multiple images, we need to match appearance descriptors or "signatures" in their neighborhoods
  - Descriptors that are *locally* invariant w.r.t. scale and rotation can handle a wide range of *global* transformations



Invariant descriptors

- We looked at invariant / equivariant **detectors**

- Most feature descriptors are also designed to be invariant to:
  - Translation, 2D rotation, scale

- They can usually also handle
  - Limited 3D rotations (SIFT works up to about 60 degrees)
  - Limited affine transforms (some are fully affine invariant)
  - Limited illumination/contrast changes

Scale Invariant Feature Transform

Basic idea:

- Take 16x16 square window around detected feature point
- Compute edge orientation (angle of the gradient - 90°) for each pixel
- Throw out weak edges (threshold gradient magnitude)
- Create histogram of surviving edge orientations

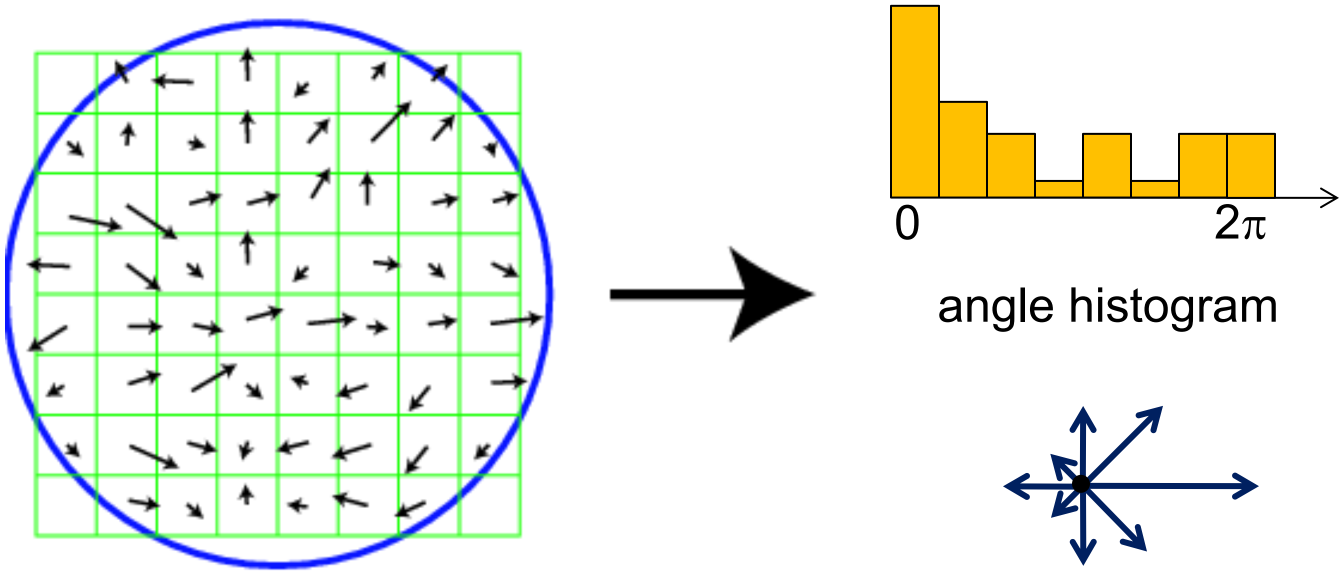


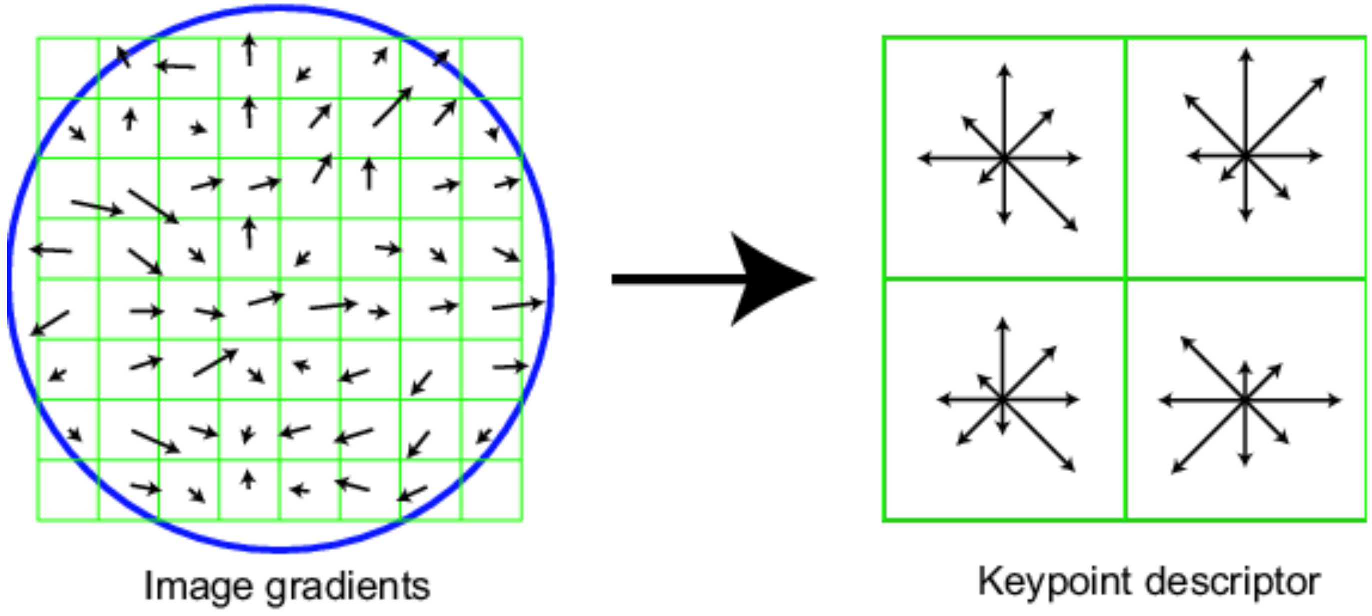
Image gradients

Adapted from slide by David Lowe

SIFT descriptor

Full version

- Divide the 16x16 window into a 4x4 grid of cells (2x2 case shown below)
- Compute an orientation histogram for each cell
- 16 cells * 8 orientations = 128 dimensional descriptor

