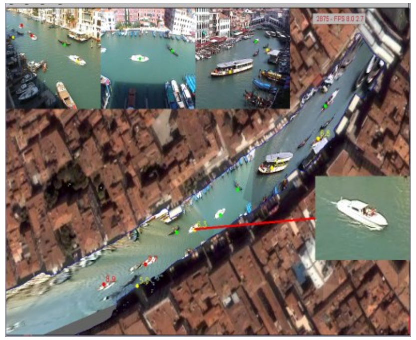
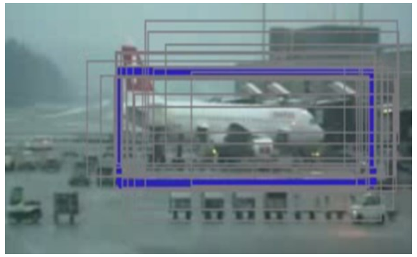
UNIVERSITÀ DEGLI STUDI DELLA BASILICATA

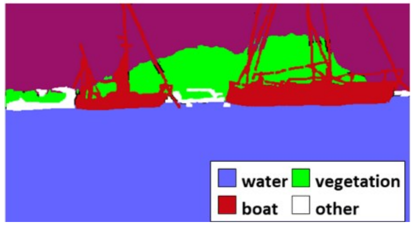
Corso di Visione e Percezione
A.A. 2019/2020

Docente
Domenico Daniele Bloisi

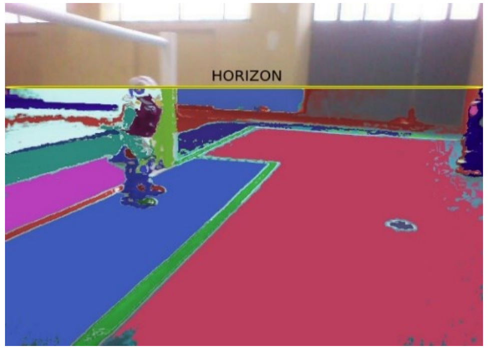


Feature Matching





Aprile 2020



Il corso

- Home page del corso
  http://web.unibas.it/bloisi/corsi/visione-e-percezione.html

- Docente: Domenico Daniele Bloisi

- Periodo: II semestre marzo 2020 – giugno 2020

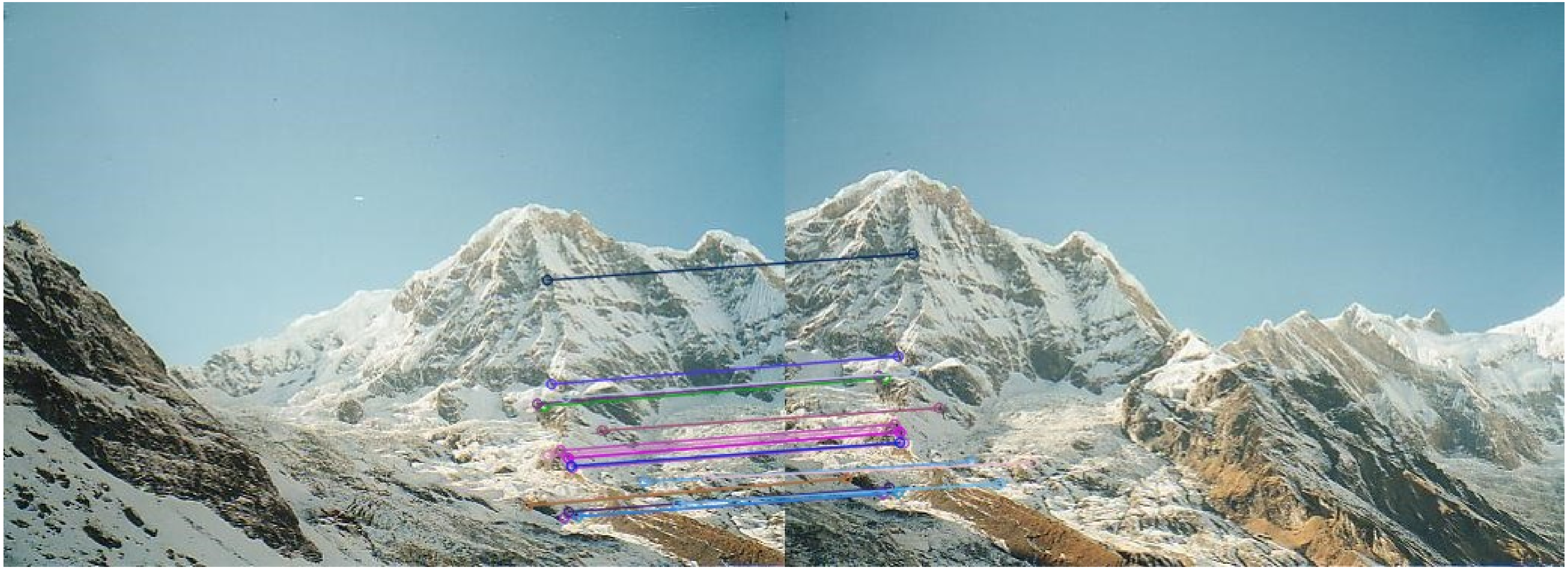
  Martedì 17:00-19:00 (Aula GUGLIELMINI)
  Mercoledì 8:30-10:30 (Aula GUGLIELMINI)

Riferimenti

- Queste slide sono adattate da
  Noah Snavely - CS5670: Computer Vision
  "Lecture 5: Feature descriptors and matching“
  "Lecture 7: Transformations and warping"

- 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

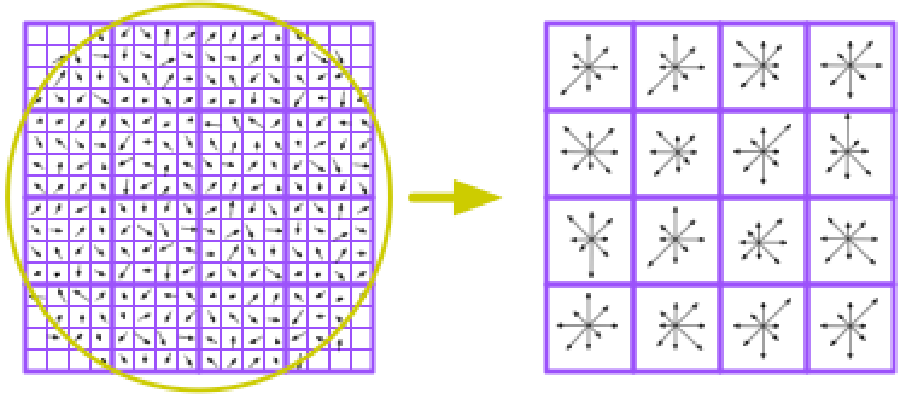
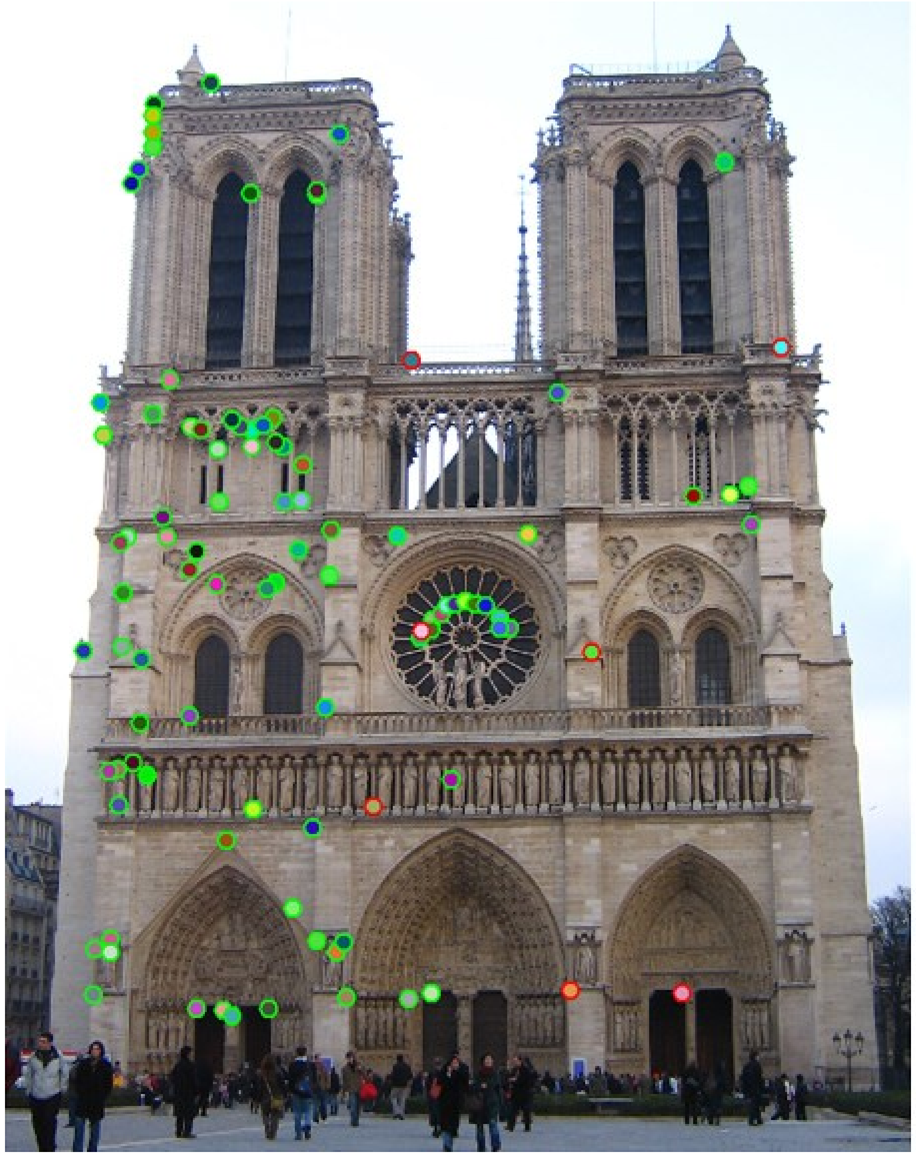
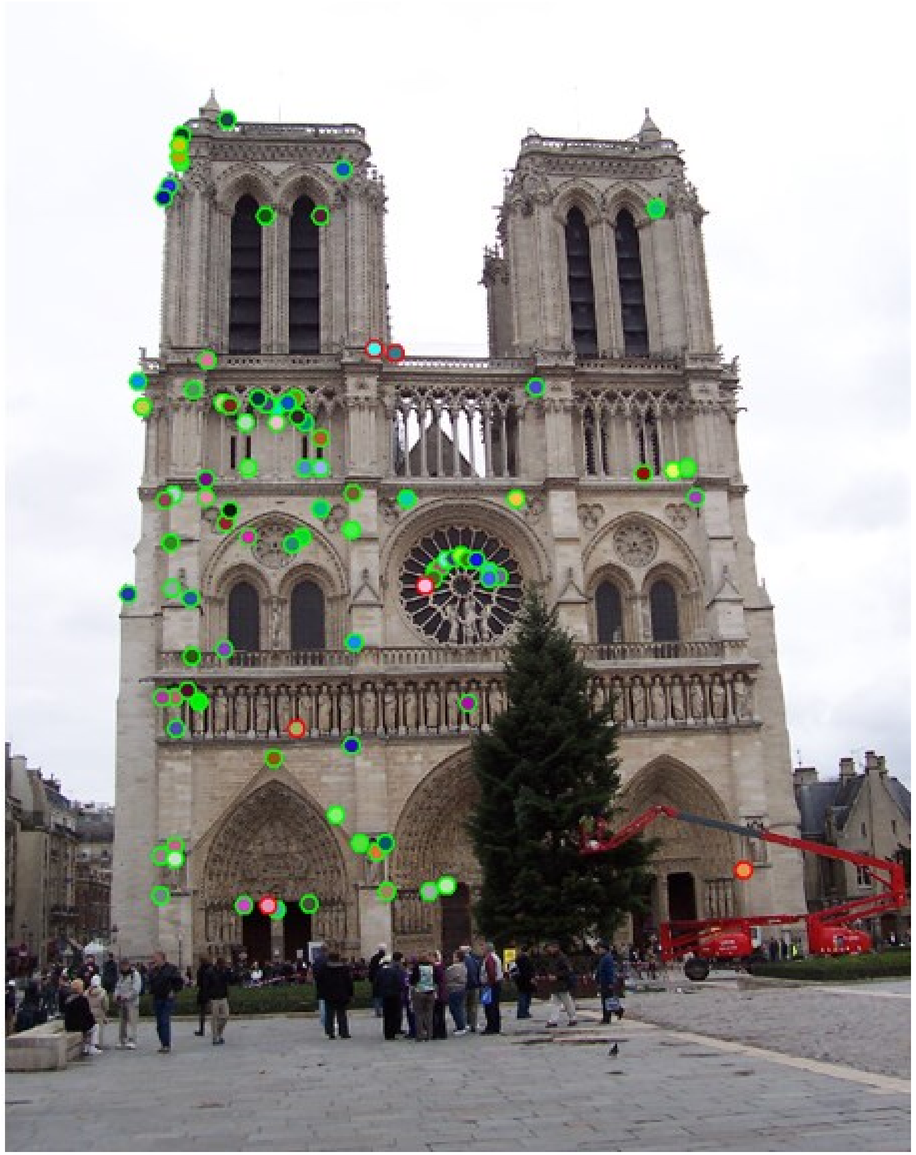


