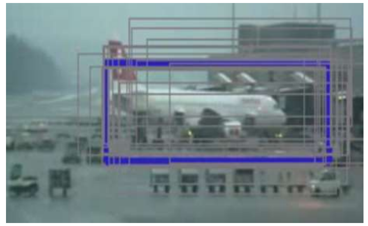
UNIVERSITÀ DEGLI STUDI
DELLA BASILICATA

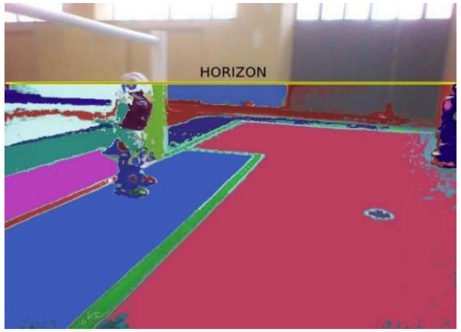
Corso di Visione e Percezione

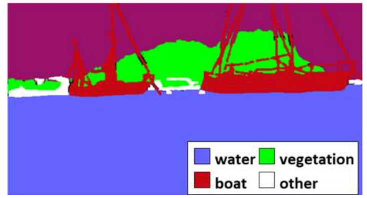
Docente

Domenico D. Bloisi

Feature Matching



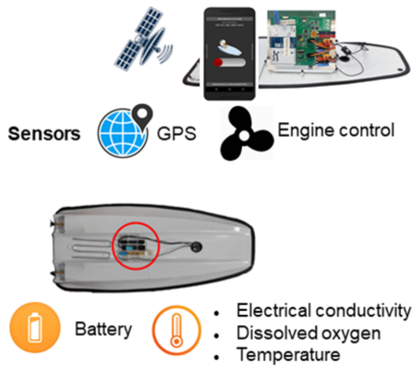


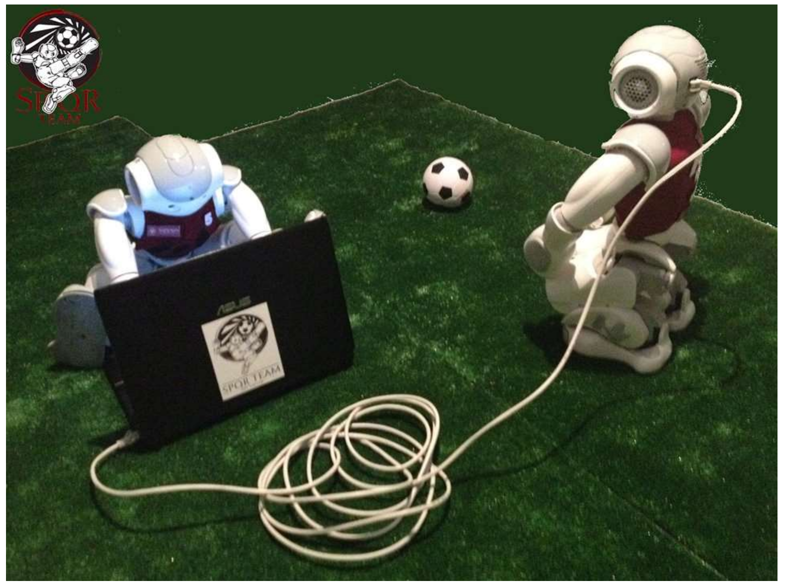


Domenico Daniele Bloisi

- Ricercatore RTD B
  Dipartimento di Matematica, Informatica ed Economia
  Università degli studi della Basilicata
  http://web.unibas.it/bloisi

- SPQR Robot Soccer Team
  Dipartimento di Informatica, Automatica e Gestionale Università degli studi di Roma “La Sapienza”
  http://spqr.diag.uniroma1.it





Informazioni sul corso

- Home page del corso
  http://web.unibas.it/bloisi/corsi/visione-e-percezione.html
- Docente: Domenico Daniele Bloisi
- Periodo: II semestre marzo 2021 – giugno 2021

  Martedì 17:00-19:00 (Aula COPERNICO)
  Mercoledì 8:30-10:30 (Aula COPERNICO)

Codice corso Google Classroom:
https://classroom.google.com/c/NjI2MjA4MzgzNDFa?cjc=xgolays

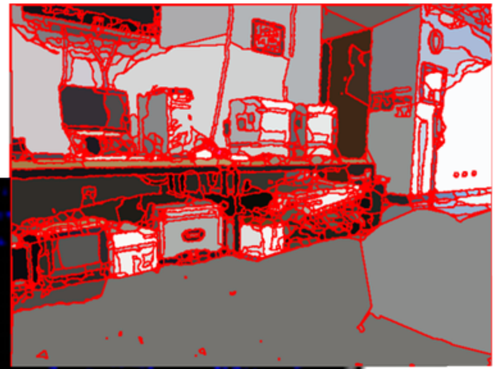
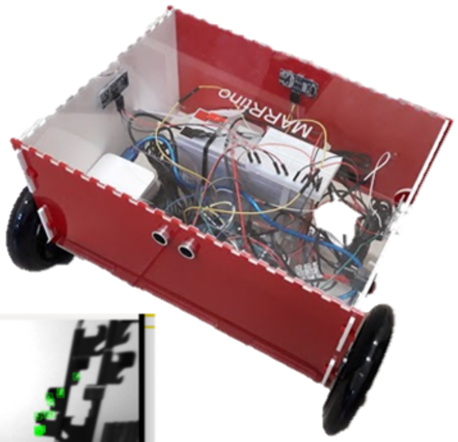
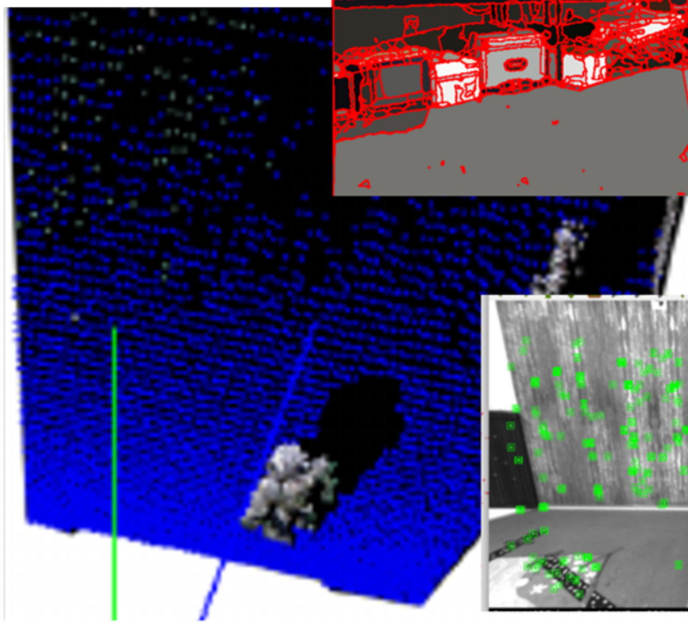
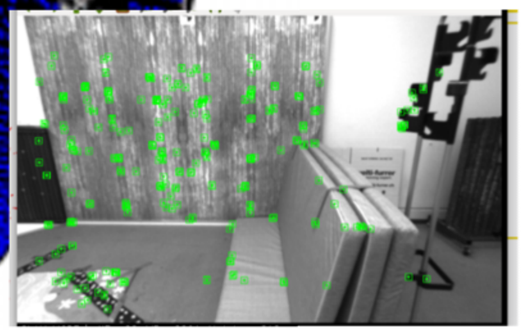
Ricevimento

- Su appuntamento tramite Google Meet

Per prenotare un appuntamento inviare una email a domenico.bloisi@unibas.it

Programma – Visione e Percezione

- Introduzione al linguaggio Python
- Elaborazione delle immagini con Python
- Percezione 2D – OpenCV
- Introduzione al Deep Learning
- ROS
- Il paradigma publisher and subscriber
- Simulatori
- Percezione 3D - PCL

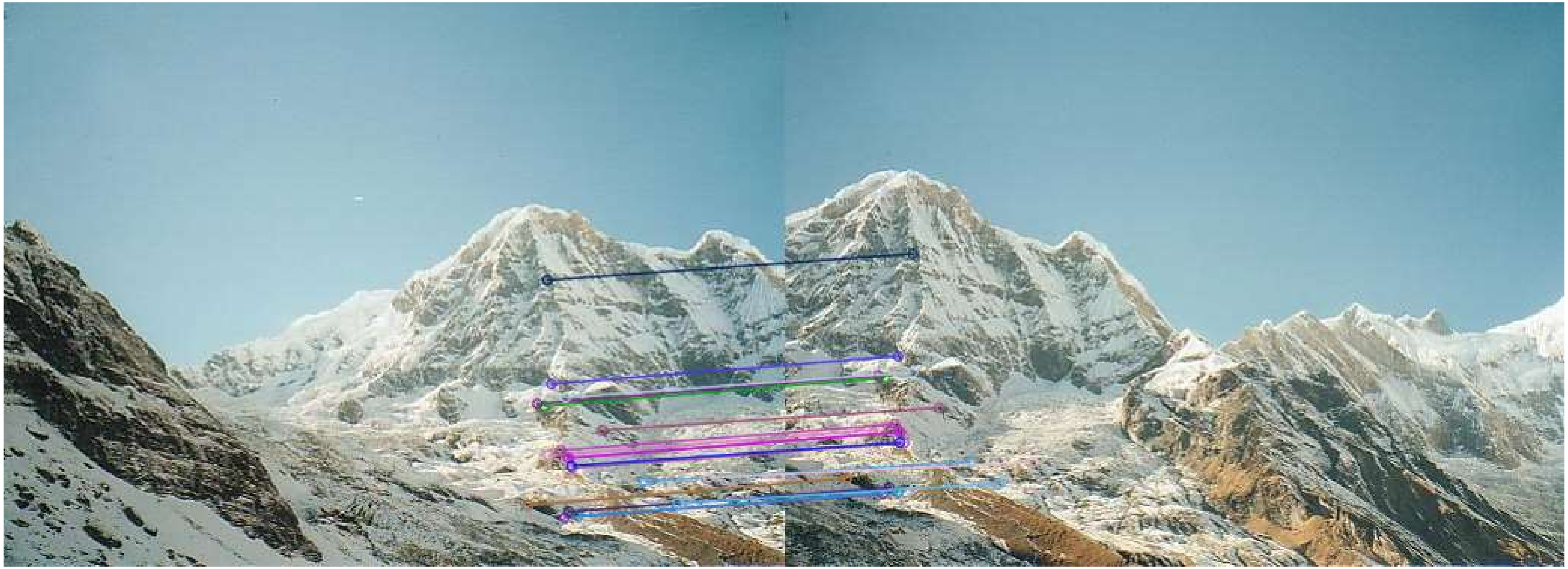





Riferimenti

- Queste slide sono adattate da
  Noah Snavely - CS5670: Computer Vision
  "Lecture 5: Feature descriptors and matching“
  "Lecture 9: RANSAC"

- I contenuti fanno riferimento ai capitoli 3 e 4 del libro
  "Computer Vision: Algorithms and Applications"
  di Richard Szeliski, disponibile al seguente indirizzo
  http://szeliski.org/Book/

Problem: Feature matching



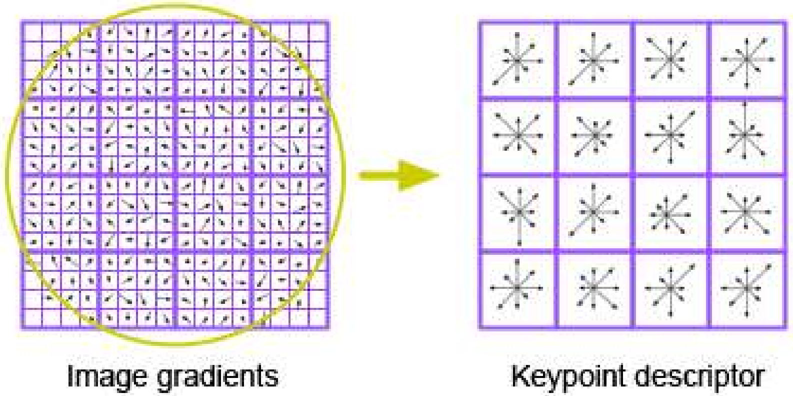
Recap

Keypoint detection: repeatable and distinctive

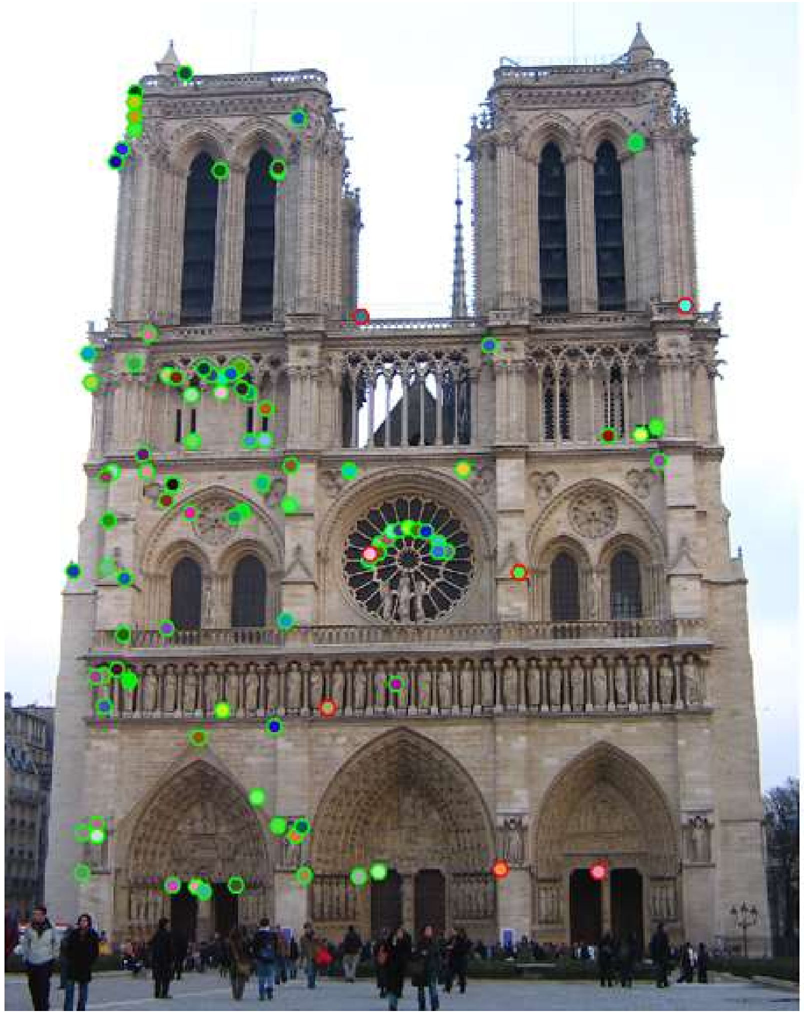
- Corners, blobs, stable regions
- Harris

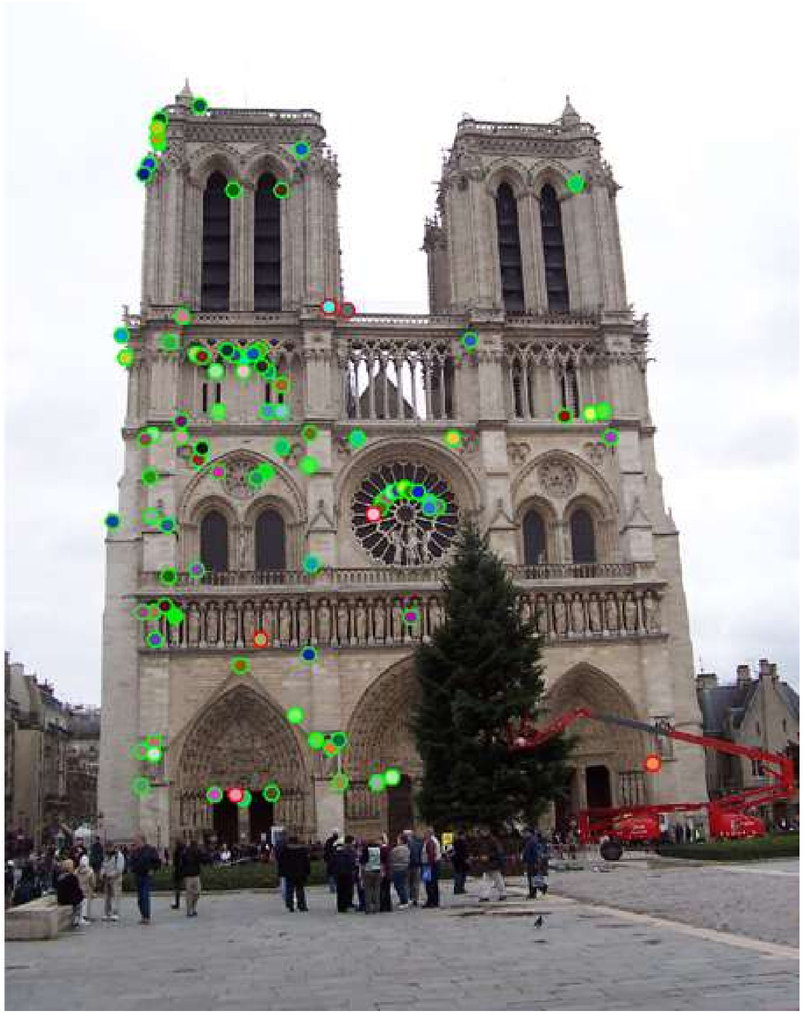
Descriptors: robust and selective

- spatial histograms of orientation
- SIFT and variants are typically good for stitching and recognition



Which features match?

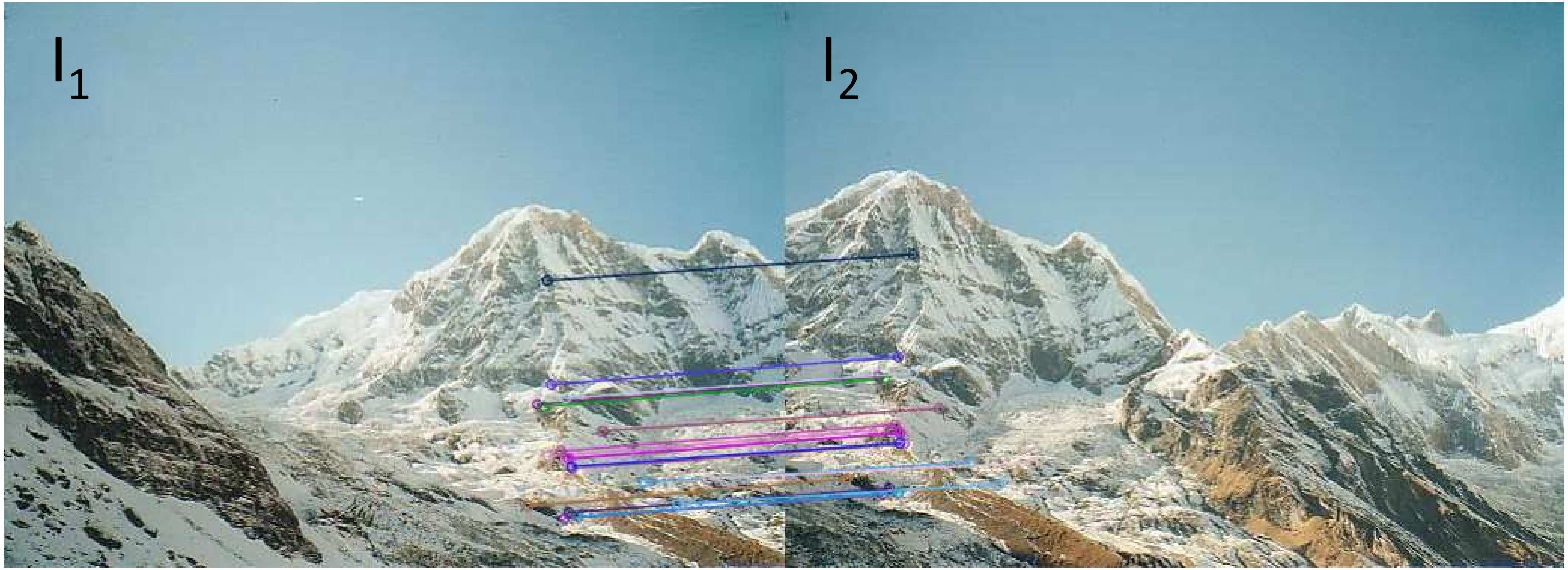




Features matching

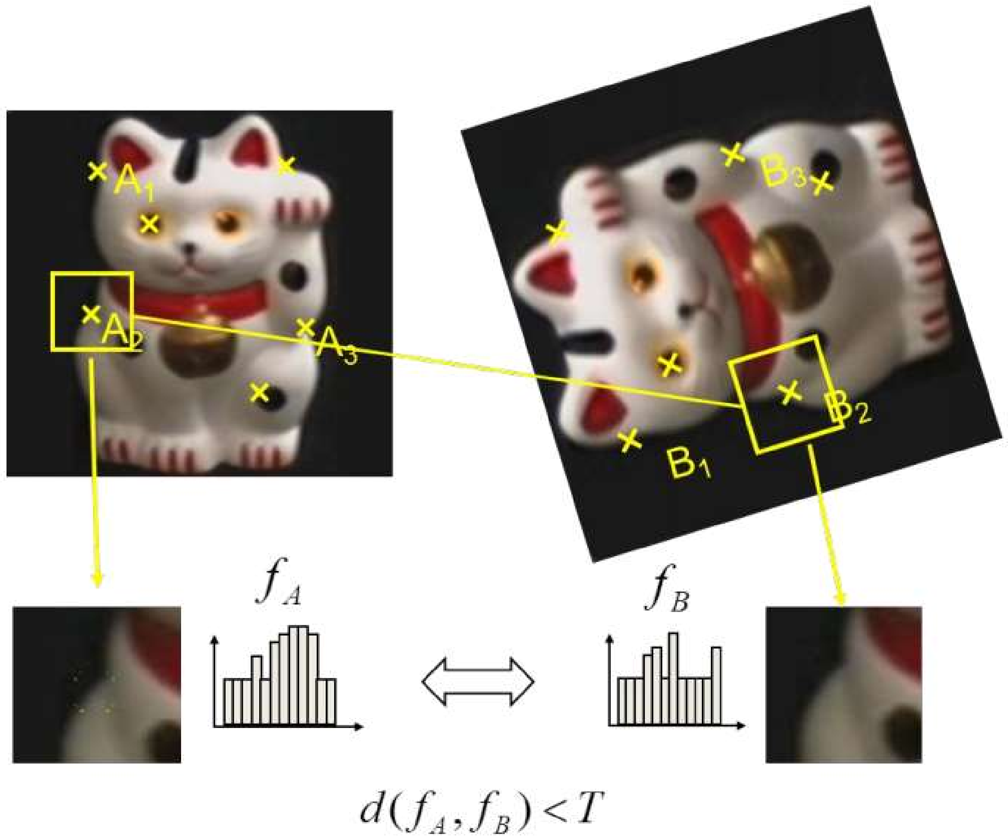
Given a feature in I_1, how to find the best match in I_2?