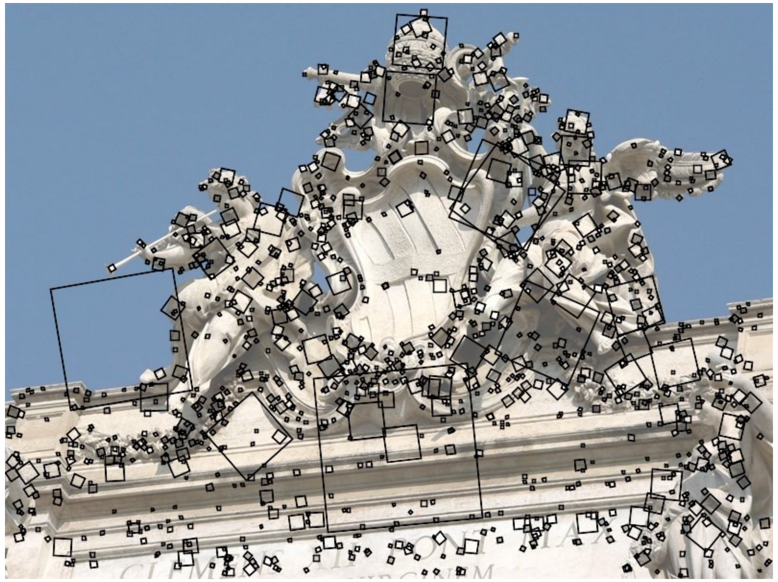


Inspiration: complex neurons in the primary visual cortex

Adapted from slide by David Lowe

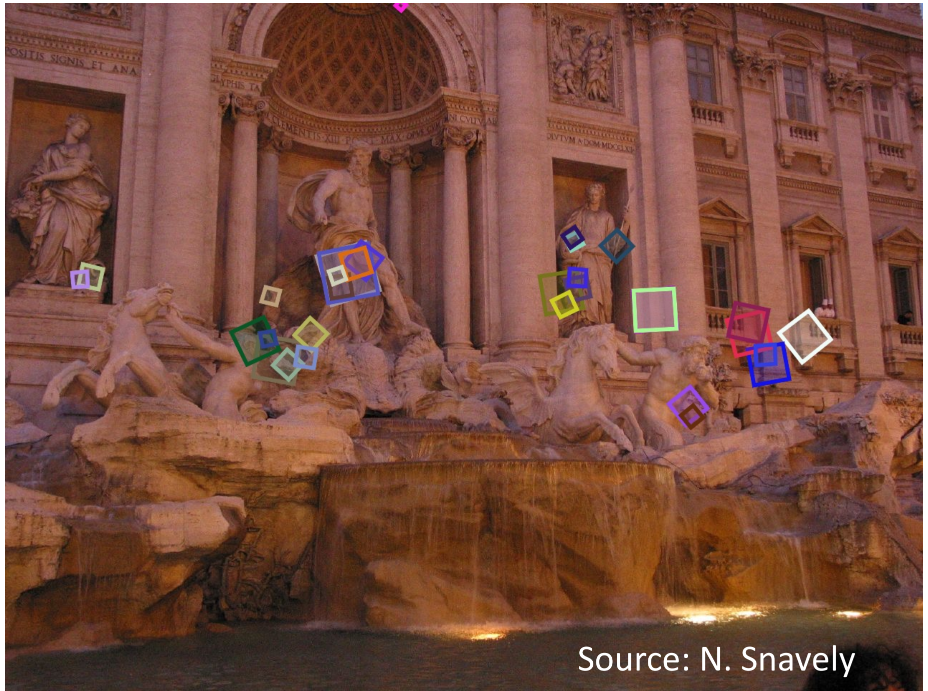
SIFT detector: Example outputs

- Detected keypoints with characteristic scales and orientations:



SIFT for matching

- Extraordinarily robust detection and description technique
  - Can handle changes in viewpoint
    - Up to about 60 degree out-of-plane rotation
  - Can handle significant changes in illumination
    - Sometimes even day vs. night
  - Fast and efficient—can run in real time
  - Lots of code available

Source: N. Snavely

Other descriptors

- HOG: Histogram of Gradients (HOG)
  - Simply calculate histogram of gradients for every pixel
  - Dalal/Triggs
  - Sliding window, pedestrian detection
  - Good for object detection/classification

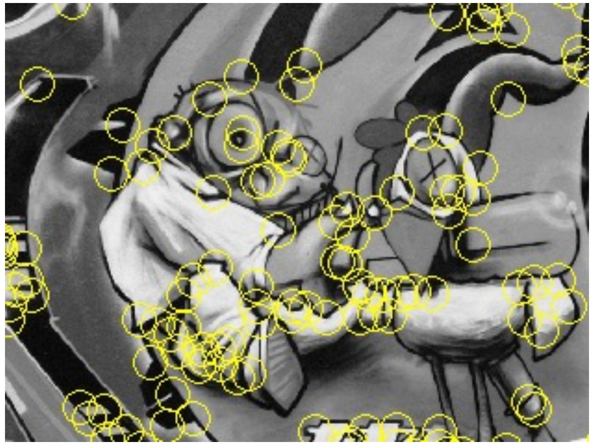
- FREAK: Fast Retina Keypoint
  - Perceptually motivated
  - Can run in real-time; used in Visual SLAM on-device

- LIFT: Learned Invariant Feature Transform
  - Learned via deep learning – along with many other recent features

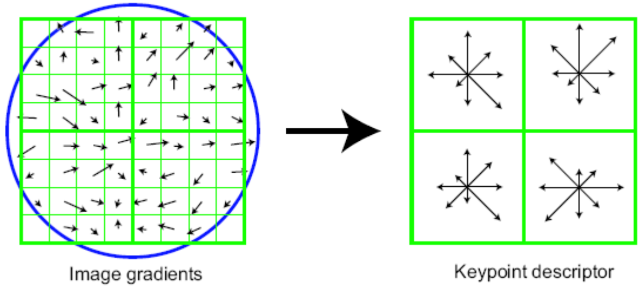
    https://arxiv.org/abs/1603.09114

Summary

- Keypoint detection: repeatable and distinctive
  - Corners, blobs, stable regions
  - Harris, SIFT



- Descriptors: robust and selective
  - spatial histograms of orientation
  - SIFT and variants are typically good for stitching and recognition



