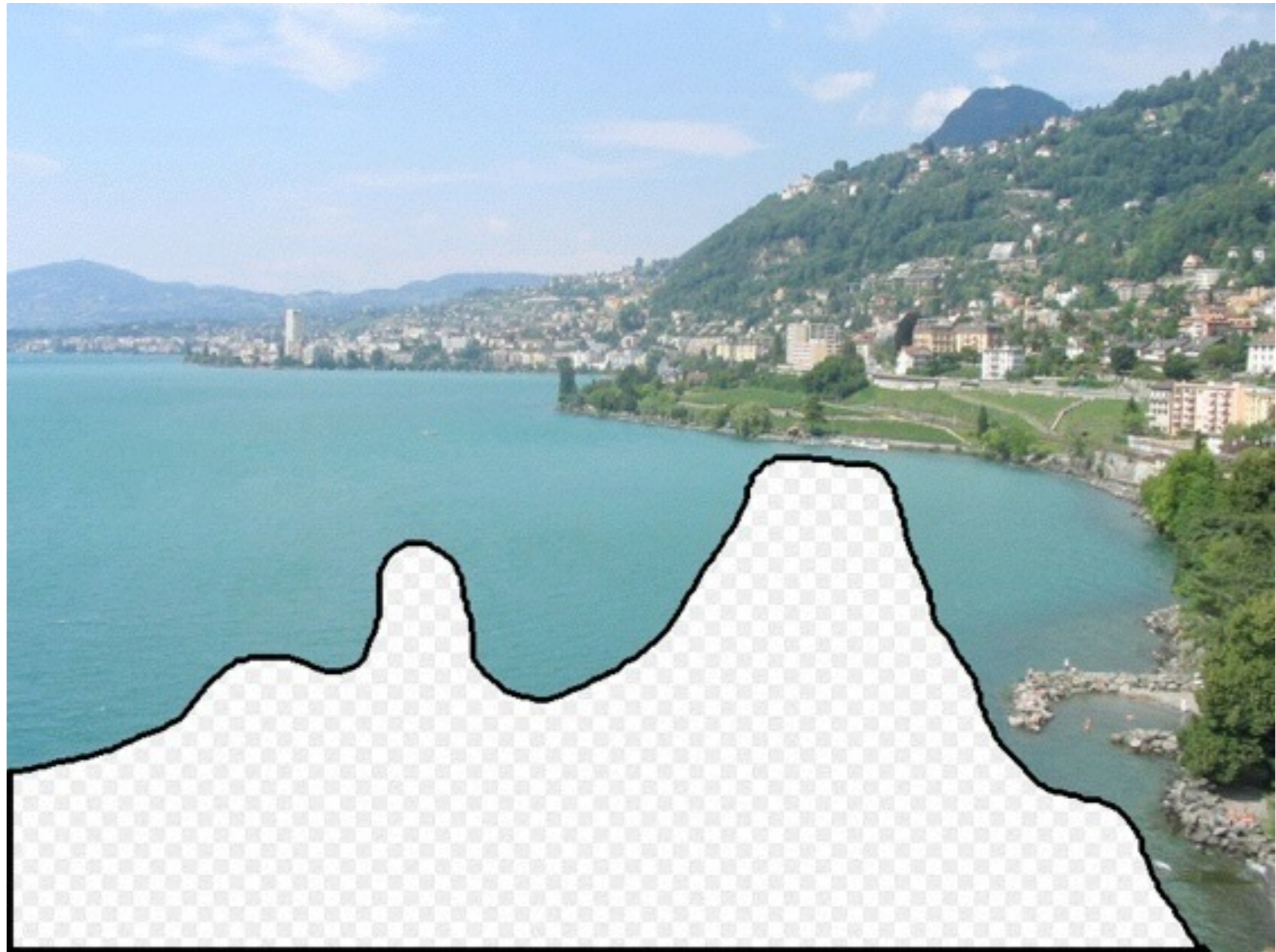


Données à grande échelle, partie 2

GIF-4105/7105 Photographie Algorithmique
Jean-François Lalonde

Qu'est-ce qu'il devrait y avoir dans la région?









Quel est l'original?



(a)



(b)

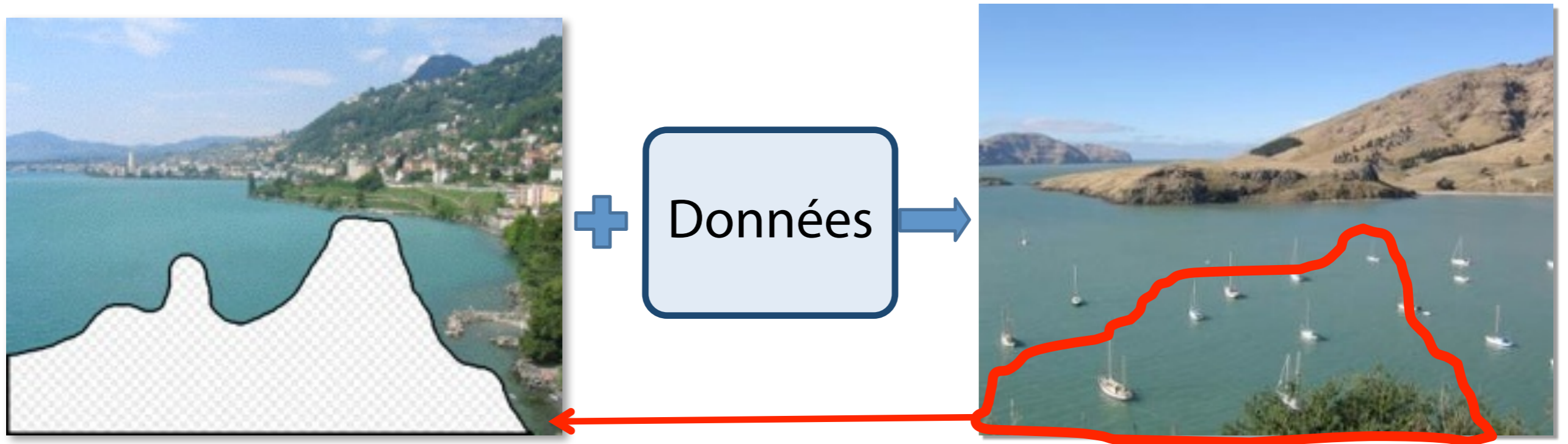


(c)

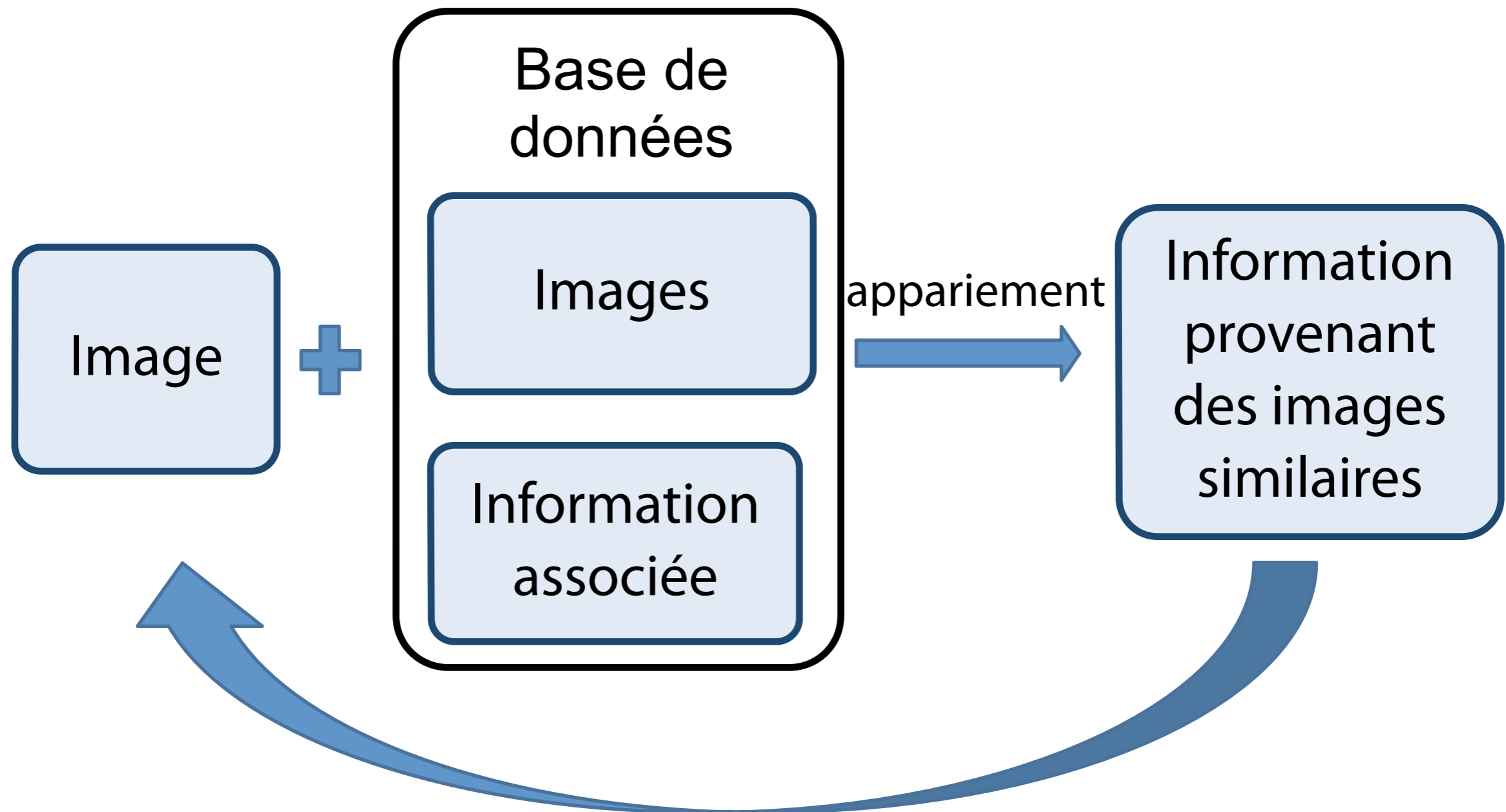
Comment ça marche

Trouver une image similaire dans une base de données

Copier une région dans le trou

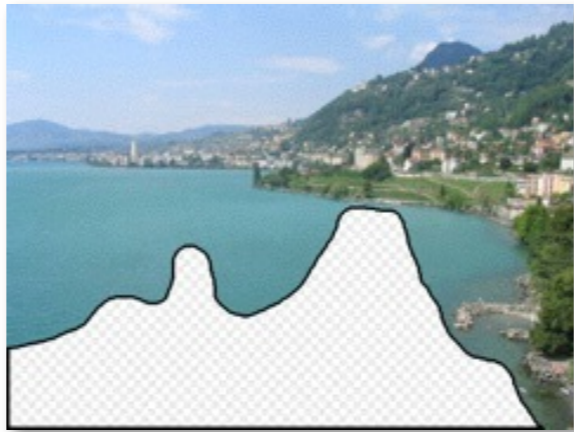


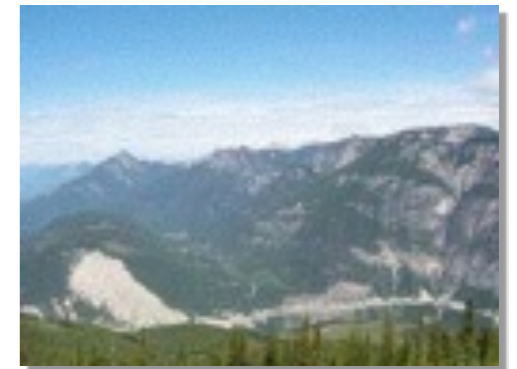
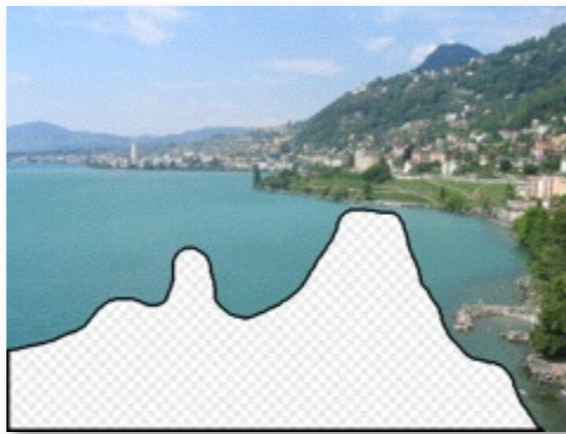
Utiliser beaucoup de données!



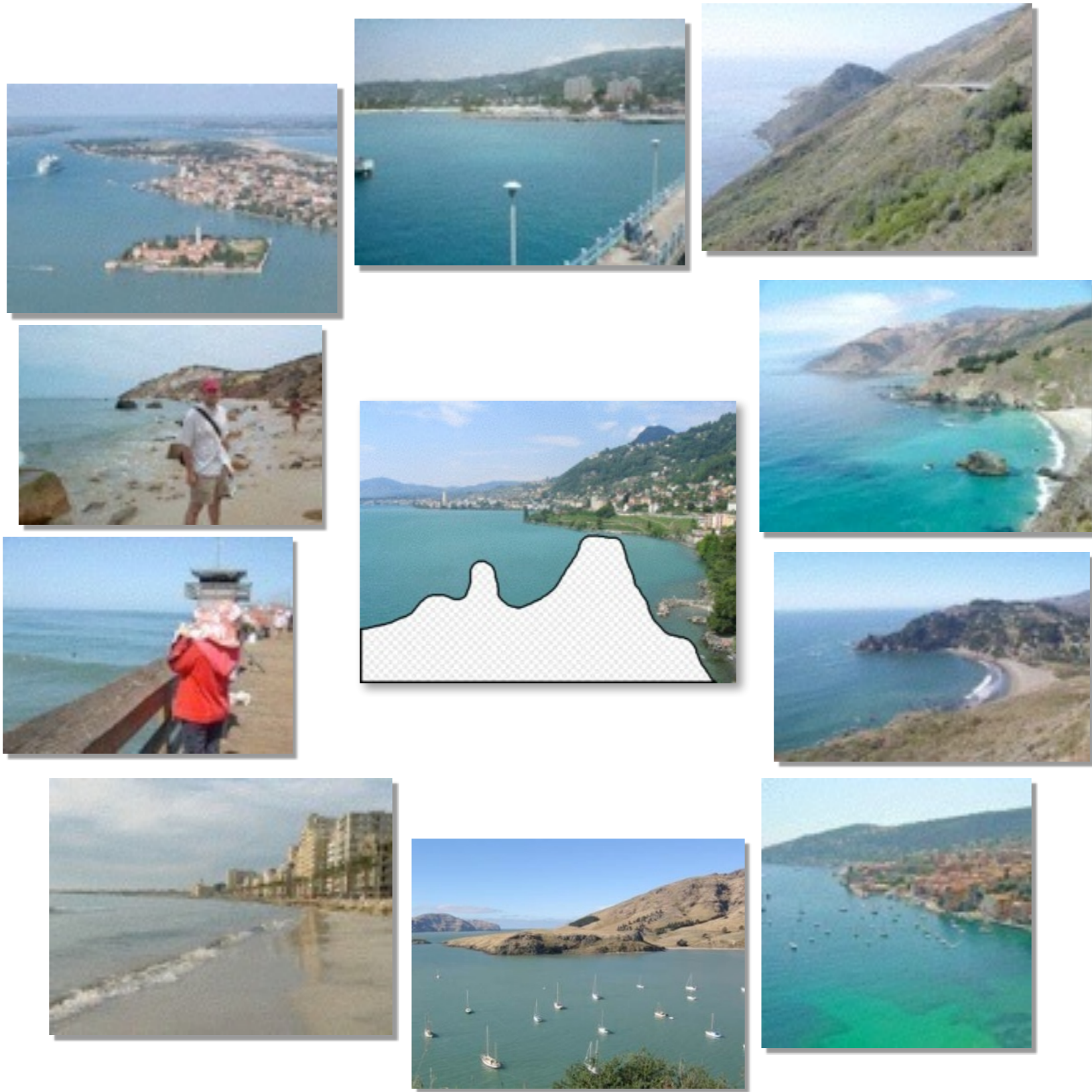
Truc: si vous avez assez d'images, la base de données devrait contenir des images suffisamment similaires, faciles à trouver!

Combien d'images?





20,000 images



2,000,000 images

Aujourd'hui

Transférer de l'information

- Emplacement GPS
- Autre information (en fonction de l'emplacement)

Améliorer l'appariement

- Apparier des portions de l'image
- Déterminer ce qu'il faut apparier

im2gps (Hays & Efros, CVPR 2008)



6 millions d'images avec GPS

Quelle information géographique est disponible dans une image?