Image gradients Keypoint descriptor

Which features match?

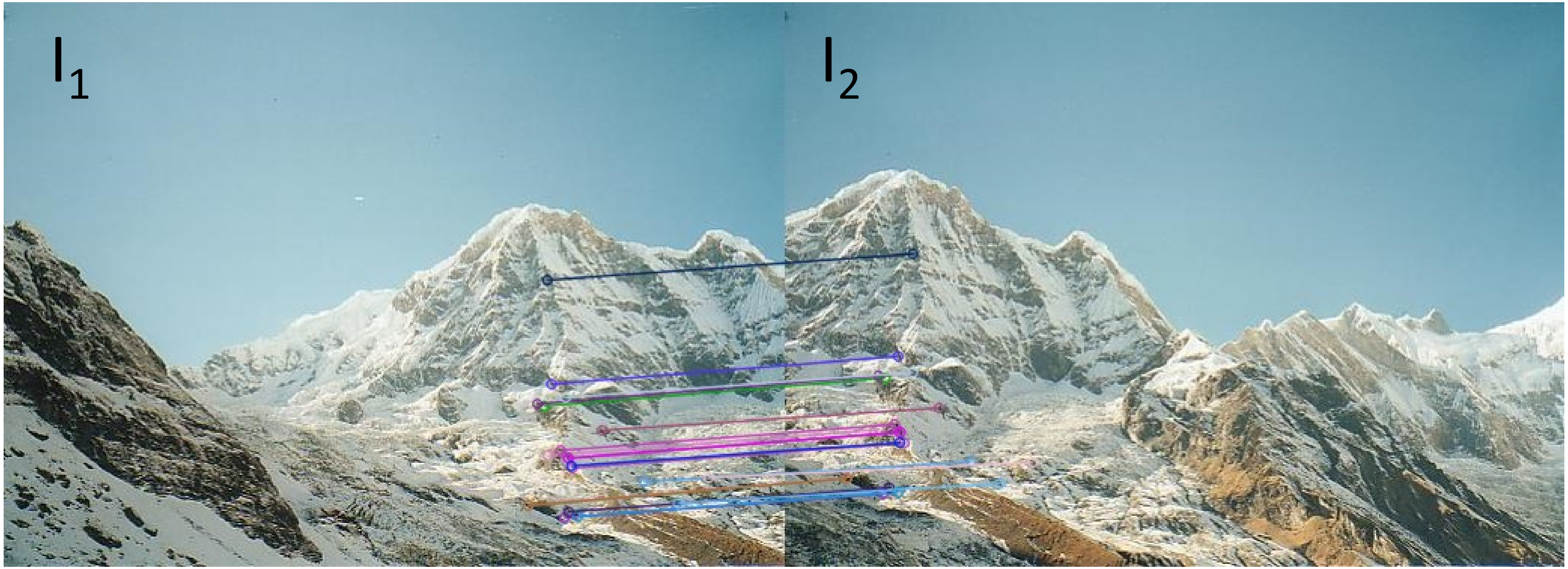




Features matching

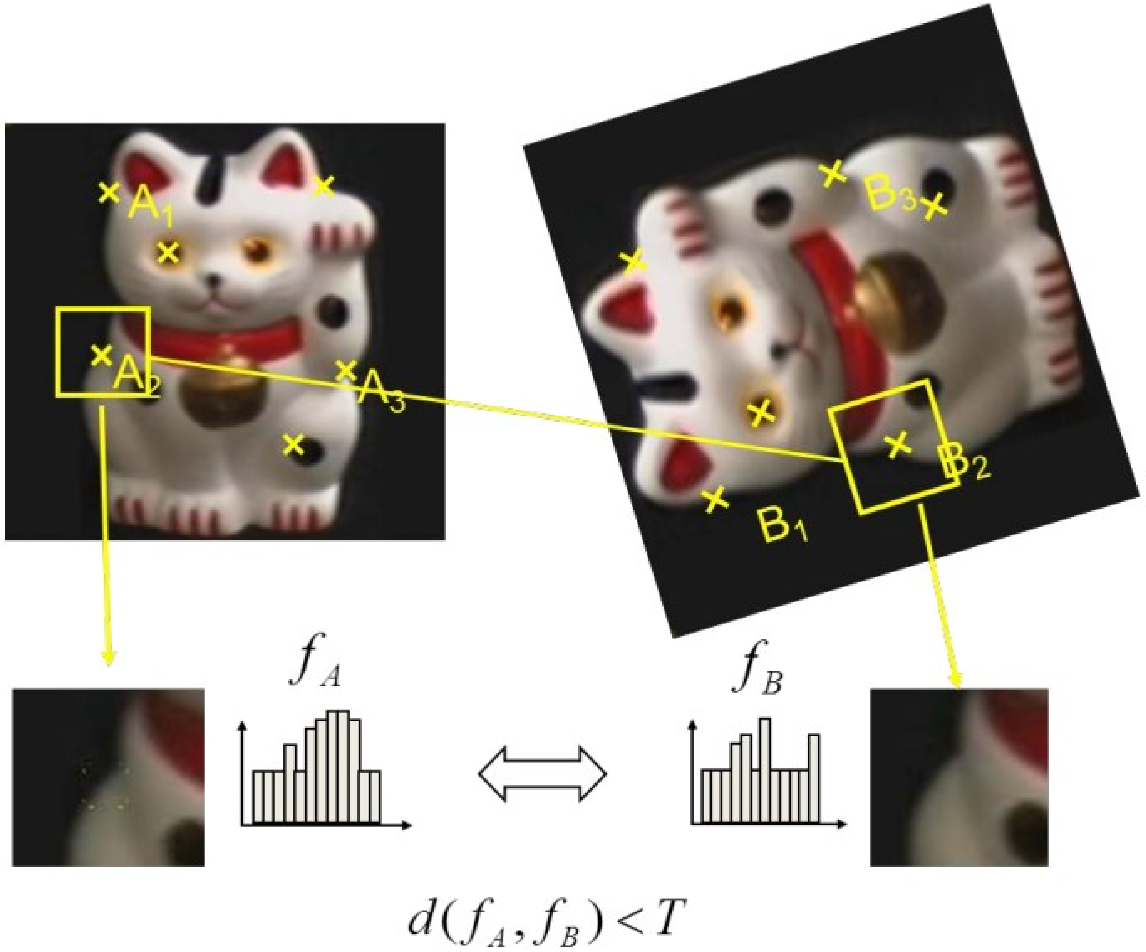
Given a feature in I_1, how to find the best match in I_2?

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):

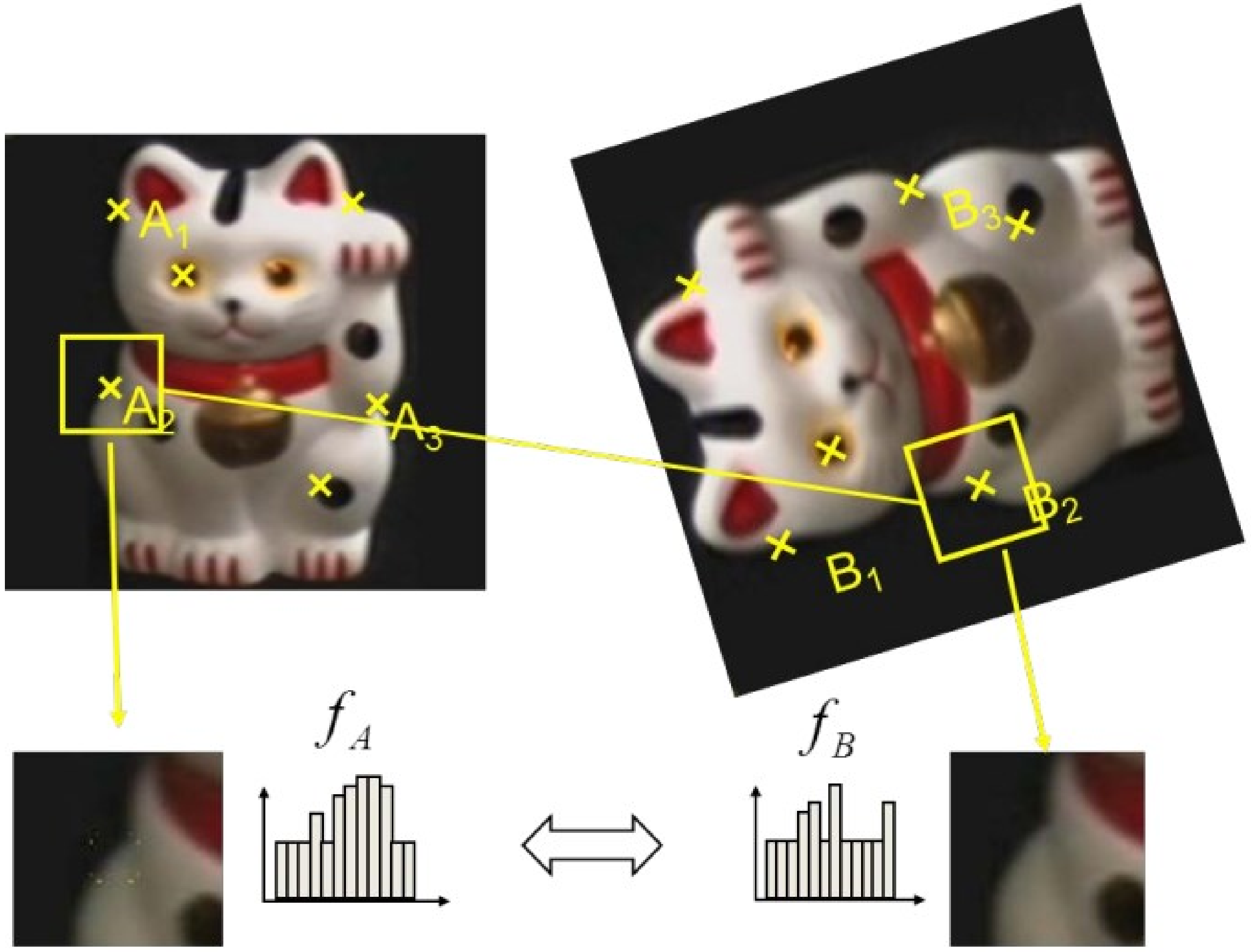
$$d(f_a, f_b) = \sum |f_a - f_b|$$

- L_2 distance (SSD):