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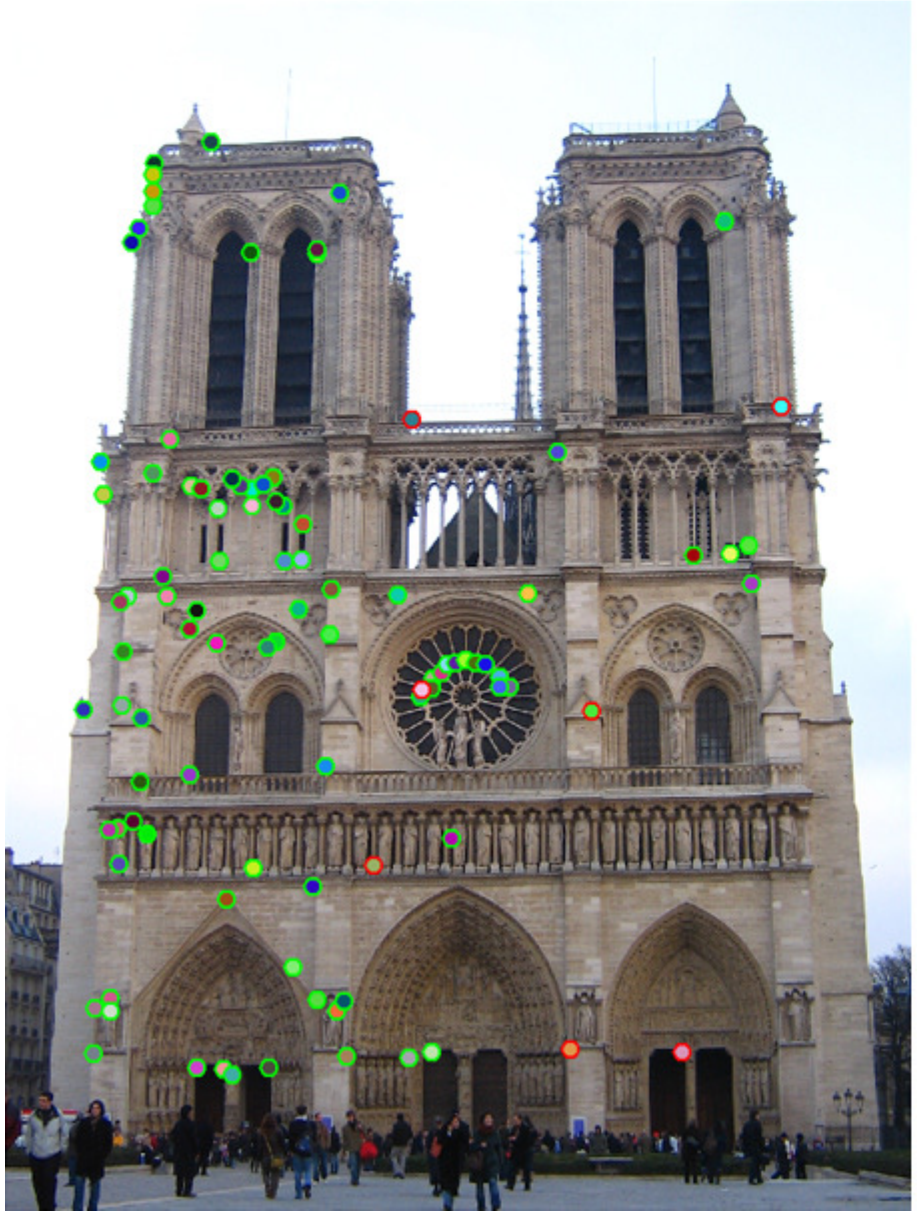
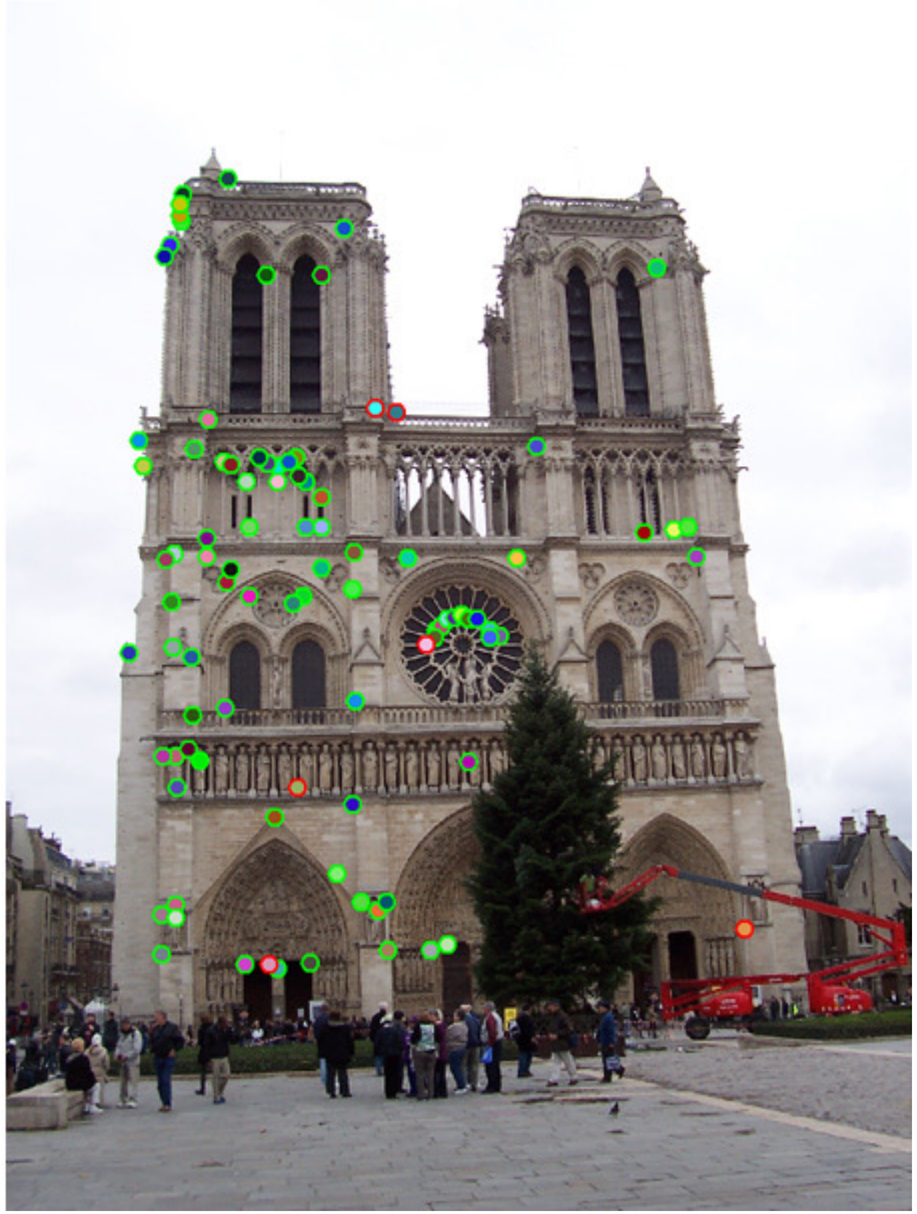
Which features match?





Feature matching

Given a feature in I_1, how to find the best match in I_2?

1. Define distance function that compares two descriptors
   - Any distance metric, *d(f1,f2)*, would work: L2, L1 loss are commonly used

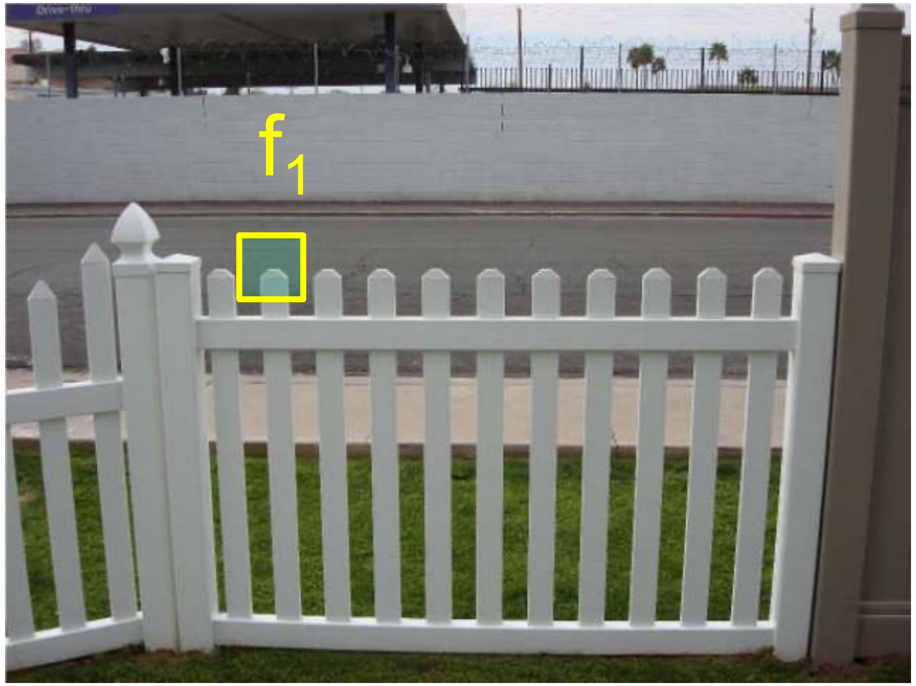
2. Test all the features in I_2, find the one with min distance

(OR)