Paris



Paris



Paris



Paris



Paris



Paris



Paris



Madrid



Rome



Paris



Cuba



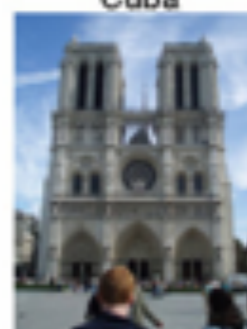
Paris



Paris



Poland



Paris



Paris





Examples



Madrid



england



France



Paris



Croatia



heidelberg



Macau



Malta



Cairo



Italy



Italy



Italy



Latvia



europa

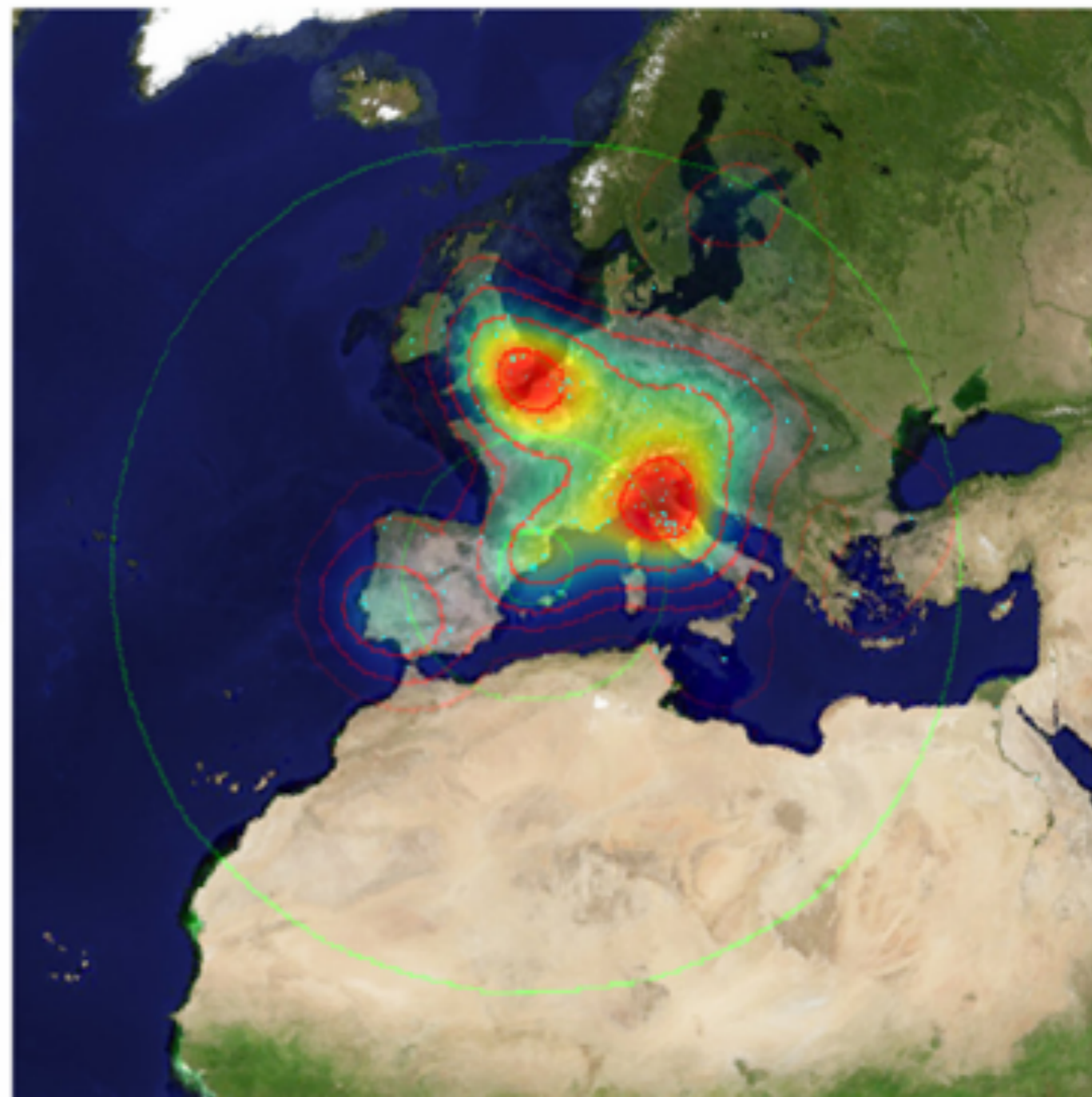


Barcelona



Austria

Votes







Philippines



Houston



Thailand



Houston



Maldives



Philippines



NewZealand



Bermuda



Palau



Mexico2



Brazil



Mendoza



Brazil



Thailand



Arkansas



Hawaii





Switzerland



SouthAfrica



California



Barcelona



Italy



Italy



Nevada



Washington



Paris



Madrid



California



Oregon



SouthDakota



USA



Bangkok

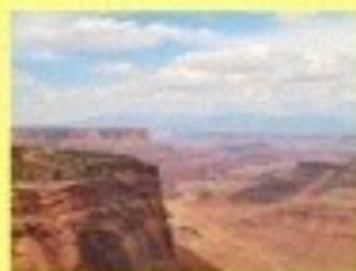


Italy





USA



Utah



Arizona



Utah



Utah



Utah



Tunisia



Kenya



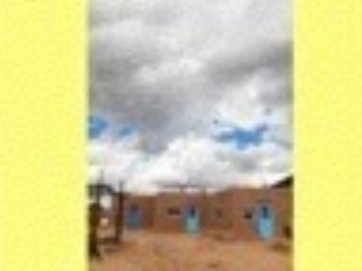
Utah



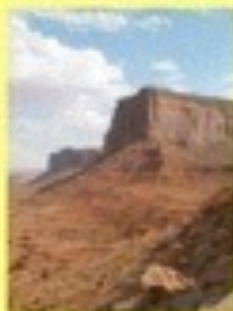
LosAngeles



Burundi



NewMexico



Utah



Utah



Utah



Mendoza





California



Oklahoma



SouthAfrica



Zambia



Kenya



Hyderabad



Mongolia



SouthAfrica



Kenya



Kenya



Zambia



Ethiopia



Nevada