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

- Hamming distance:

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



$$f_A \qquad f_B$$

$$d(f_A, f_B) < T$$

Source: Trym Vegard Haavardsholm

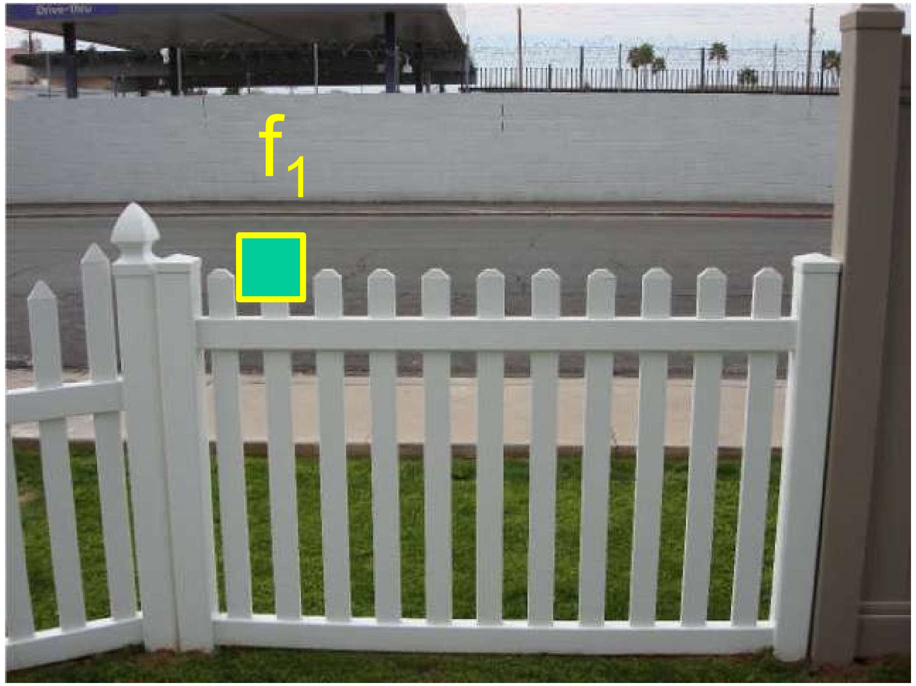
Features distance: SSD

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

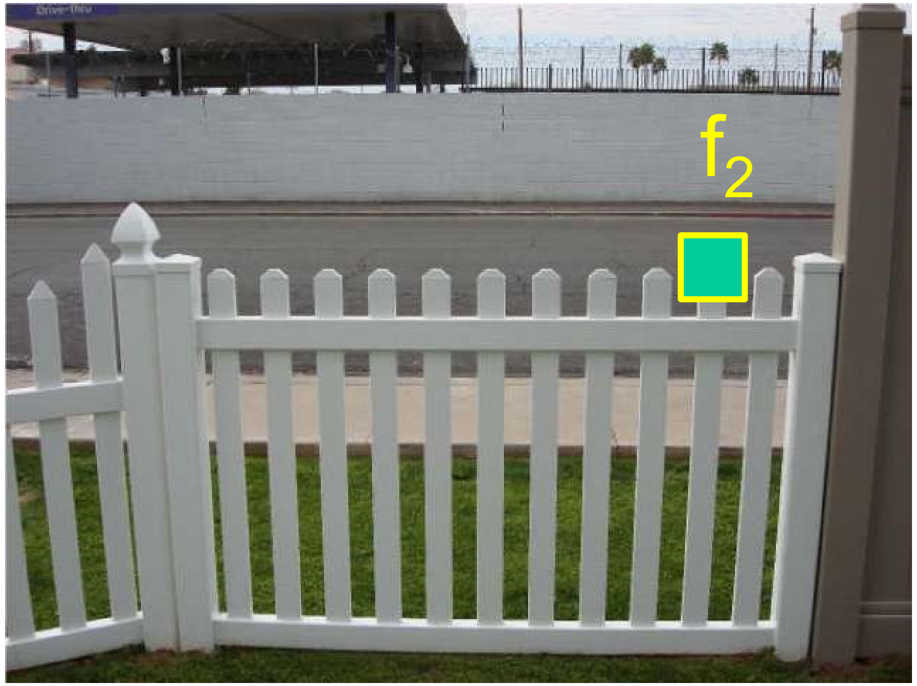
- Simple approach: L_2 distance, $||f_1 - f_2||$

  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

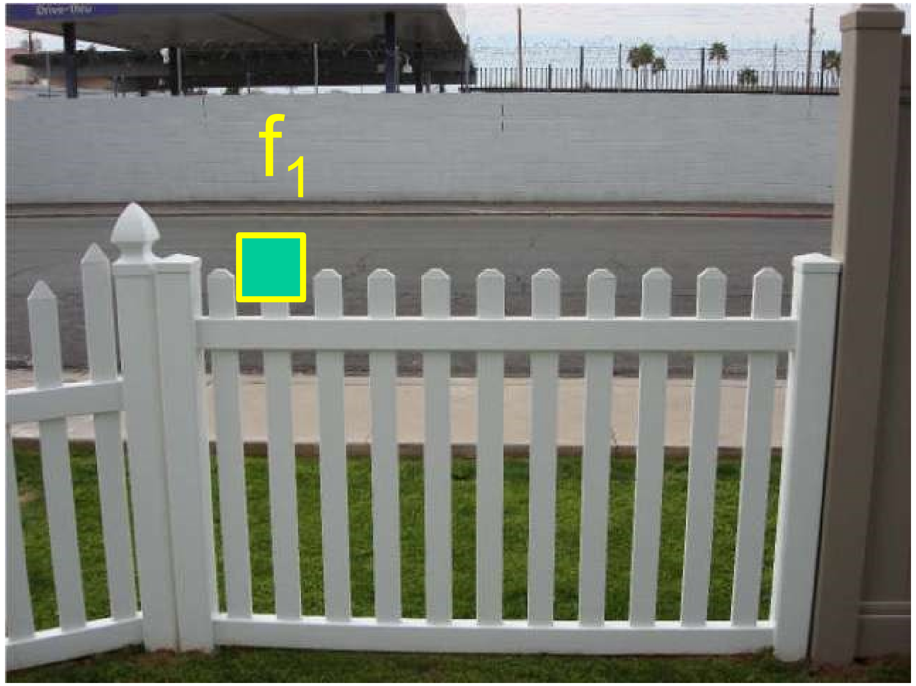


I_2

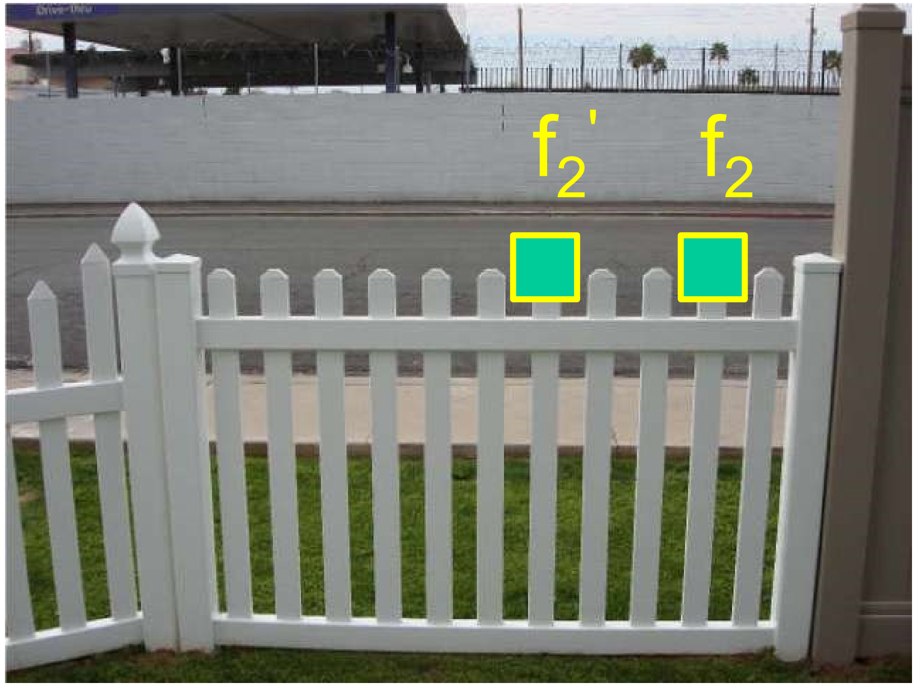
Features distance: Ratio of SSDs

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



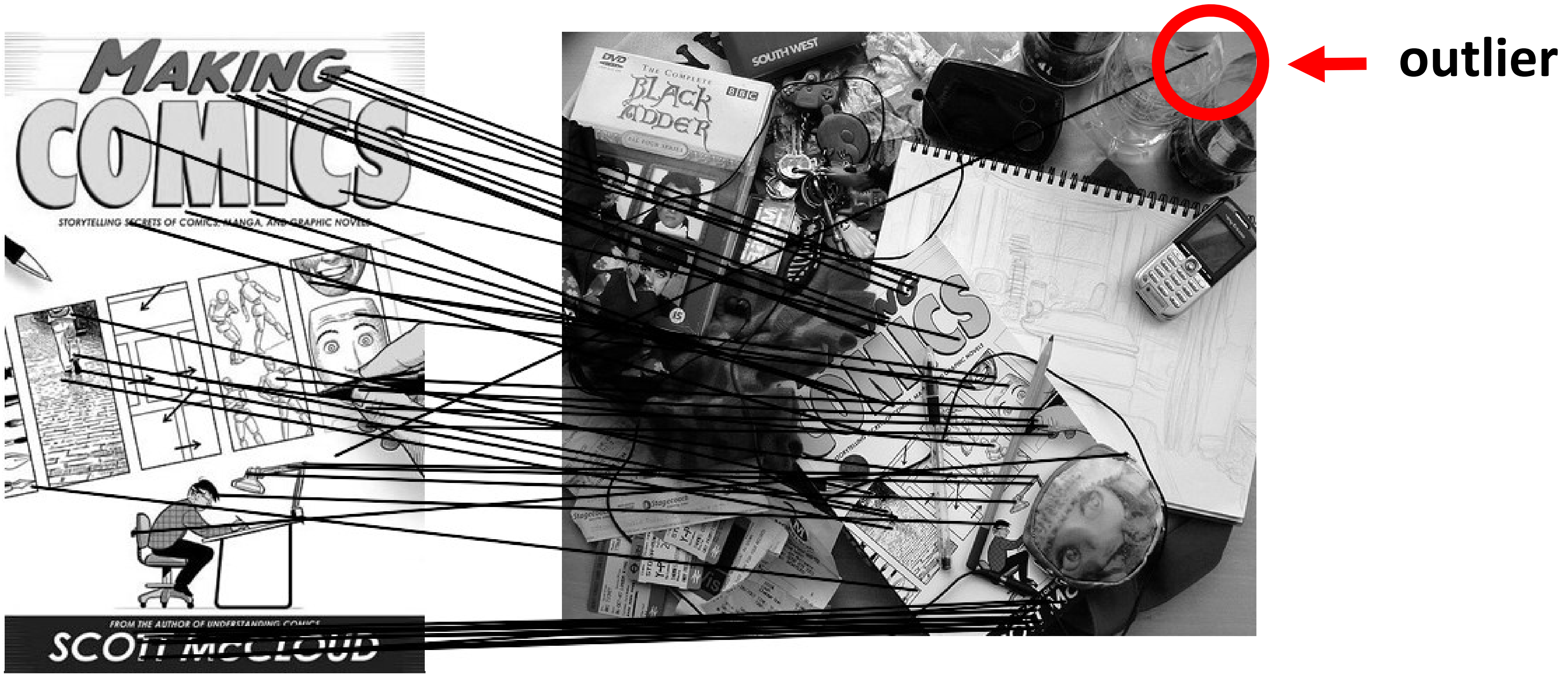
I_2

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

Feature matching example

58 matches (thresholded by ratio score)