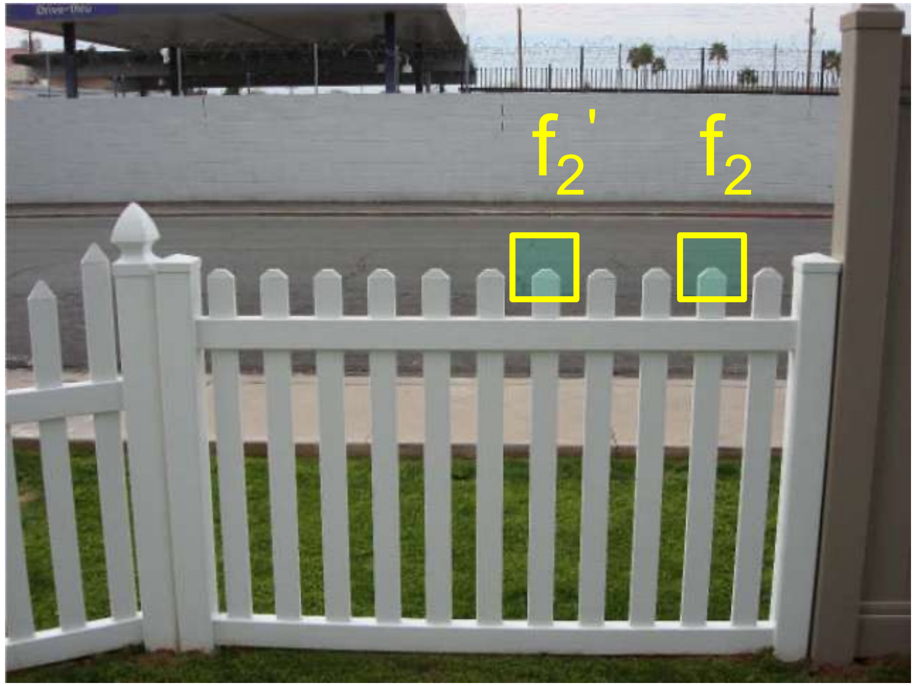
2. Test all the features in I_2, find top k matches

Feature distance: Ratio Test

- Often matches can be ambiguous. f1 can have similar distance to both f2 and f2’
- Ratio Test:
  - Keep top 2 match: f2, f2’
  - If d(f1,f2) < 0.75 * d(f1,f2’), then: match f1 with f2 and keep the point.
    - Else reject the match as ambiguous
  - If d(f1,f2) < Threshold, then: keep this as ‘strong’ match, else: ‘reject’



I_1

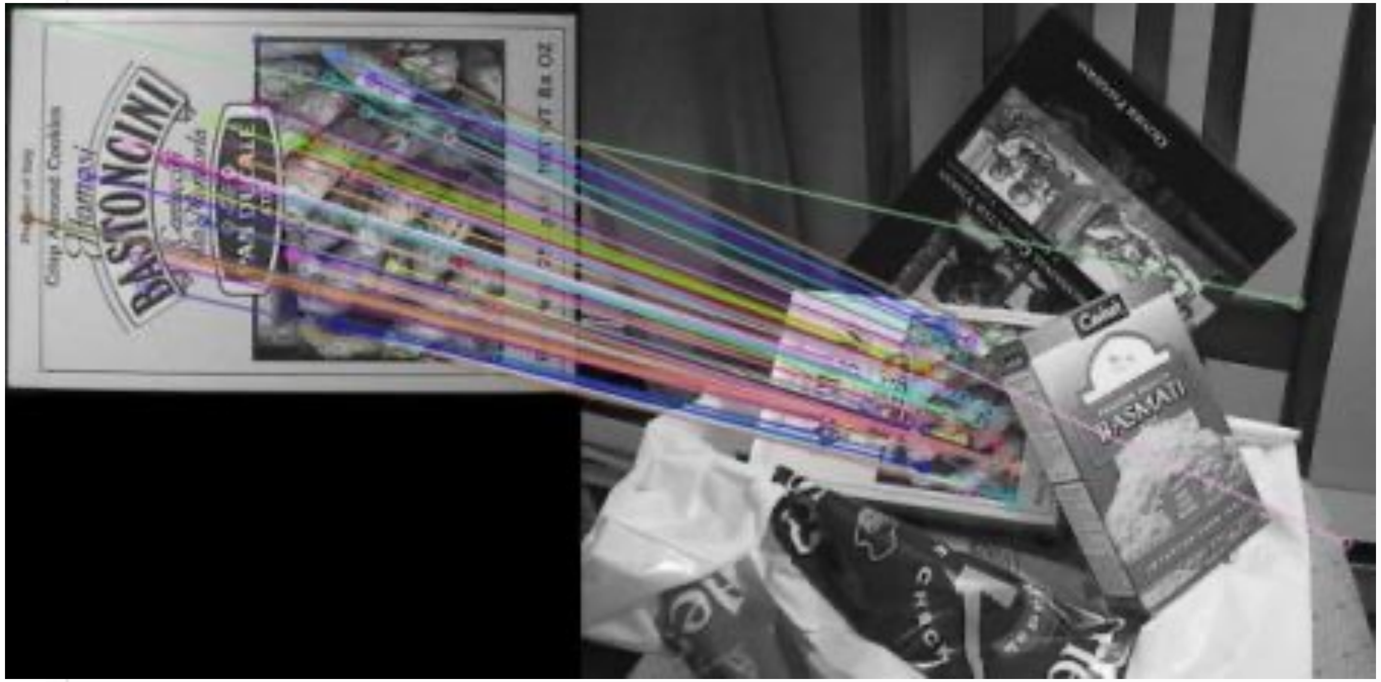


I_2

Image Matching in OpenCV

```
import numpy as np
import cv2
from matplotlib import pyplot as plt

img1 = cv2.imread('box.png',0)          # queryImage
img2 = cv2.imread('box_in_scene.png',0) # trainImage
```




```
# cv2.drawMatchesKnn expects list of lists as matches.
img3 = cv2.drawMatchesKnn(img1,kp1,img2,kp2,good,flags=2)

plt.imshow(img3),plt.show()
```