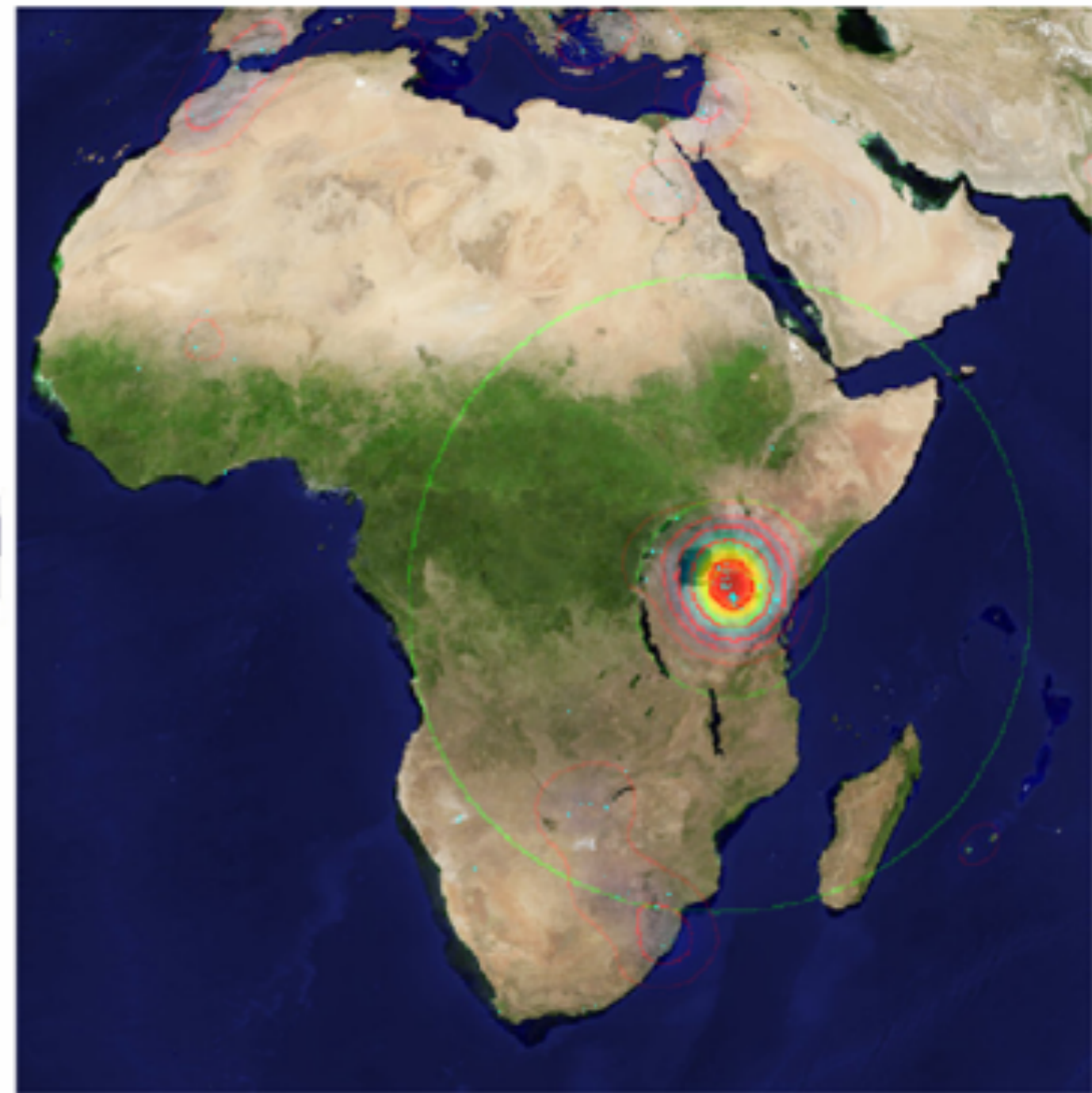
africa



Morocco



Tennessee





Toronto



Florida



NewYork



Boston



Boston



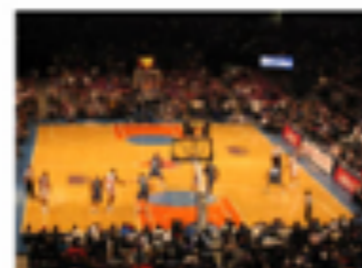
Oregon



Oregon



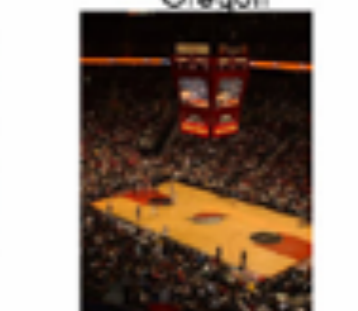
Oregon



NewYork



Barcelona



Oregon



Chicago



Ohio



Philadelphia



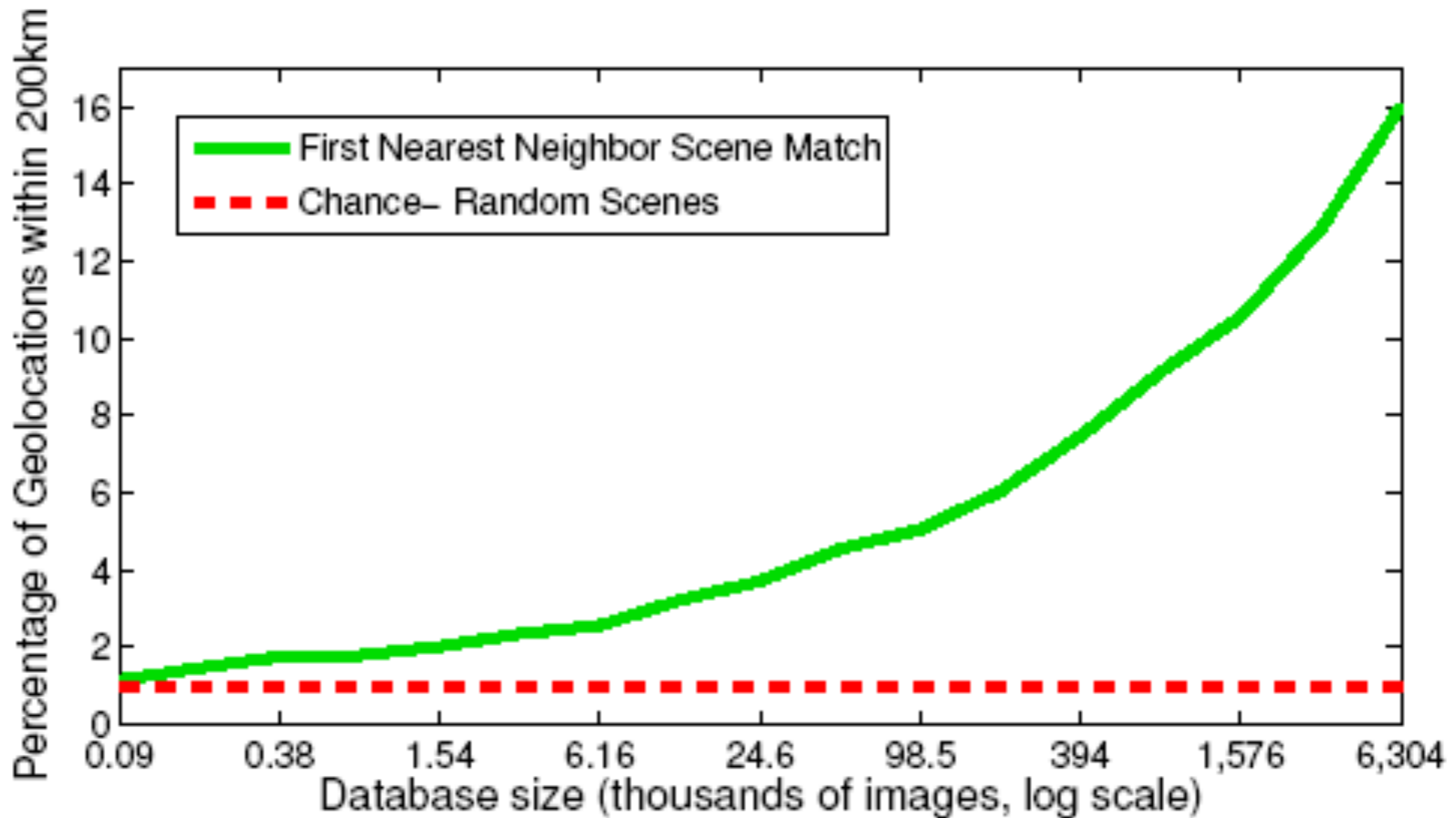
NewYorkCity



Boston



L'importance des données



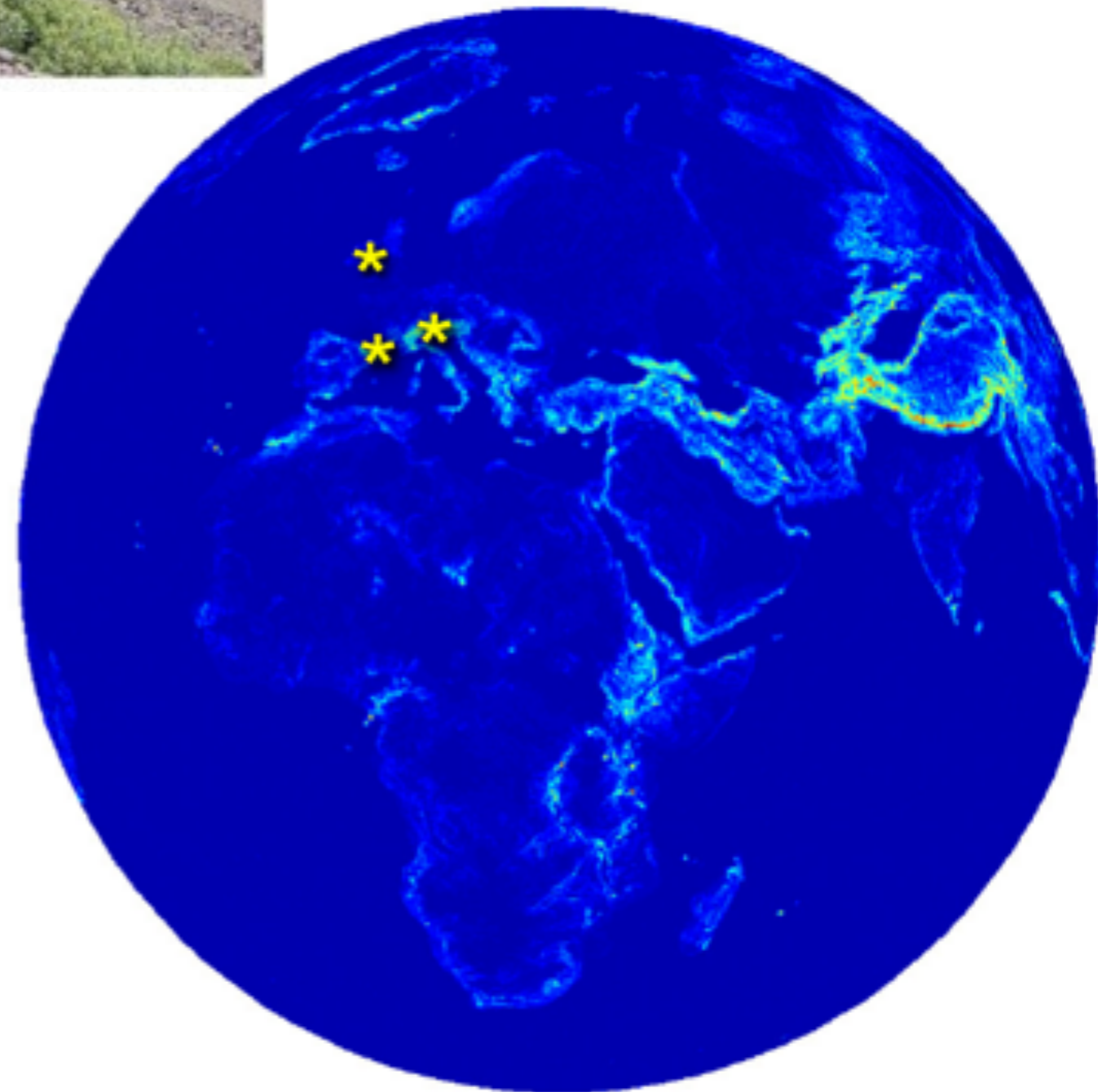
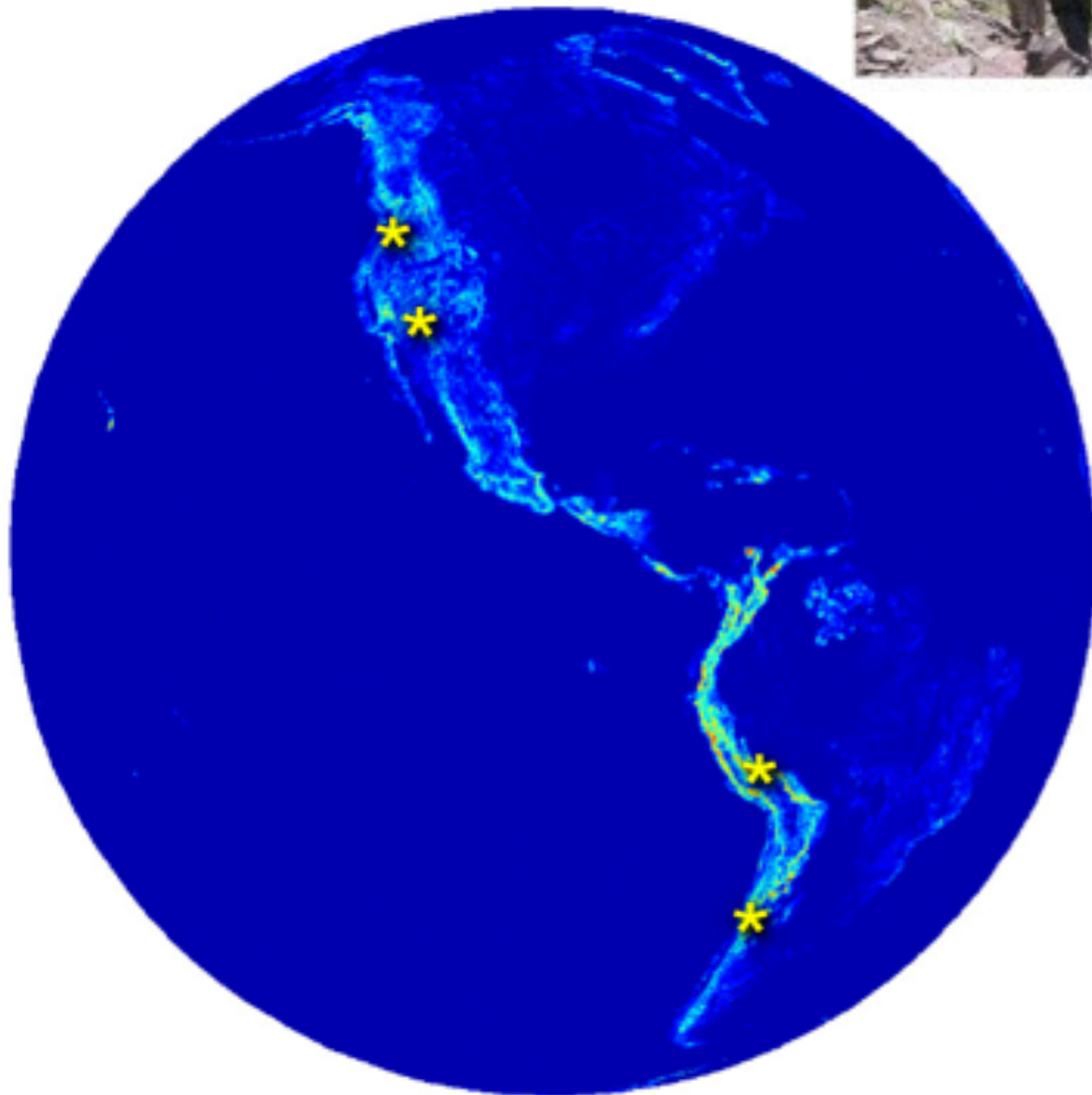
Data-driven categories



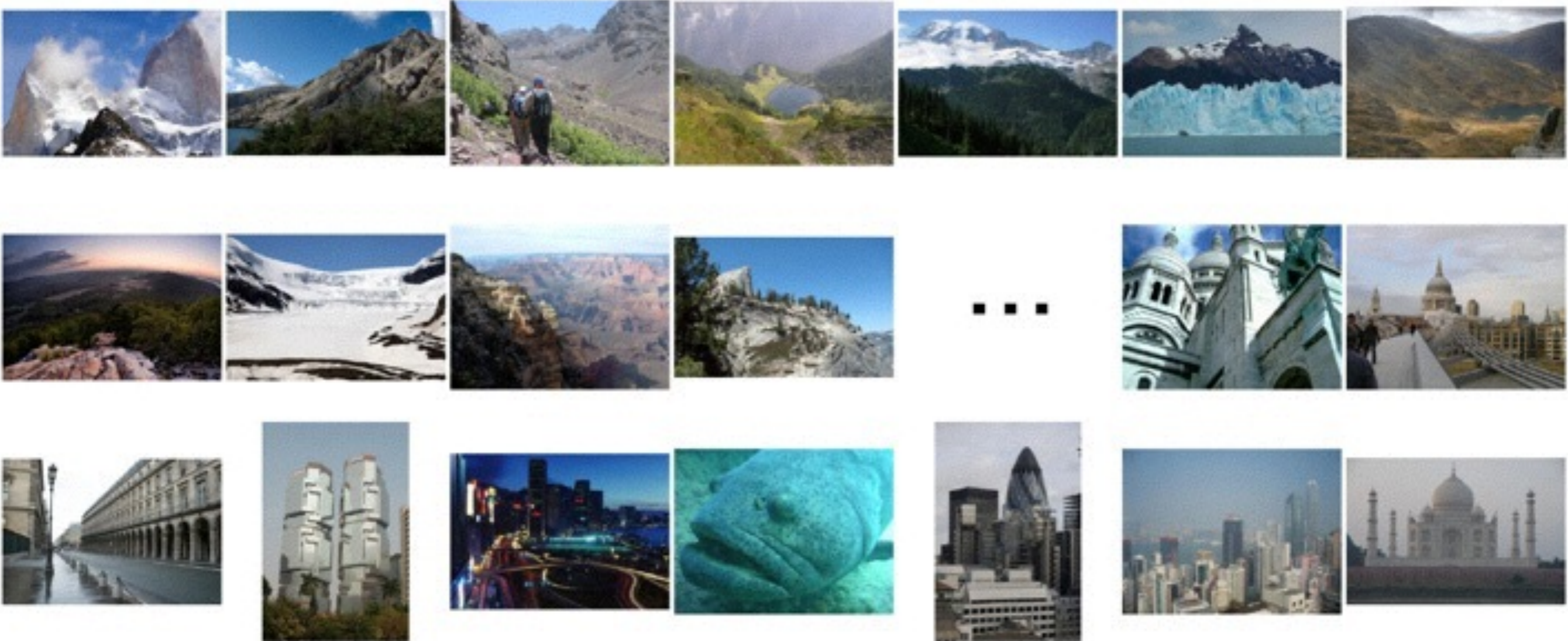
 <p>Argentina</p>	 <p>Andorra</p>	 <p>Andorra</p>	 <p>Iceland</p>
 <p>Idaho</p>	 <p>Switzerland</p>	 <p>Argentina</p>	 <p>Bolivia</p>
 <p>Nevada</p>	 <p>Hawaii</p>	 <p>Hawaii</p>	 <p>Egypt</p>
 <p>China</p>	 <p>Arizona</p>	 <p>Peru</p>	 <p>Oregon</p>



Elevation gradient = 112 m / km



Elevation gradient magnitude ranking



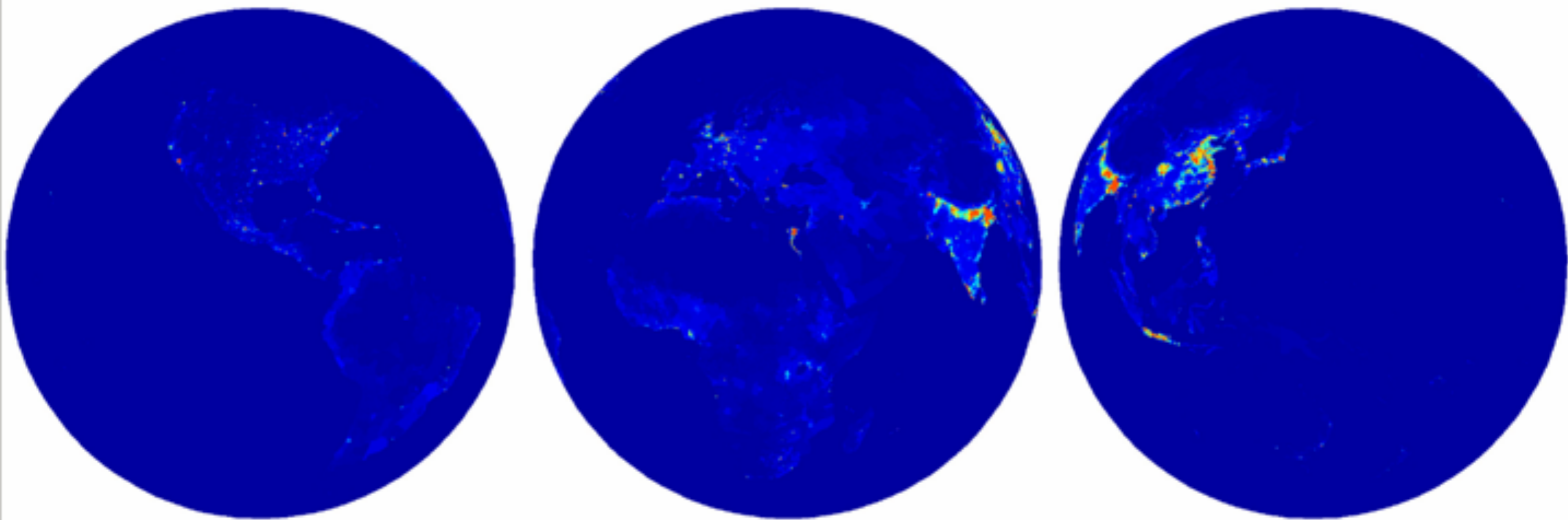


Figure 2. Global population density map.

Population density ranking



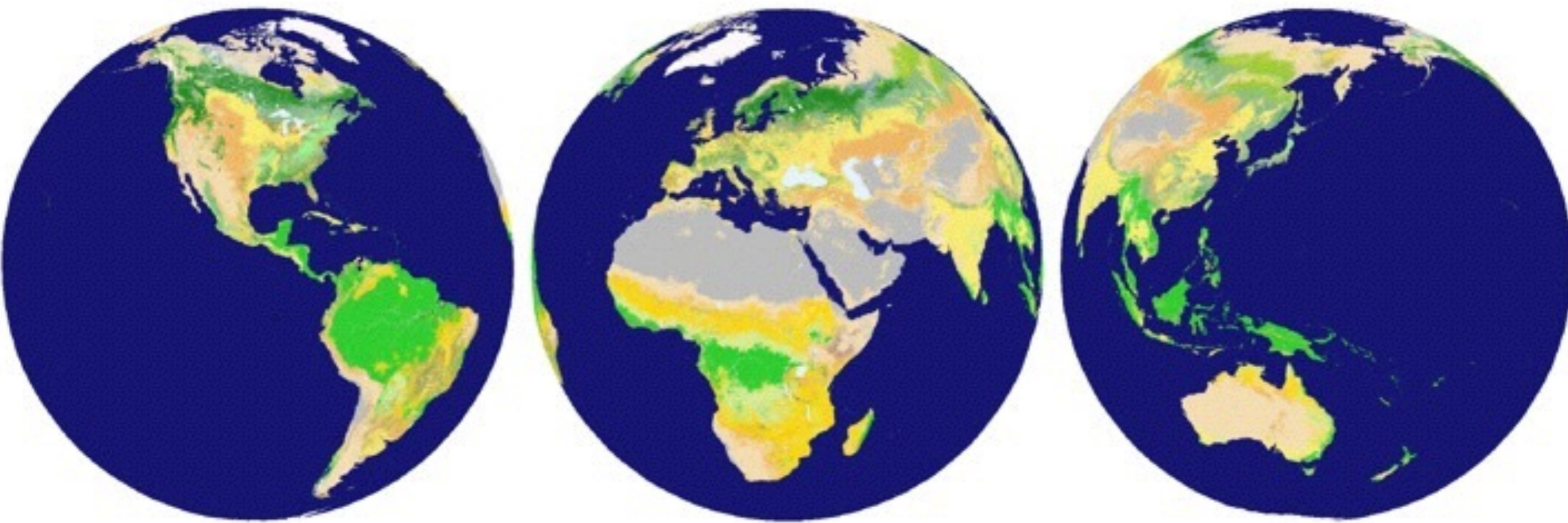


Figure 4. Global land cover classification map.



Barren or sparsely populated



Urban and built up



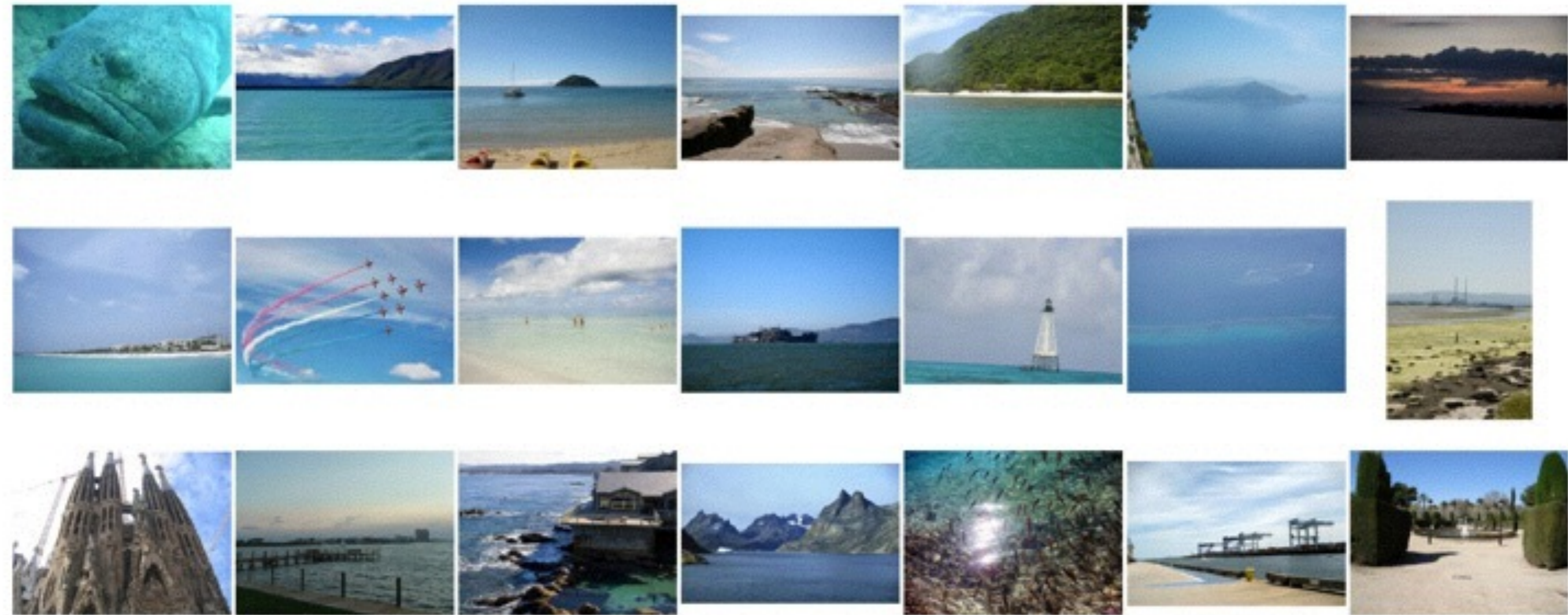
Snow and Ice



Savannah



Water



Où est-ce?