Feature matching example

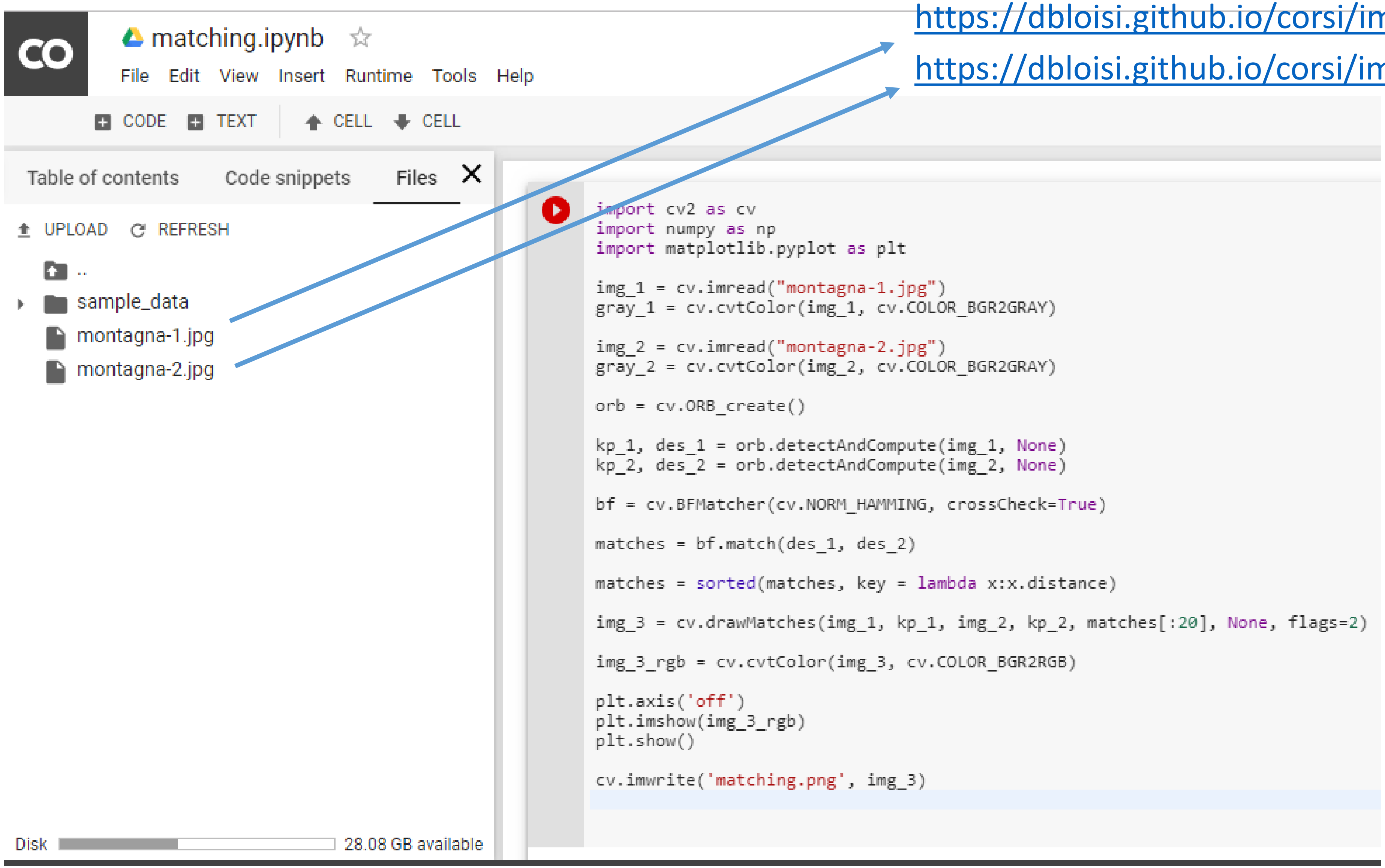


51 matches (thresholded by ratio score)

Example in Colab

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

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



Example in Colab: ORB detection

```
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)
```

Example in Colab: 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.

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

matches = bf.match(des_1, des_2)

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

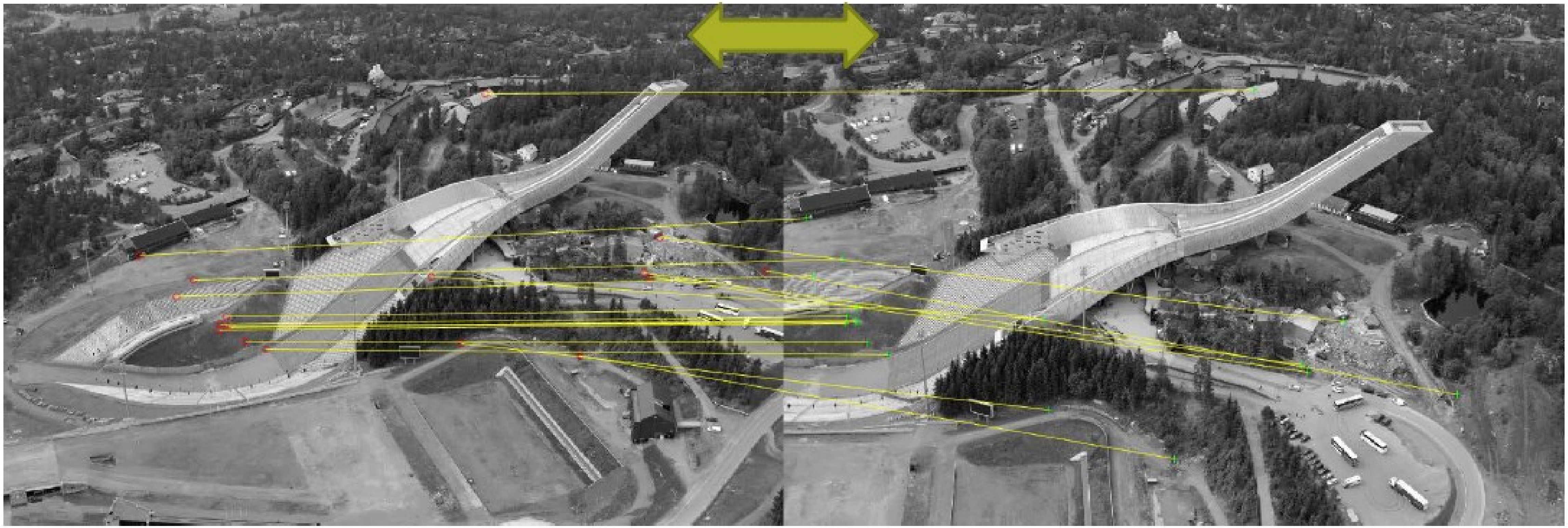
Cross check test

- 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

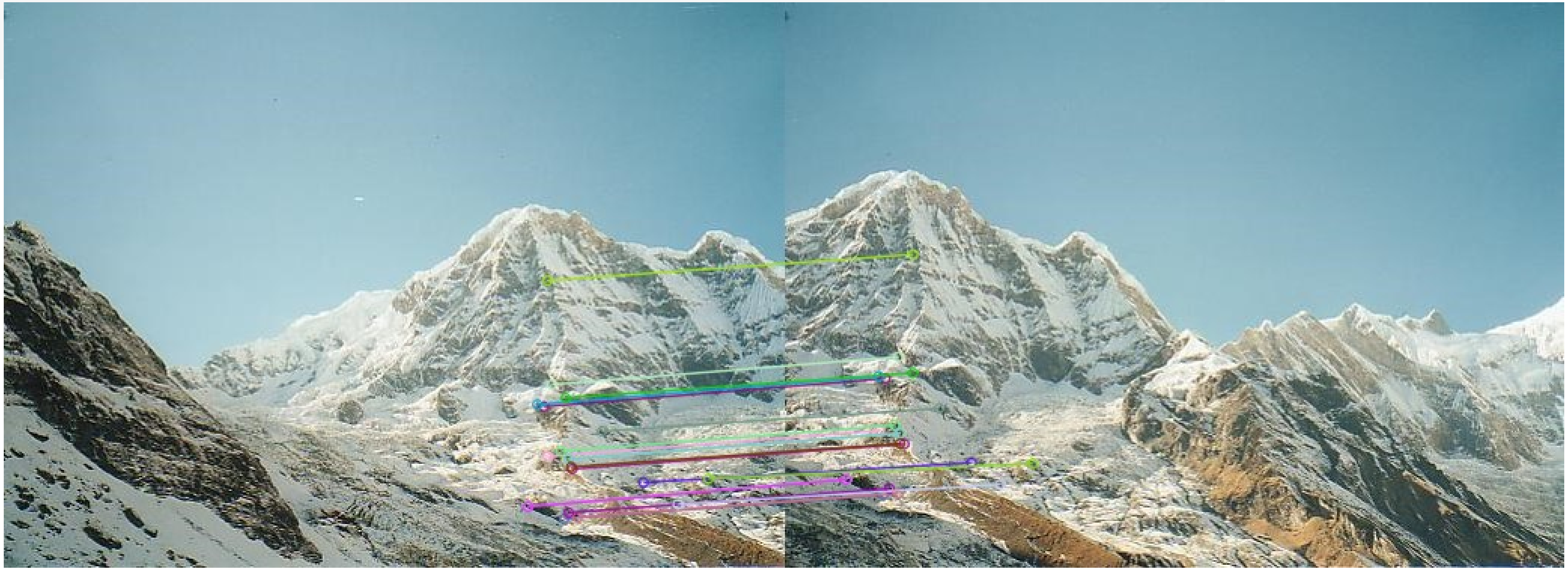
Example in Colab: sorting

```
bf = cv.BFMatcher(cv.NORM_HAMMING, crossCheck=True)
matches = bf.match(des_1, des_2)
matches = sorted(matches, key = lambda x:x.distance)
```