Read Image

Compute SIFT

Feature matching

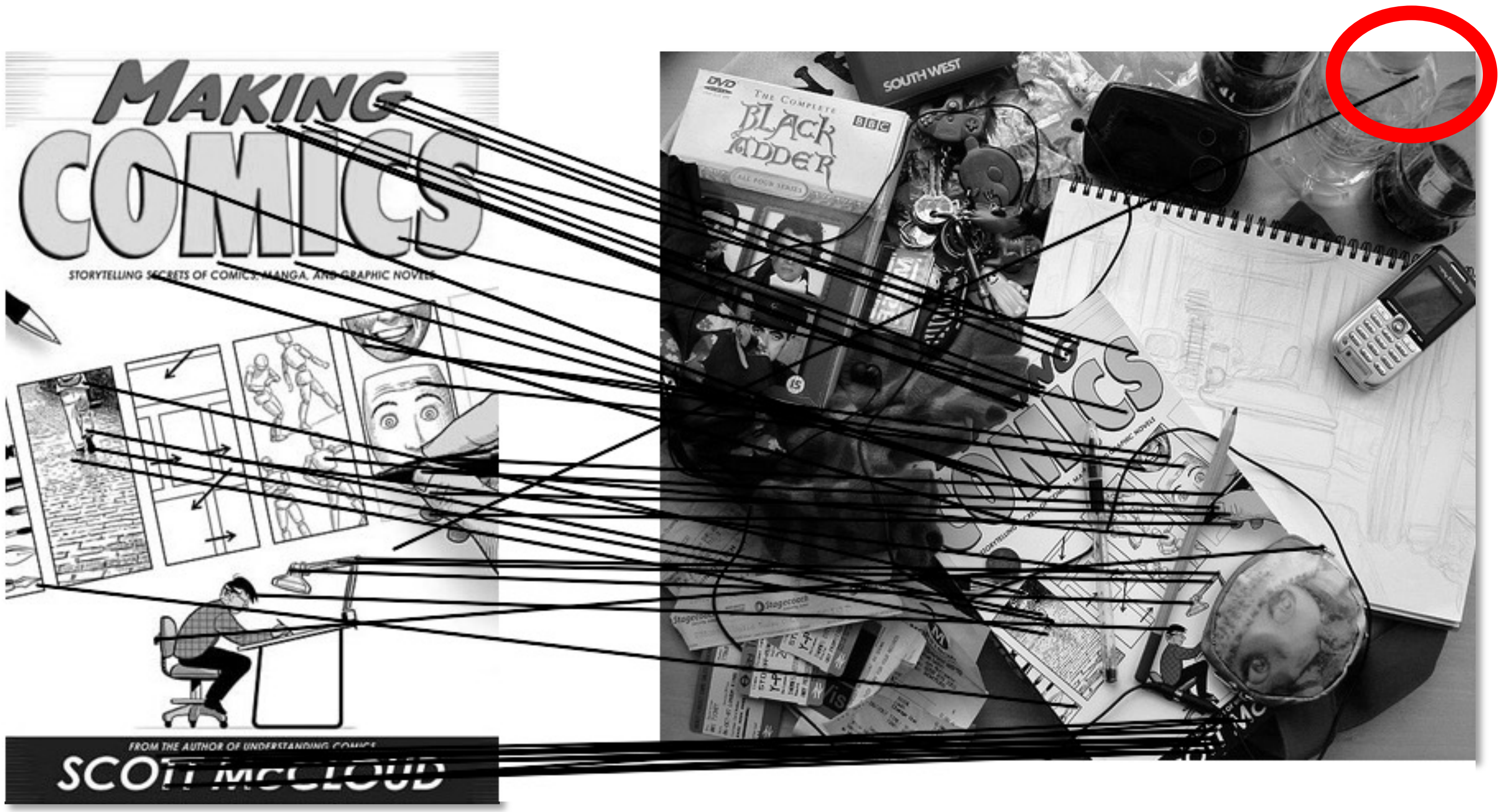
Ratio Test

Visualization

Feature matching example

We'll deal with **outliers** later

RANSAC next week!



51 matches (thresholded by ratio score)

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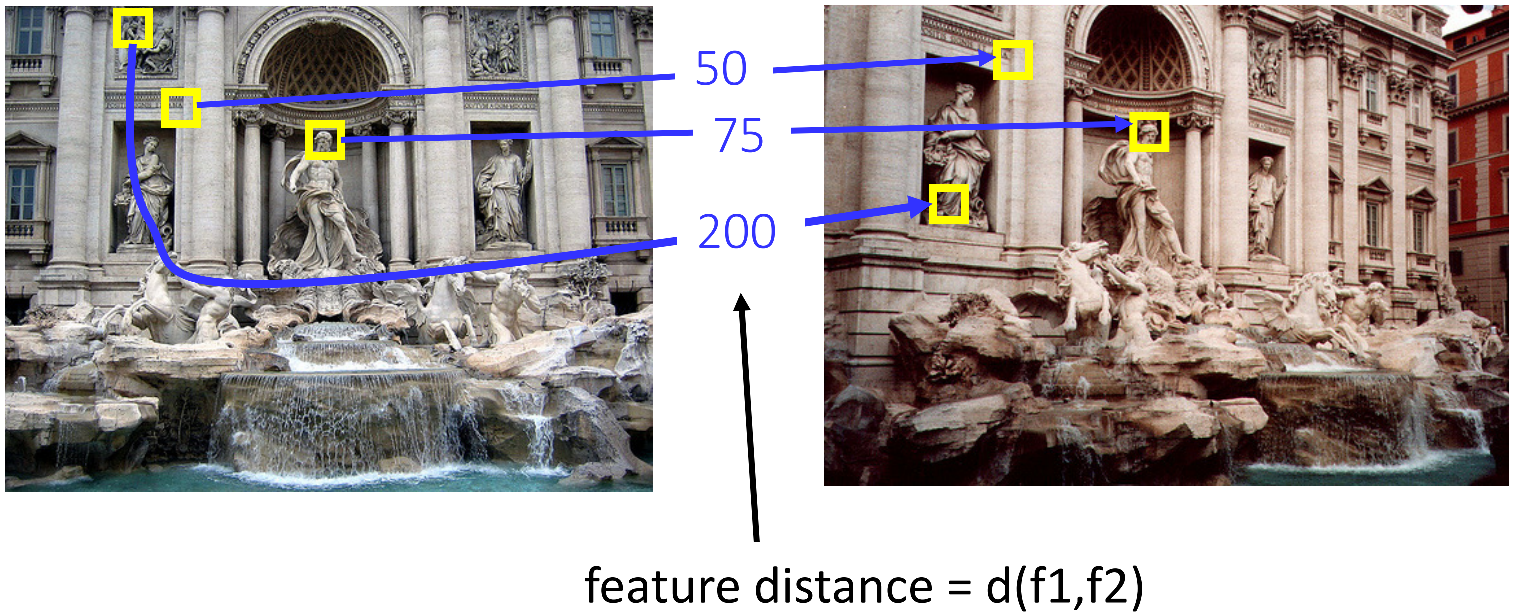
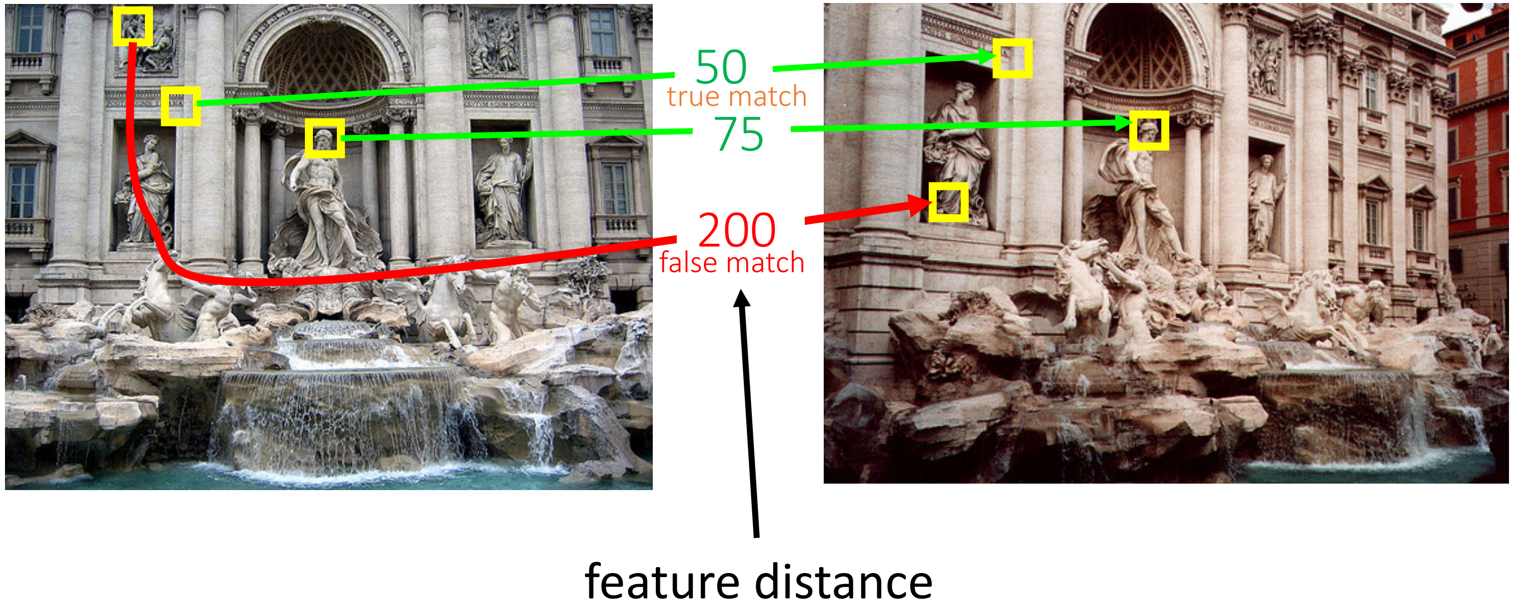
Evaluating the results

How can we measure the performance of a feature matcher?



True/false positives

How can we measure the performance of a feature matcher?



We can choose distance threshold to decide if the match is ‘good’ or not.