O. Vesselova, V. Kalogerakis, A. Hertzmann, J. Hays, A. A. Efros. "Image Sequence Geolocation,"
ICCV 2009

Où est-ce?



Où sont ces images?



15:14,
June 18th, 2006



16:31,
June 18th, 2006

Où sont ces images?



15:14,
June 18th, 2006



16:31,
June 18th, 2006



17:24,
June 19th, 2006

Résultats (geo-loc < 400 km)

im2gps – 10%

temporal im2gps – 56%

Aujourd'hui

Transférer de l'information

- Emplacement GPS
- Autre information (en fonction de l'emplacement)

Améliorer l'appariement

- Apparier des portions de l'image
- Déterminer ce qu'il faut apparier



Fontaine de Médici, Paris

A. Shrivastava, T. Malisiewicz, A. Gupta, A. A. Efros, "Data-driven visual similarity for cross-domain image matching," SIGGRAPH Asia 2011



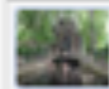
Search by image



Drop image here

[→ Move](#)

[Watch a short video to learn more.](#)



medici_summer.jpg [×](#)

luxembourg gardens



Search

About 2 results (0.29 seconds)

Everything

Images

Maps

Videos

News

Shopping

More



Image size:
1024 × 829

No other sizes of this image found.

Visually similar





Medici Fountain, Paris (winter)



 medici_winter.png  luxembourg gardens 

Search

About 2 results (0.29 seconds)

Everything

Images

Maps

Videos

News

Shopping

More



Image size:
713 × 600

No other sizes of this image found.

Visually similar







 painting.png  describe image here 

Search

About 2 results (0.29 seconds)

Everything

Images

Maps

Videos

News

Shopping

More



Image size:
319 × 482

No other sizes of this image found.

Visually similar







medici_sketch.bmp x describe image here



Search

About 2 results (0.29 seconds)

Everything

Images

Maps

Videos

News

Shopping

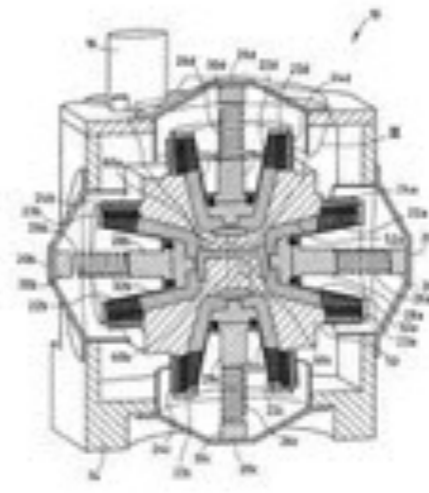
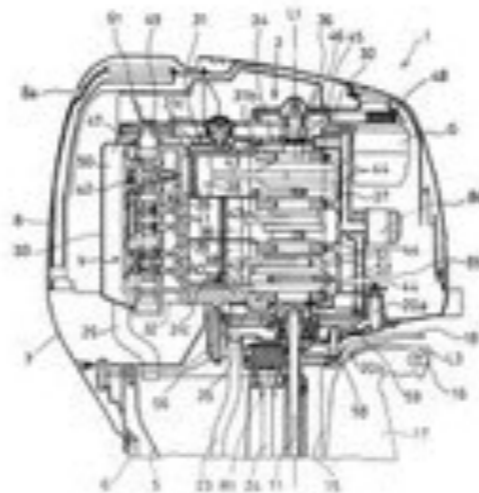
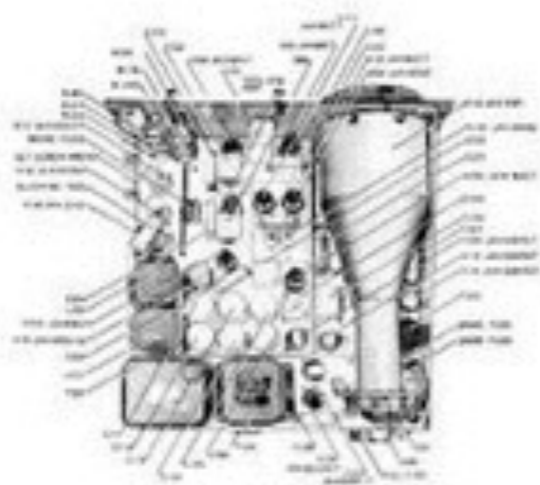
More



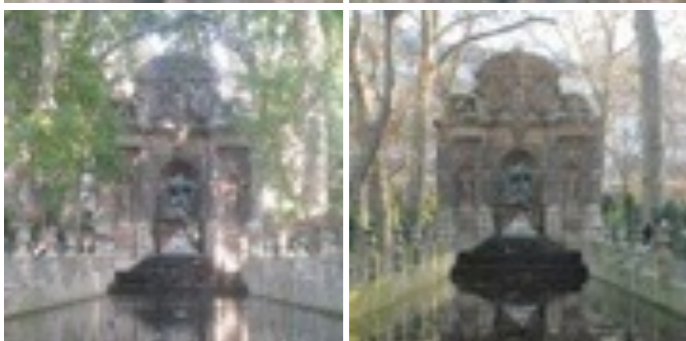
Image size:
443 × 482

No other sizes of this image found.

Visually similar



But



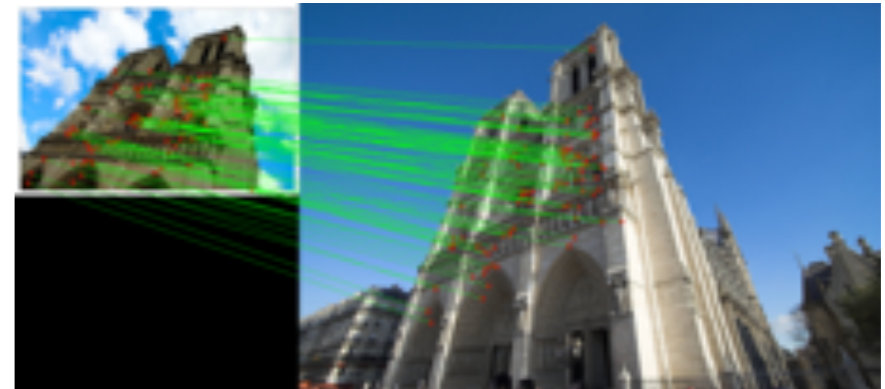
Pourquoi c'est si difficile?



Comparer les images

SIFT

(représentation des gradients
autour des coins)

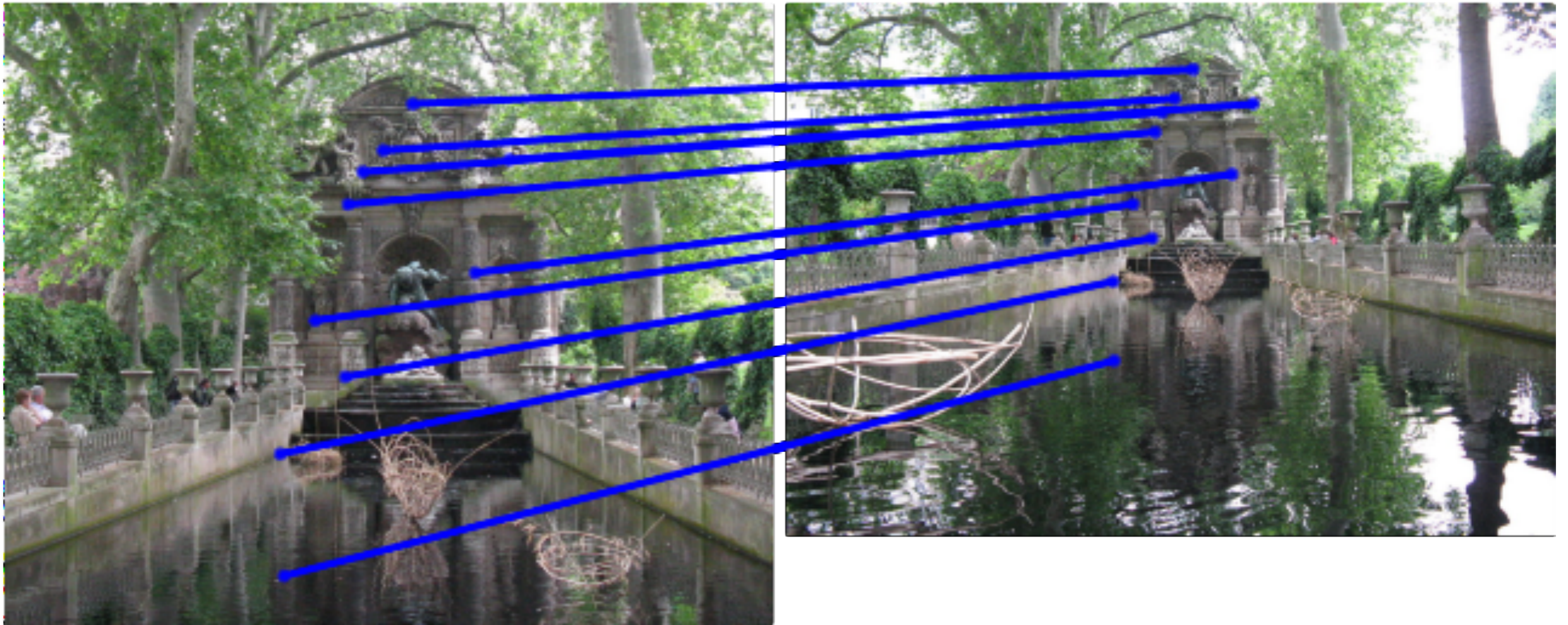


GIST

(représentation des gradients
dans l'image)

