Données visuelles massives

GIF-4105/7105 Photographie Algorithmique, Hiver 2016

Jean-François Lalonde

L’art de Cassandra Jones

http://www.youtube.com/watch?v=5H7WrlBrDRg

Problèmes

- Quel genre de photos y a-t-il sur Internet?
- Comment pouvons-nous y avoir accès?
- Qu’est-ce qu’on peut en faire?

Photos spécifiques

Photos du Colisée (Snavely et al.)

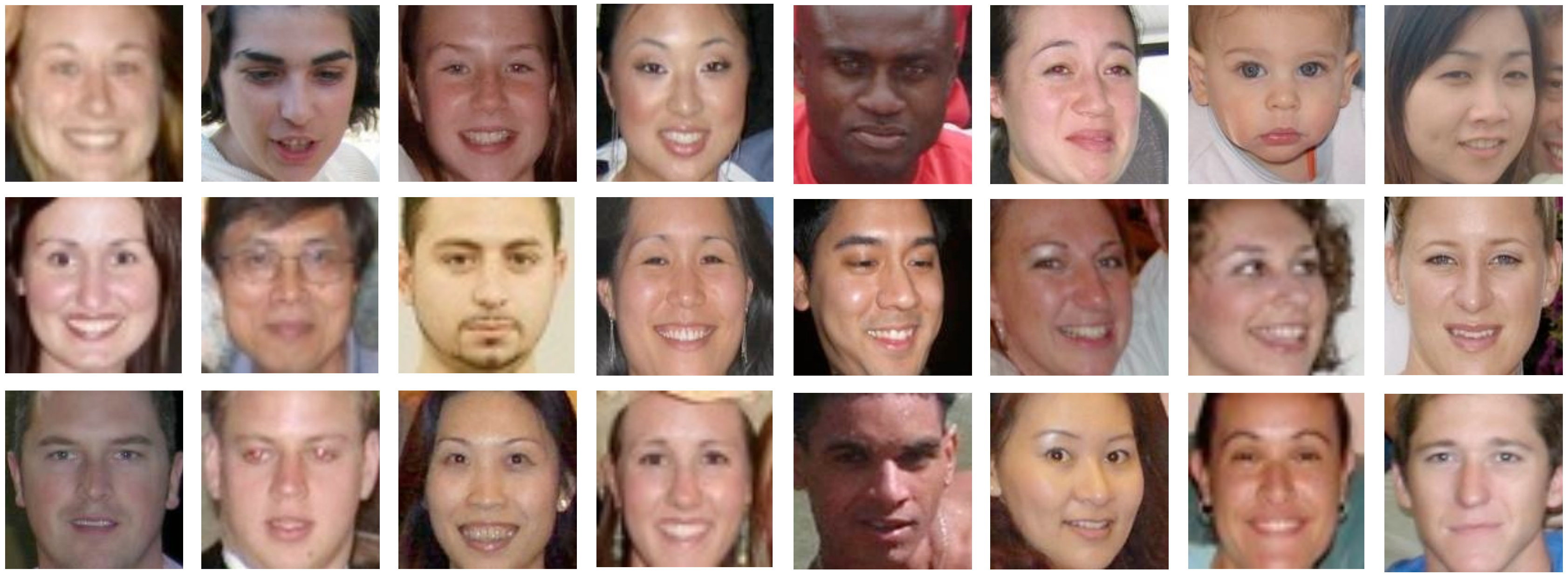
Portraits de Bill Clinton

La plupart des photos sont “génériques”