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

Example in Colab: 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)
```

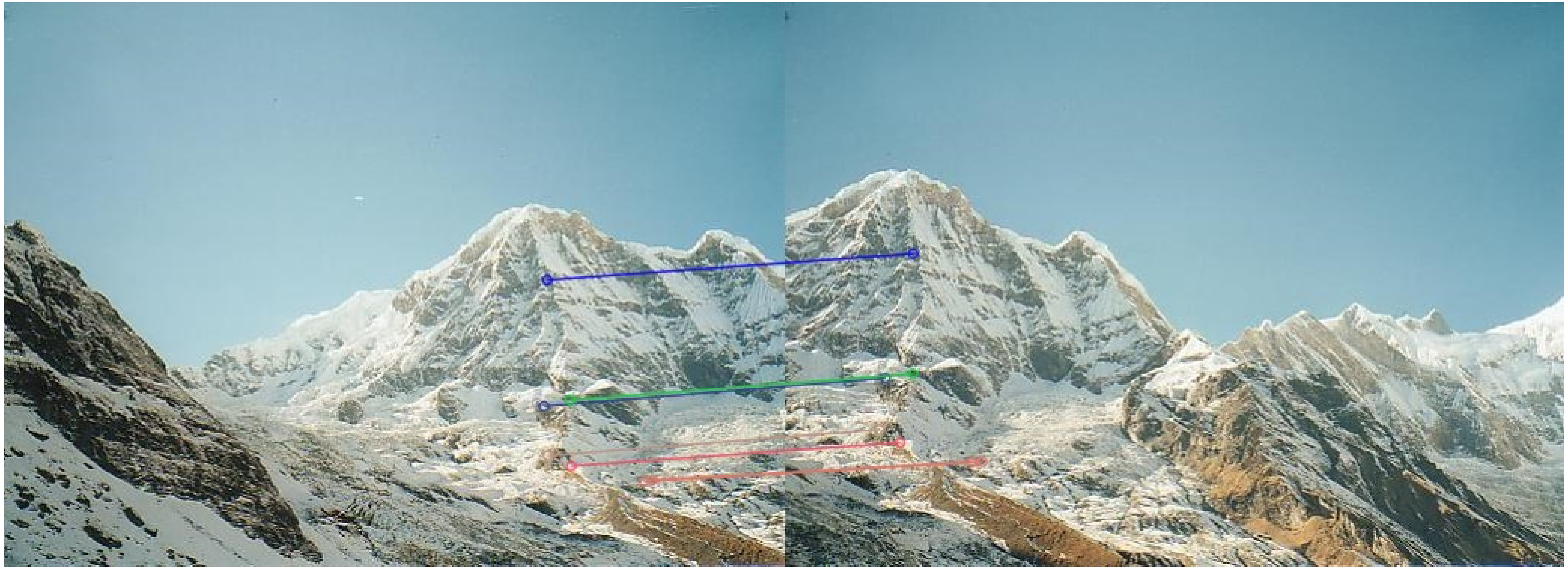


Example in Colab: ratio test