1. Define distance function that compares two descriptors
2. Test all the features in I_2, find the one with min distance



Overview of point feature matching

1. Detect a set of distinct feature points
2. Define a patch around each point
3. Extract and normalize the patch
4. Compute a local descriptor
5. Match local descriptors



Source: Trym Vegard Haavardsholm

Distance between descriptors

- L_1 distance (SAD):

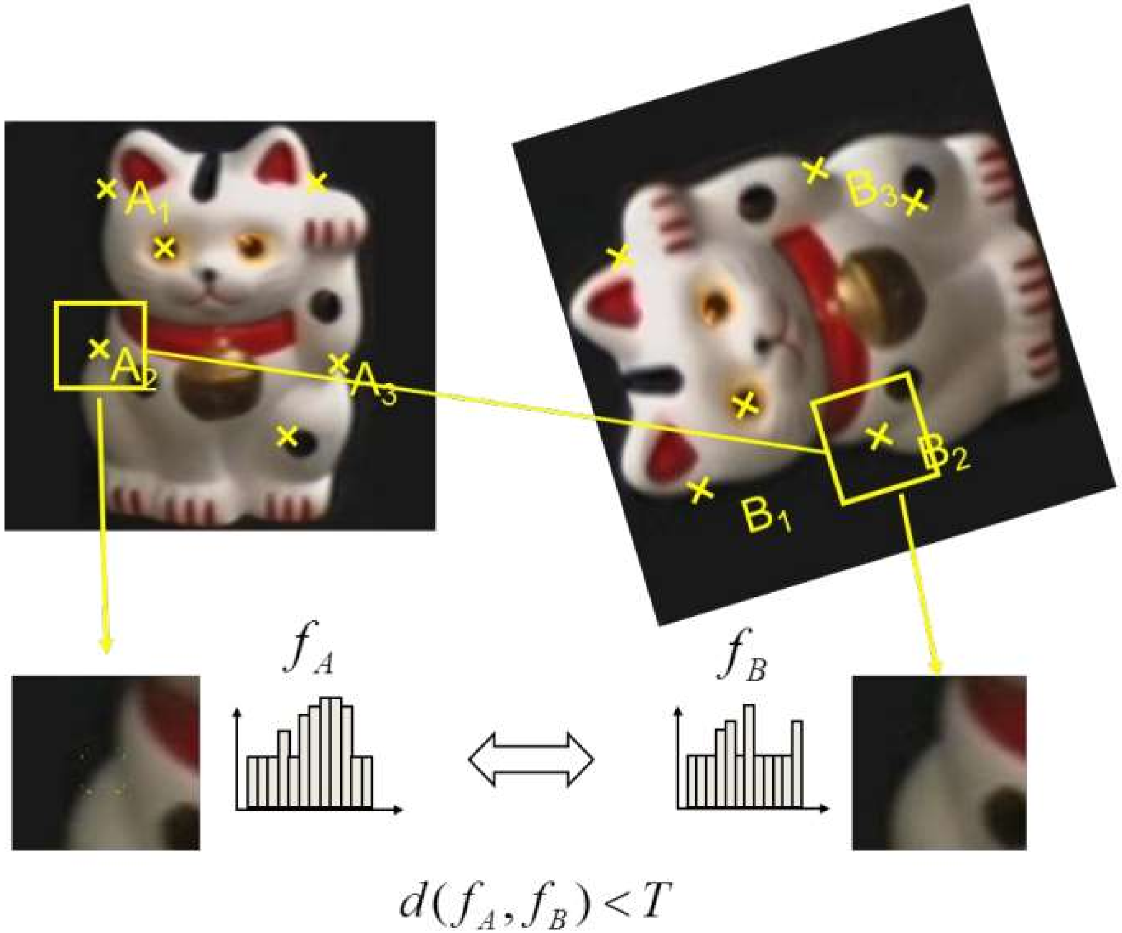
$$d(f_a, f_b) = \sum |f_a - f_b|$$

- L_2 distance (SSD):

$$d(f_a, f_b) = \sum (f_a - f_b)^2$$

- Hamming distance:

$$d(f_a, f_b) = \sum \mathrm{XOR}(f_a, f_b)$$

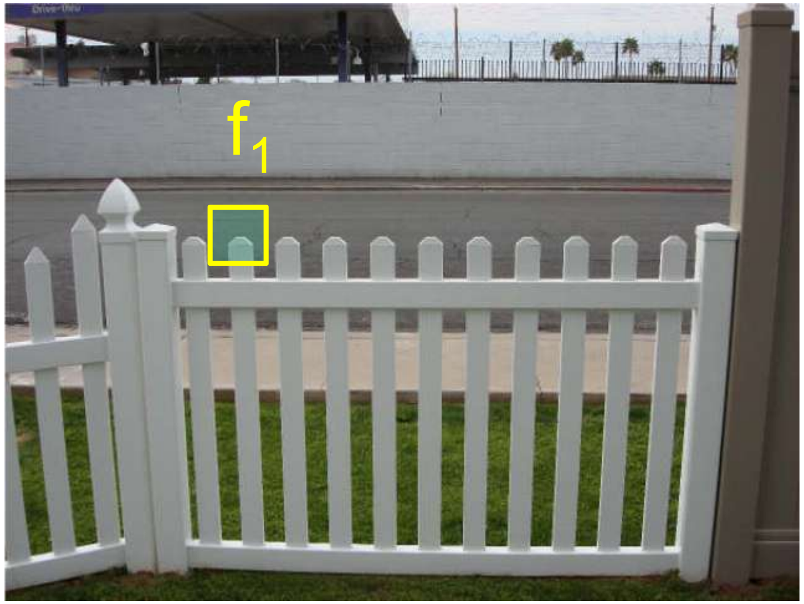


Source: Trym Vegard Haavardsholm

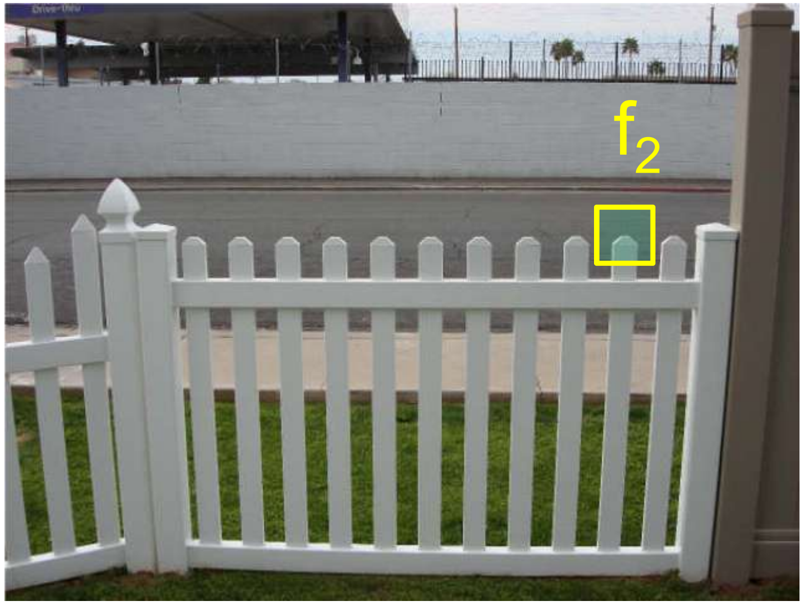
Features distance: SSD

How to define the difference between two features f_1, f_2?

- Simple approach: L_2 distance, $||f_1 - f_2||$
  i.e., sum of square differences (SSD) between entries of the two descriptors
- can give small distances for ambiguous (incorrect) matches
  i.e., does not provide a way to discard ambiguous (bad) matches



I_1

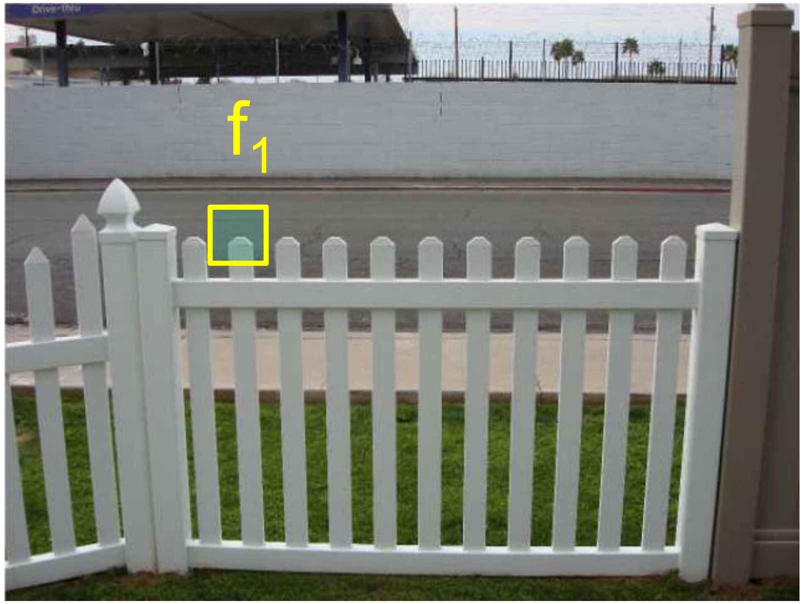


I_2

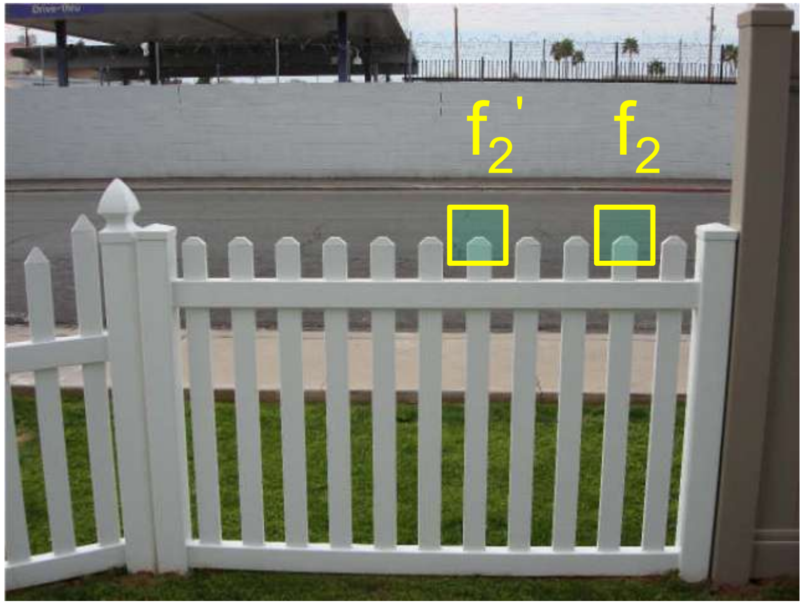
Features distance: Ratio of SSDs

How to define the difference between two features f_1, f_2?

- Better approach: ratio distance = SSD(f_1, f_2) / SSD(f_1, f_2’)
  - – f_2 is best SSD match to f_1 in I_2
  - – f_2’ is 2nd best SSD match to f_1 in I_2
  - – An ambiguous/bad match will have ratio close to 1
  - – Look for unique matches which have low ratio



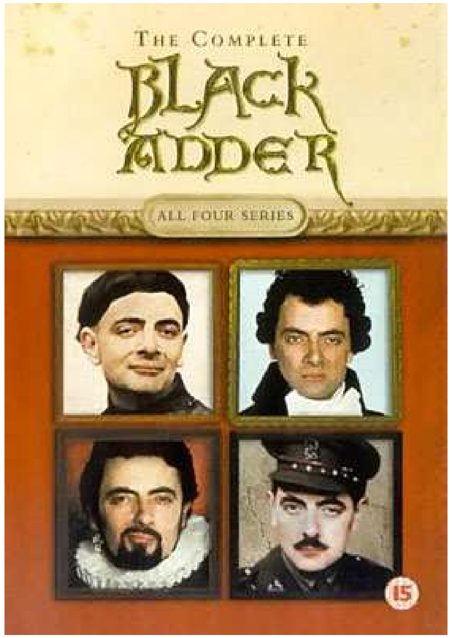
I_1



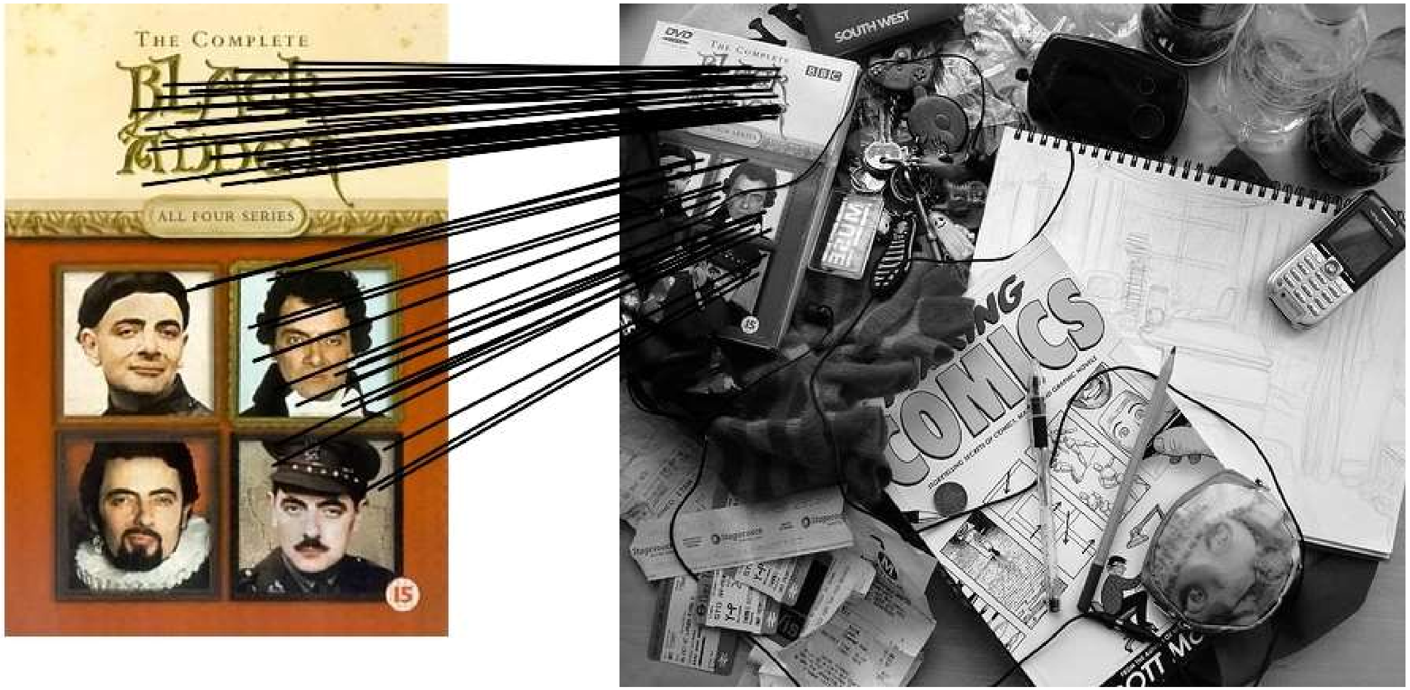
I_2

https://courses.cs.washington.edu/courses/cse455/09wi/Lects/lect7.pdf

Feature matching example



Feature matching example



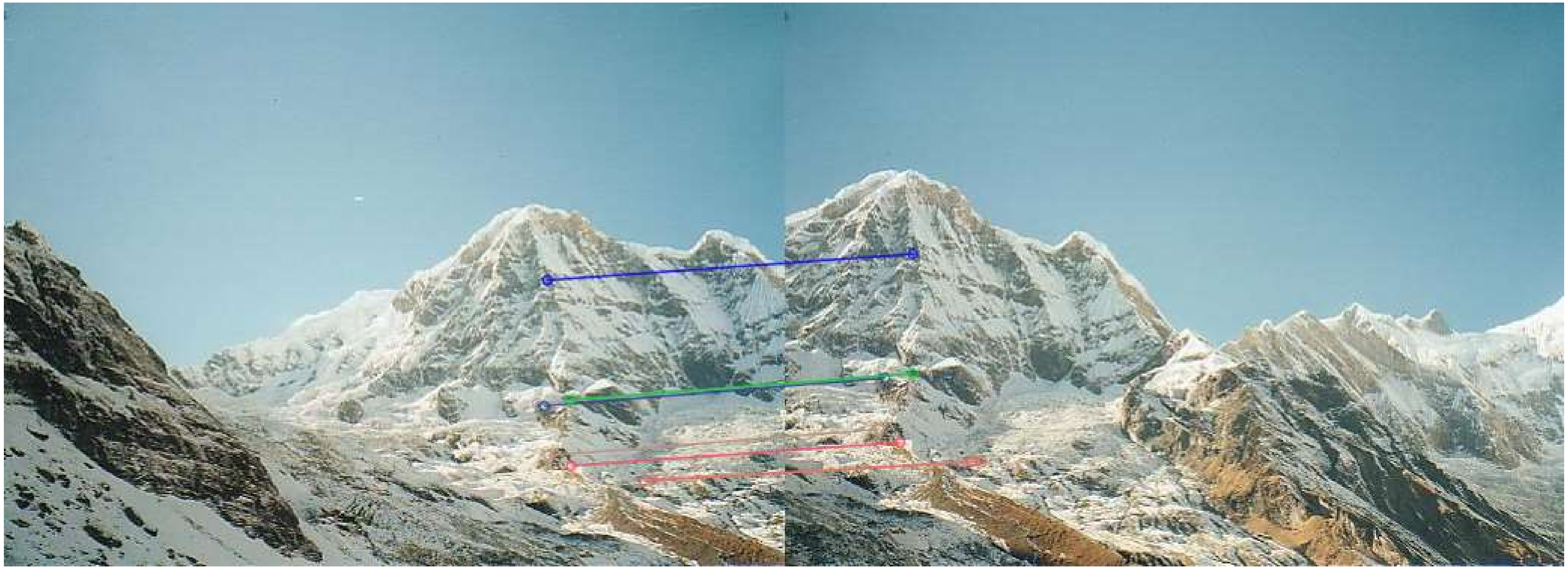
58 matches (thresholded by ratio score)

Example in Colab: ratio test

```
orb = cv.ORB_create()

kp_1, des_1 = orb.detectAndCompute(img_1, None)
kp_2, des_2 = orb.detectAndCompute(img_2, None)

bf = cv.BFMatcher()

matches = bf.knnMatch(des_1, des_2, k=2)

# Apply ratio test
good = []
for m,n in matches:
    if m.distance < 0.7*n.distance:
        good.append([m])

img_3 = cv.drawMatchesKnn(img_1, kp_1, img_2, kp_2, good[:20], None, flags=2)

img_3_rgb = cv.cvtColor(img_3, cv.COLOR_BGR2RGB)

plt.axis('off')
plt.imshow(img_3_rgb)
plt.show()

cv.imwrite('matching.png', img_3)
```

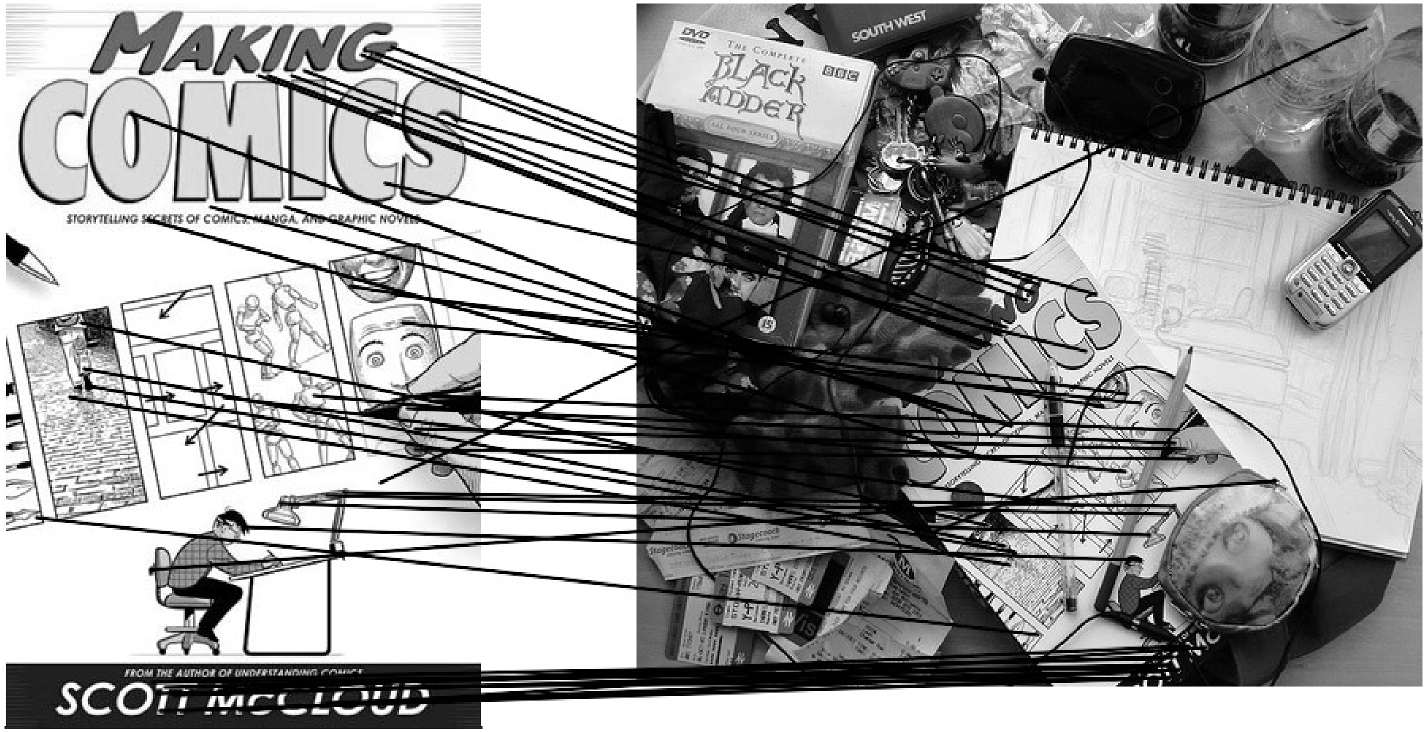
BFMatcher.knnMatch() to get k best matches. In this example, we will take k=2 so that we can apply ratio test