Données génériques

rues

nourriture



visages

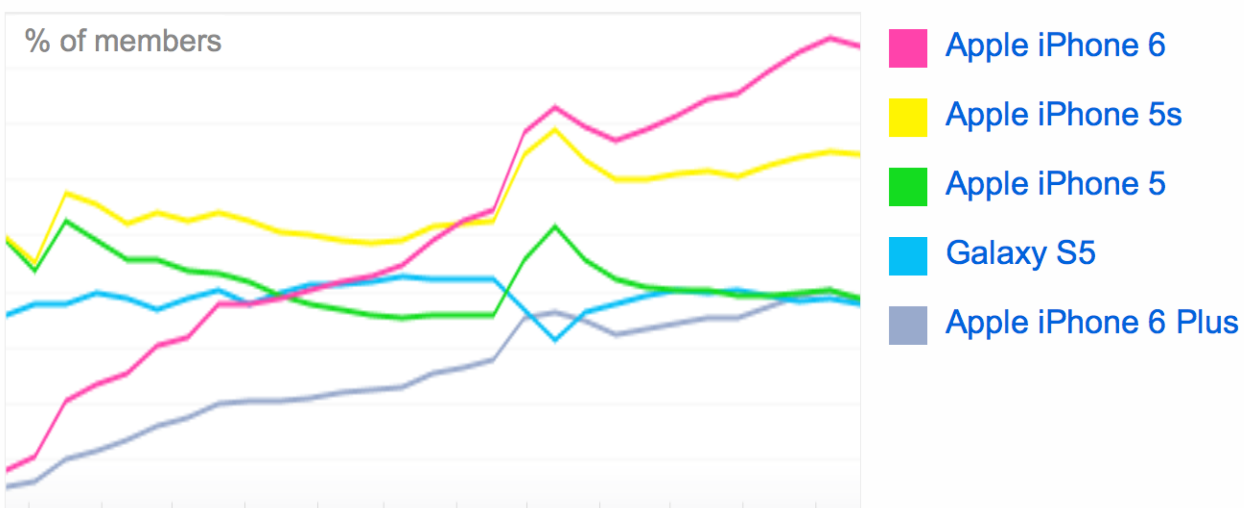
personnes

Les sources d'images sur Internet

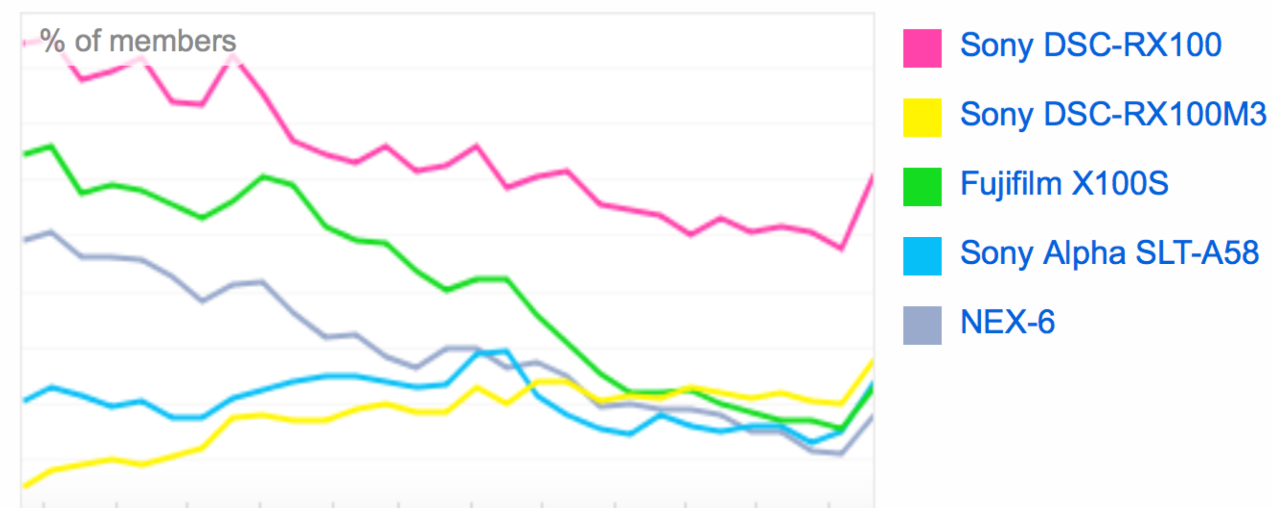
- Engins de recherche
  - Google, Bing, Yahoo
- Réseaux sociaux
  - Facebook, Google+, Twitter, Instagram
- Sites de partage de photos
  - **Flickr**, Picasa, Panoramio, photo.net, dpchallenge.com
- Base de données en recherche
  - CalTech 256, PASCAL VOC, LabelMe, Tiny Images, ESP game, Squigl, Matchin, SUN, ImageNet, …

Quelle est la caméra la plus populaire?