```
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)
```

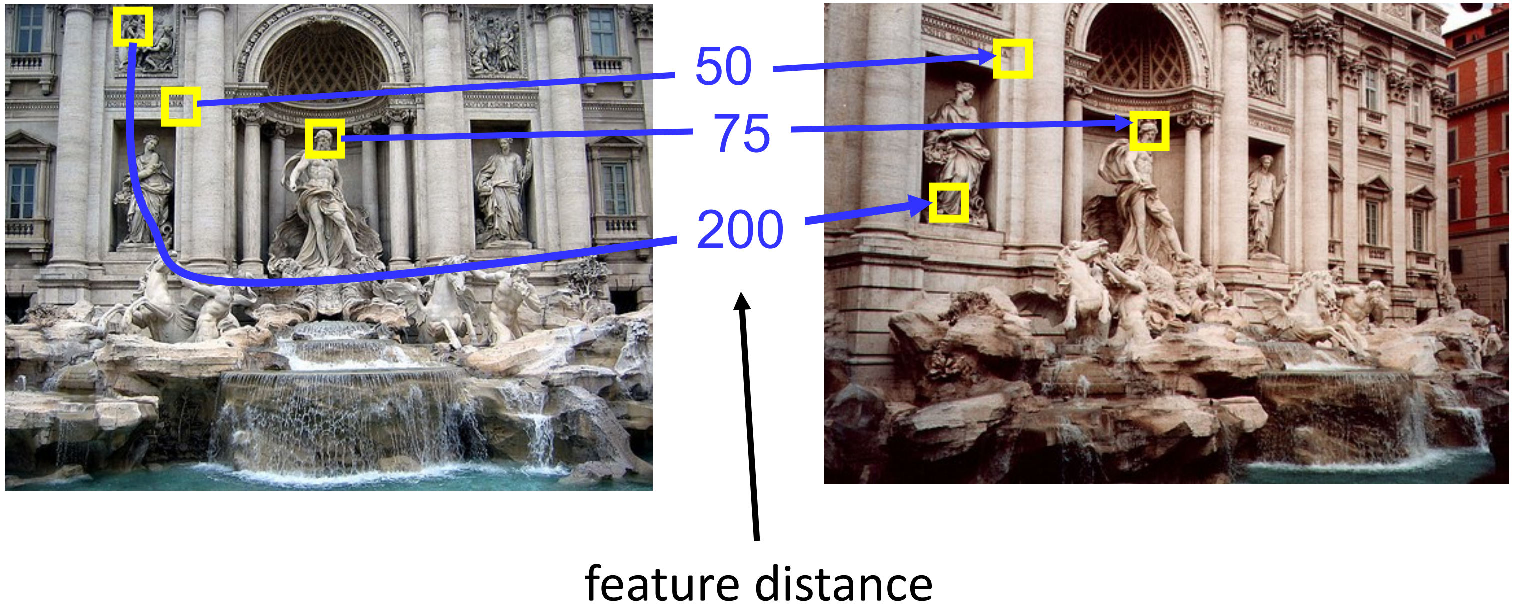
BFMatcher.knnMatch() to get k best matches. In this example, we will take k=2 so that we can apply ratio test

Example in Colab: ratio test results



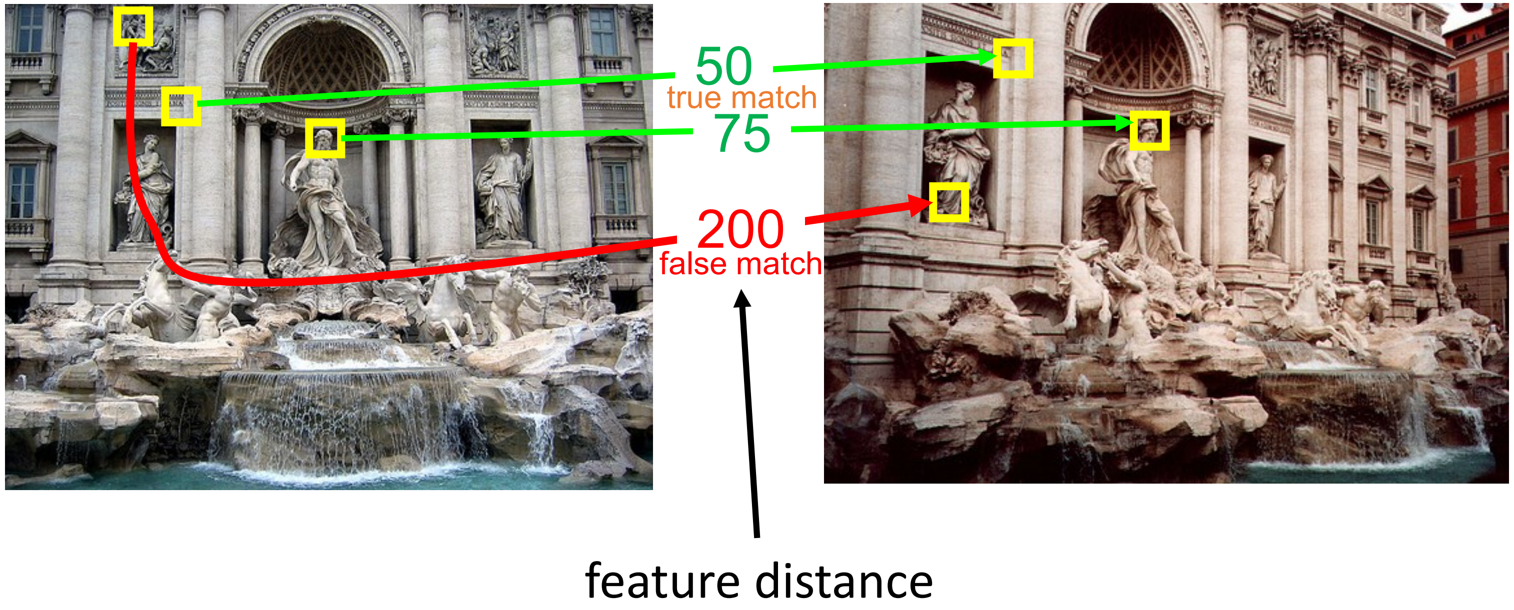
Evaluating the results

How can we measure the performance of a feature matcher?



True/false positives

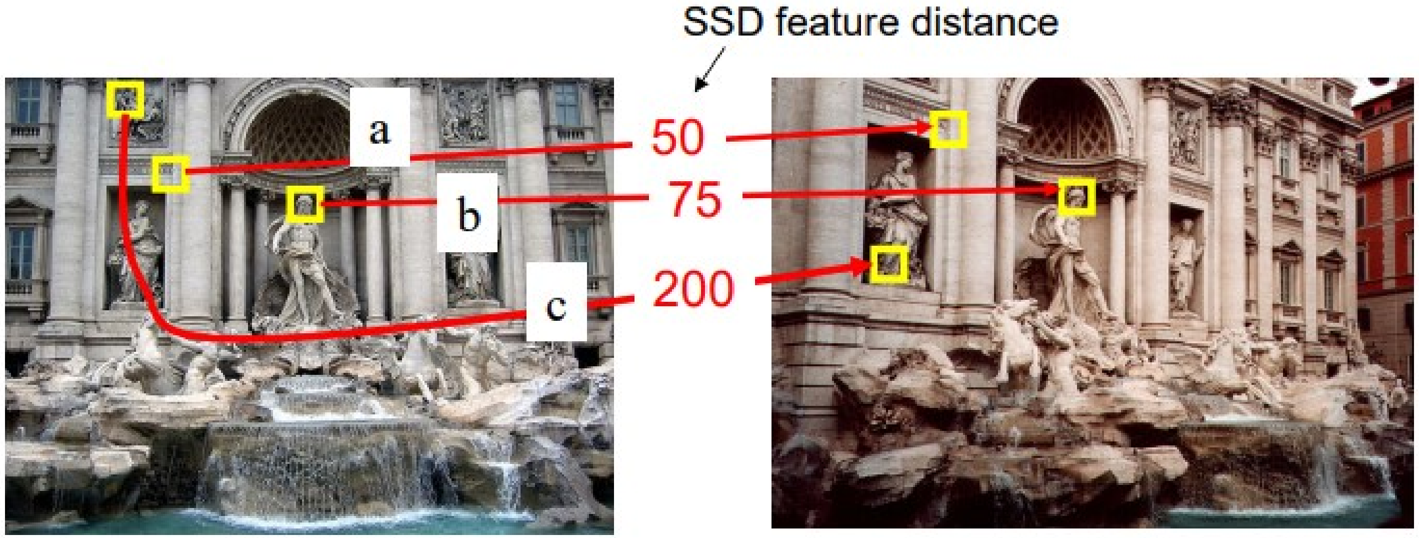
How can we measure the performance of a feature matcher?



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?

Effect of threshold T



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**")

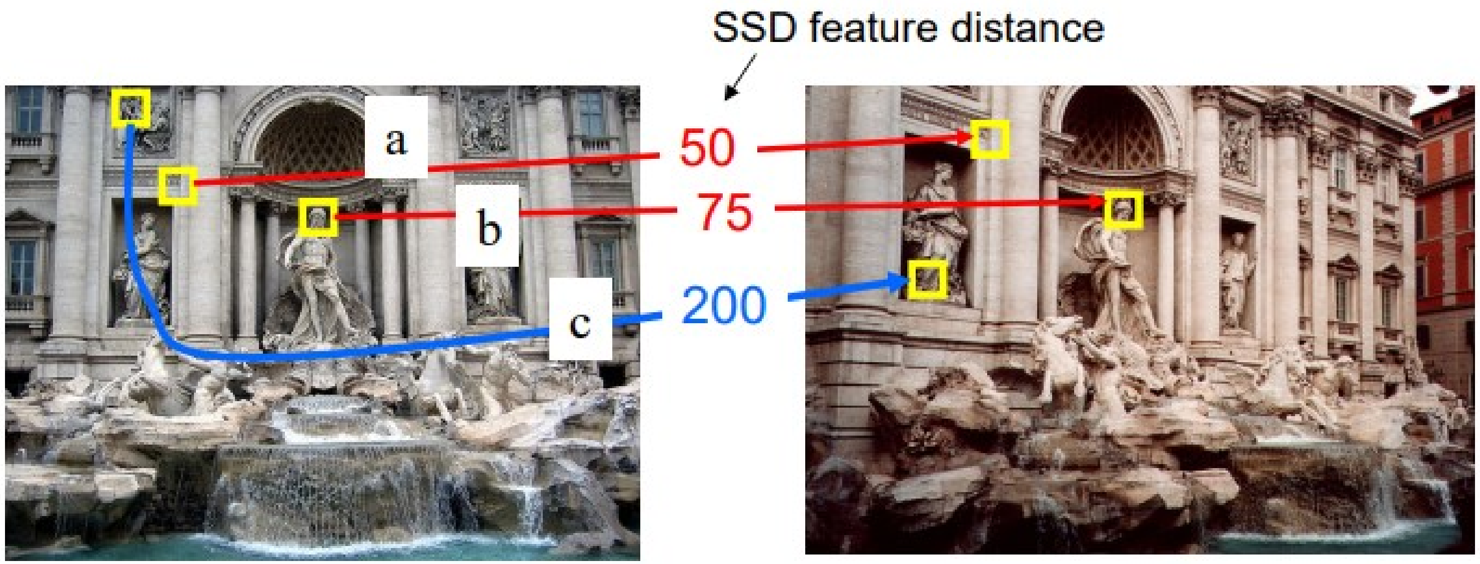
– they are actually matches

c is a false match ("**false positive**")

– actually not a match

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

Effect of threshold T



Decision rule: Accept match if SSD < T

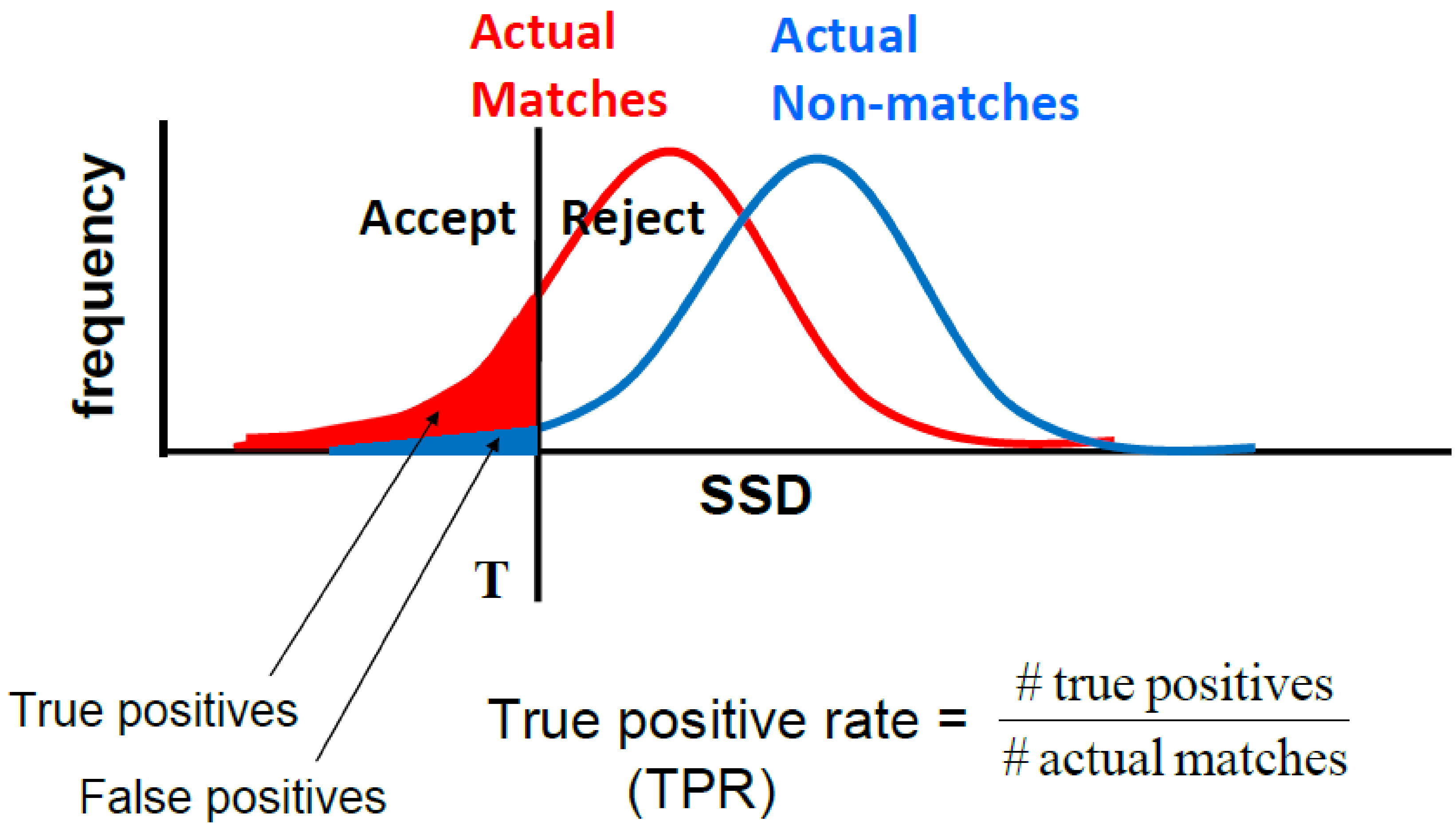