Example in Colab: ratio test results



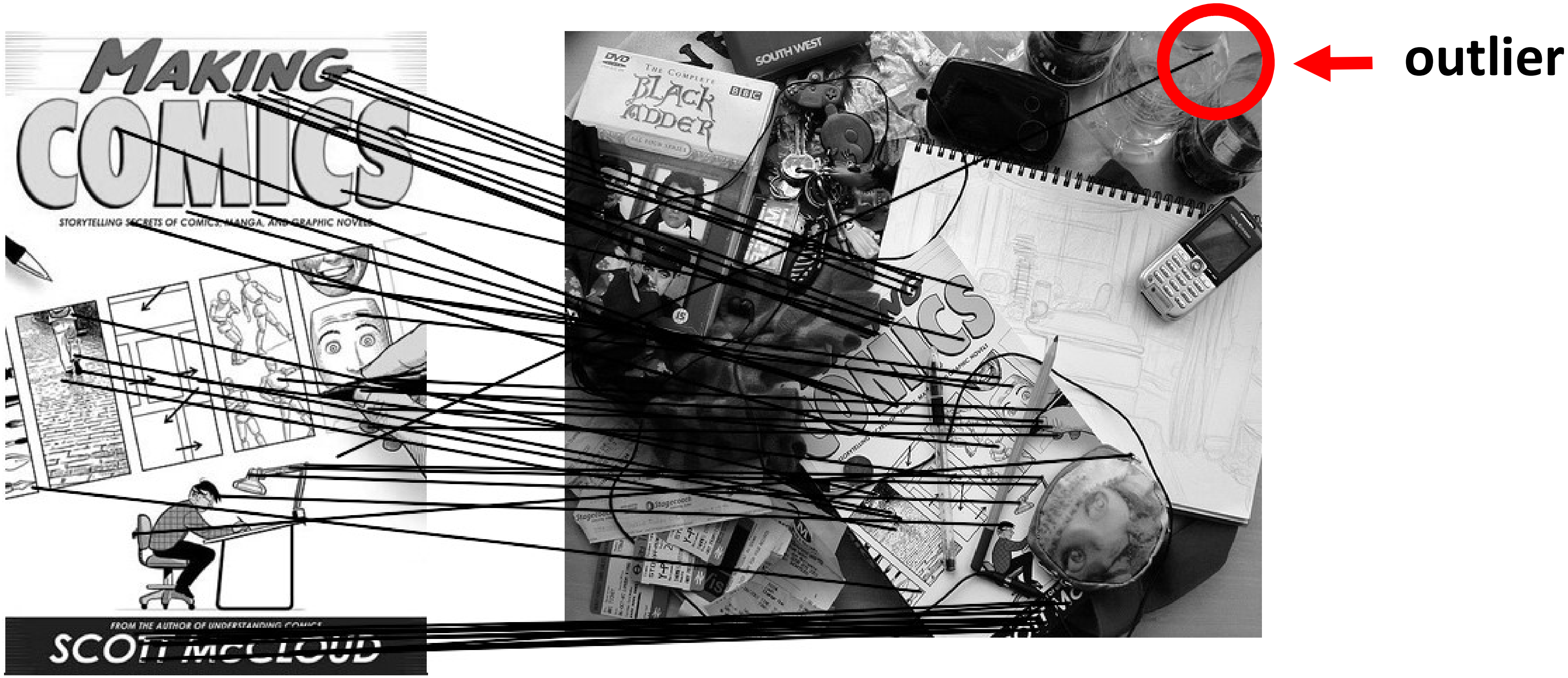
Feature matching example

Feature matching example



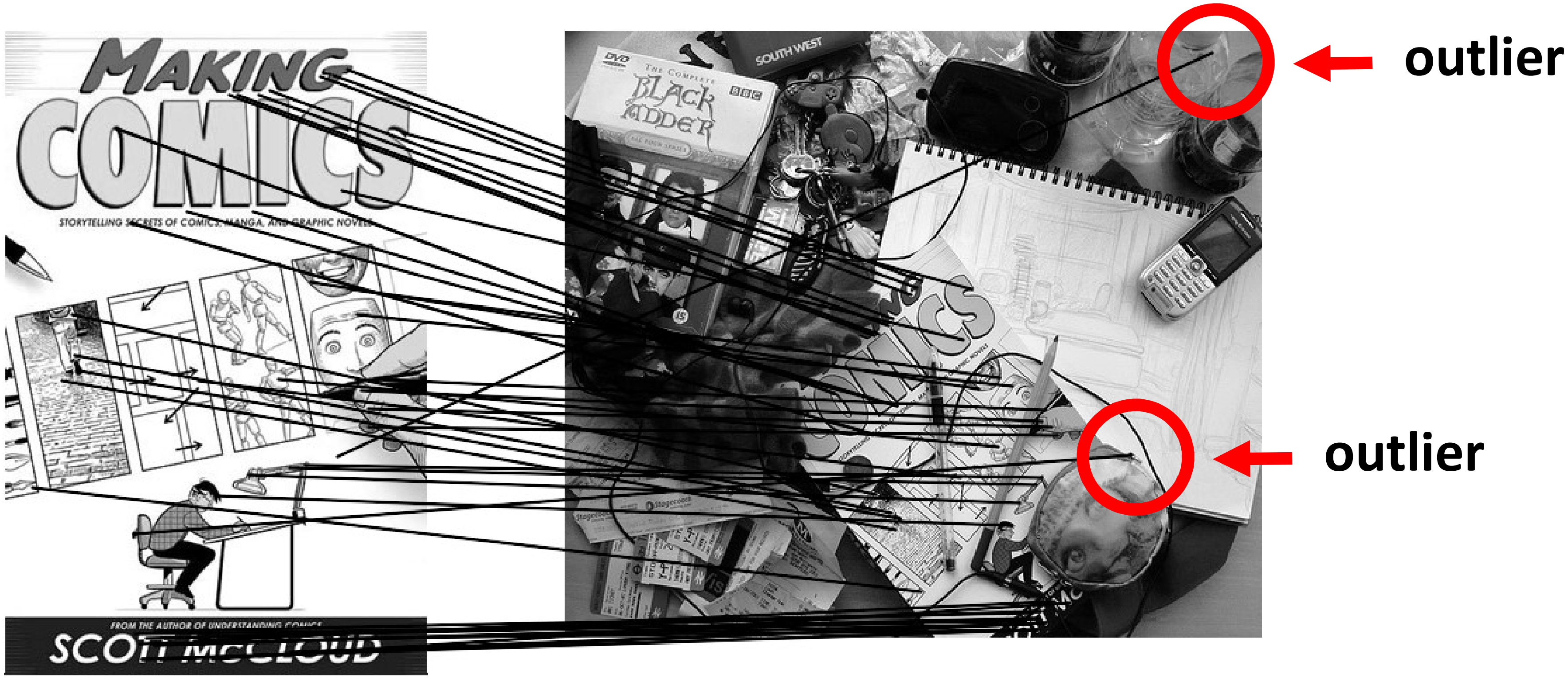
51 matches (thresholded by ratio score)

Feature matching example



51 matches (thresholded by ratio score)

Feature matching example



51 matches (thresholded by ratio score)

Evaluating the results

How can we measure the performance of a feature matcher?

Evaluating the results

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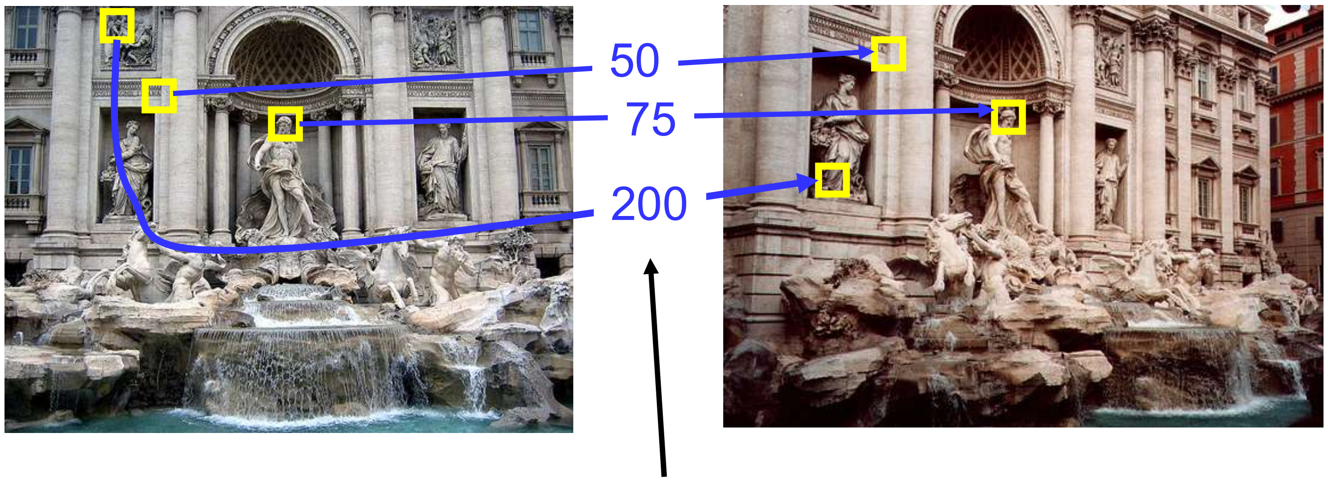
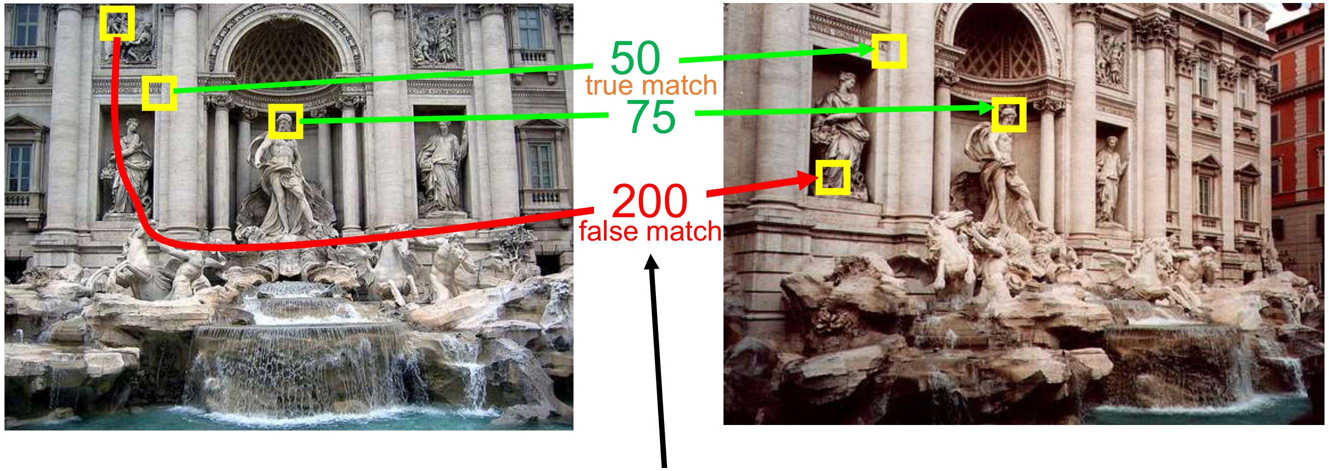


feature distance (e.g., SSD)

True/false positives

How can we measure the performance of a feature matcher?



feature distance (e.g., SSD)

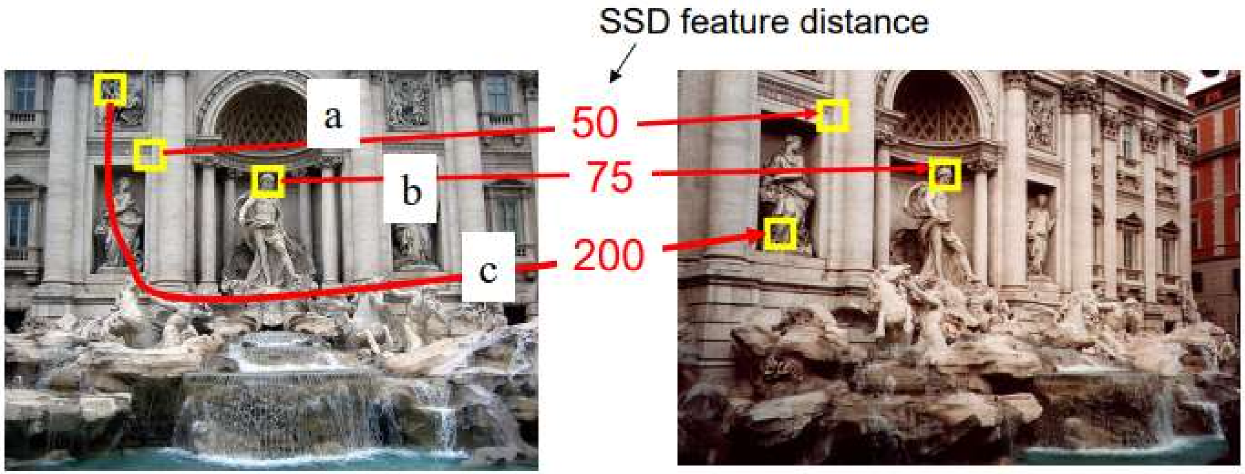
The distance threshold affects performance

- True positives = # of detected matches that are correct
  - Suppose we want to maximize these—how to choose threshold?
- False positives = # of detected matches that are incorrect
  - Suppose we want to minimize these—how to choose threshold?

Large threshold T

Maximize TP

https://courses.cs.washington.edu/courses/cse455/09wi/Lects/lect6.pdf



Decision rule: Accept match if SSD < T

Example: **Large T**

T = 250 ⇒ a, b, c are all accepted as matches

a and b are true matches (“**true positives**”)

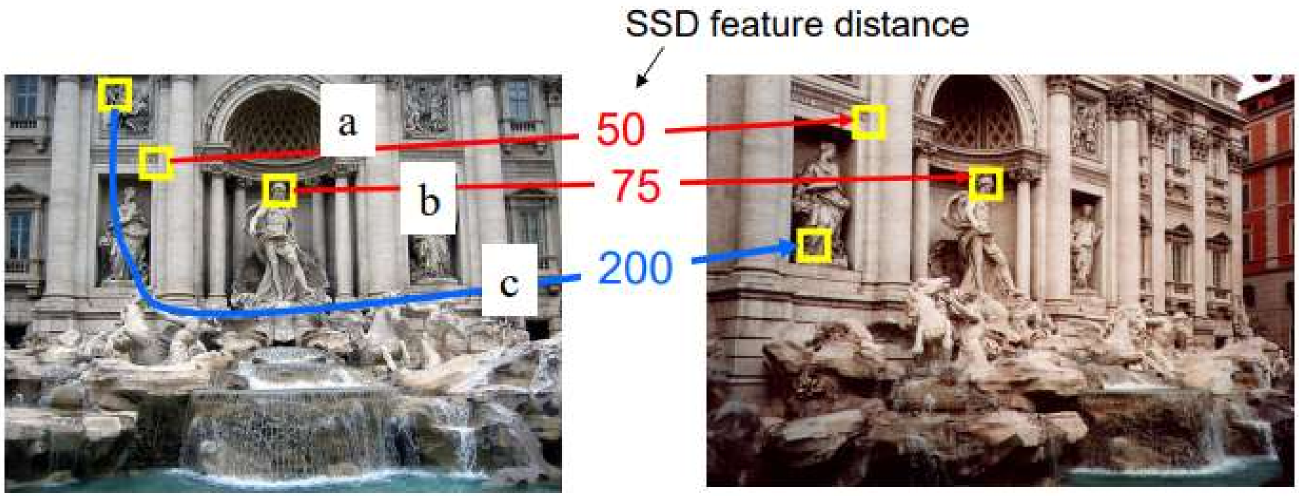
– they are actually matches

c is a false match (“**false positive**”)

– actually not a match

Small threshold T

Minimize FP



Decision rule: Accept match if SSD < T

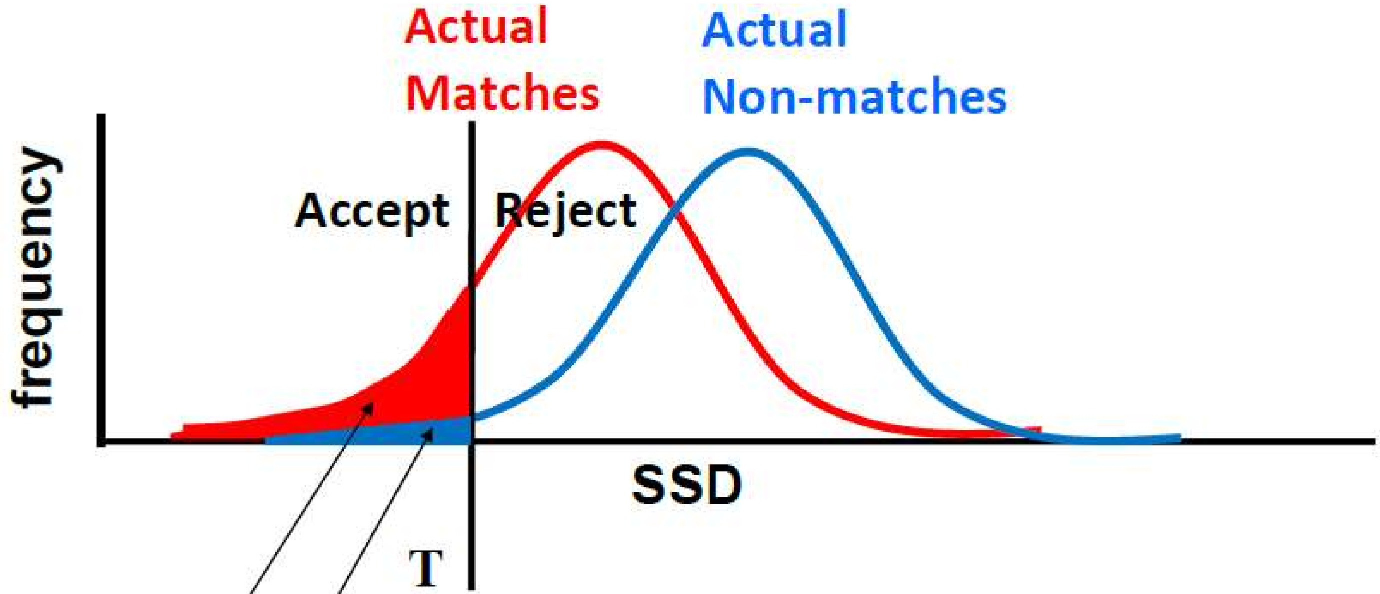
Example: **Smaller T**

$T = 100 \Rightarrow$ only a and b are accepted as matches

a and b are true matches ("true positives")
c is no longer a "false positive" (it is a "true negative")

https://courses.cs.washington.edu/courses/cse455/09wi/Lects/lect6.pdf

True positives and false positives



True positives

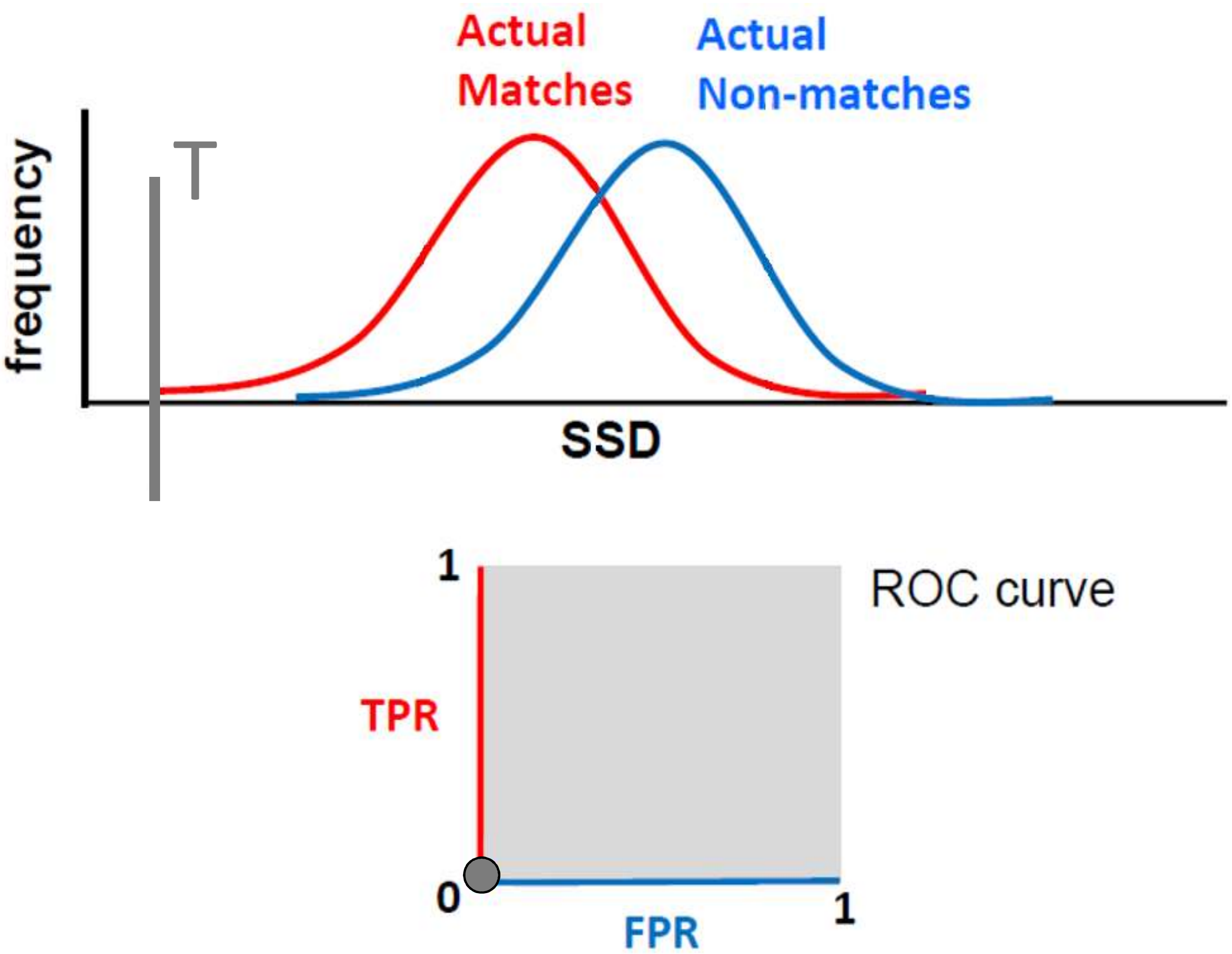
False positives

$$\text{True positive rate (TPR)} = \frac{\#\,\text{true positives}}{\#\,\text{actual matches}}$$