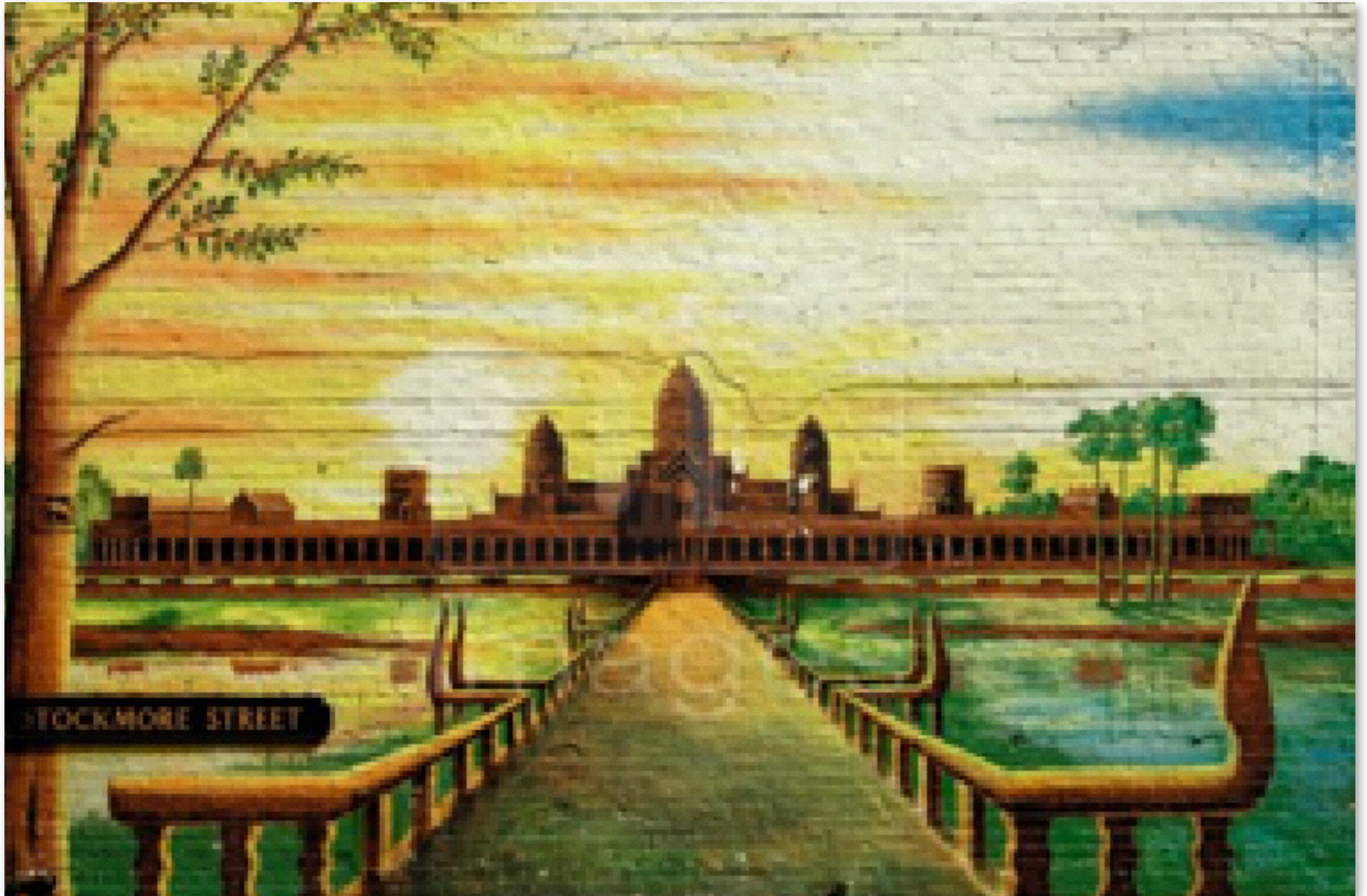


Exemple: appariement SIFT



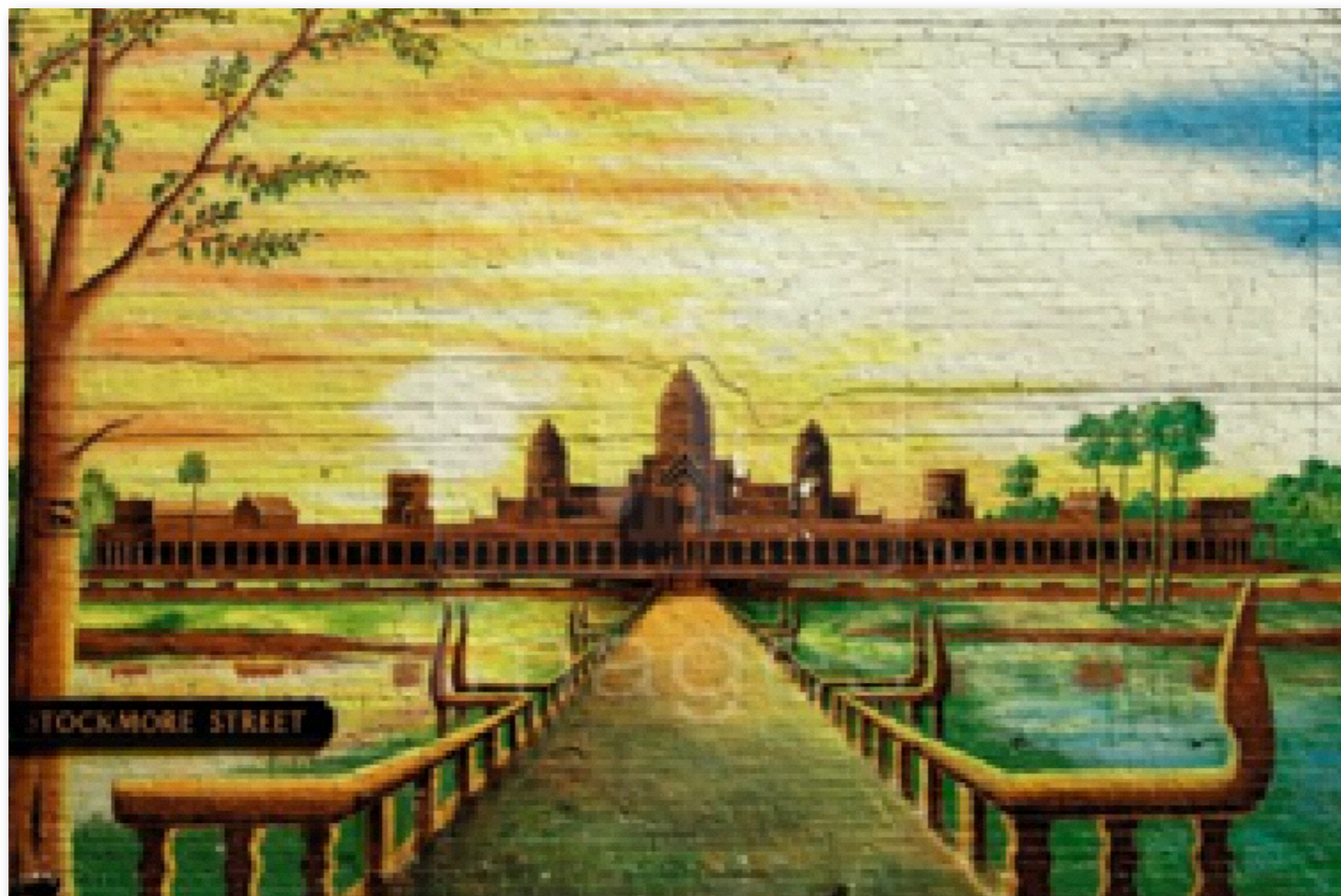
Exemple: appartiment SIFT





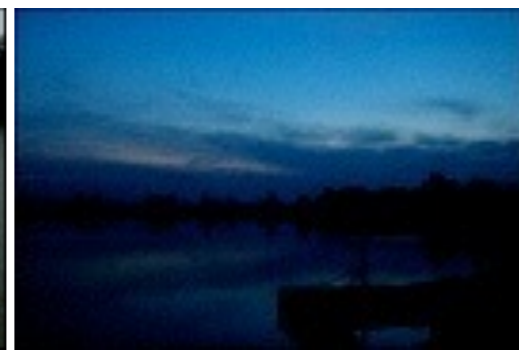
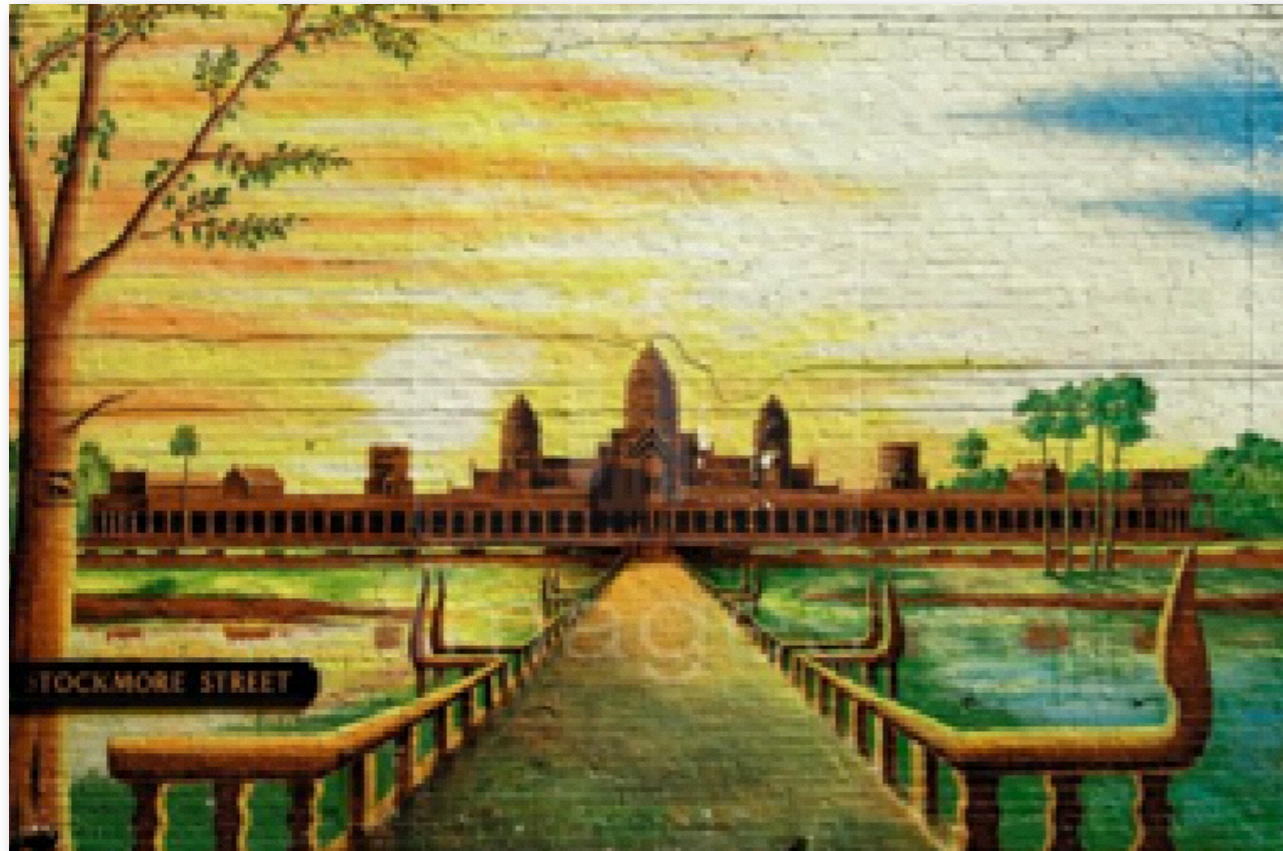
STOCKMORE STREET

Image



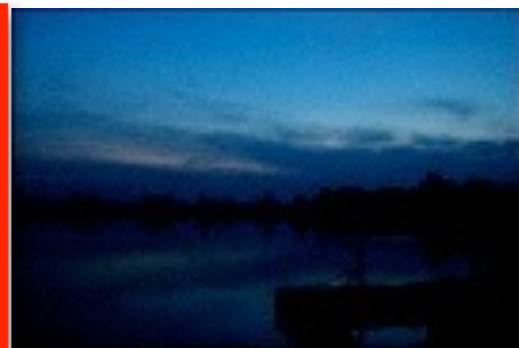
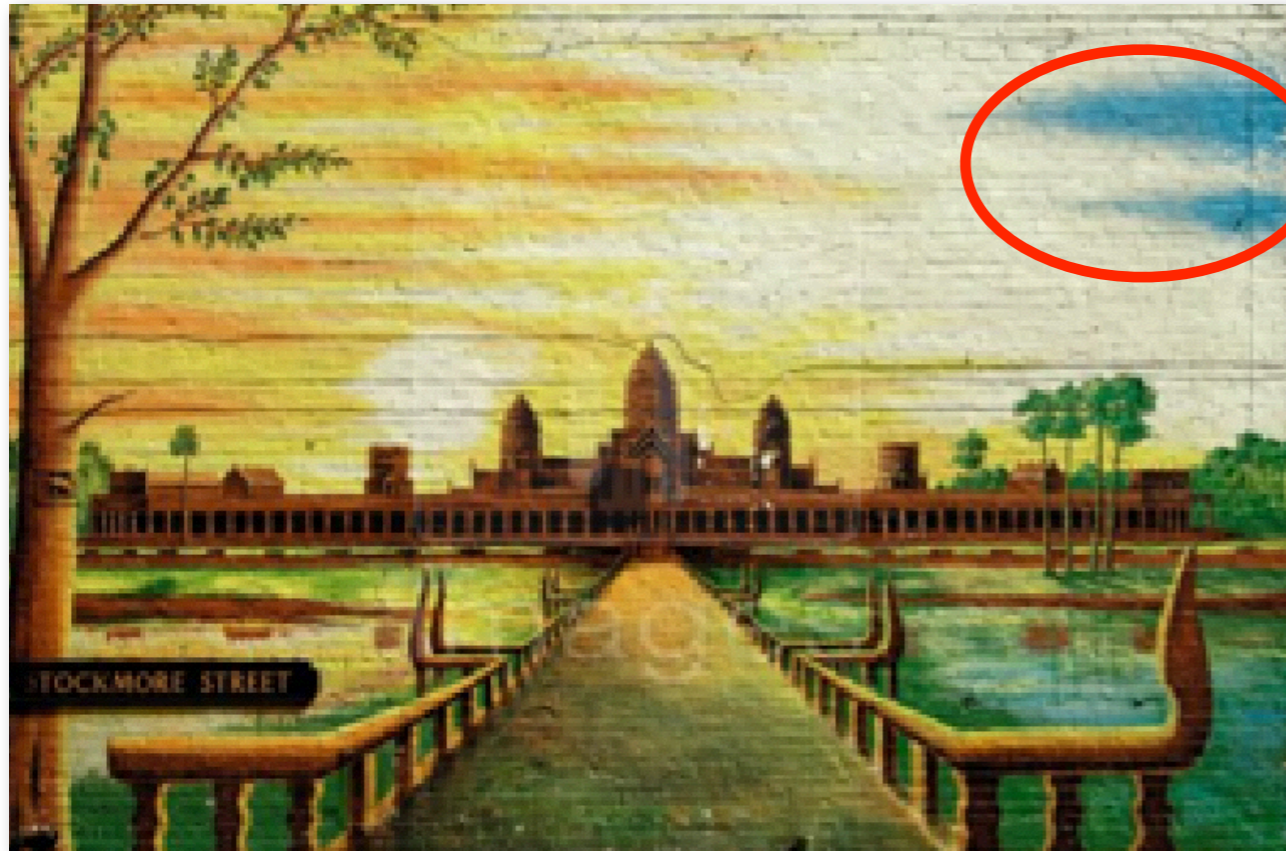
Plus proches voisins

Image



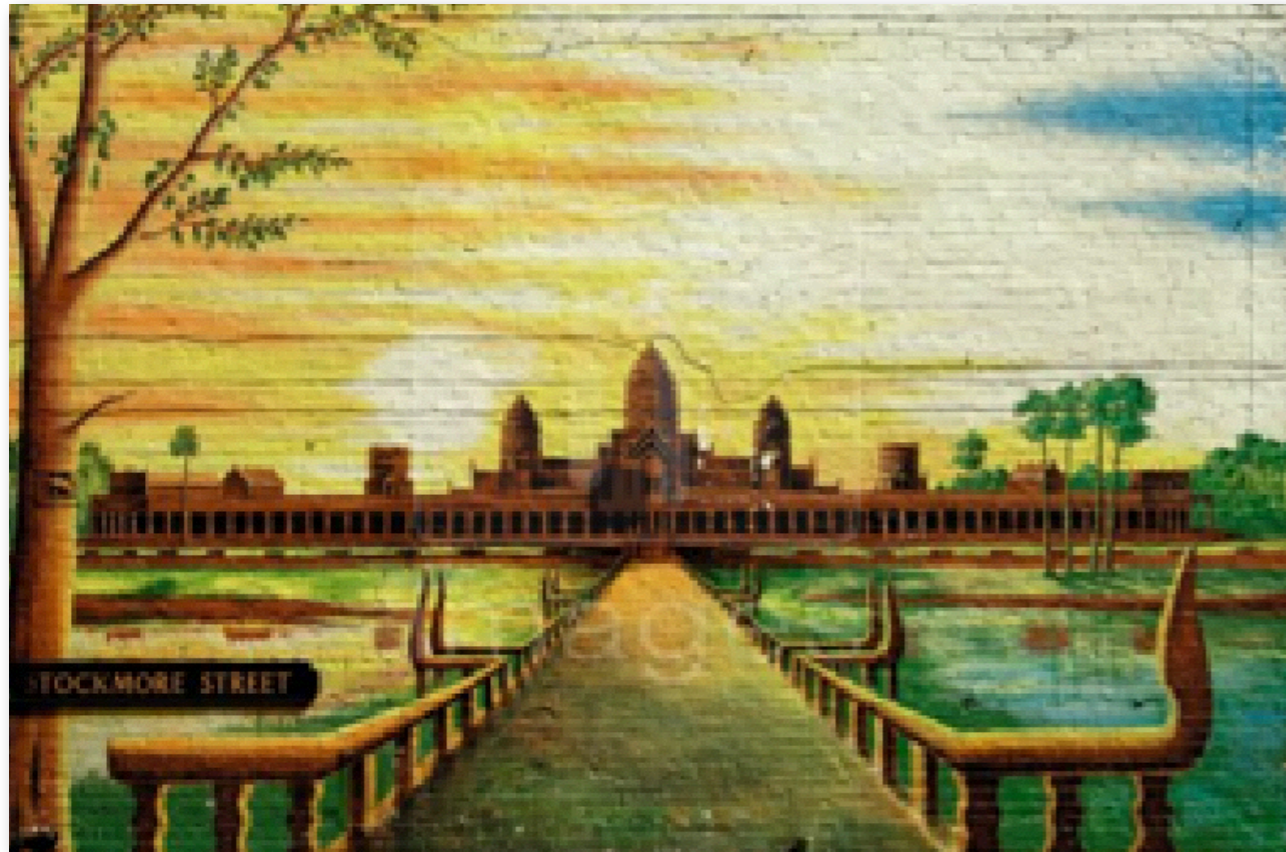
Plus proches voisins

Image



Plus proches voisins

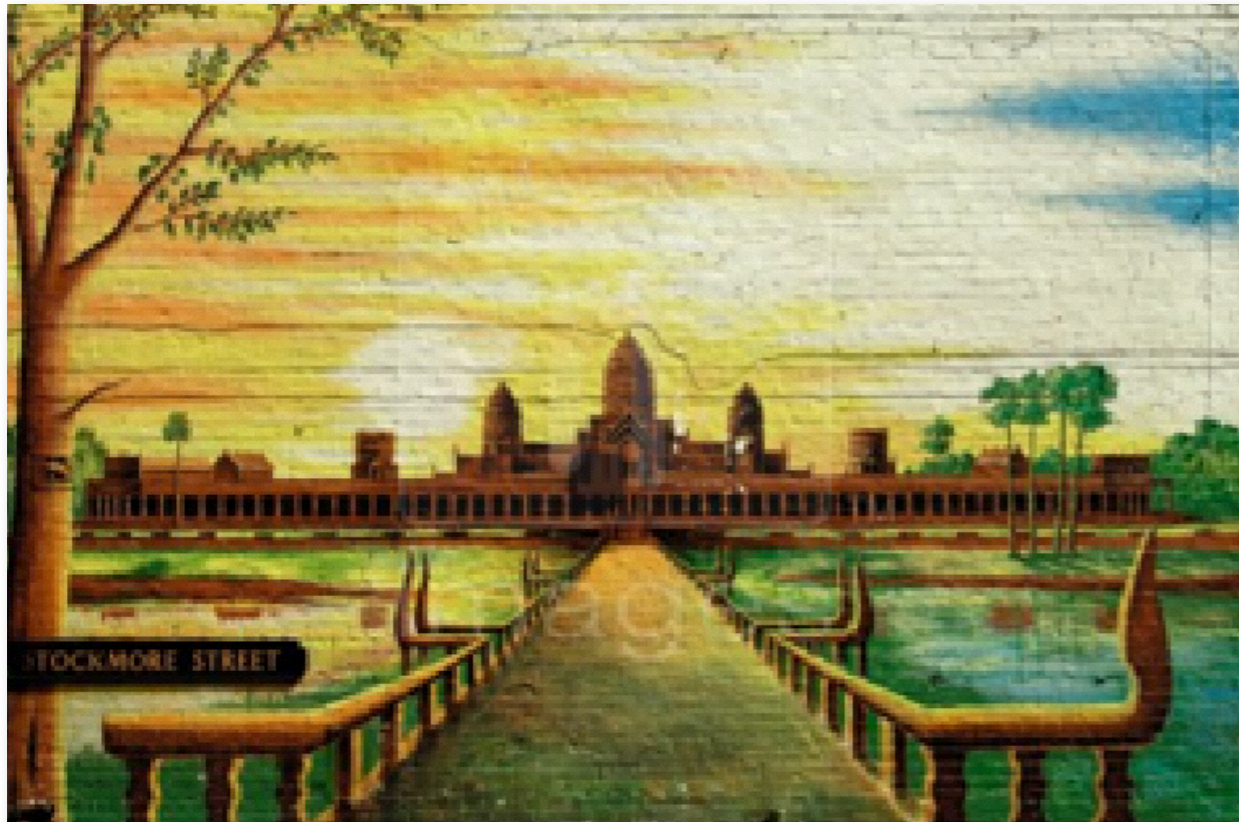
Image



Parties importantes

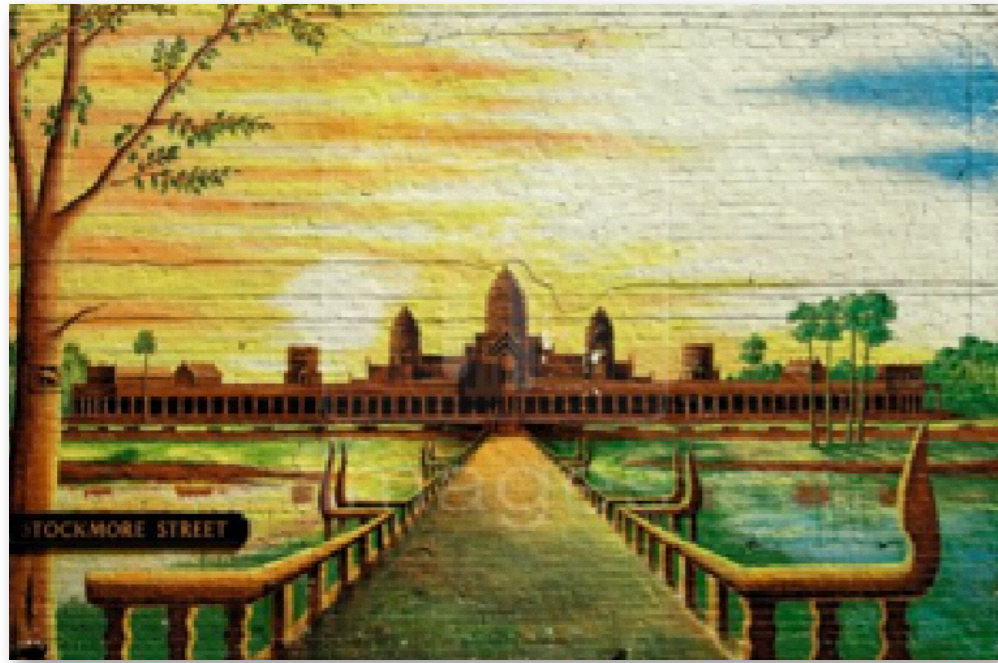


Image

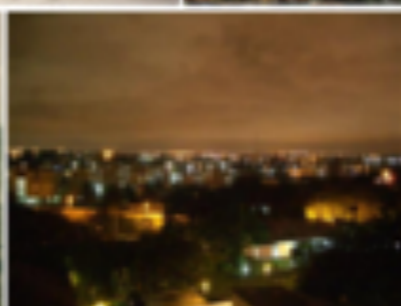
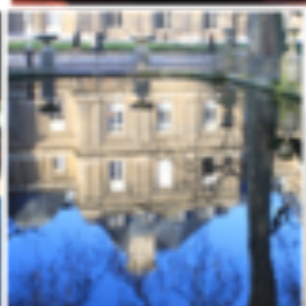