Example: **Smaller T**

T = 100 ⇒ 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

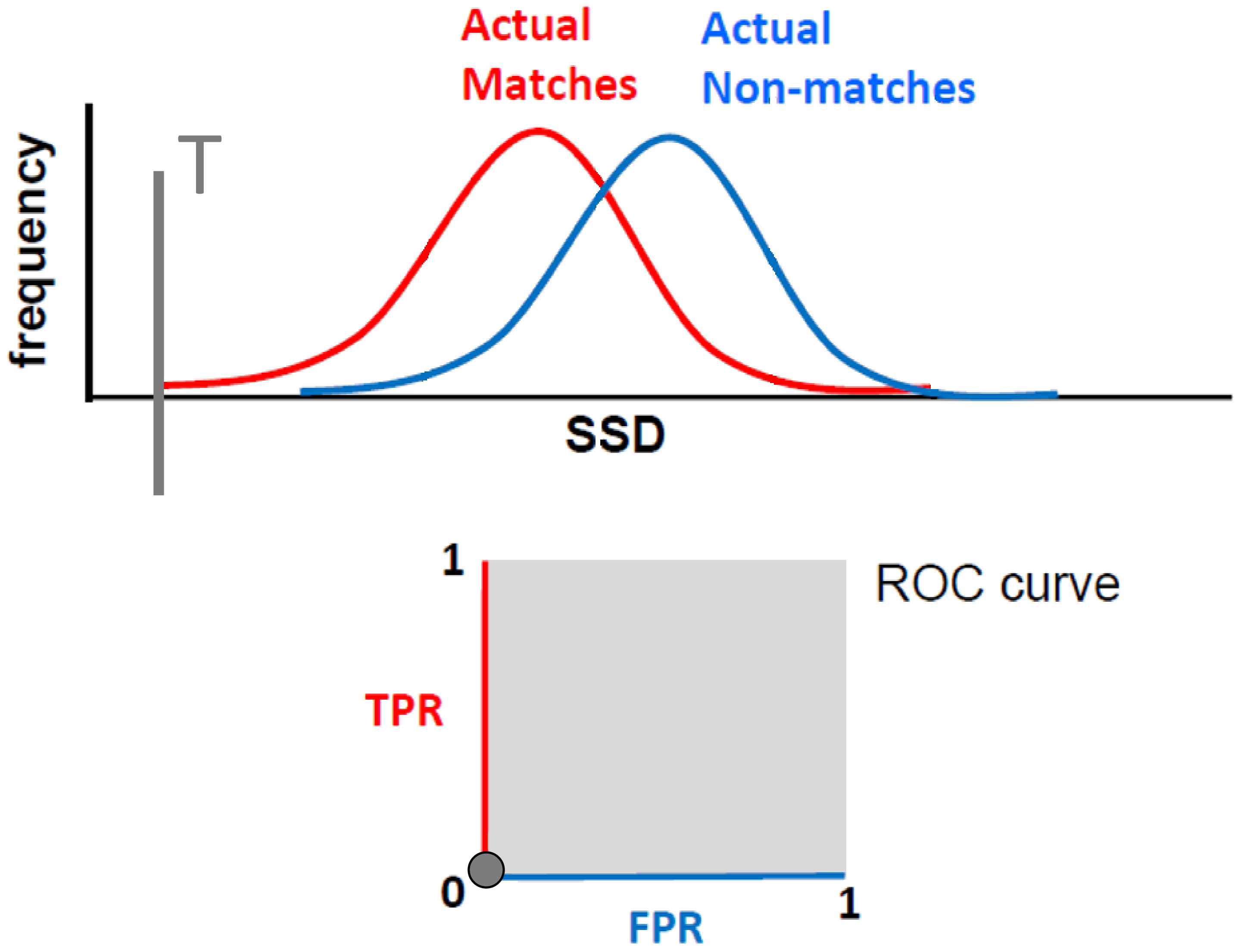


True positive rate (TPR) = $\frac{\#\text{ true positives}}{\#\text{ actual matches}}$

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

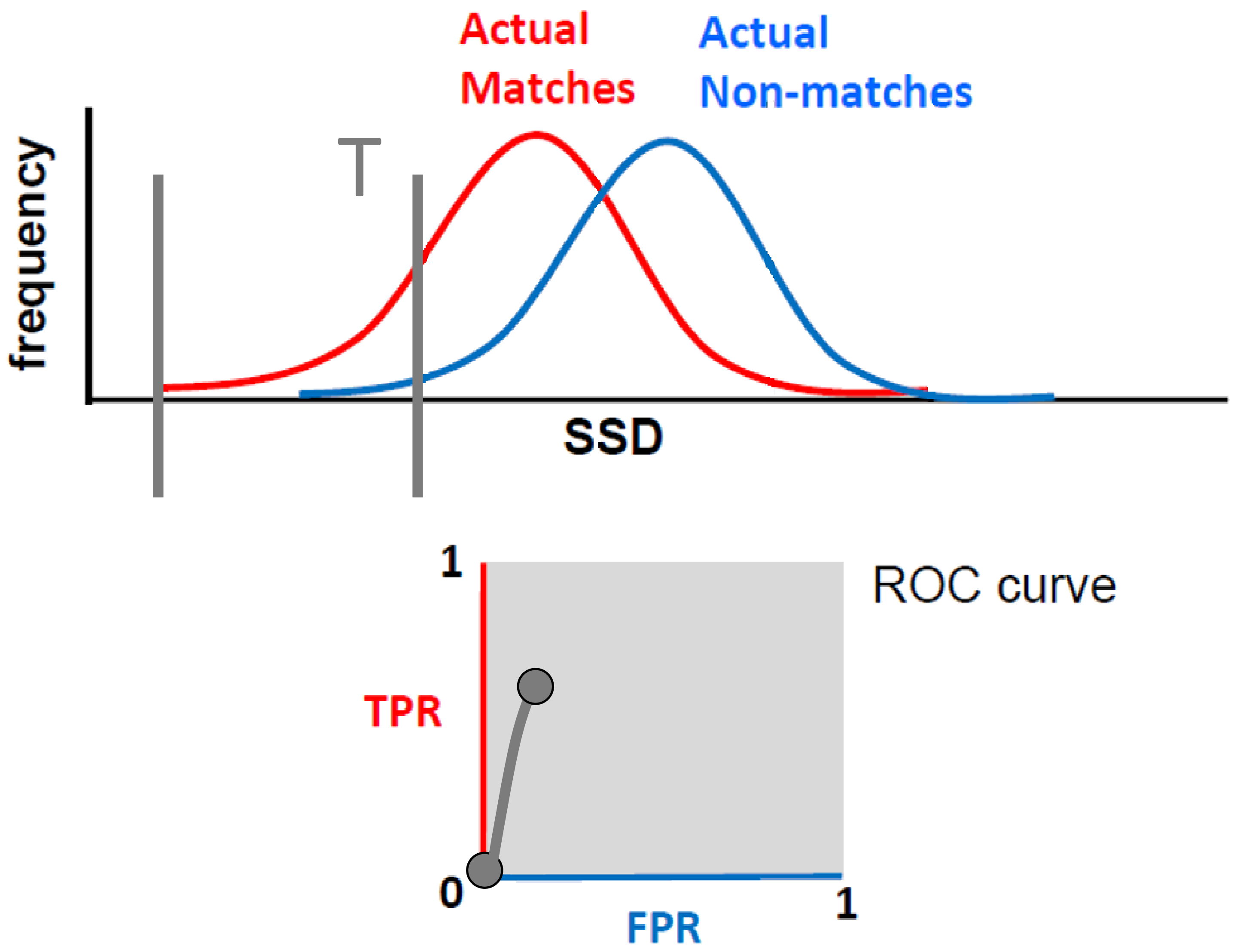
https://courses.cs.washington.edu/courses/cse455/09wi/Lects/lect6.pdf

Receiver Operating Characteristic (ROC) curve



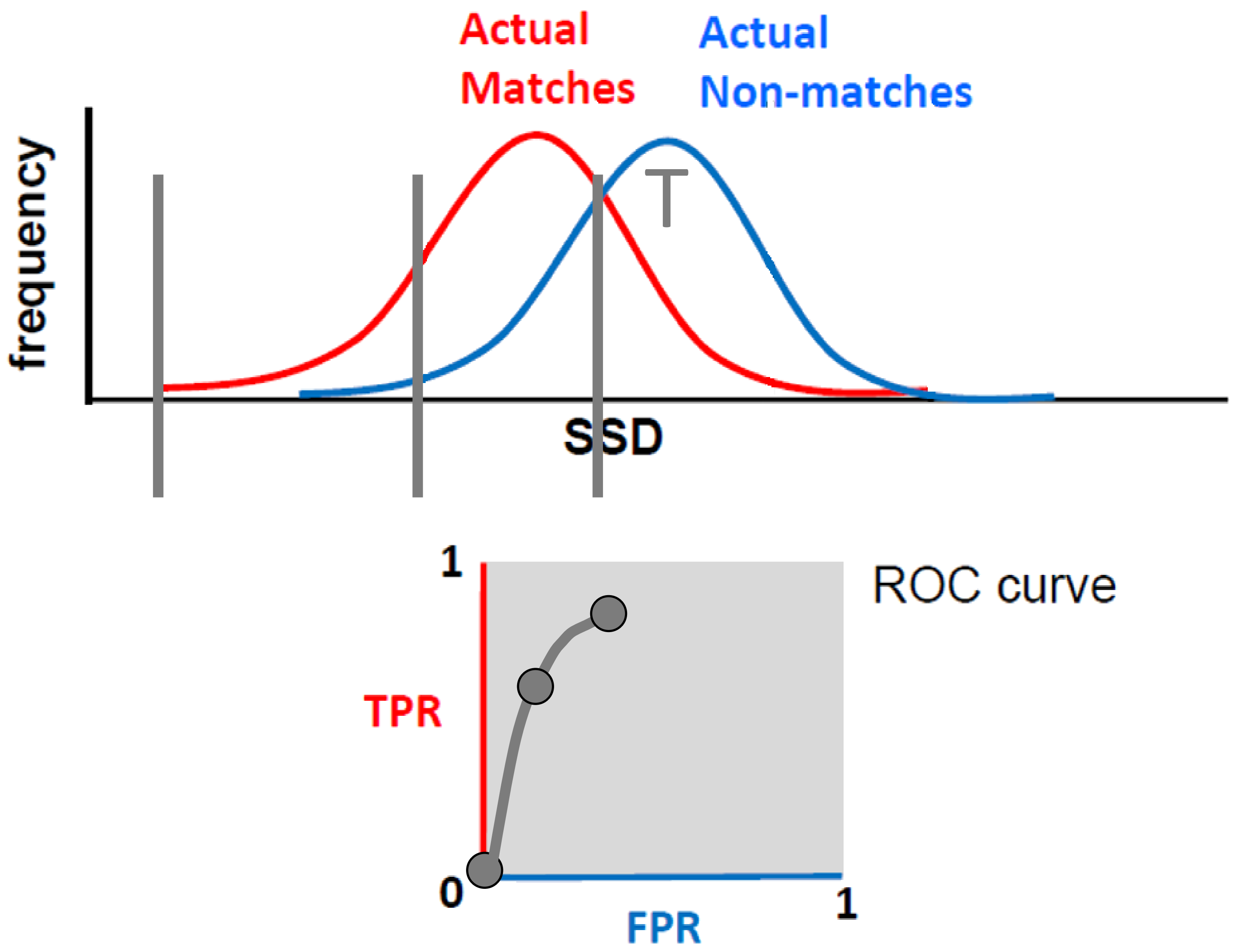
https://courses.cs.washington.edu/courses/cse455/09wi/Lects/lect6.pdf

Receiver Operating Characteristic (ROC) curve



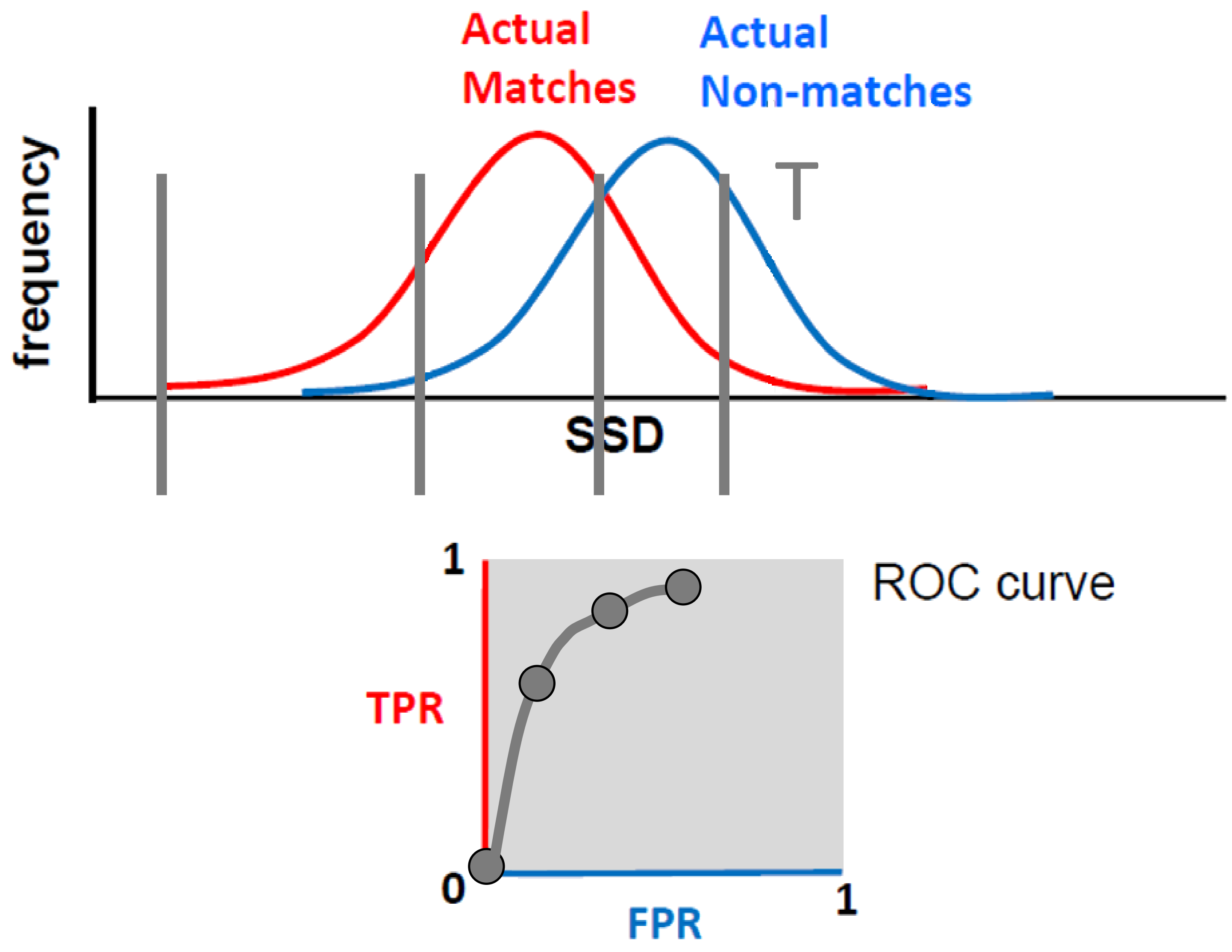
https://courses.cs.washington.edu/courses/cse455/09wi/Lects/lect6.pdf

Receiver Operating Characteristic (ROC) curve



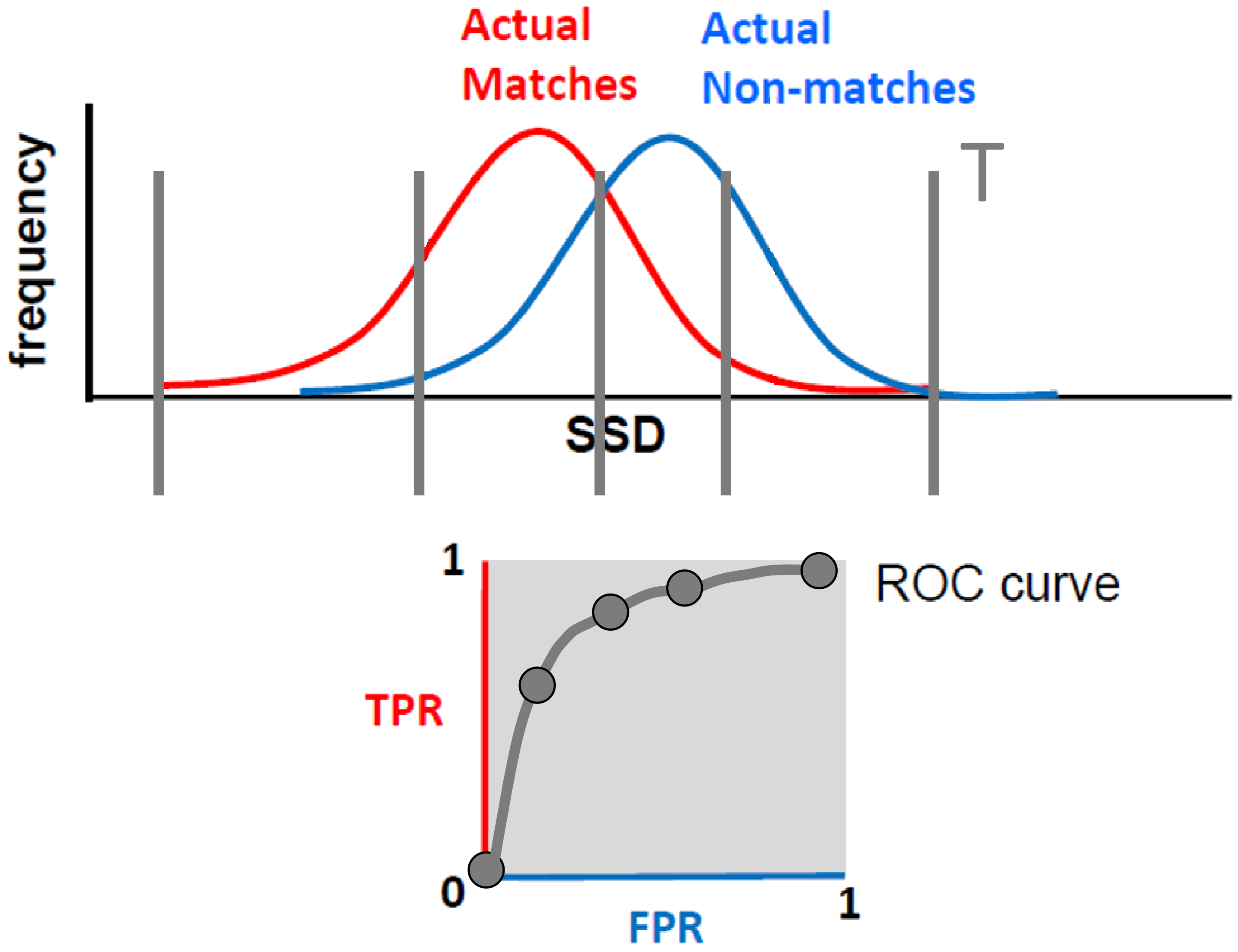
https://courses.cs.washington.edu/courses/cse455/09wi/Lects/lect6.pdf

Receiver Operating Characteristic (ROC) curve



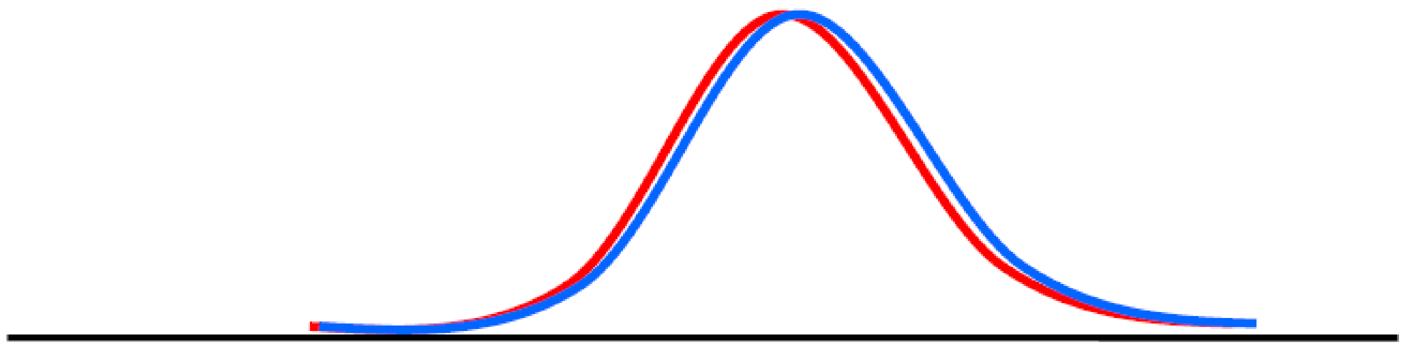