$$\text{False positive rate (FPR)} = \frac{\#\,\text{false positives}}{\#\,\text{actual nonmatches}}$$

https://courses.cs.washington.edu/courses/cse455/09wi/Lects/lect6.pdf

Receiver Operating Characteristic (ROC) curve



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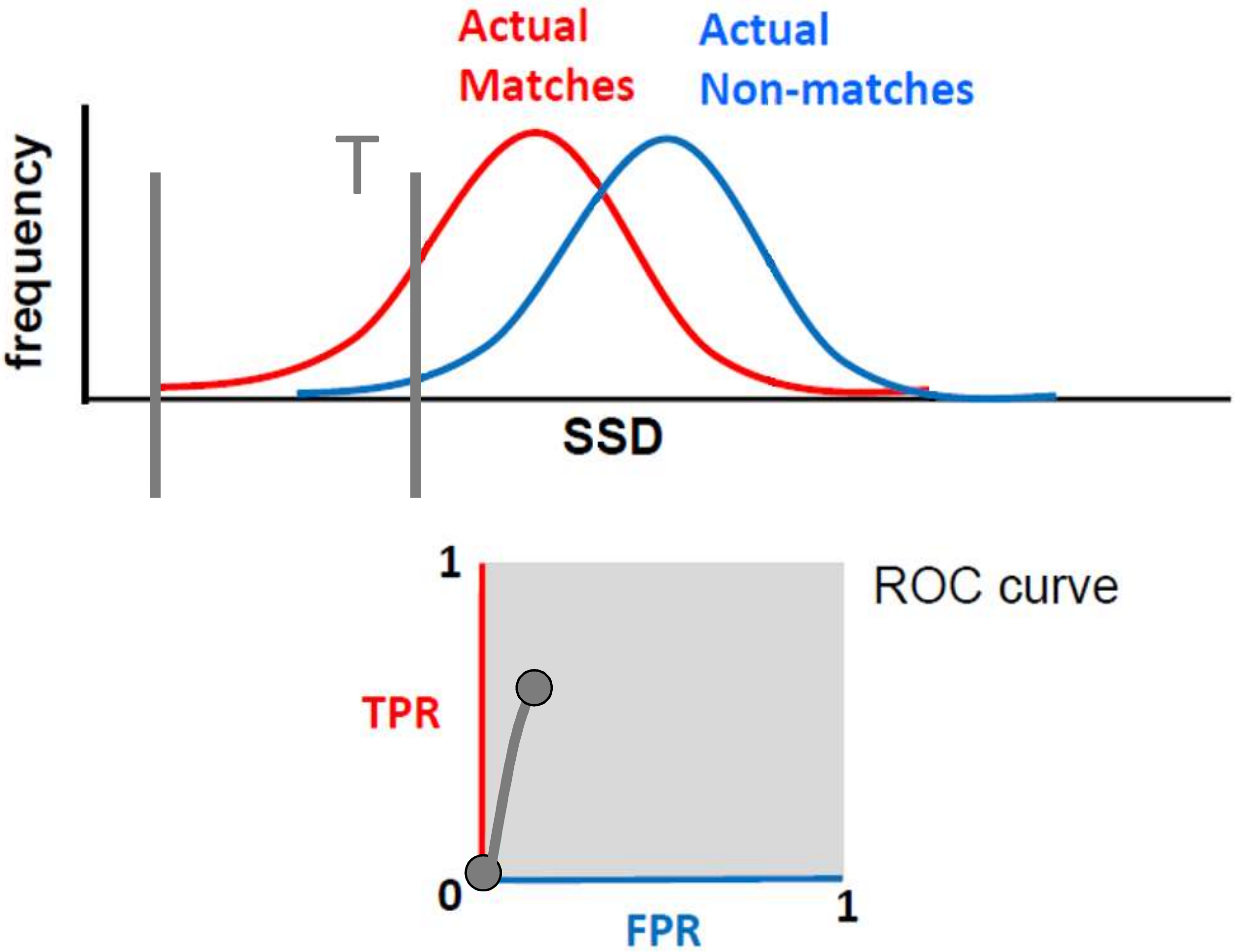
Receiver Operating Characteristic (ROC) curve



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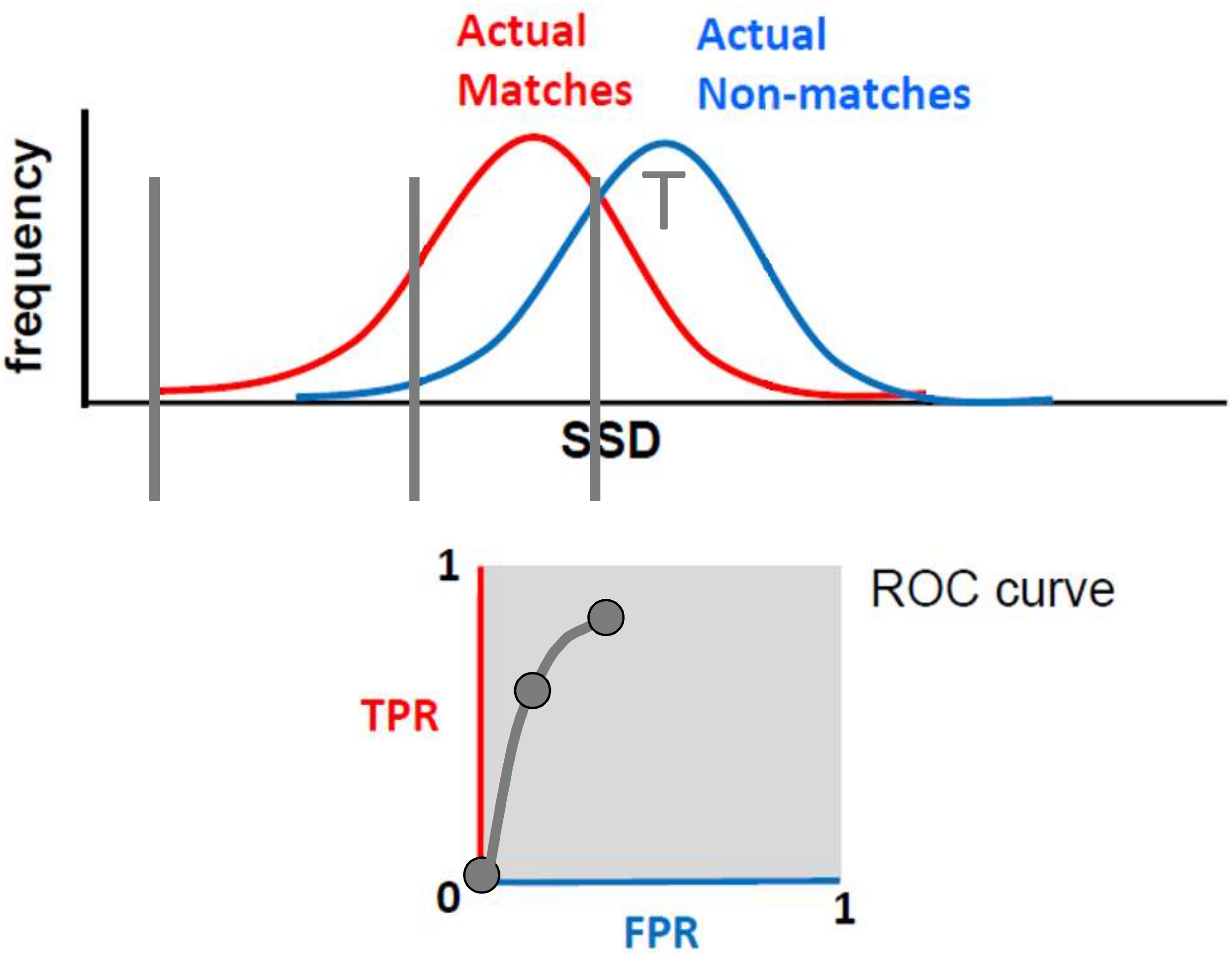
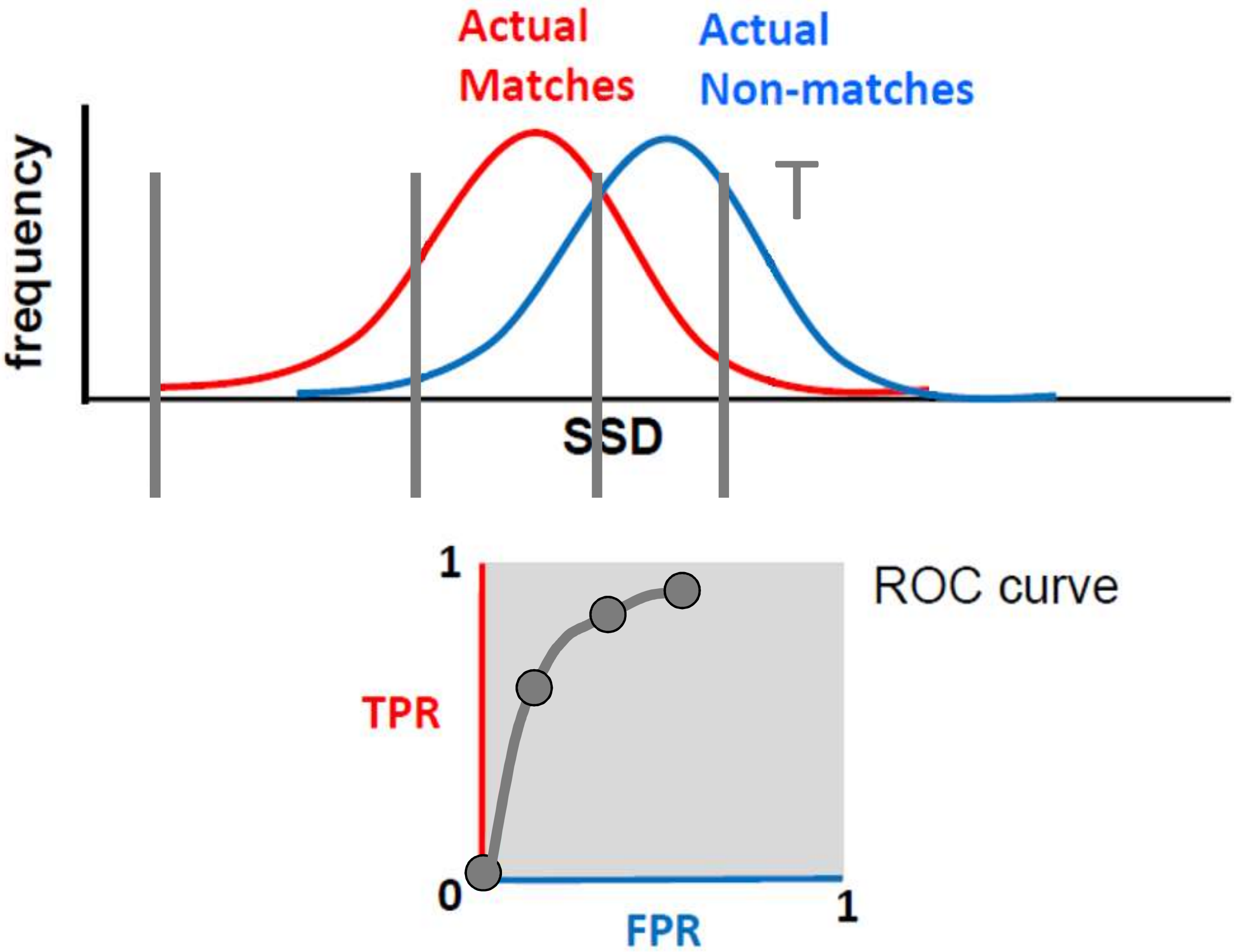
Receiver Operating Characteristic (ROC) curve



Receiver Operating Characteristic (ROC) curve



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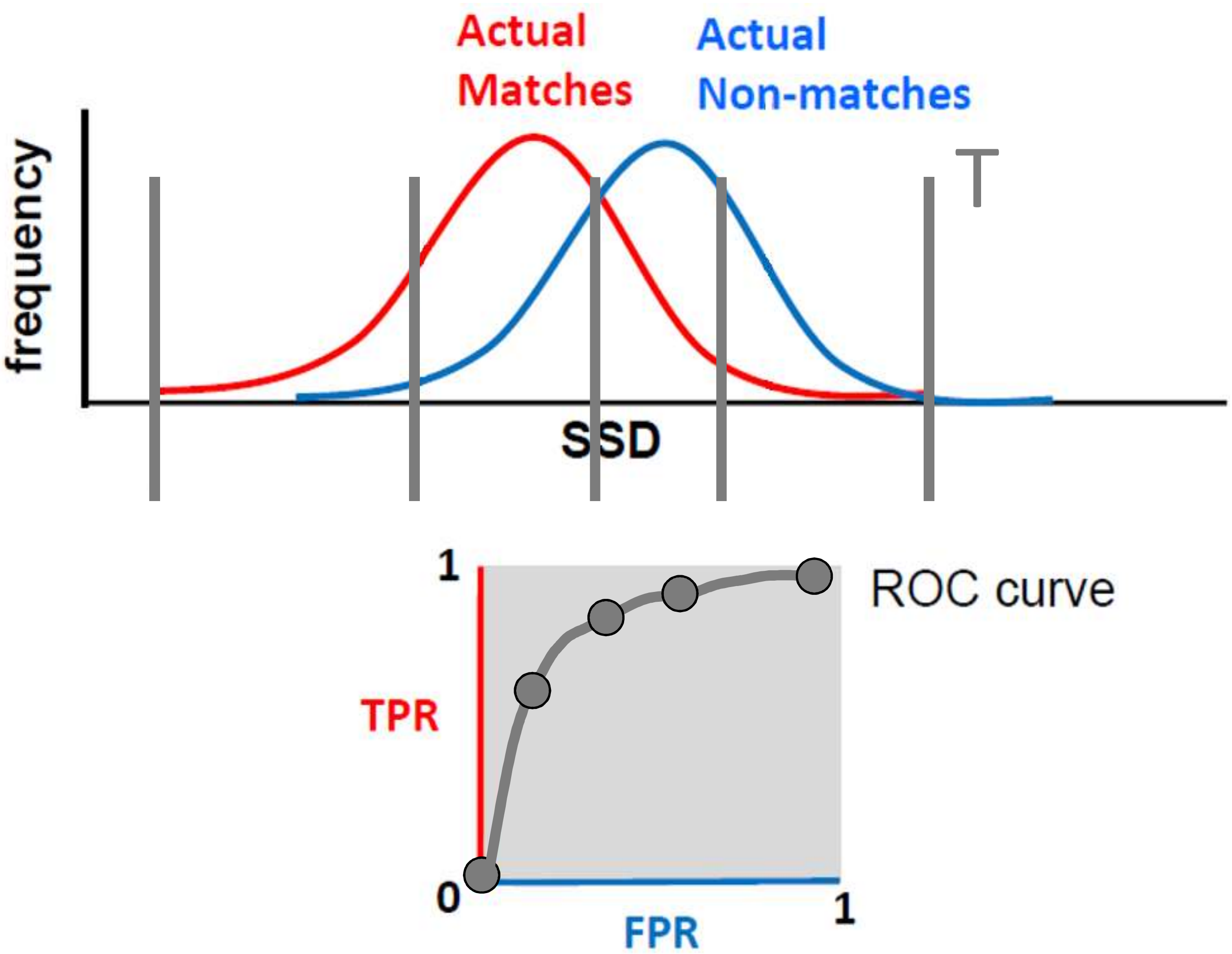
Receiver Operating Characteristic (ROC) curve



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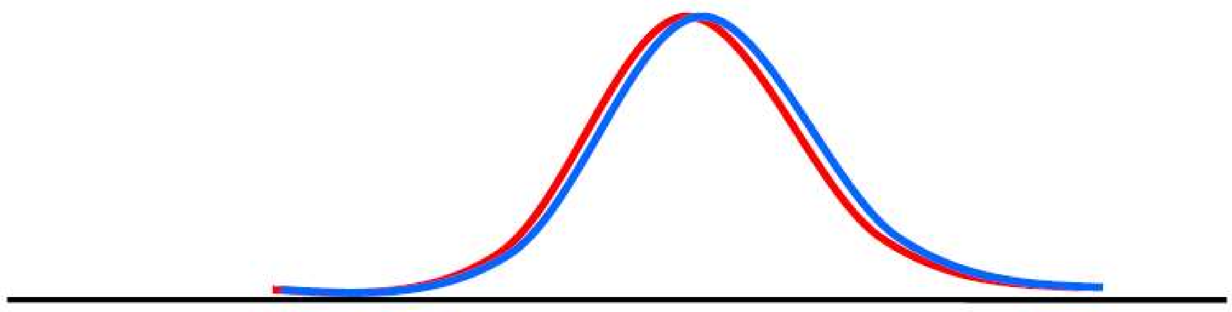
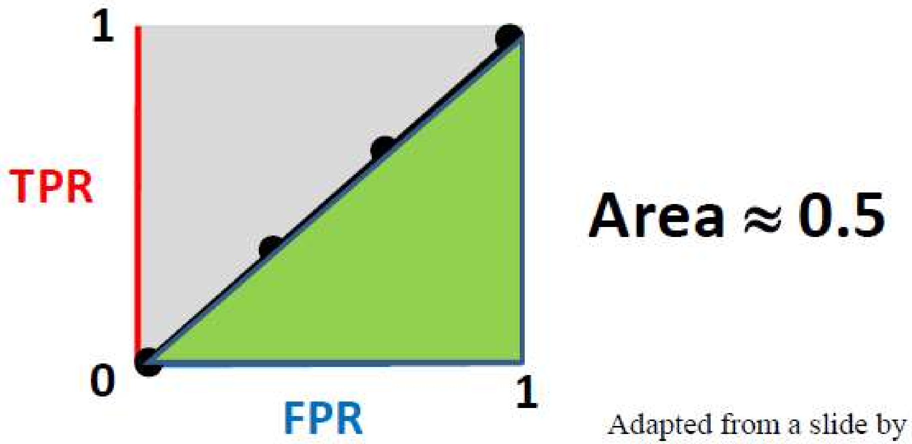
If the features selected were bad…

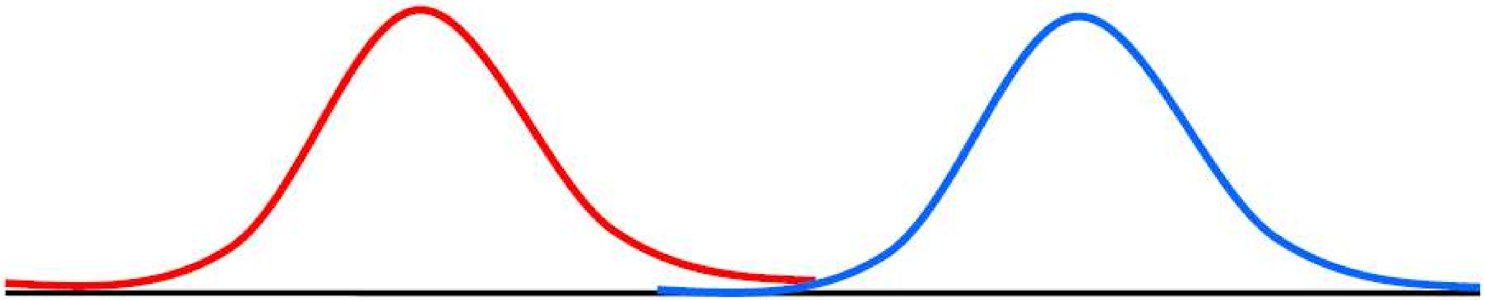


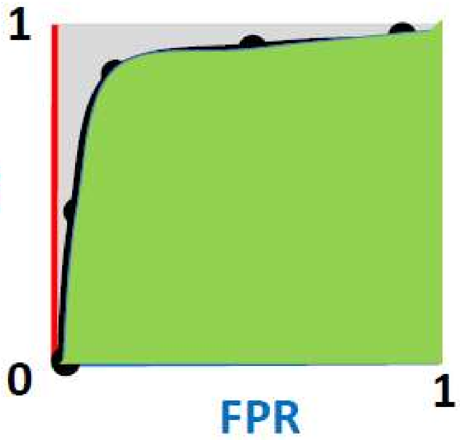


Adapted from a slide by Shin Kira

https://courses.cs.washington.edu/courses/cse455/09wi/Lects/lect6.pdf

If the features selected were good…





Area ≈ 1.0

Adapted from a slide by Shin Kira

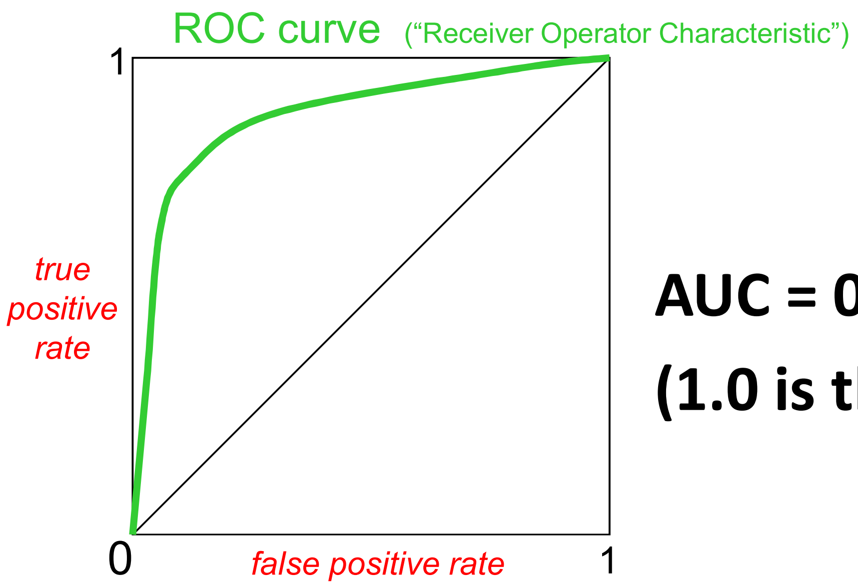
https://courses.cs.washington.edu/courses/cse455/09wi/Lects/lect6.pdf