Plus proches voisins

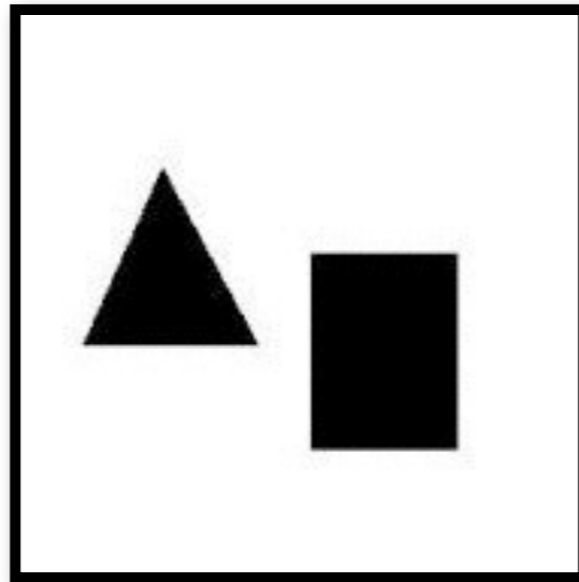




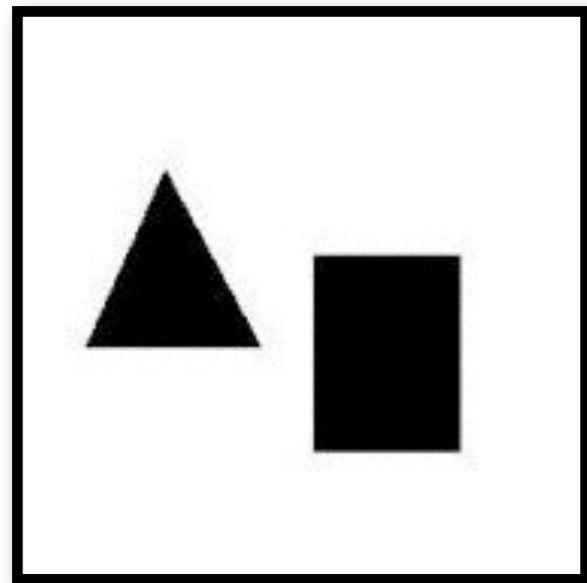
Utiliser les données pour déterminer ce qui est unique



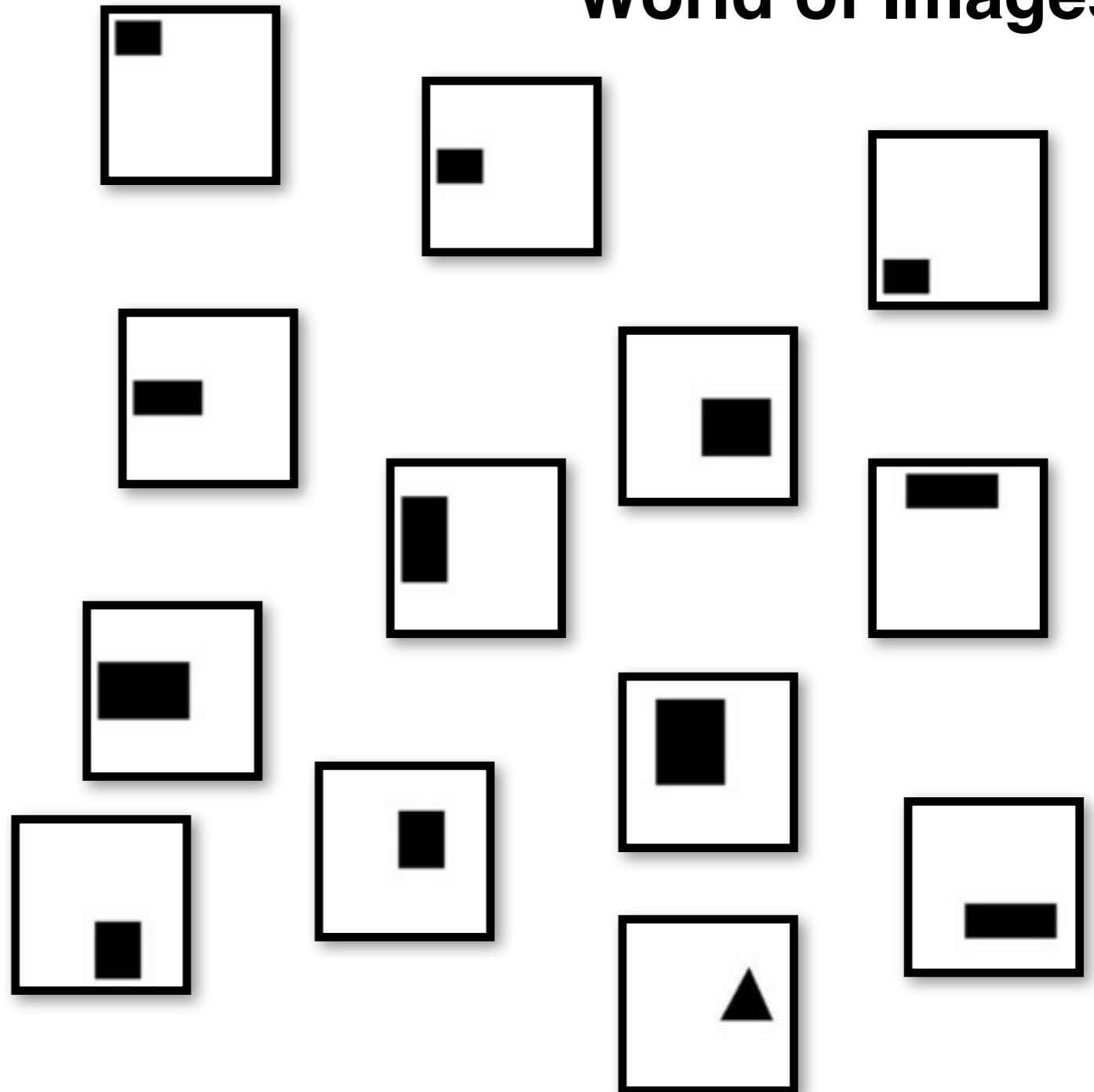
Qu'est-ce qui est unique?



Qu'est-ce qui est unique *étant donné le monde*?

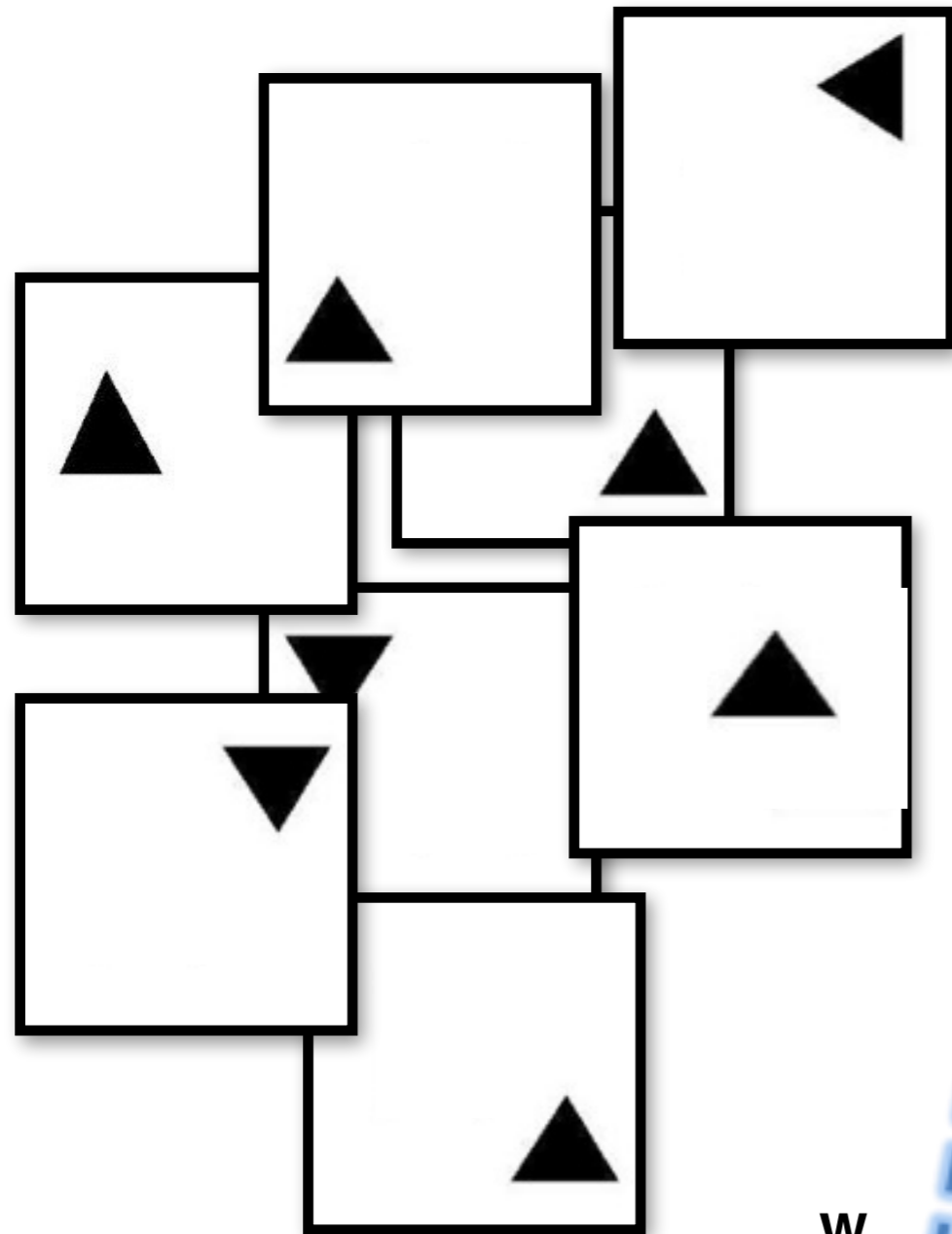


World of Images

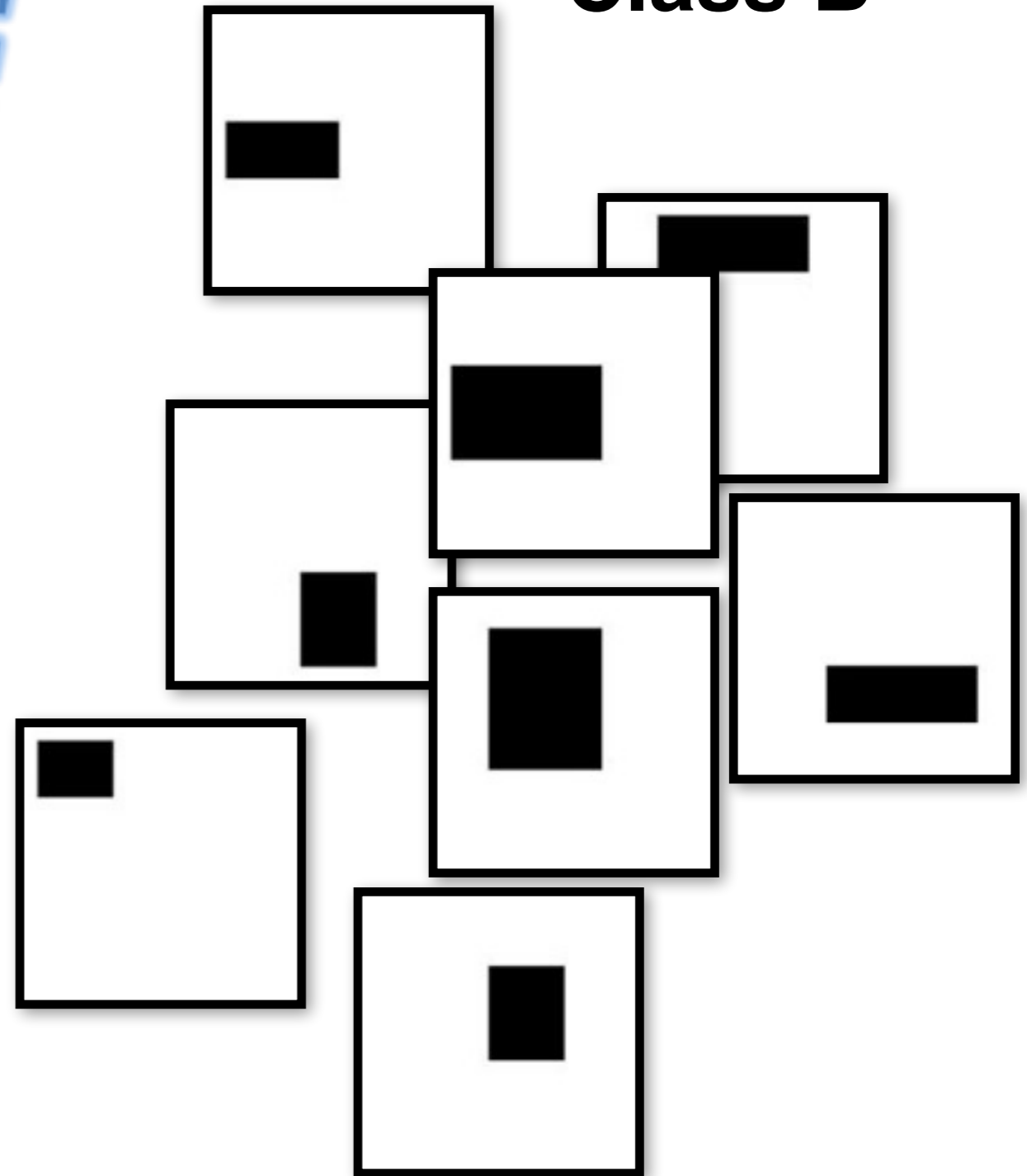


Support vector machine (SVM)