https://courses.cs.washington.edu/courses/cse455/09wi/Lects/lect6.pdf

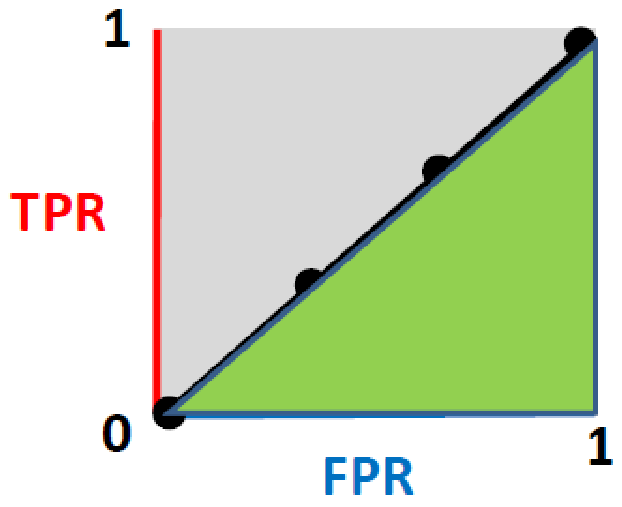
Receiver Operating Characteristic (ROC) curve



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

If the features selected were bad…



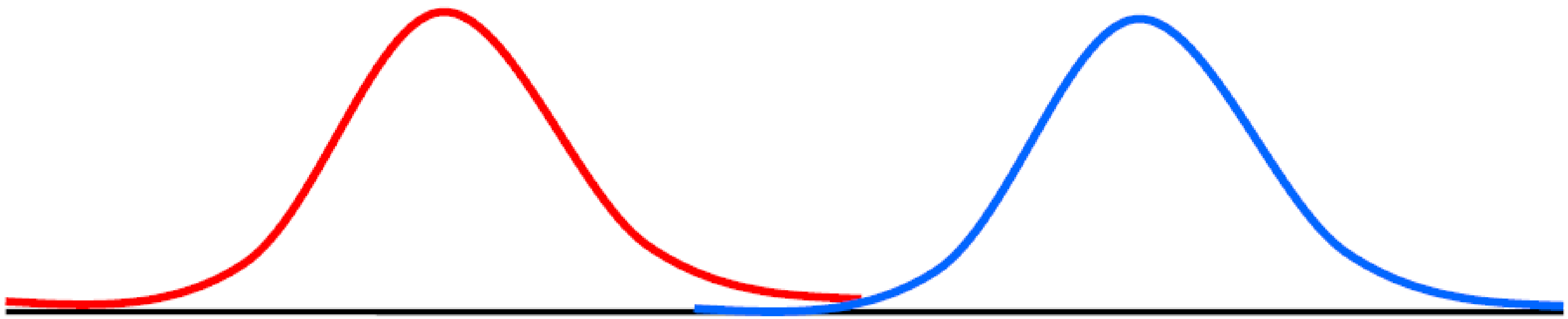


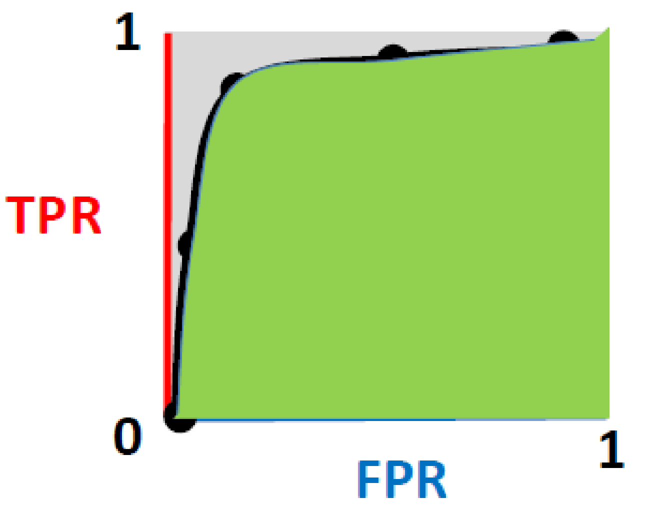
Area ≈ 0.5

Adapted from a slide by Shin Kira

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

If the features selected were good…





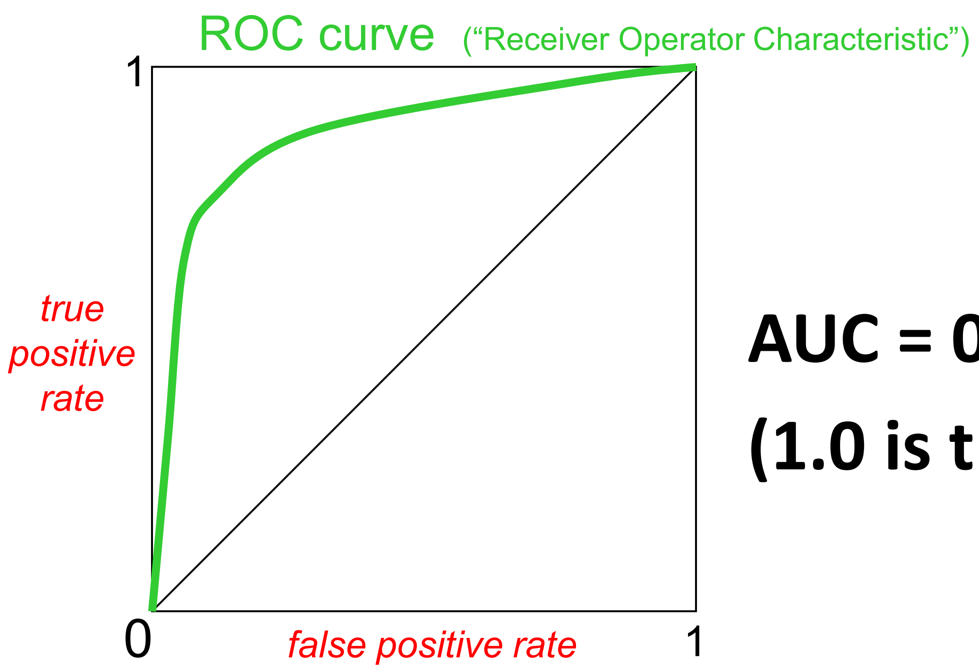
Area ≈ 1.0

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

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

1 - *specificity*

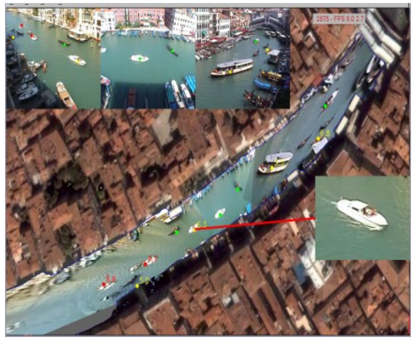
AUC = 0.87

(1.0 is the best)

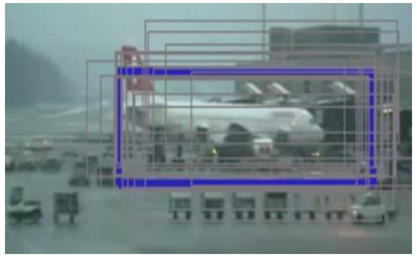
UNIVERSITÀ DEGLI STUDI DELLA BASILICATA

Corso di Visione e Percezione
A.A. 2019/2020

Docente
Domenico Daniele Bloisi



Feature Matching



Aprile 2020