Area under the curve

Single number: Area Under the Curve (AUC)

$$\frac{\#\text{ true positives}}{\#\text{ matching features (positives)}}$$

recall



AUC = 0.87

(1.0 is the best)

$$\frac{\#\text{ false positives}}{\#\text{ unmatched features (negatives)}}$$

1 - *specificity*

Feature matching: example using ORB

https://dbloisi.github.io/corsi/images/montagna-1.jpg

https://dbloisi.github.io/corsi/images/montagna-2.jpg

matching.ipynb

File Edit View Insert Runtime Tools Help

CODE TEXT CELL CELL

Table of contents Code snippets Files

UPLOAD REFRESH

..
sample_data
montagna-1.jpg
montagna-2.jpg

Disk 28.08 GB available

```python
import cv2 as cv
import numpy as np
import matplotlib.pyplot as plt

img_1 = cv.imread("montagna-1.jpg")
gray_1 = cv.cvtColor(img_1, cv.COLOR_BGR2GRAY)

img_2 = cv.imread("montagna-2.jpg")
gray_2 = cv.cvtColor(img_2, cv.COLOR_BGR2GRAY)

orb = cv.ORB_create()

kp_1, des_1 = orb.detectAndCompute(img_1, None)
kp_2, des_2 = orb.detectAndCompute(img_2, None)

bf = cv.BFMatcher(cv.NORM_HAMMING, crossCheck=True)

matches = bf.match(des_1, des_2)

matches = sorted(matches, key = lambda x:x.distance)

img_3 = cv.drawMatches(img_1, kp_1, img_2, kp_2, matches[:20], None, flags=2)

img_3_rgb = cv.cvtColor(img_3, cv.COLOR_BGR2RGB)

plt.axis('off')
plt.imshow(img_3_rgb)
plt.show()

cv.imwrite('matching.png', img_3)
```

ORB

```
import cv2 as cv
import numpy as np
import matplotlib.pyplot as plt

img_1 = cv.imread("montagna-1.jpg")
gray_1 = cv.cvtColor(img_1, cv.COLOR_BGR2GRAY)

img_2 = cv.imread("montagna-2.jpg")
gray_2 = cv.cvtColor(img_2, cv.COLOR_BGR2GRAY)

orb = cv.ORB_create()

kp_1, des_1 = orb.detectAndCompute(img_1, None)
kp_2, des_2 = orb.detectAndCompute(img_2, None)
```

Brute force matching

Brute-Force matcher is simple. It takes the descriptor of one feature in first set and is matched with all other features in second set using some distance calculation. And the closest one is returned.

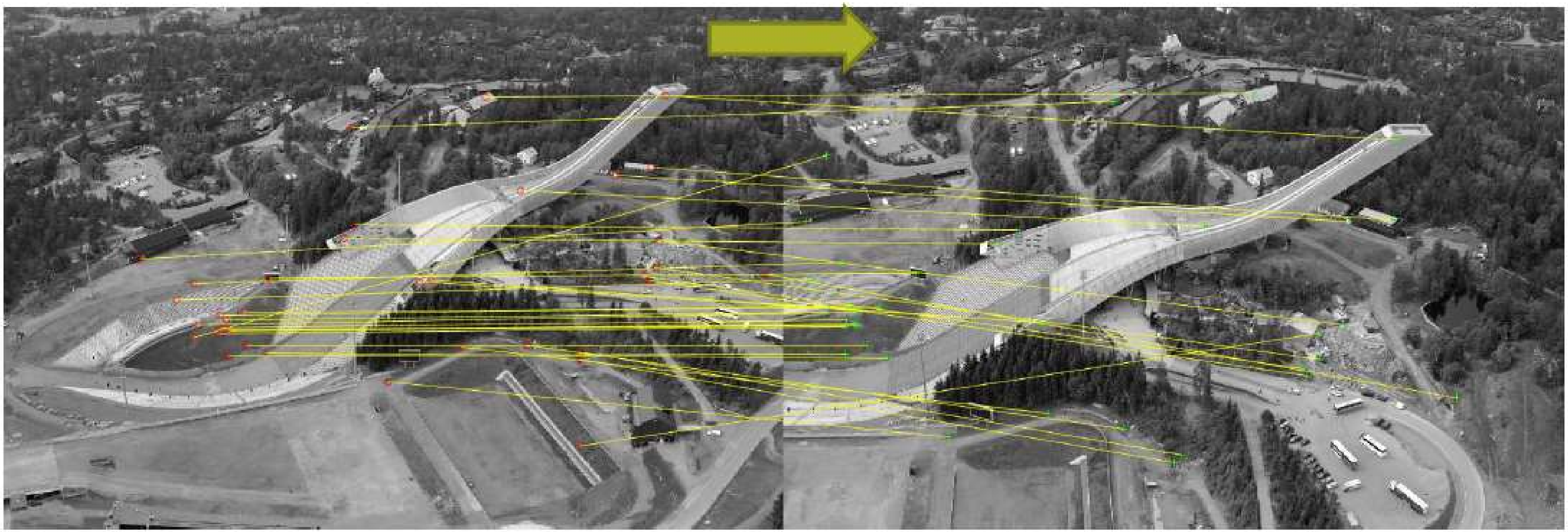
Hamming distance:

$$d(f_a, f_b) = \sum \mathrm{XOR}(f_a, f_b)$$

```
bf = cv.BFMatcher(cv.NORM_HAMMING, crossCheck=True)
matches = bf.match(des_1, des_2)
```

Cross check test

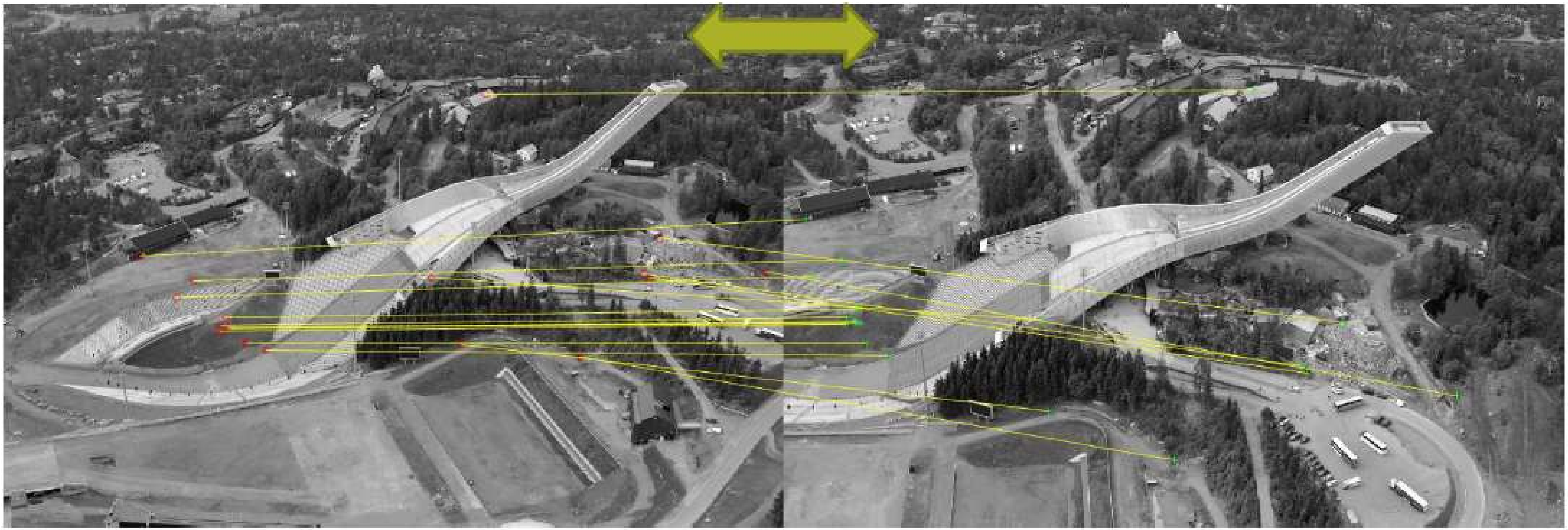
- Choose matches (f_a, f_b) so that
  - f_b is the best match for f_a in I_b
  - And f_a is the best match for f_b in I_a
- Alternative to ratio test



https://www.uio.no/studier/emner/matnat/its/UNIK4690/v17/forelesninger/lecture_4_2_feature_matching.pdf

Cross check test

- Choose matches (f_a, f_b) so that
  - f_b is the best match for f_a in I_b
  - And f_a is the best match for f_b in I_a
- Alternative to ratio test



https://www.uio.no/studier/emner/matnat/its/UNIK4690/v17/forelesninger/lecture_4_2_feature_matching.pdf

Sorting

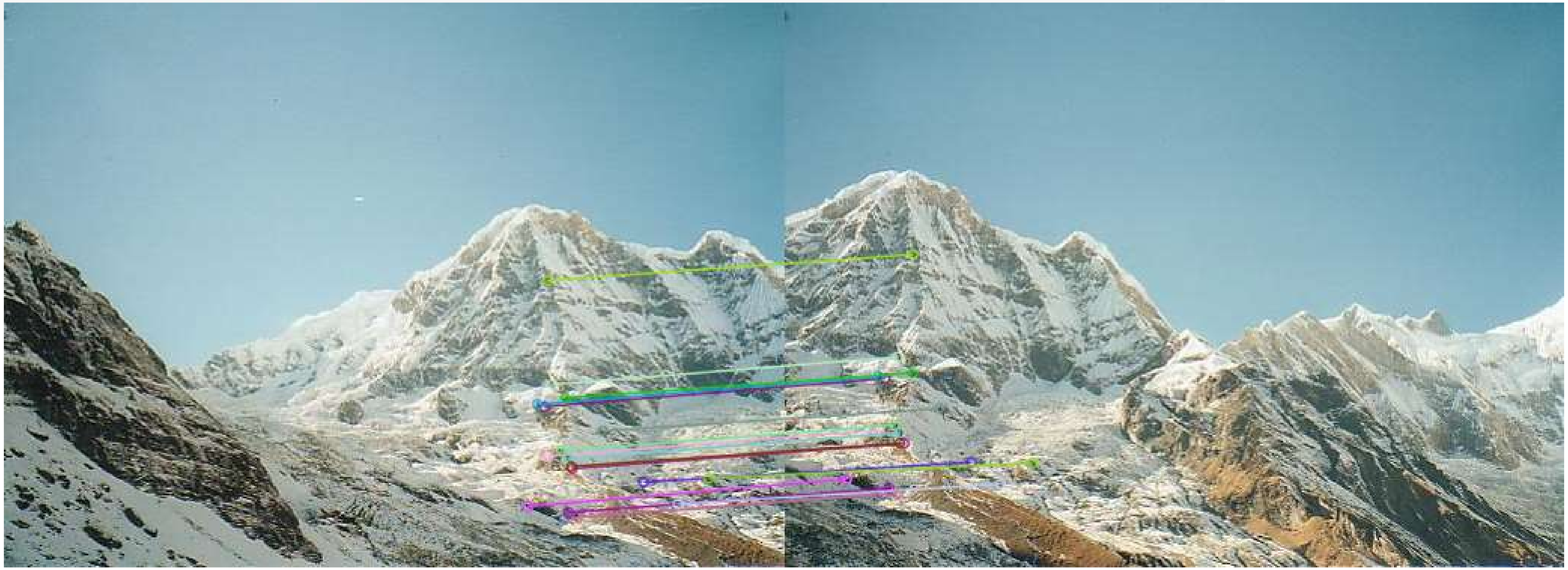
Matches are sorted in ascending order of their distances so that best matches (with low distance) come to front.

```
bf = cv.BFMatcher(cv.NORM_HAMMING, crossCheck=True)

matches = bf.match(des_1, des_2)

matches = sorted(matches, key = lambda x:x.distance)
```

In Python, le funzioni lambda, dette anche funzioni anonime, sono funzioni che vengono usate per un periodo di tempo limitato e sono legate a funzioni di più alto livello

Result

```
img_3 = cv.drawMatches(img_1, kp_1, img_2, kp_2, matches[:20], None, flags=2)

img_3_rgb = cv.cvtColor(img_3, cv.COLOR_BGR2RGB)

plt.axis('off')
plt.imshow(img_3_rgb)
plt.show()

cv.imwrite('matching.png', img_3)
```



SIFT Example

Univ4.jpg

Univ3.jpg

http://programmingcomputervision.com/

SIFT Example

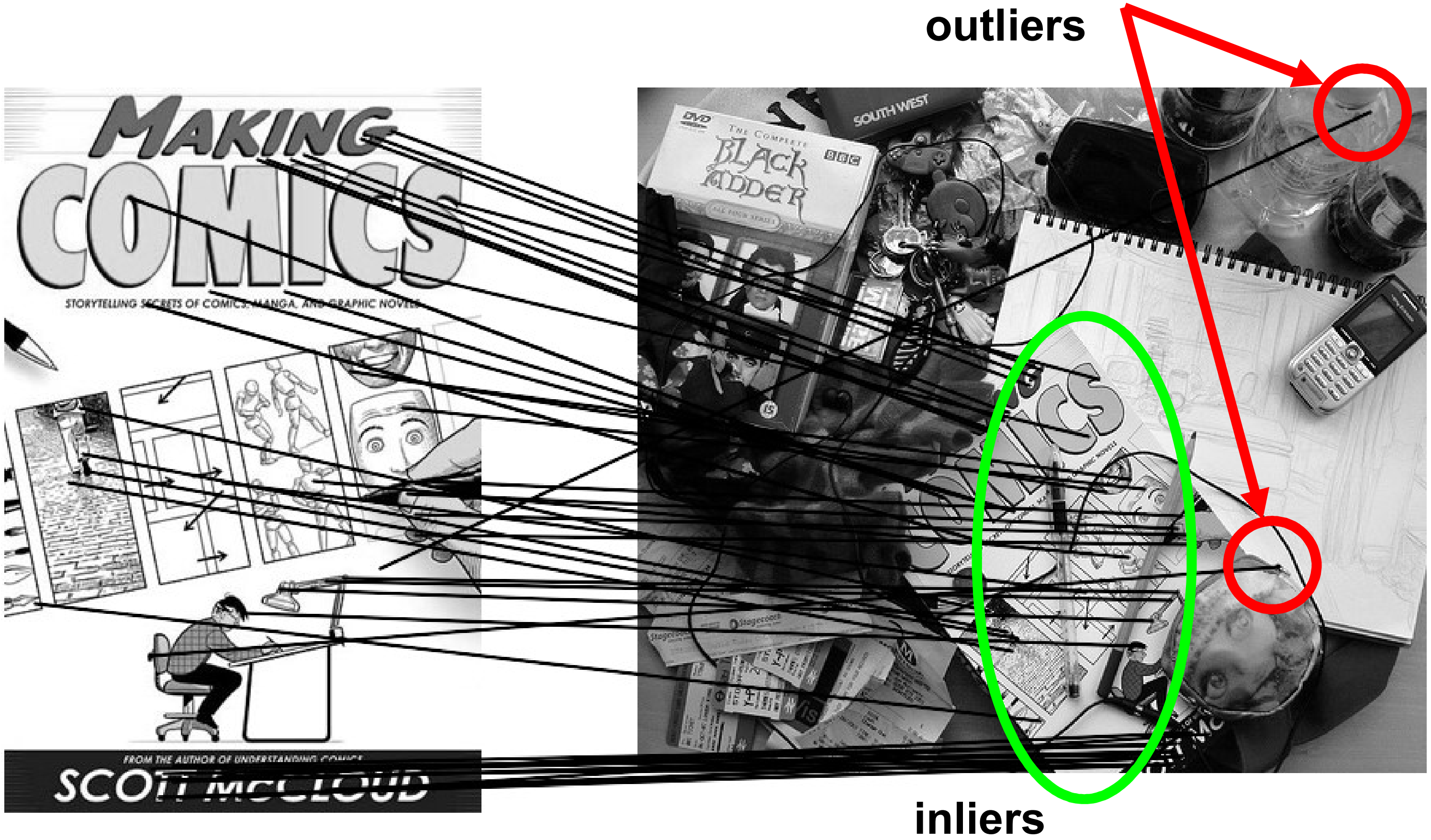
https://dbloisi.github.io/corsi/lezionivep/sift.ipynb

SIFT vs ORB

https://dbloisi.github.io/corsi/lezionivep/sift.ipynb

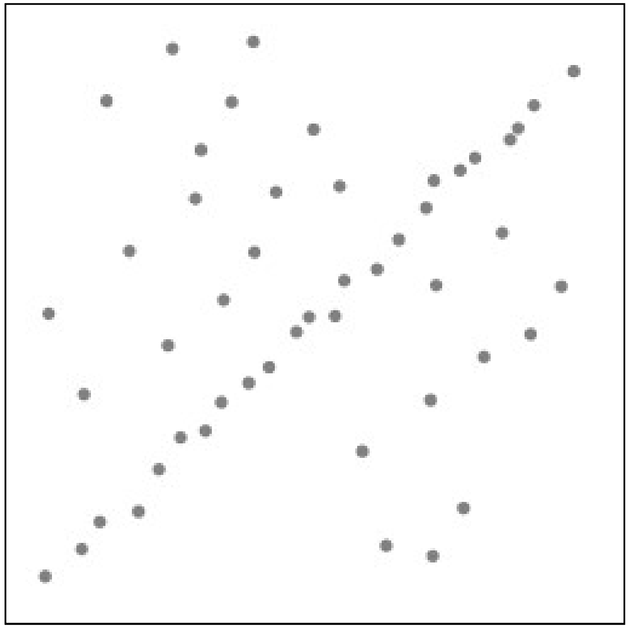
https://dbloisi.github.io/corsi/lezionivep/orb.ipynb