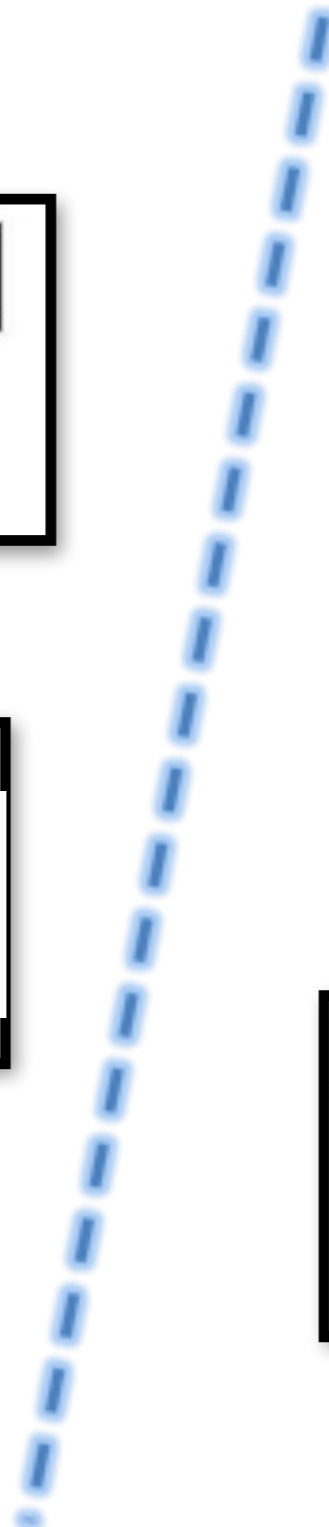
Class A



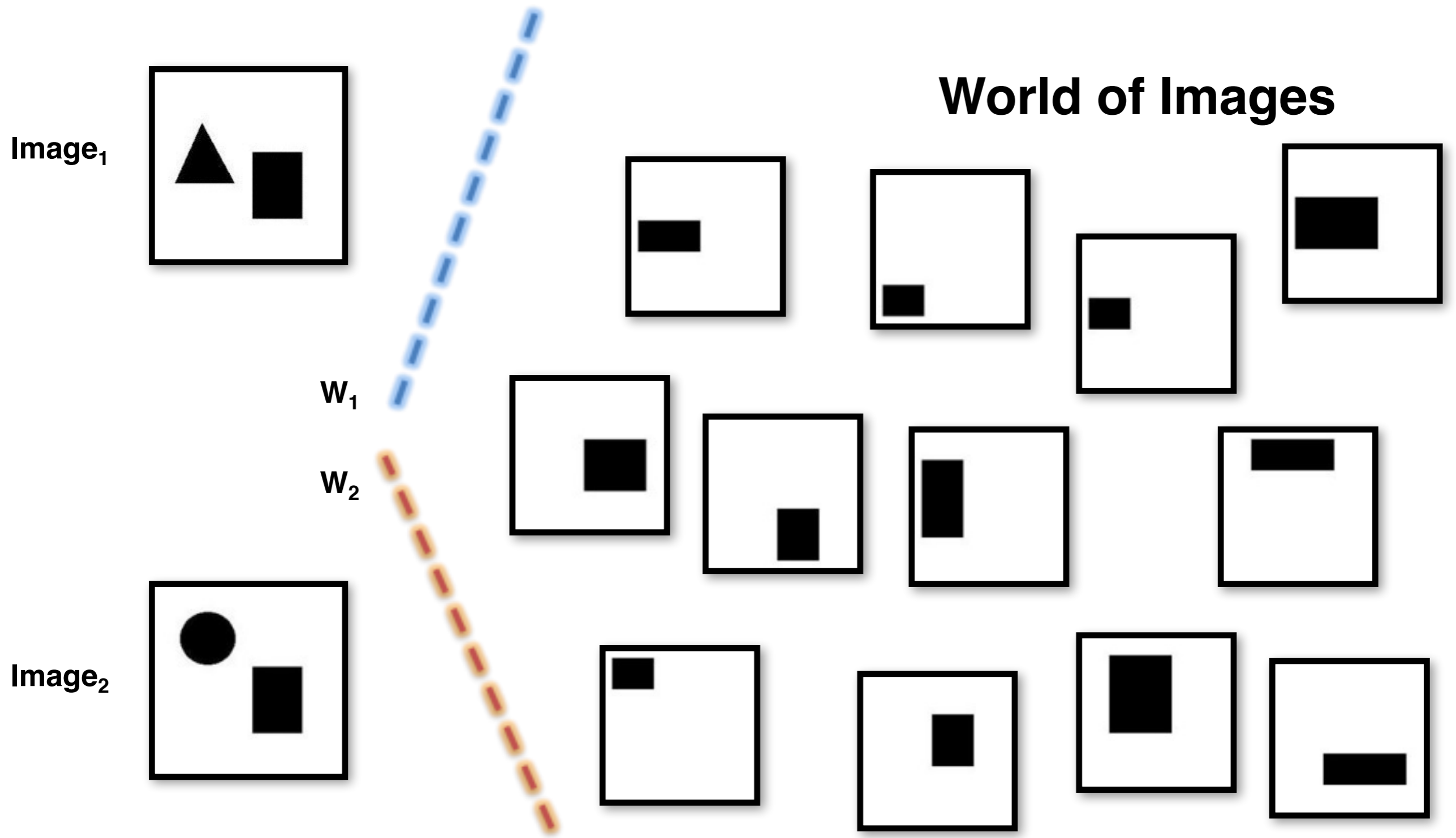
Class B



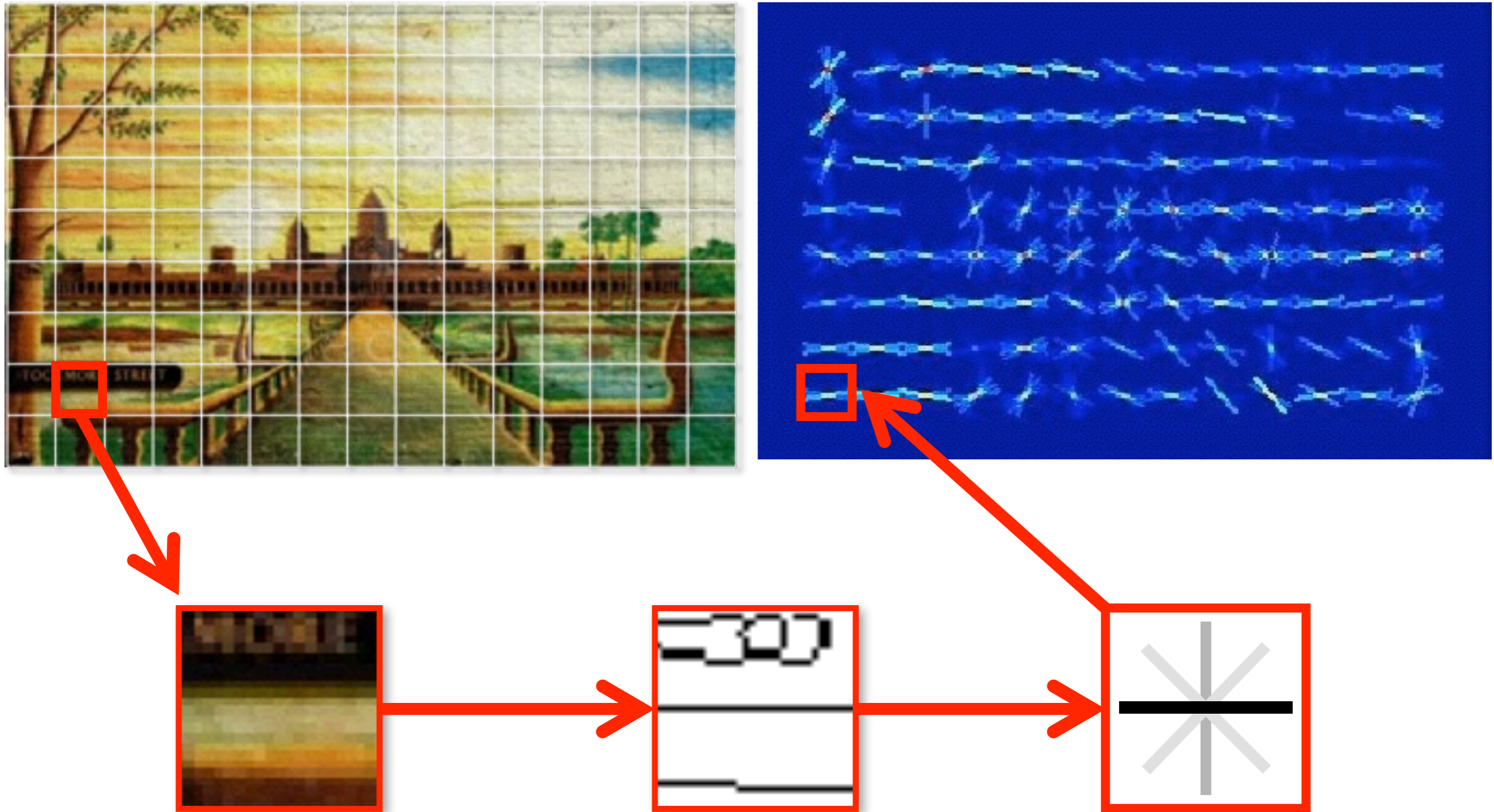
w_1



Per-exemplar SVM



Histogram of oriented gradients (HOG)

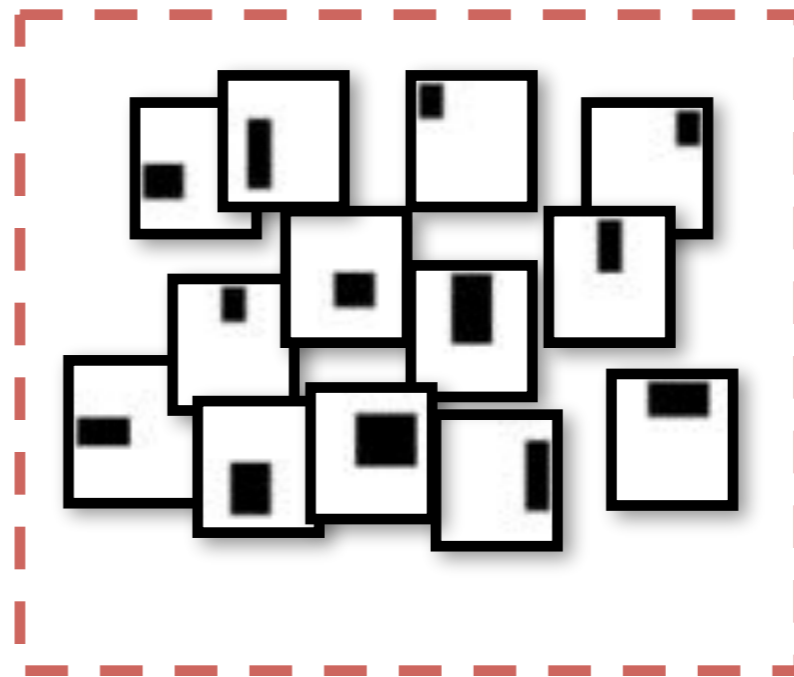
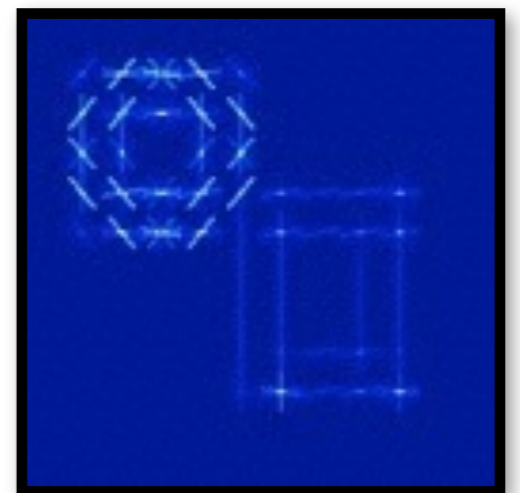
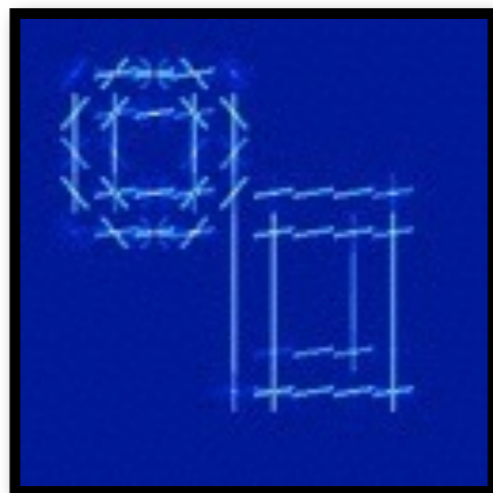
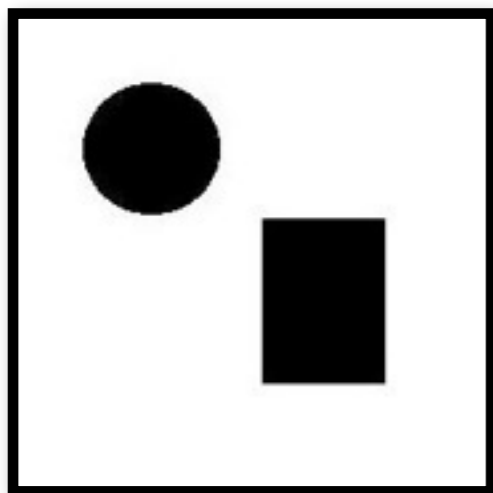
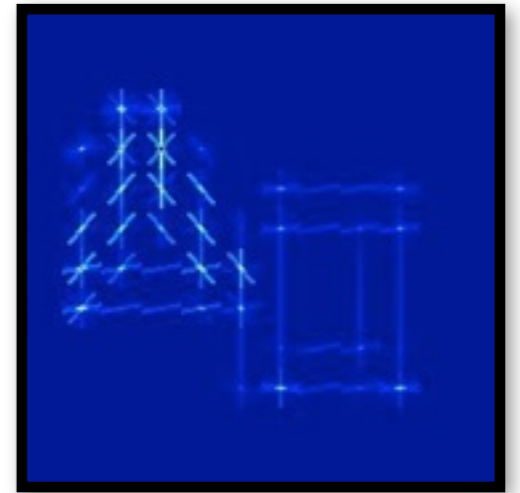
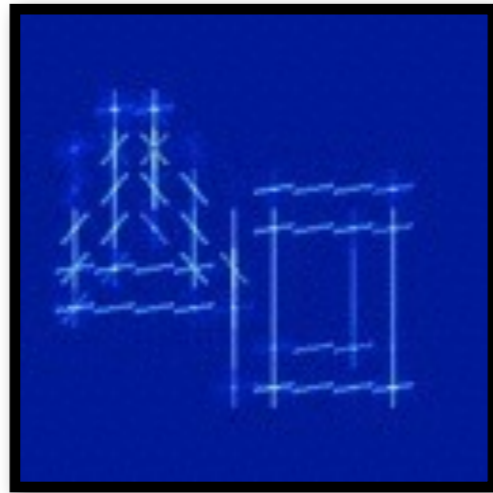
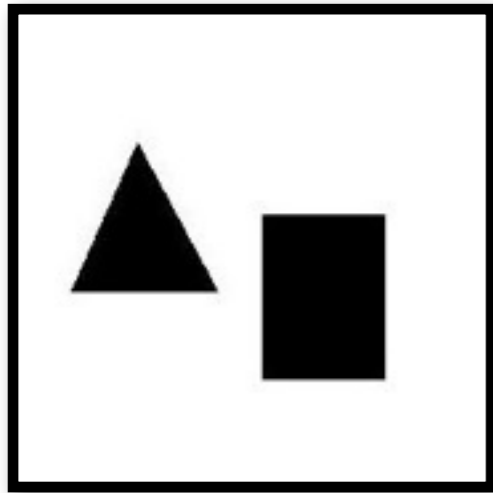