The distance threshold affects performance

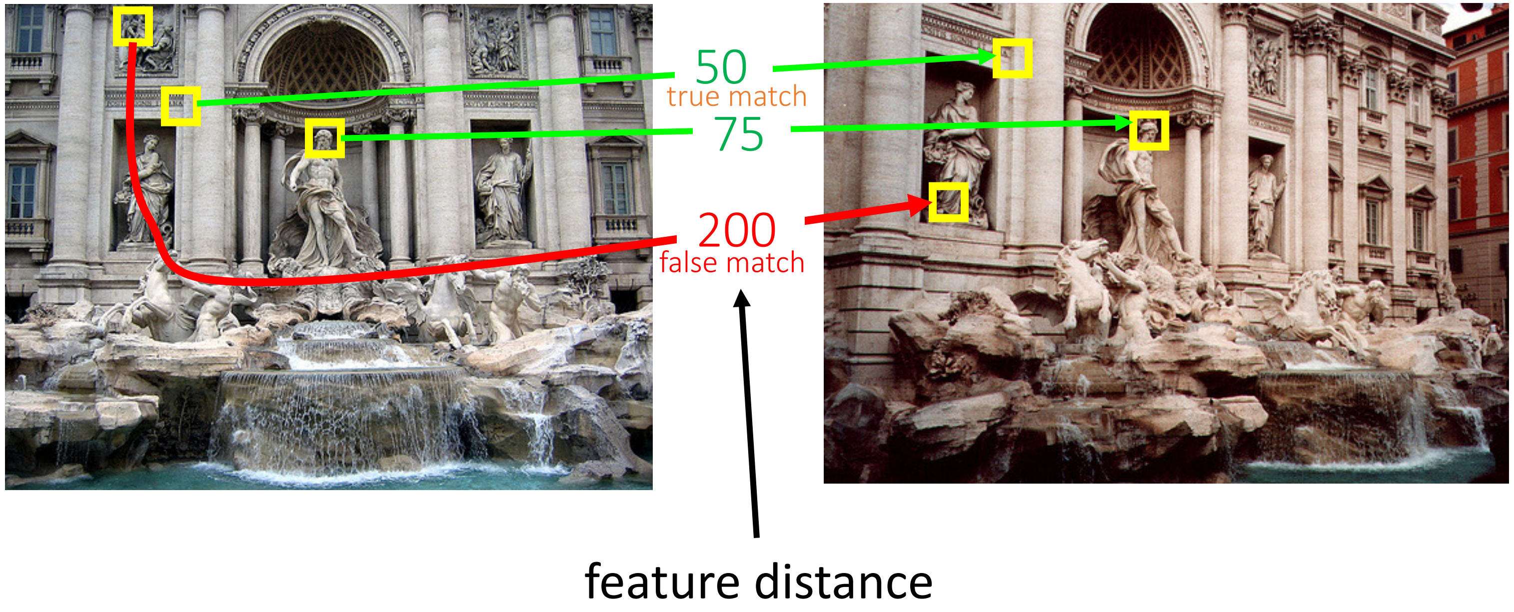
- True positives = # of detected matches that survive the threshold that are correct
- False positives = # of detected matches that survive the threshold that are incorrect

Example

- Suppose our matcher computes 1,000 matches between two images.
  - 800 are correct matches, 200 are incorrect (according to an oracle that gives us ground truth matches)
  - A given threshold (e.g., ratio distance = 0.6) gives us 600 correct matches and 100 incorrect matches that survive the threshold
  - True positives = # of detected matches that survive the threshold that are correct
  - False positives = # of detected matches that survive the threshold that are incorrect
  - True positive rate = 600 / 800 = ¾
  - False positive rate = 100 / 200 = ½

True/false positives

How can we measure the performance of a feature matcher?

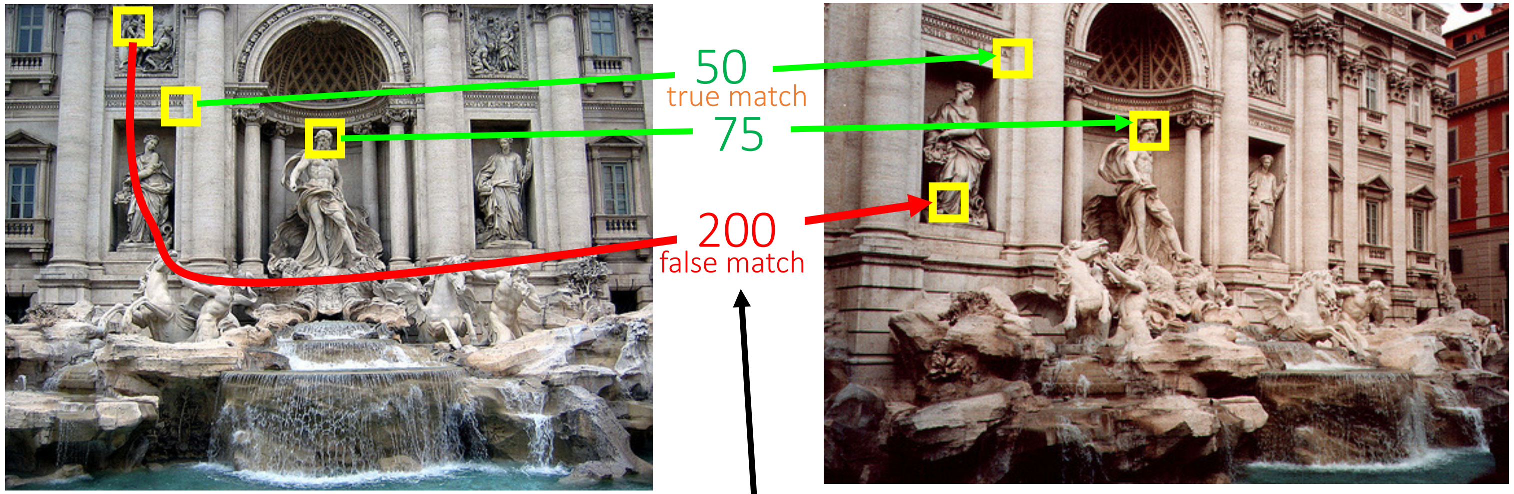


True positives = # of detected matches that survive the threshold that are correct
False positives = # of detected matches that survive the threshold that are incorrect

Suppose we want to maximize true positives. How do we set the threshold? (We keep all matches with distance below the threshold.)

True/false positives

How can we measure the performance of a feature matcher?



feature distance

True positives = # of detected matches that survive the threshold that are correct
False positives = # of detected matches that survive the threshold that are incorrect

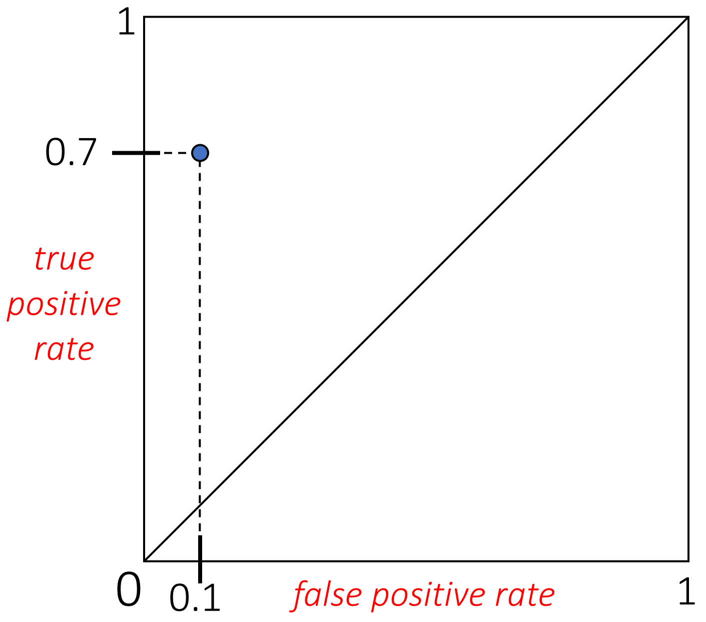
Suppose we want to minimize false positives. How do we set the threshold? (We keep all matches with distance below the threshold.)