Excluding outliers



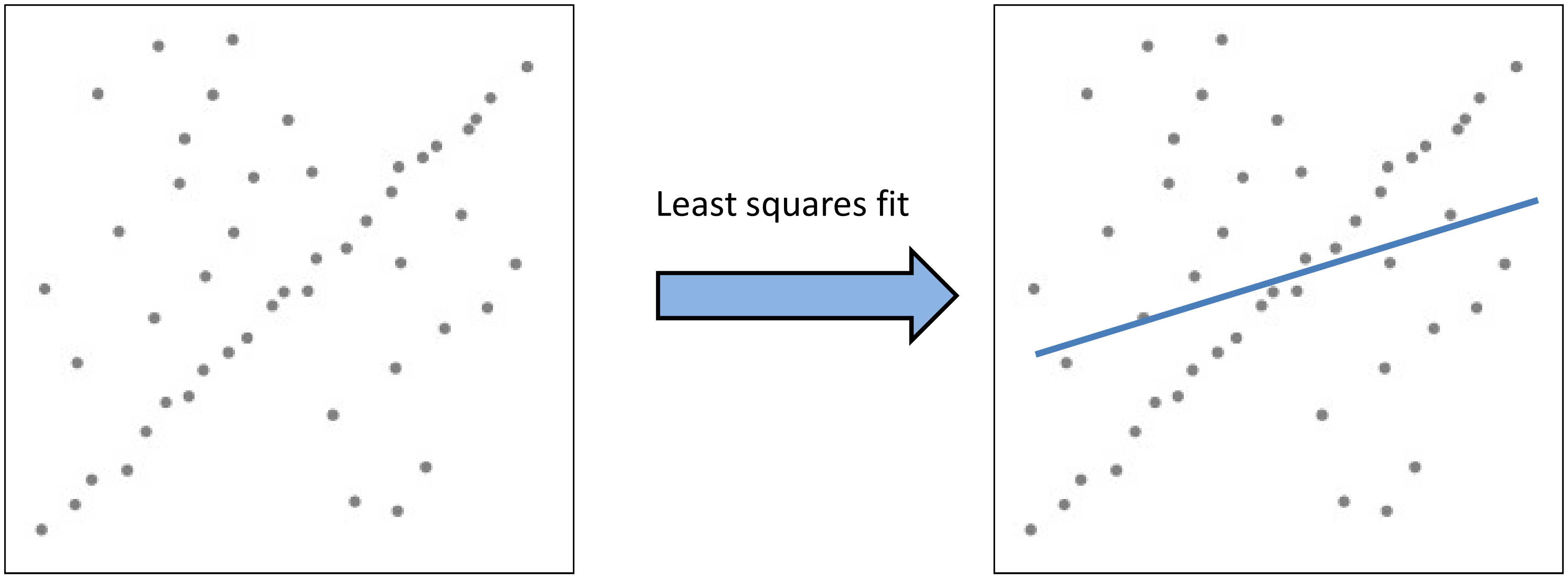
Robustness

Problem: Fit a line to these datapoints



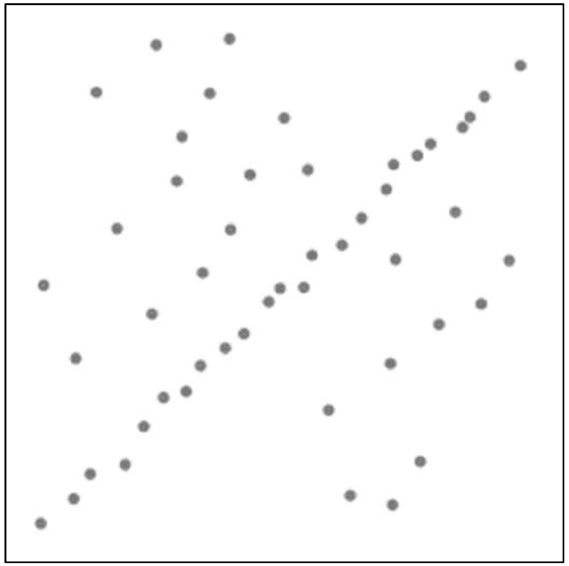
Robustness

Problem: Fit a line to these datapoints



Least Squares Fit

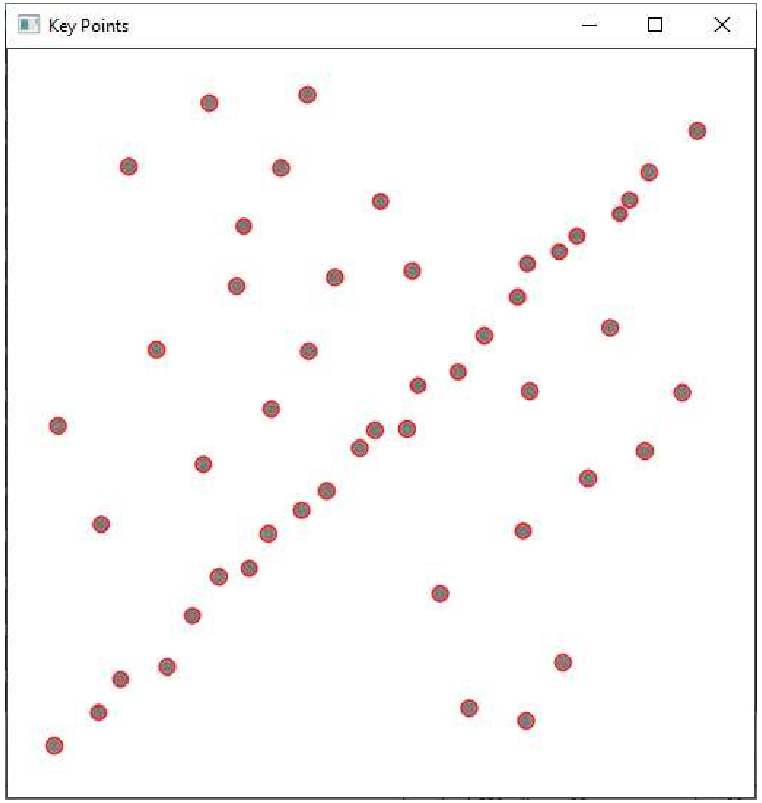
```
import numpy as np
import cv2 as cv
import math

# Read image
im = cv.imread("punti.png", cv.IMREAD_GRAYSCALE)

# Setup SimpleBlobDetector parameters.
params = cv.SimpleBlobDetector_Params()

# Change thresholds
params.minThreshold = 10;
params.maxThreshold = 200;

# Set up the detector with default parameters.
detector = cv.SimpleBlobDetector_create(params)

# Detect blobs.
keypoints = detector.detect(im)
```



punti.png

Least Squares Fit

```

# Draw detected blobs as red circles.
# cv2.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS ensures the size of the circle corresponds to the size of blob
im_with_keypoints = cv.drawKeypoints(im, keypoints, np.array([]), (0,0,255), cv.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)

cv.namedWindow("Key Points", cv.WINDOW_AUTOSIZE);
cv.imshow("Key Points", im_with_keypoints);
cv.waitKey(0);
```

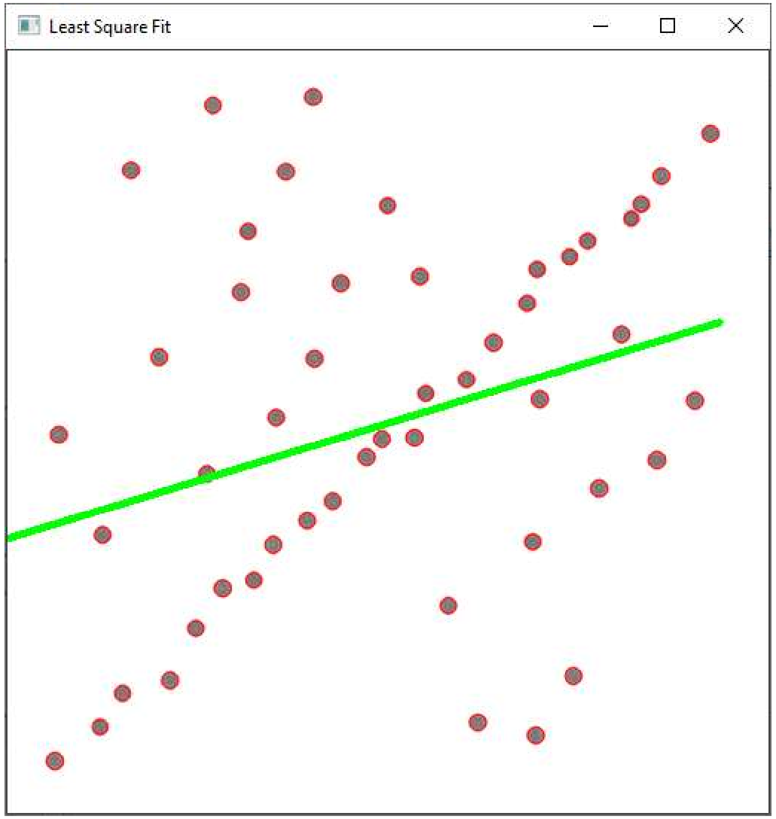


Least Squares Fit

```
v = []
for elem in keypoints:
    #print(elem.pt[0])
    v.append([elem.pt[0],elem.pt[1]])
points = np.array(v)

y = points[:,0]
x = points[:,1]

m, c = np.polyfit(x, y, 1)      # calculate least square fit line

# calculate two cordinates (x1,y1),(x2,y2) on the line
angle = np.arctan(m)
x1, y1, length =  0, int(c), 500
x2 =  int(round(math.ceil(x1 + length * np.cos(angle)),0))
y2 =  int(round(math.ceil(y1 + length * np.sin(angle)),0))
```

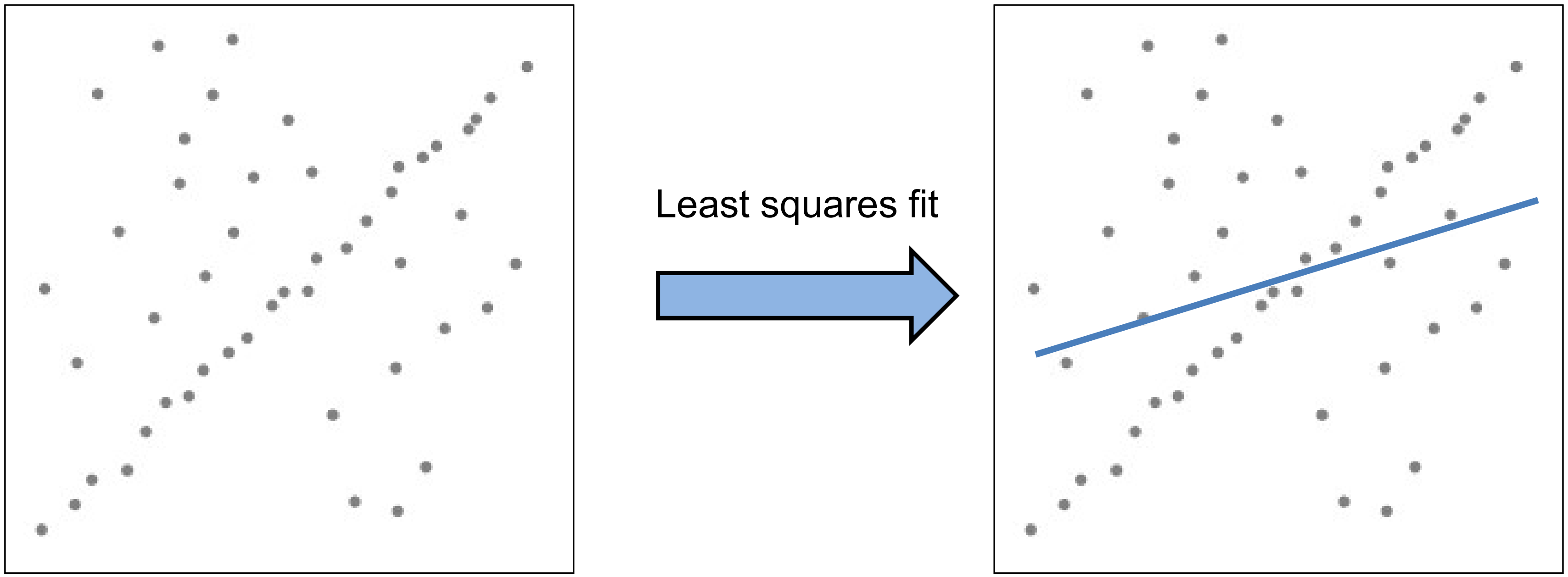
Least Squares Fit

```
# draw line on the color image
cv.line(im_with_keypoints, (x1, y1), (x2, y2), (0,255,0), 3, cv.LINE_8)

# show output the image
cv.namedWindow("Least Square Fit", cv.WINDOW_AUTOSIZE);
cv.imshow("Least Square Fit", im_with_keypoints);
cv.waitKey(0);
cv.destroyAllWindows()

```



Robustness

Problem: Fit a line to these datapoints



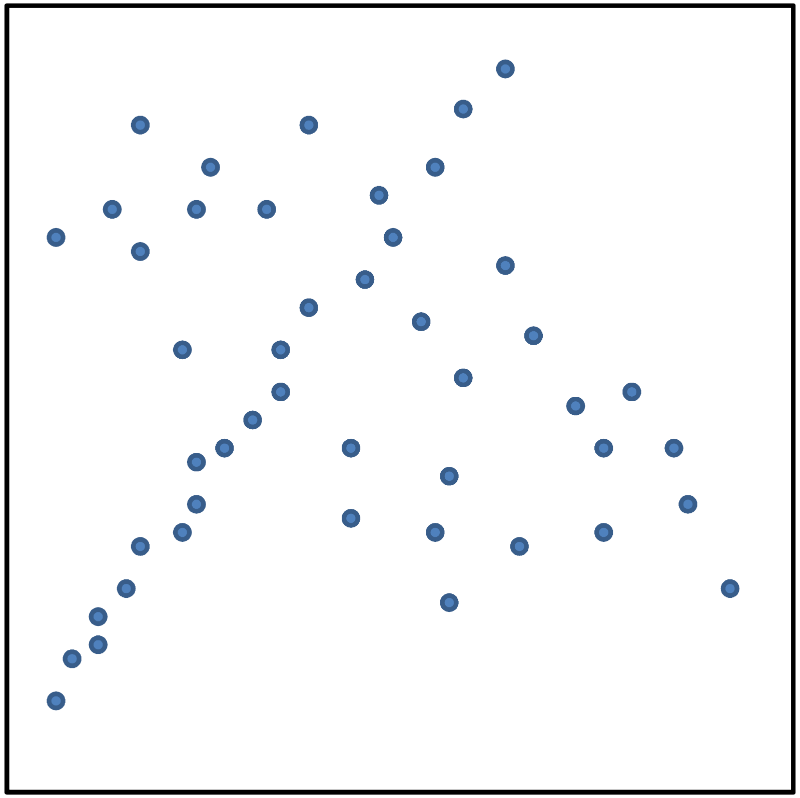
How can we fix this?

Idea

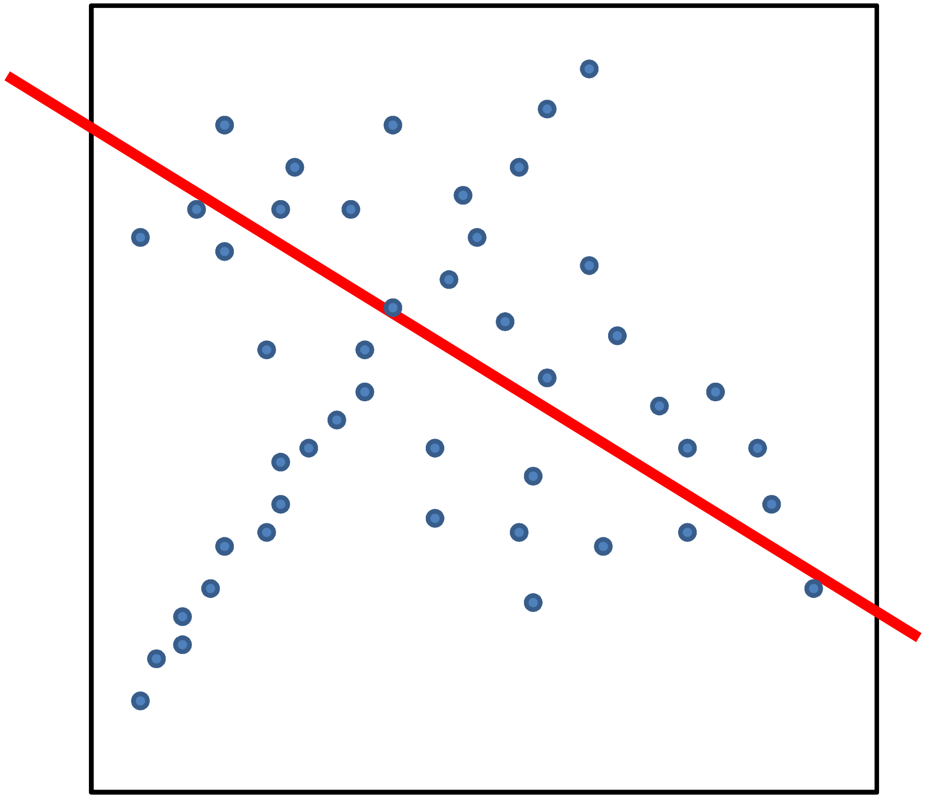
- Given a hypothesized line
- Count the number of points that “agree” with the line
  – “Agree” = within a small distance of the line
  – I.e., the **inliers** to that line