Visualizer ce qui est unique

Query

Before

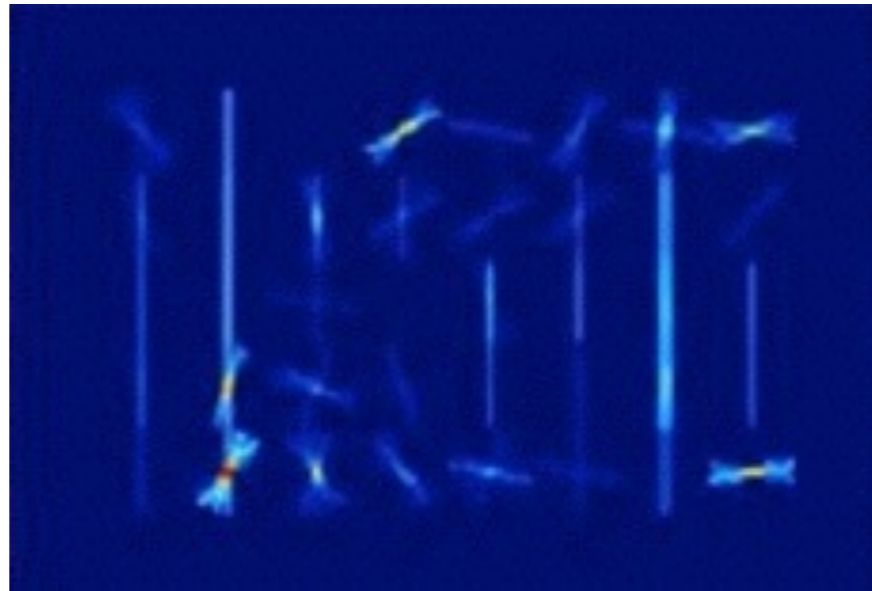
After



World of Images



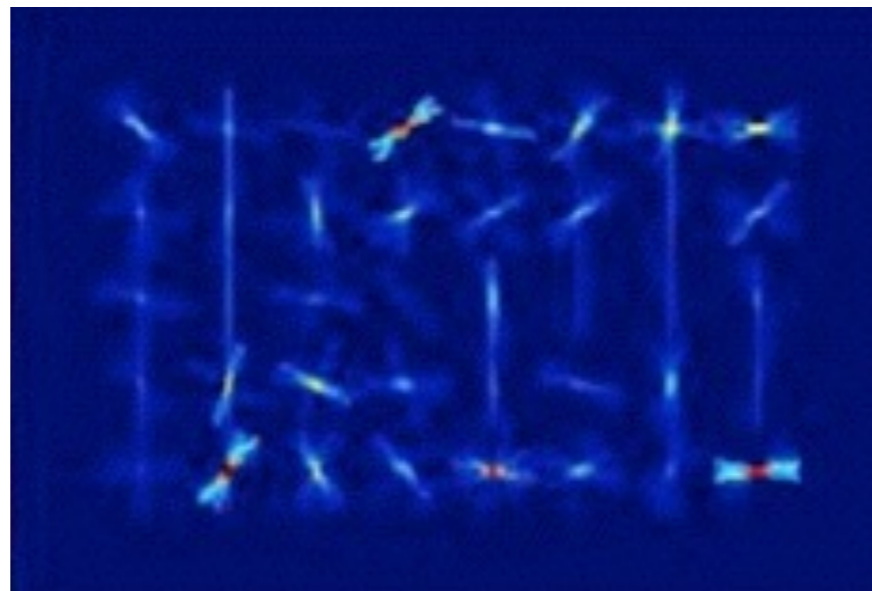
Input Query



HOG



Top Match



Learnt Weights



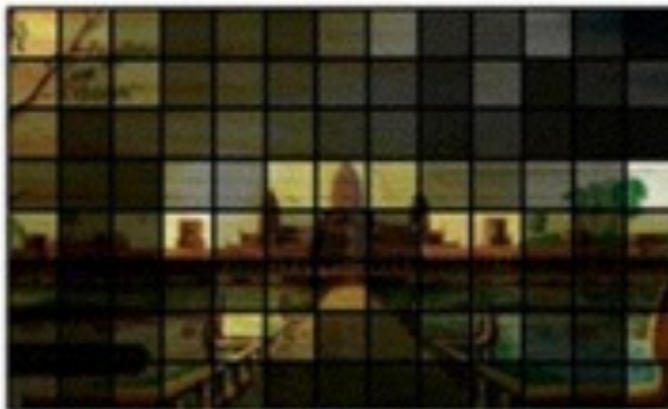
Top Match



Input Image



Uniform Weights



Learnt Weights



Uniform Weight Matches



Our Matches

Sketch based Image Retrieval

Input Sketch



Our Top Matches



Painting based Image Retrieval

Input Painting



Our Top Matches



painting2gps

Input Painting



Estimated Geo-location



Results

http://youtu.be/PY__Fo4o67I?t=1m15s

Les Dangers des Données

Biais

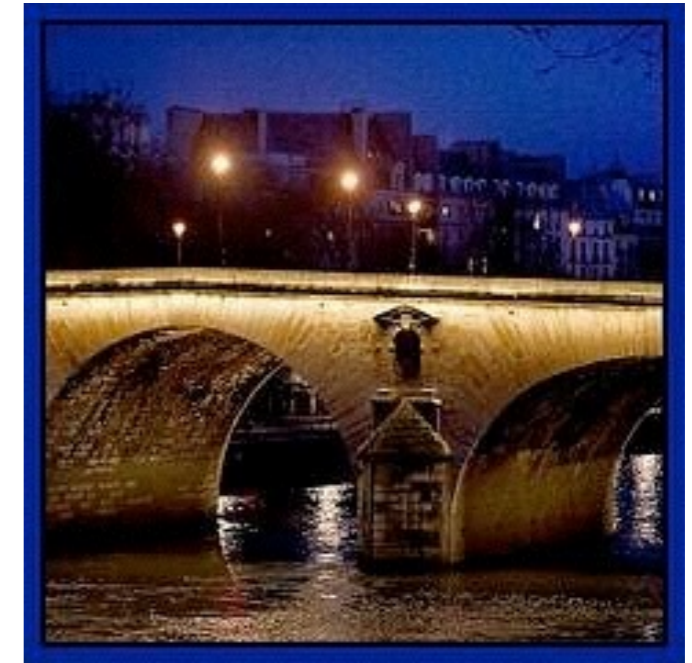
Internet contient un nombre énorme d'images
(Flickr, YouTube, Picasa, etc.)

Les images ne sont pas échantillonnées aléatoirement

Plusieurs sources de biais:

- Échantillonnage
- Photographe
- Social

Flickr Paris



Vrai Paris



Vraie Notre Dame



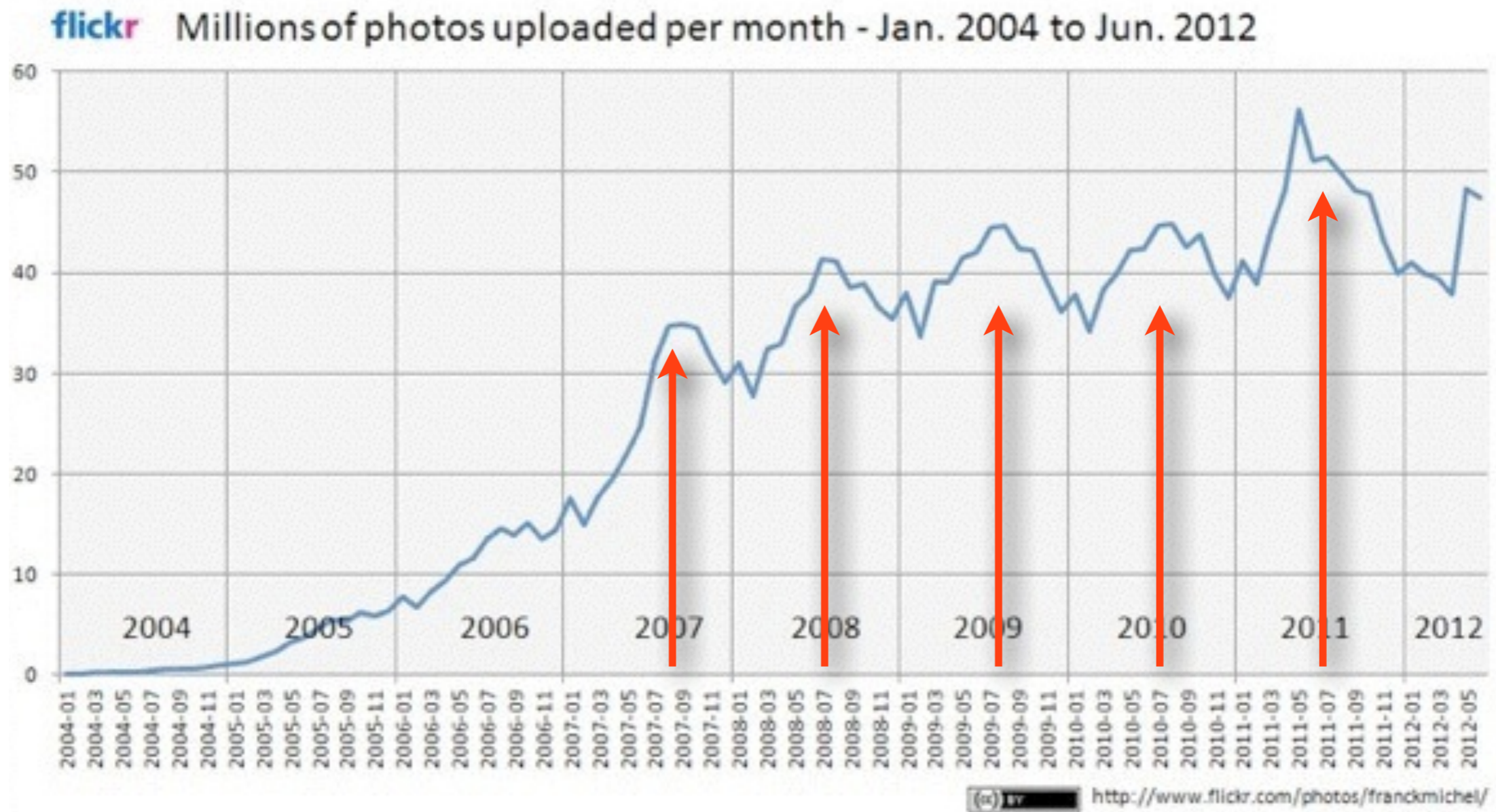
Biais d'échantillonnage

Nous aimons prendre des photos en vacances



Biais d'échantillonnage

Nous aimons prendre des photos en vacances



Biais du photographe

Nous voulons que nos photos soient intéressantes, ou reconnaissables!



VS.



Biais du photographe

Conventions photographiques



VS.



Biais social



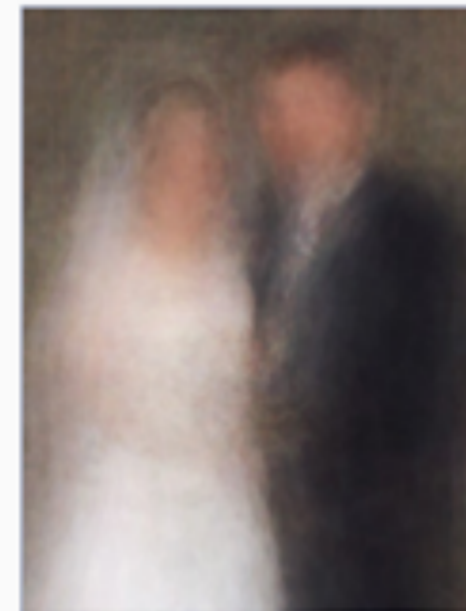
Little Leaguer



Kids with Santa



The Graduate



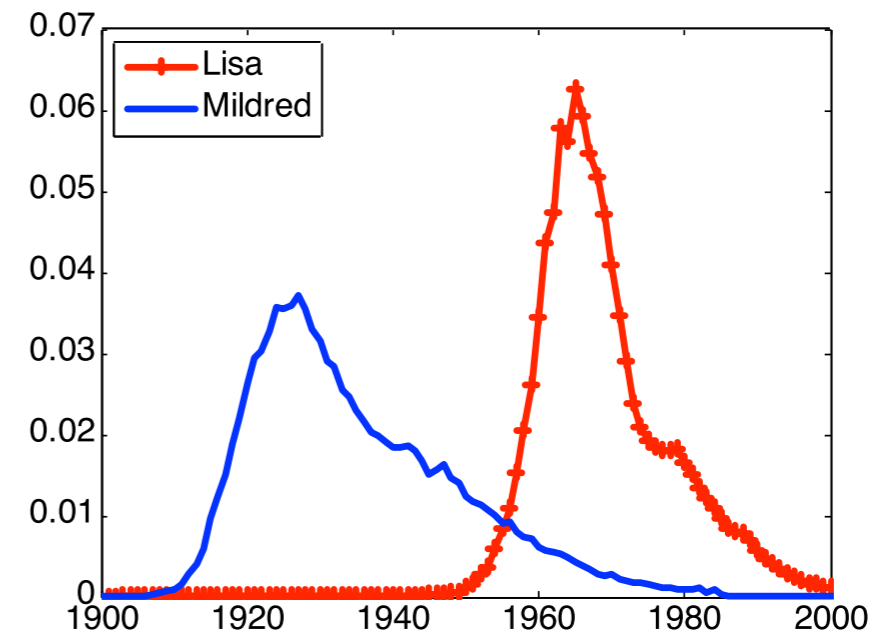
Newlyweds

“100 Special Moments” by Jason Salavon

Biais Social



Mildred and Lisa



Source: U.S. Social Security Administration

Biais social



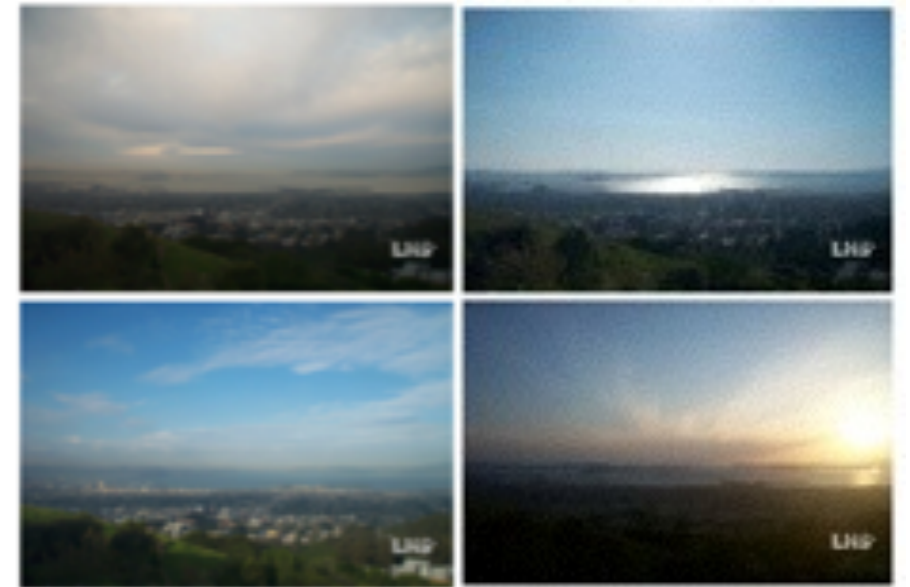
Limiter le biais



Street side
Google StreetView



Satellite
google.com

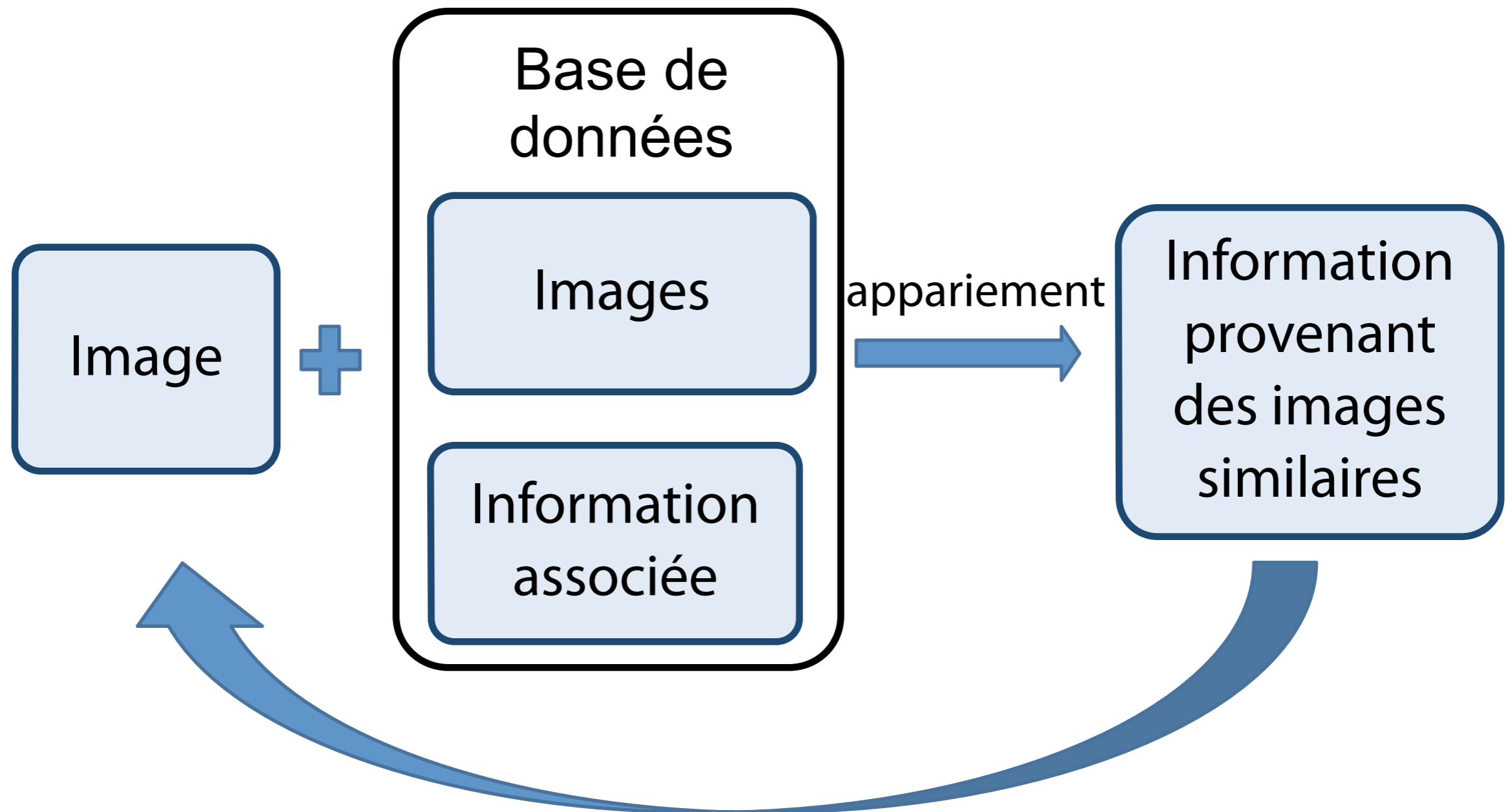


Webcams

Capture autonome réduit le biais

- On en a toujours un peu...

Survol



Truc: si vous avez assez d'images, la base de données devrait contenir des images suffisamment similaires, faciles à trouver!