Evaluating the results

How can we measure the performance of a feature matcher?

$$\frac{\text{\# true positives surviving threshold}}{\text{\# total correct matches (positives)}}$$

recall



$$\frac{\text{\# false positives surviving threshold}}{\text{\# total incorrect matches (negatives)}}$$

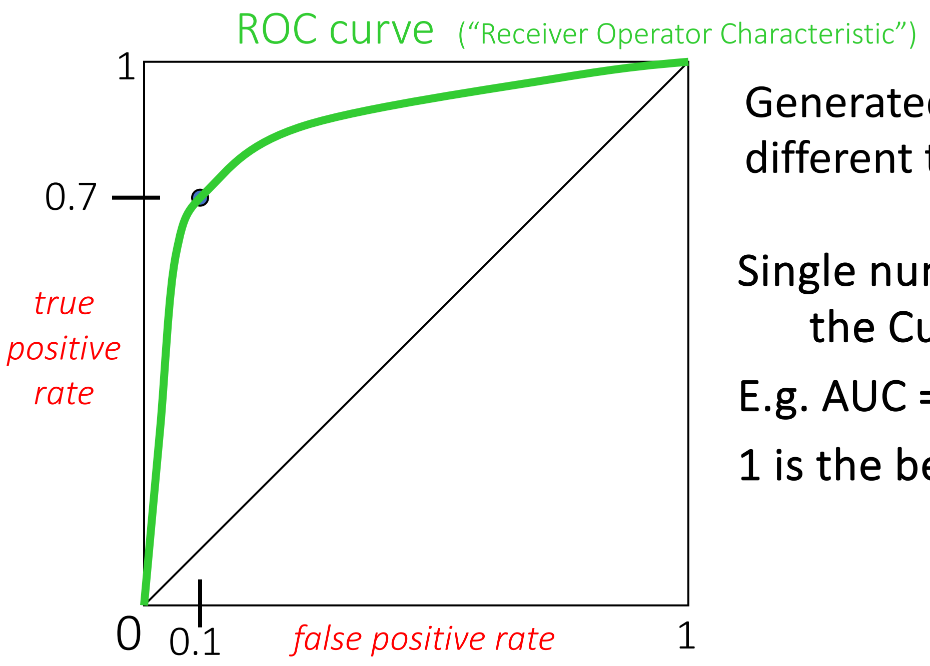
1 - *specificity*

Evaluating the results

How can we measure the performance of a feature matcher?

$$\frac{\text{\# true positives surviving threshold}}{\text{\# total correct matches (positives)}}$$

recall



$$\frac{\text{\# false positives surviving threshold}}{\text{\# total incorrect matches (negatives)}}$$

1 - *specificity*

Generated by choosing different threshold value

Single number: Area Under the Curve (AUC)

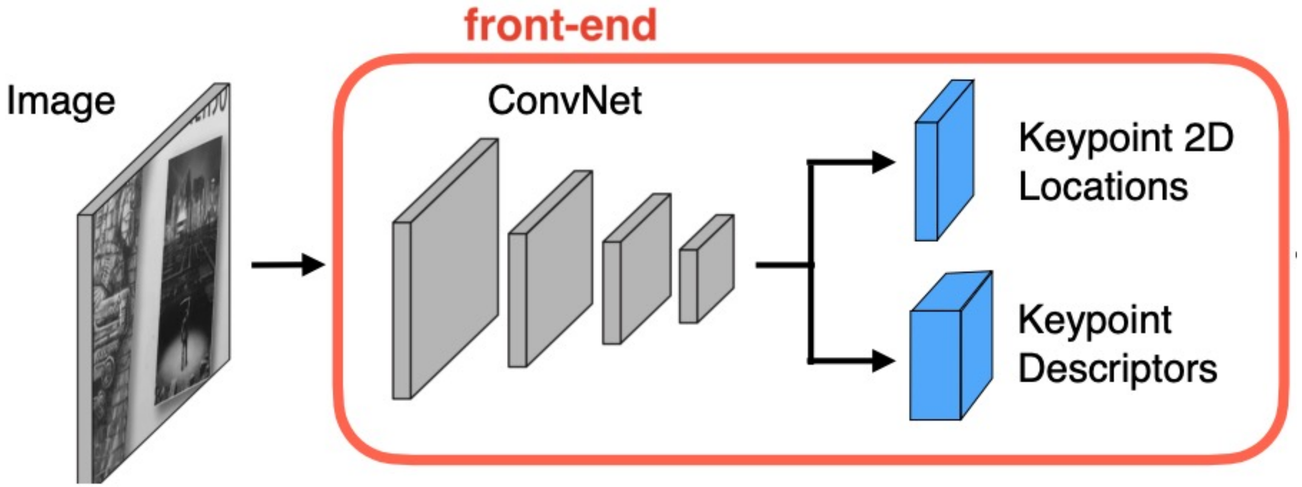
E.g. AUC = 0.87

1 is the best

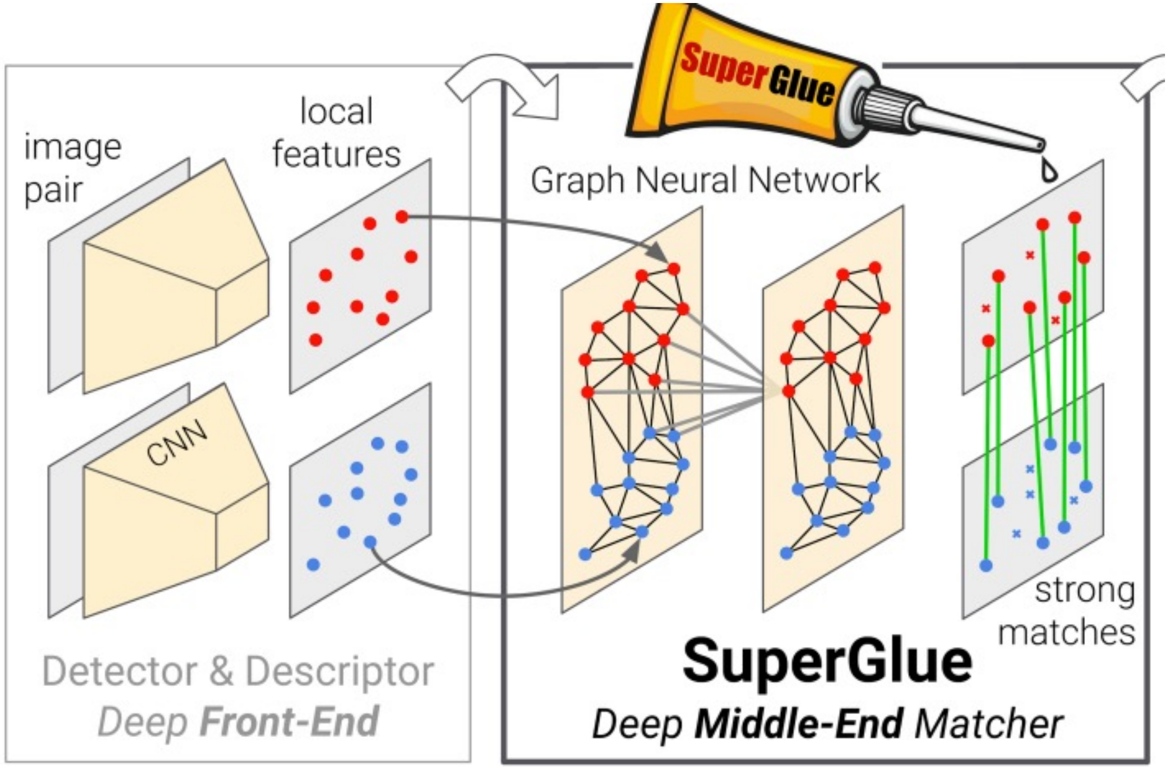
ROC curves – summary

- By thresholding the match distances at different thresholds, we can generate sets of matches with different true/false positive rates
- ROC curve is generated by computing rates at a set of threshold values swept through the full range of possible threshold
- Area under the ROC curve (AUC) summarizes the performance of a feature pipeline (higher AUC is better)
- We will come back to this in binary classification, face verification, object detection, image retrieval, etc.