- For all possible lines, select the one with the largest number of inliers

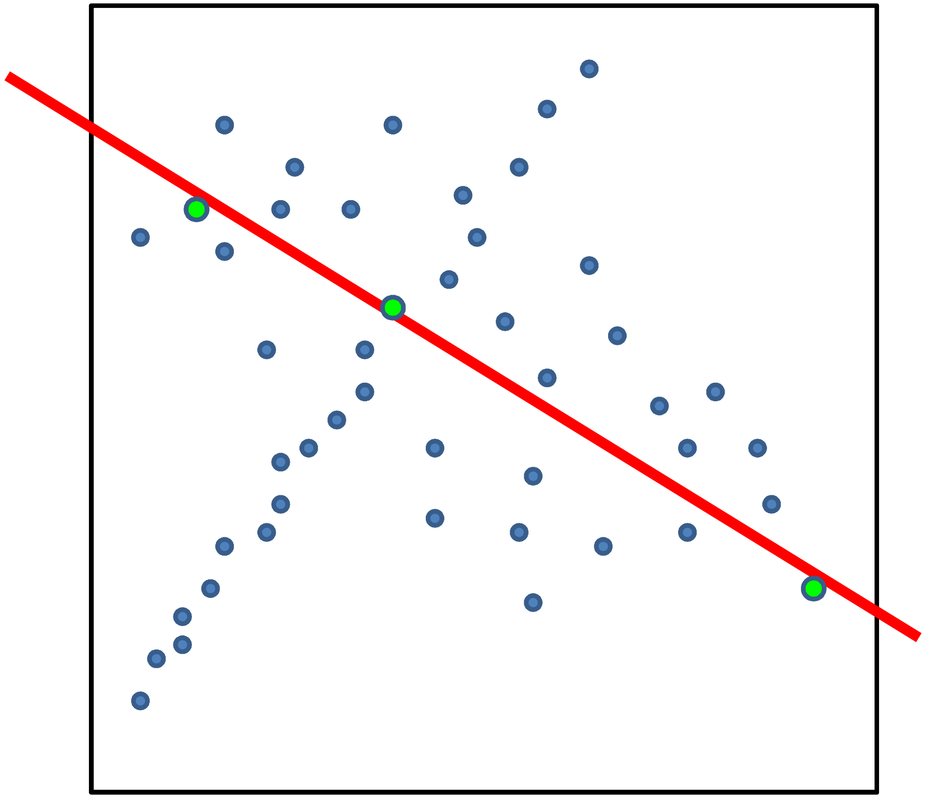
Counting inliers



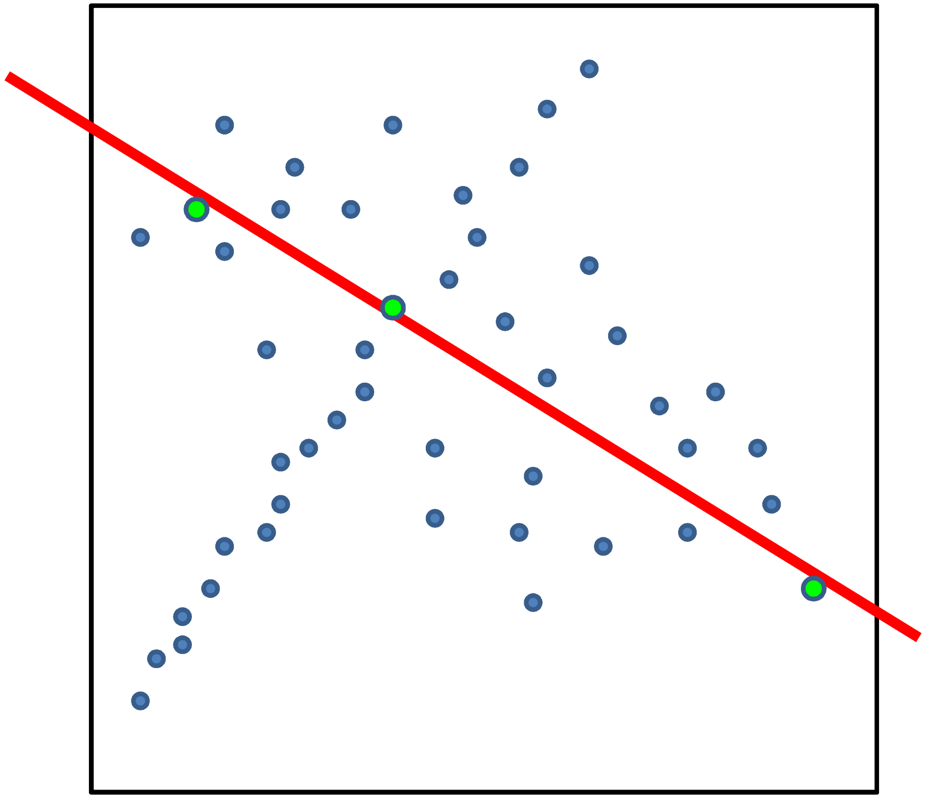
Counting inliers



Counting inliers

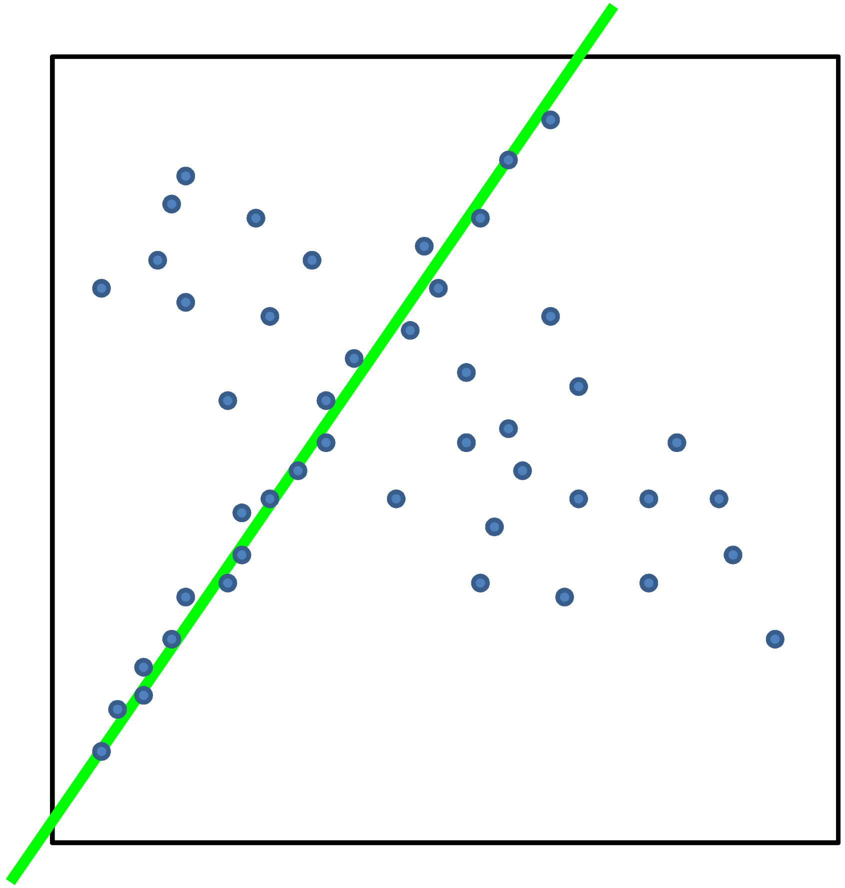


Counting inliers

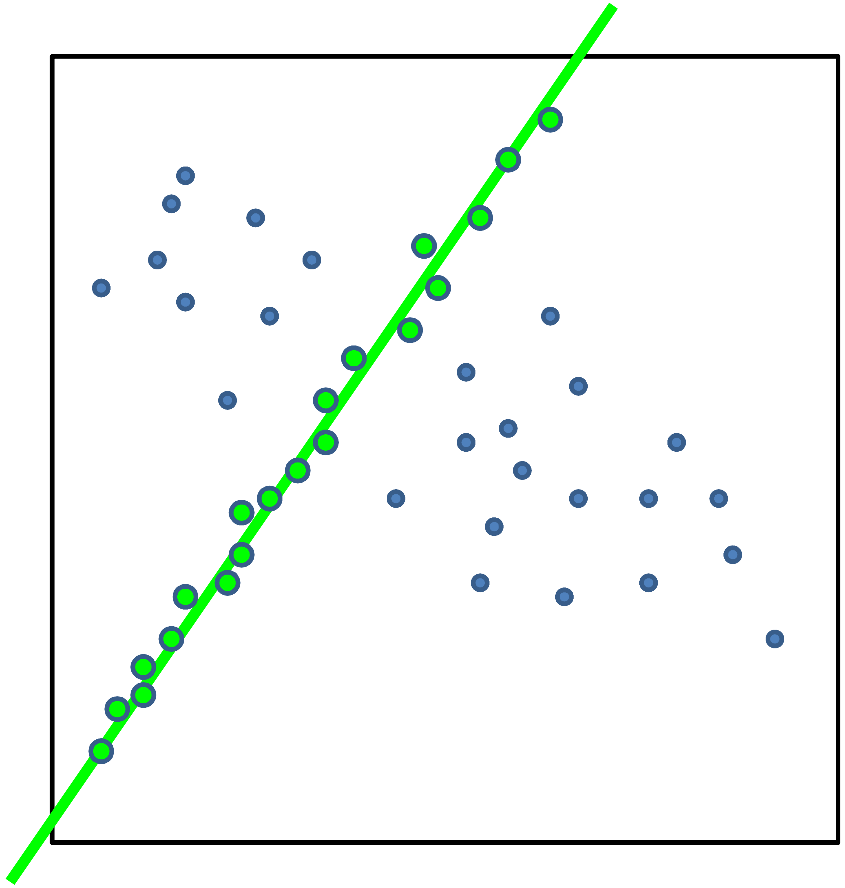


Inliers: 3

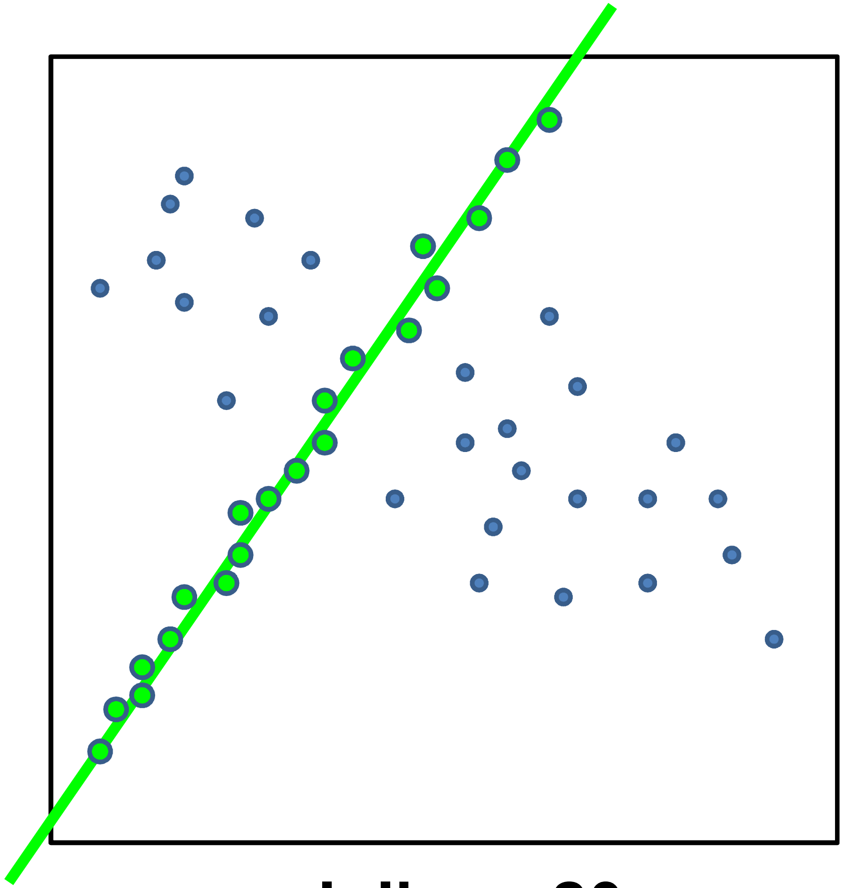
Counting inliers



Counting inliers



Counting inliers



Inliers: 20

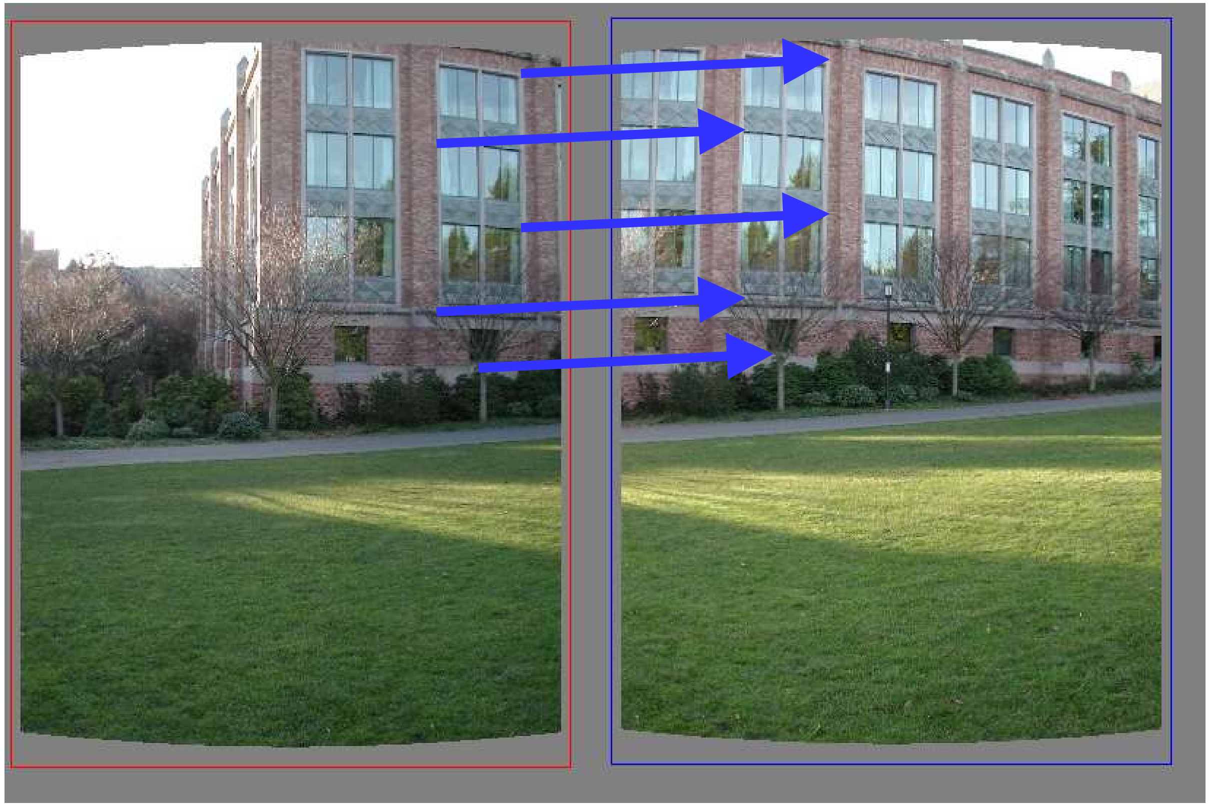
How do we find the best line?

- Unlike least-squares, no simple closed-form solution

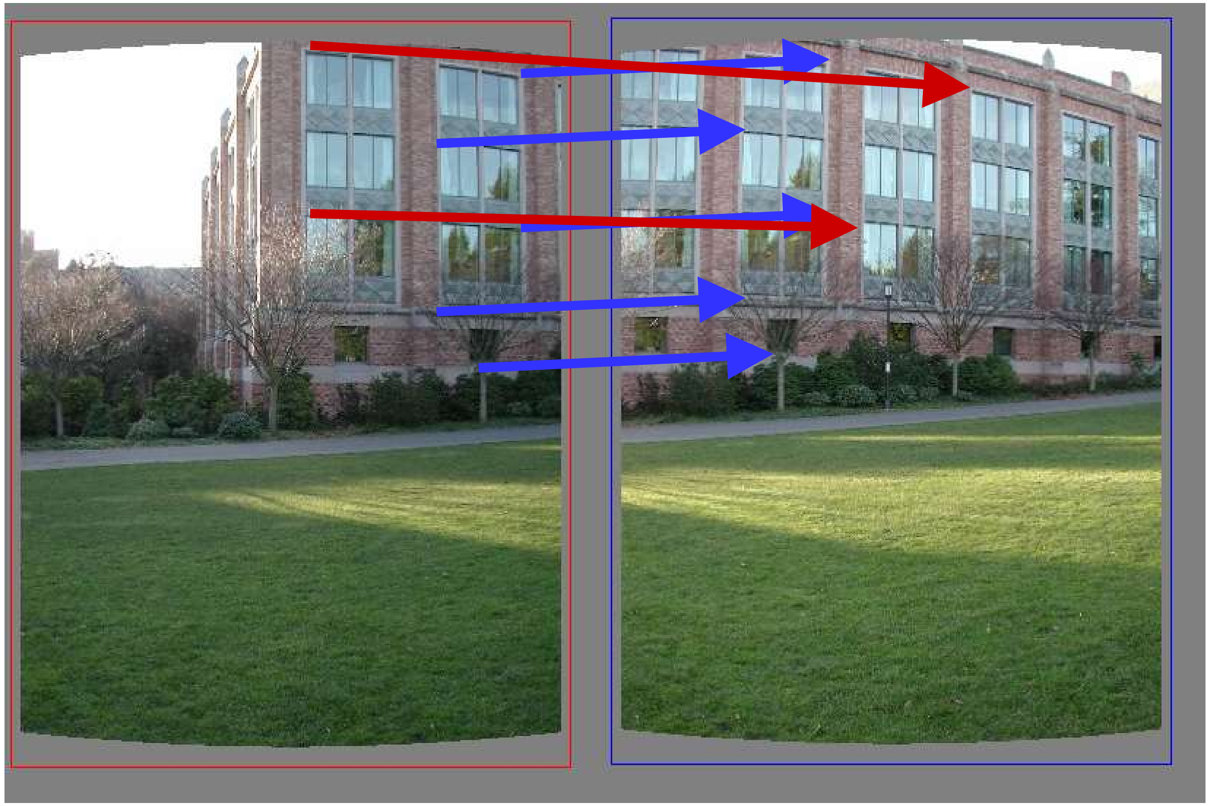
- Hypothesize-and-test
  - Try out many lines, keep the best one
  - Which lines?