Local features & matching in Deep Learning era

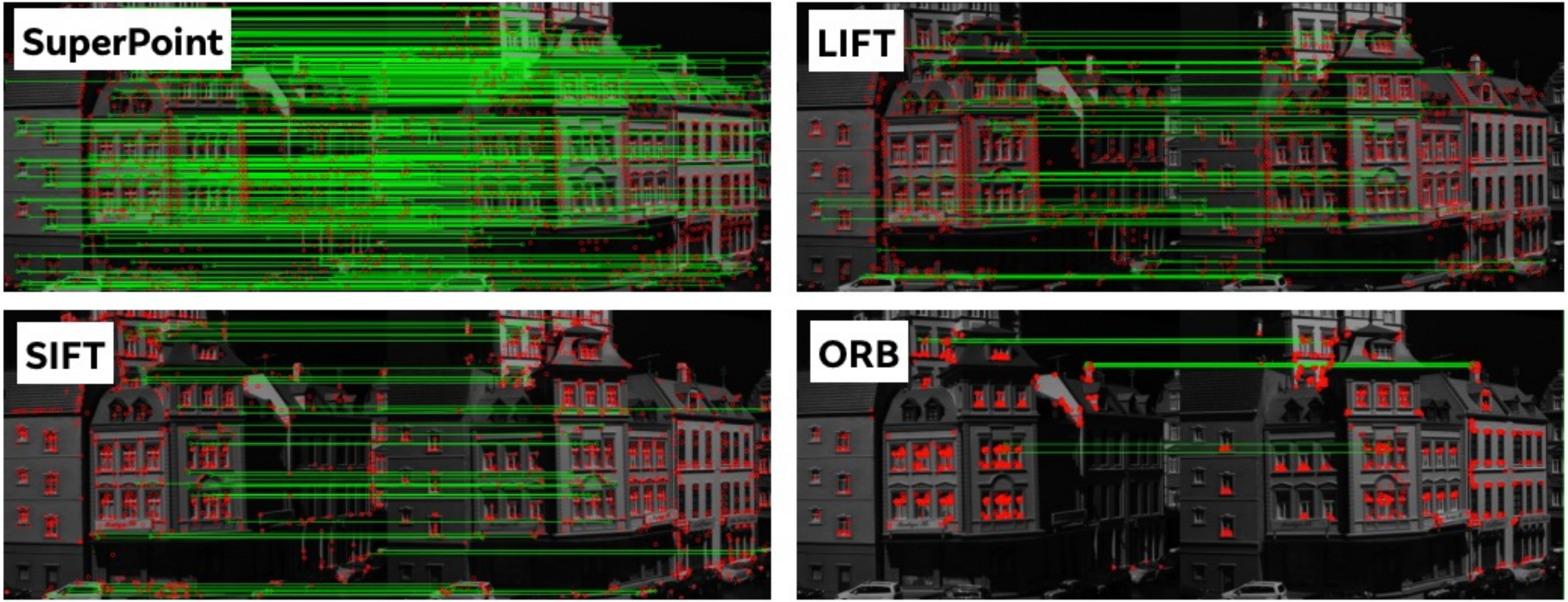


- Local Features = SuperPoint
- Train first on synthetic data
- Self-supervised learning on real data.



- Feature Matching = SuperGlue

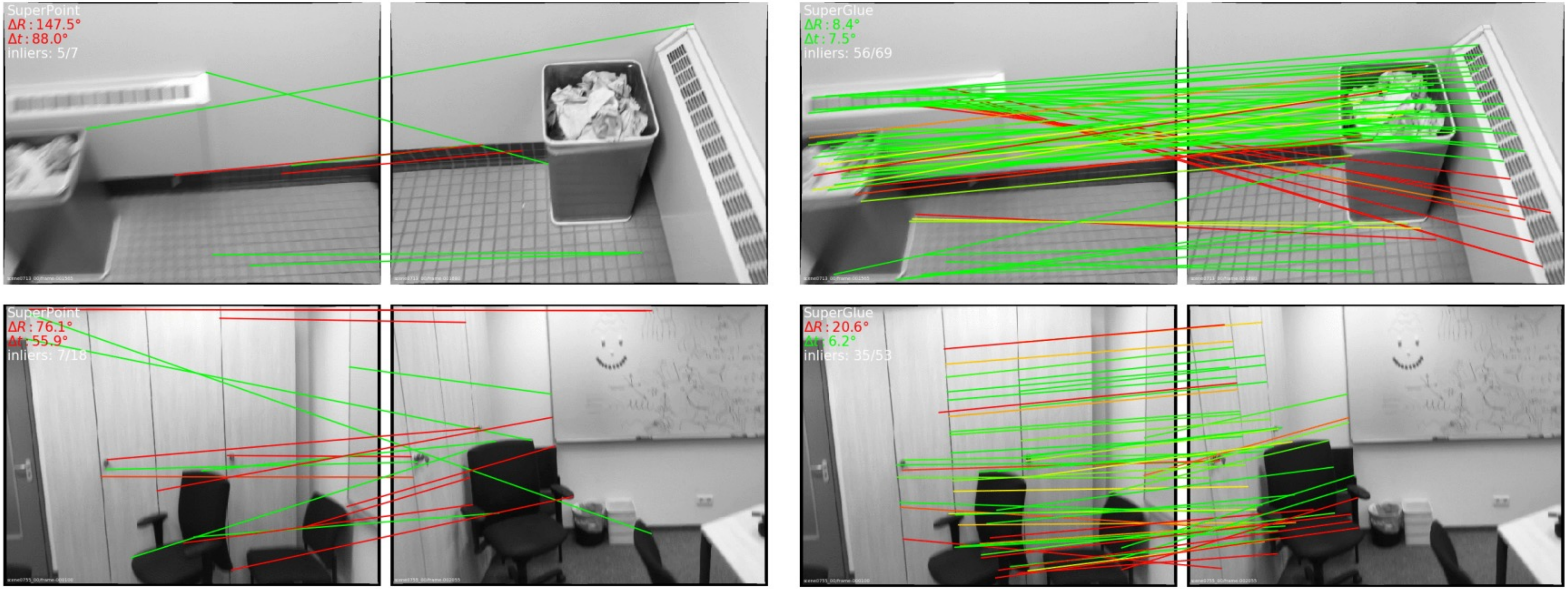
Performance of SuperPoint



Performance of SuperGlue

SuperPoint + NN + heuristics

SuperPoint + **SuperGlue**



SuperGlue: more **correct matches** and fewer **mismatches**

Slide Credits

- CS5670, Introduction to Computer Vision, **Cornell Tech, by Noah Snavely.**
- CS 194-26/294-26: Intro to Computer Vision and Computational Photography, **UC Berkeley, by Alyosha Efros.**
- Fall 2022 CS 543/ECE 549: Computer Vision, UIUC, by **Svetlana Lazebnik.**