Translations

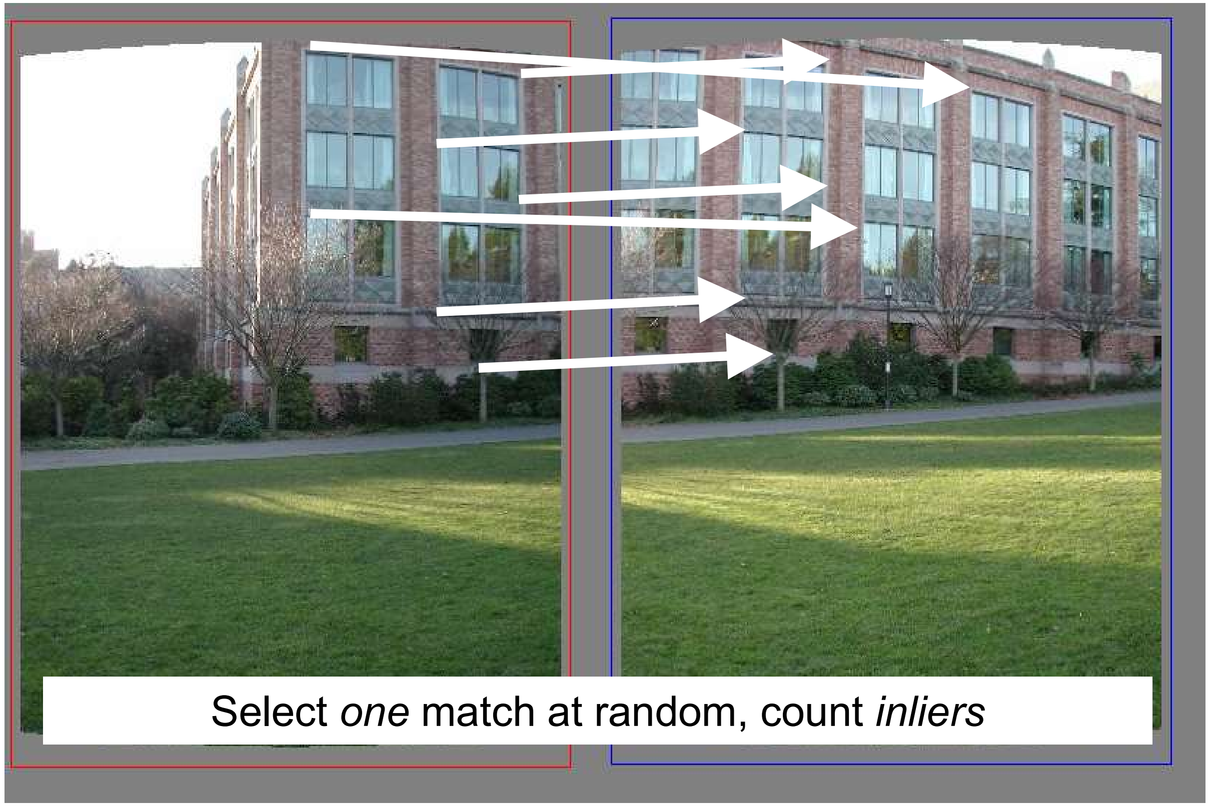
Translations



Translations

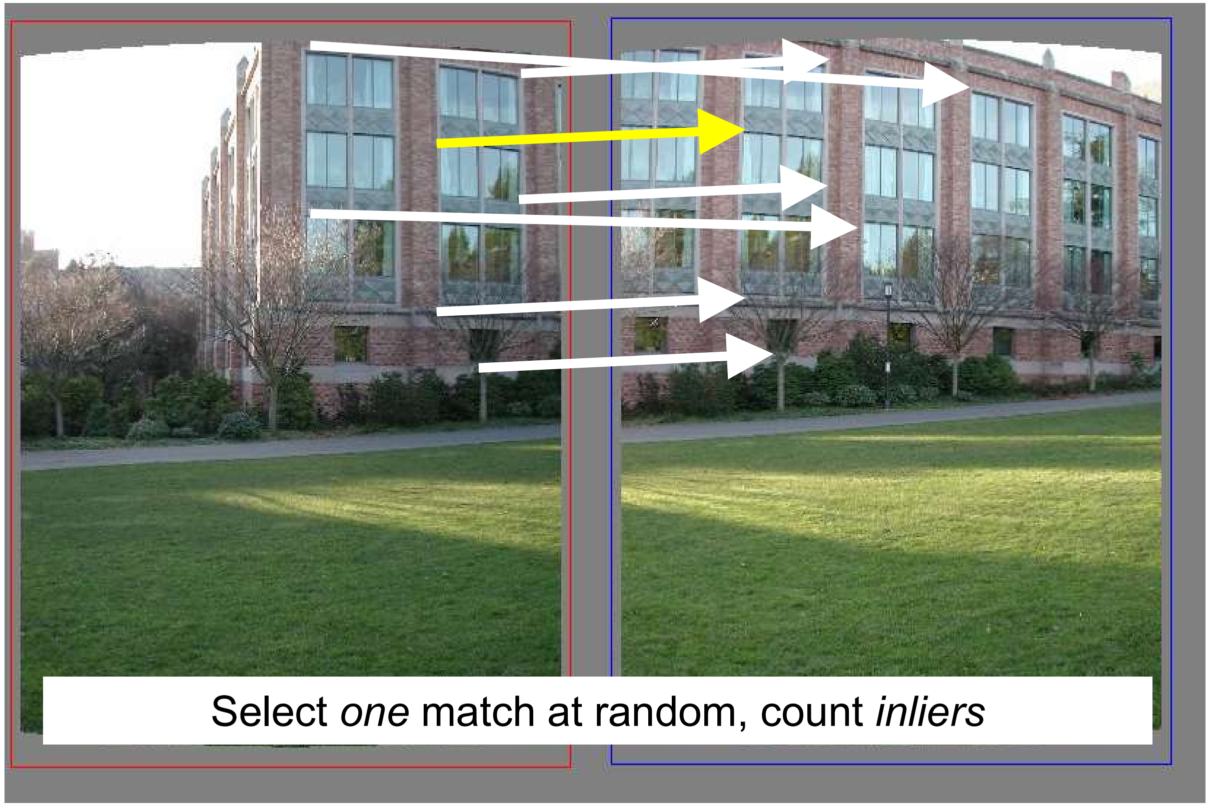


RANdom SAmple Consensus

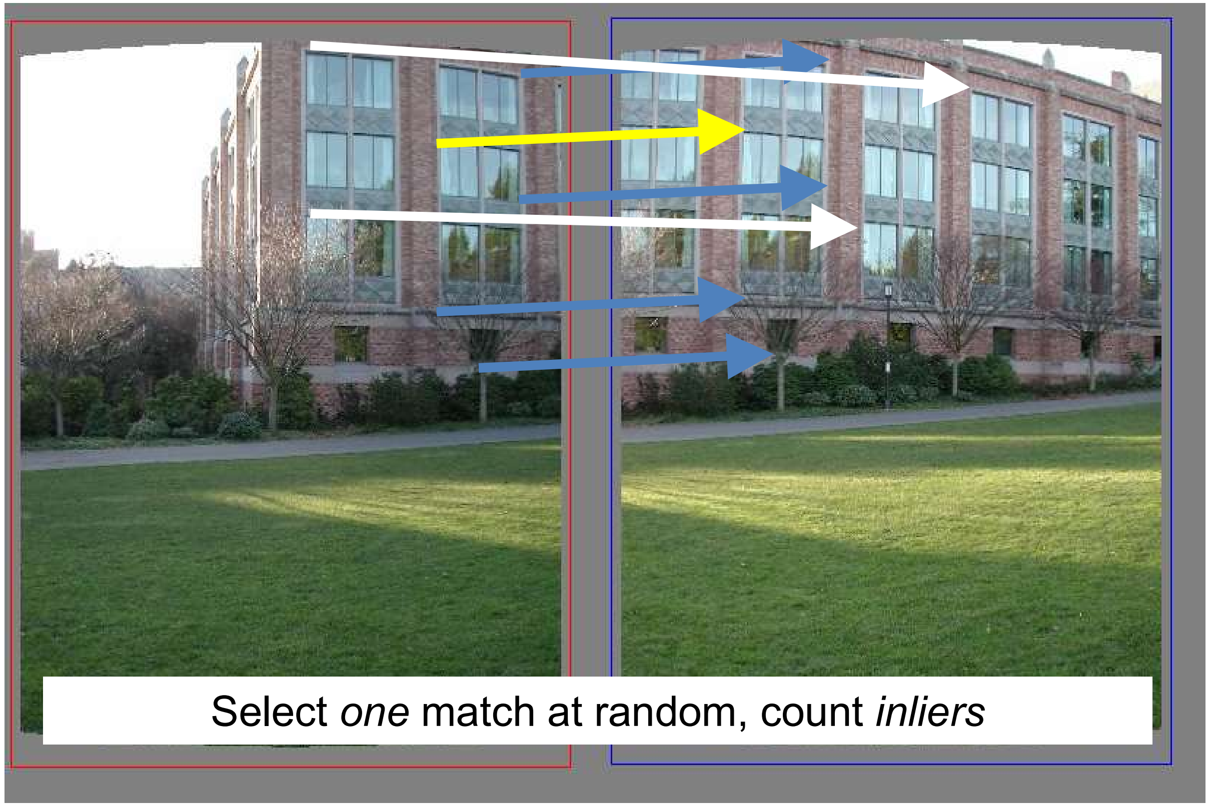


Select *one* match at random, count *inliers*

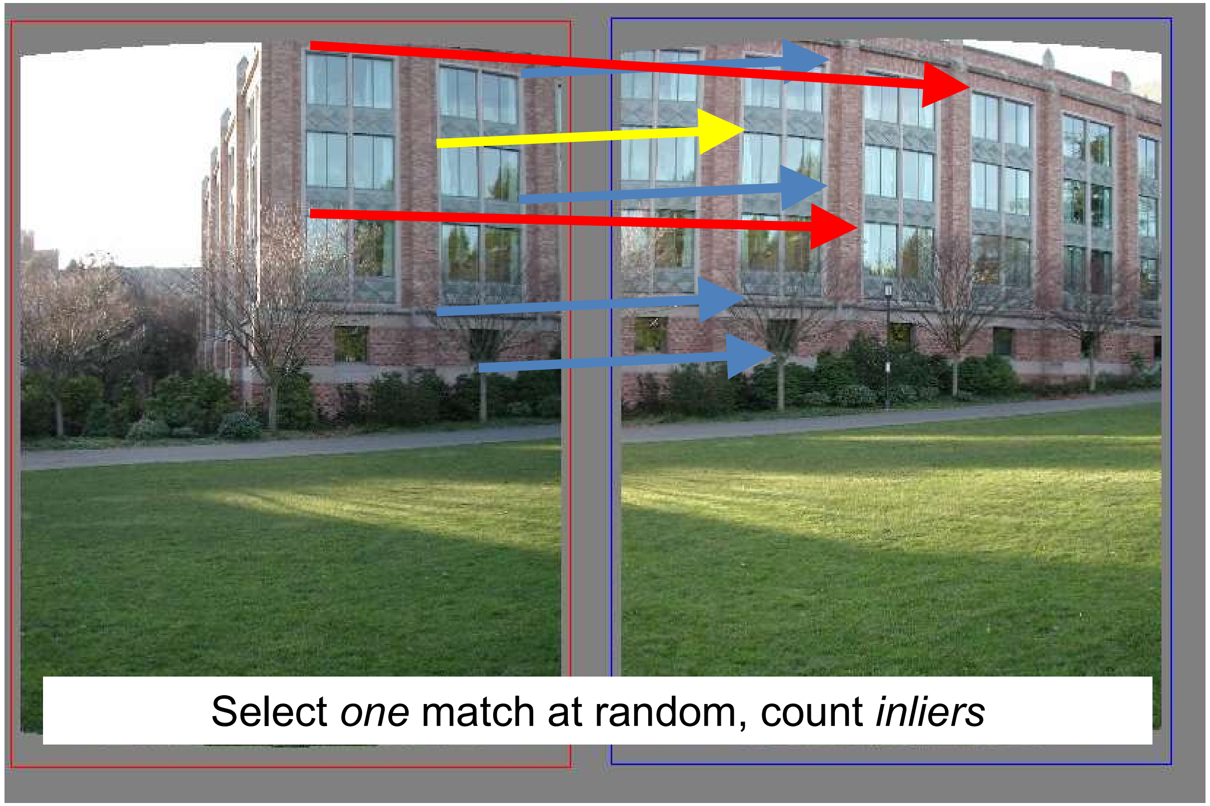
RANdom SAmple Consensus



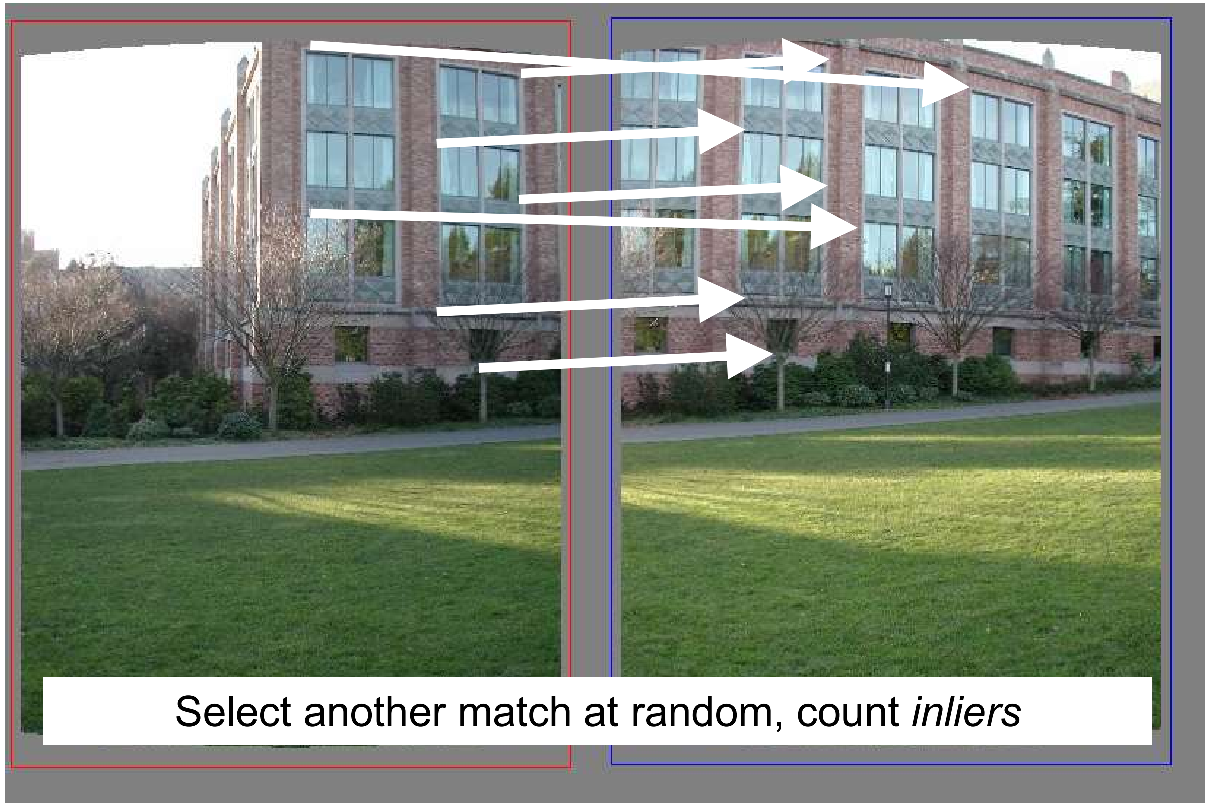
RANdom SAmple Consensus



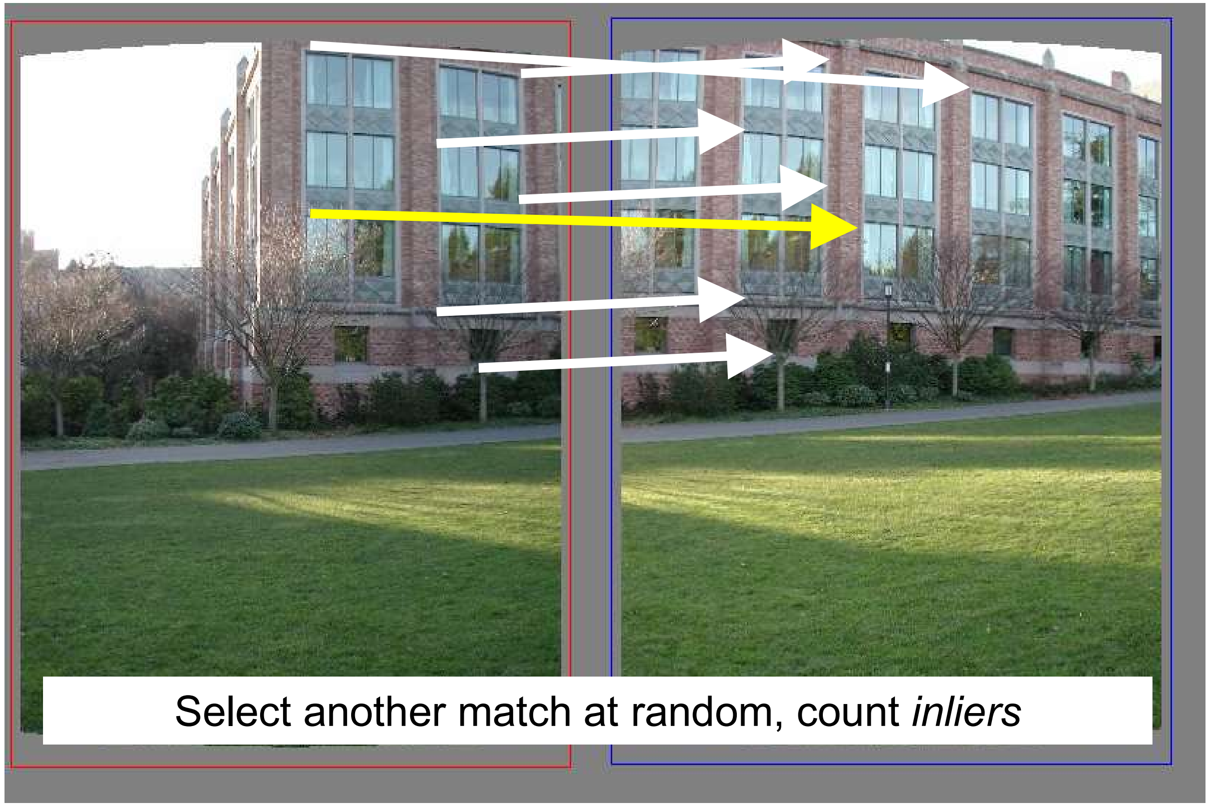
RANdom SAmple Consensus



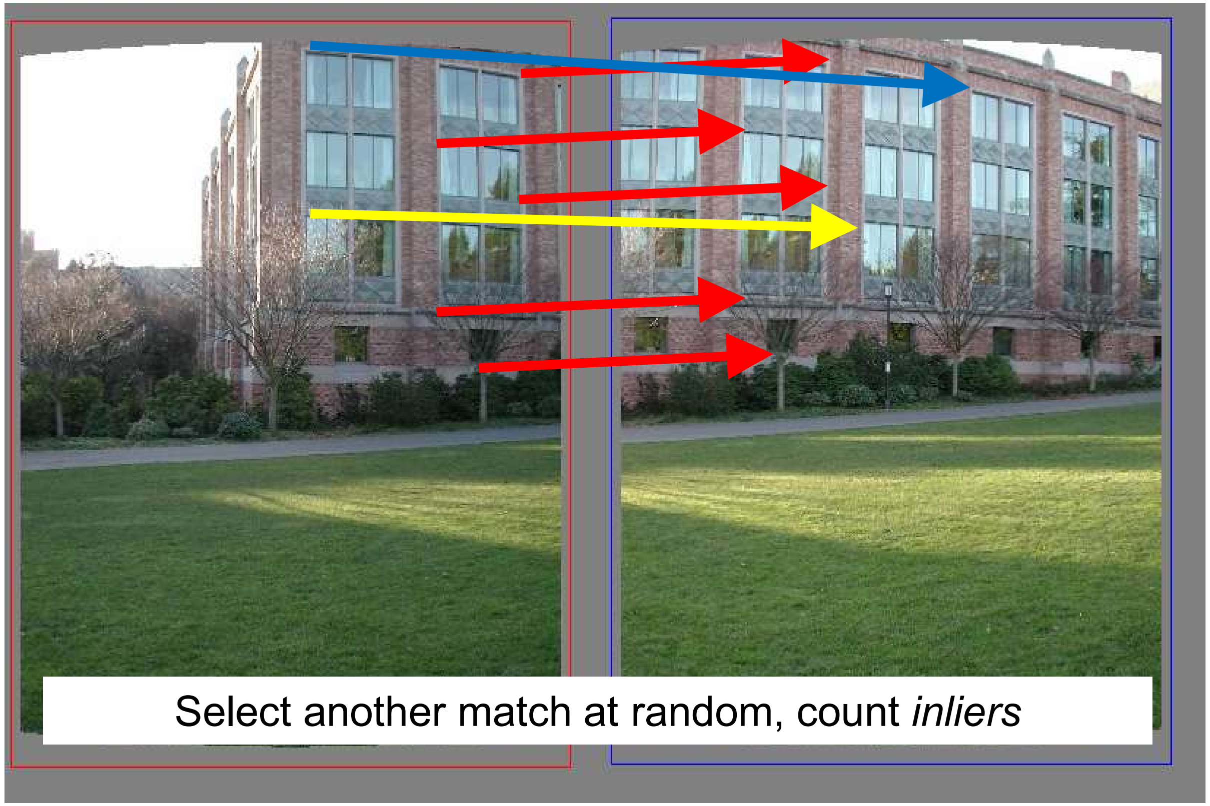
RANdom SAmple Consensus



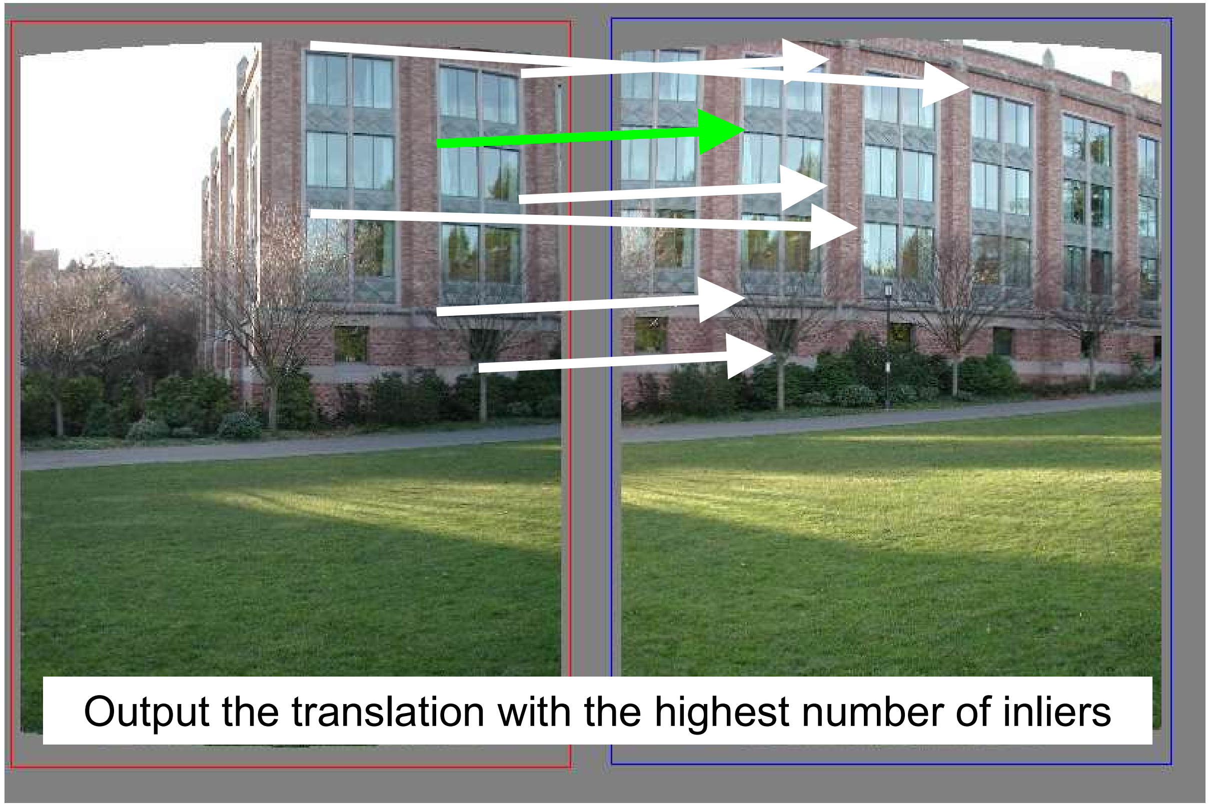
RANdom SAmple Consensus



RANdom SAmple Consensus



RANdom SAmple Consensus



RANSAC

- **Inlier threshold** related to the amount of noise we expect in inliers
  - Often model noise as Gaussian w/ some standard deviation (e.g. 3 pixels)
- **Number of rounds** related to the percentage of outliers we expect, and the probability of success we'd like to guarantee
  - Suppose there are 20% outliers, and we want to find the correct answer with 99% probability
  - How many rounds do we need?

RANSAC pros and cons

- **Pros**
  - Simple and general
  - Applicable to many different problems
  - Often works well in practice
- **Cons**
  - Parameters to tune
  - Sometimes too many iterations are required
  - Can fail for extremely low inlier ratios
  - We can often do better than brute-force sampling

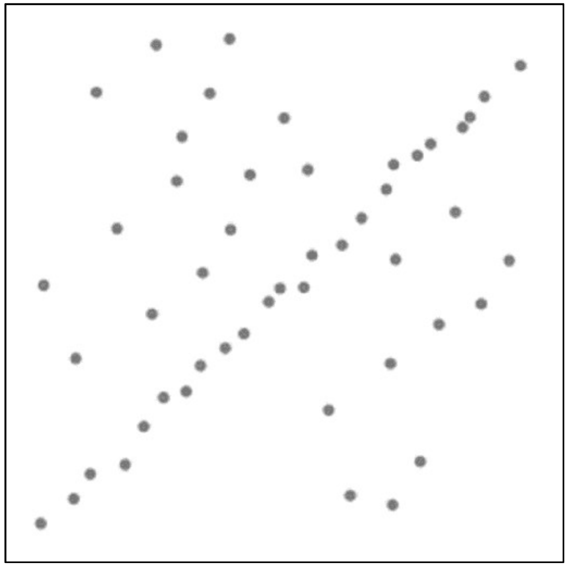
RANSAC

- Idea:
  - All the inliers will agree with each other on the translation vector; the (hopefully small) number of outliers will (hopefully) disagree with each other

- RANSAC only has guarantees if there are < 50% outliers

Fitline OpenCV

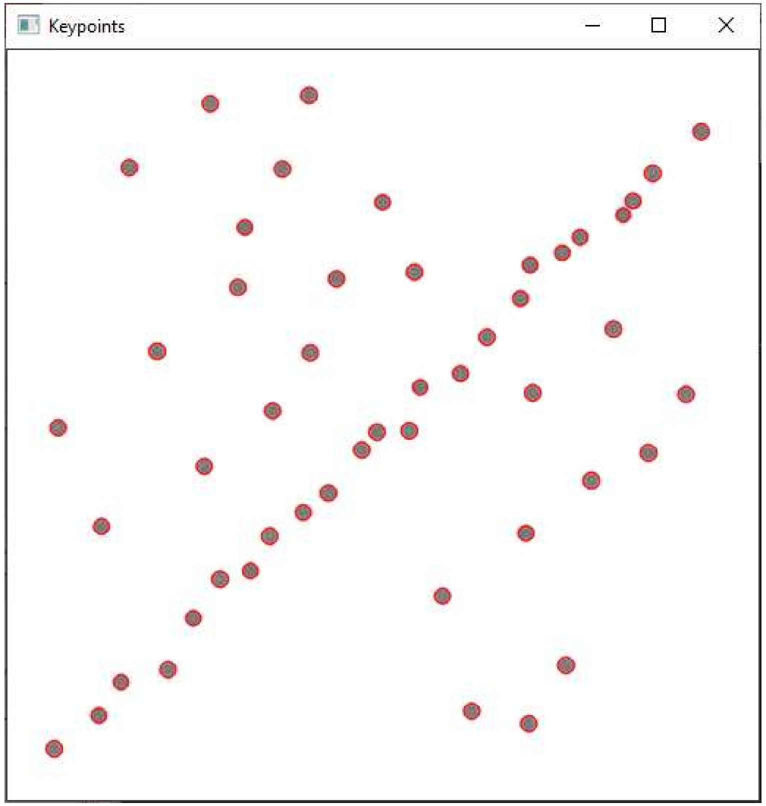
```
import cv2 as cv
import numpy as np;

# Read image
im = cv.imread("punti.png", cv.IMREAD_GRAYSCALE)

# Setup SimpleBlobDetector parameters.
params = cv.SimpleBlobDetector_Params()

# Change thresholds
params.minThreshold = 10;
params.maxThreshold = 200;

# Set up the detector with default parameters.
detector = cv.SimpleBlobDetector_create(params)

# Detect blobs.
keypoints = detector.detect(im)

v = []
for elem in keypoints:
    #print(elem.pt[0])
    v.append([elem.pt[0],elem.pt[1]])

points = np.array(v)
```



punti.png

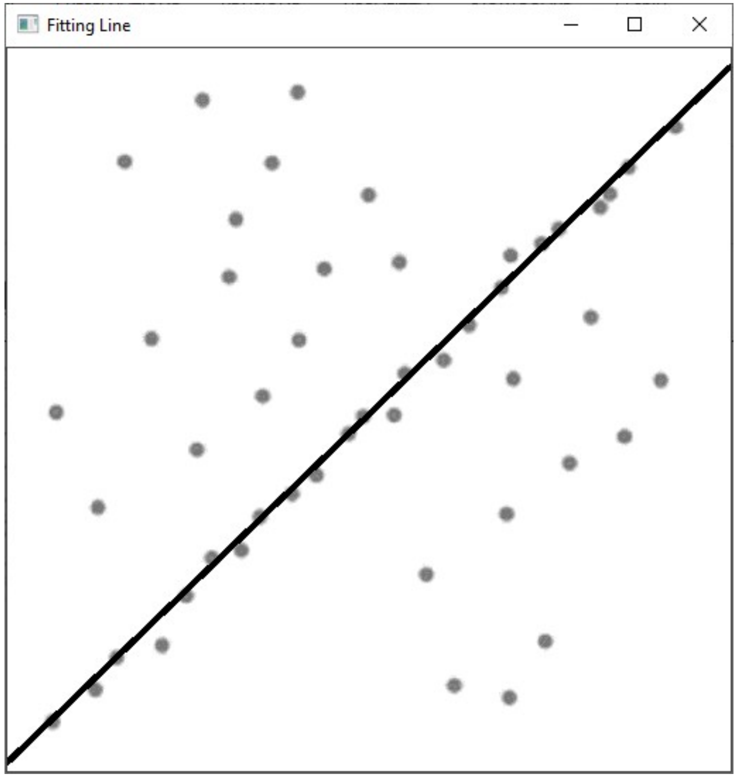
Fitline OpenCV

```
# Draw detected blobs as red circles.
# cv2.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS ensures the size of the circle corresponds to the size of blob
im_with_keypoints = cv.drawKeypoints(im, keypoints, np.array([]), (0,0,255), cv.DRAW_MATCHES_FLAGS_DRAW_RICH_KEYPOINTS)

# Show keypoints
cv.imshow("Keypoints", im_with_keypoints)
cv.waitKey(0)
```



Fitline OpenCV

```
# Show keypoints
cv.imshow("Keypoints", im_with_keypoints)
cv.waitKey(0)

vx, vy, x, y = cv.fitLine(np.float32(points),cv.DIST_L12, 0, 0.01, 0.01);

line = [float(vx),float(vy),float(x),float(y)]

left_pt = int((-x*vy/vx) + y)
right_pt = int(((im.shape[1]-x)*vy/vx)+y)
cv.line(im,(im.shape[1]-1,right_pt),(0,left_pt),0,3,cv.LINE_8)

# Show keypoints
cv.imshow("Fitting Line", im)
cv.waitKey(0)
```



Panoramas

- Now we know how to create panoramas!

- Given two images:
  - Step 1: Detect features
  - Step 2: Match features
  - Step 3: Compute a homography using RANSAC
  - Step 4: Combine the images together (somehow)

What if we have more than two images?

UNIVERSITÀ DEGLI STUDI
DELLA BASILICATA



Corso di Visione e Percezione

Docente
Domenico D. Bloisi

Feature Matching