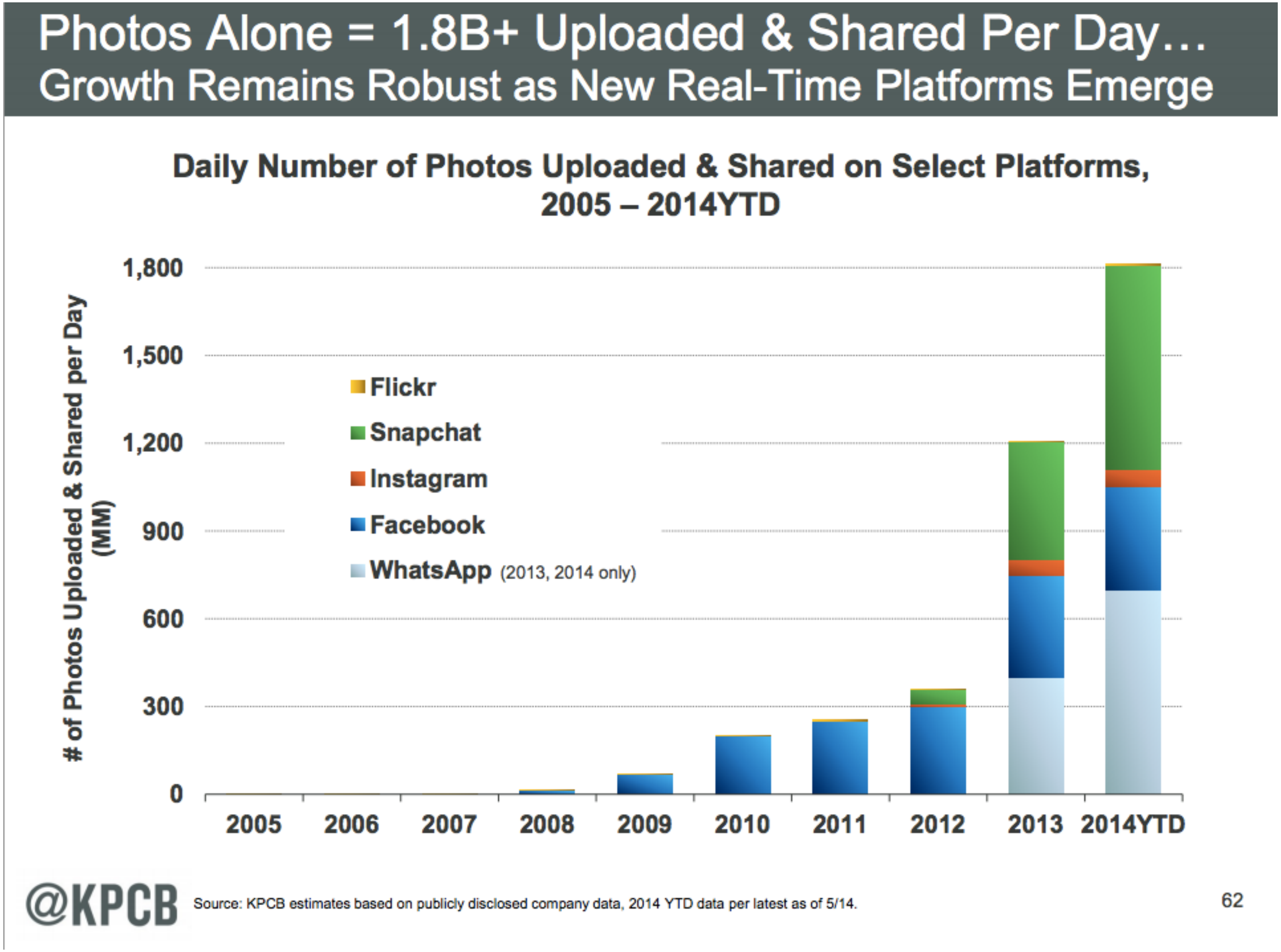
Most Popular Cameras in the Flickr Community



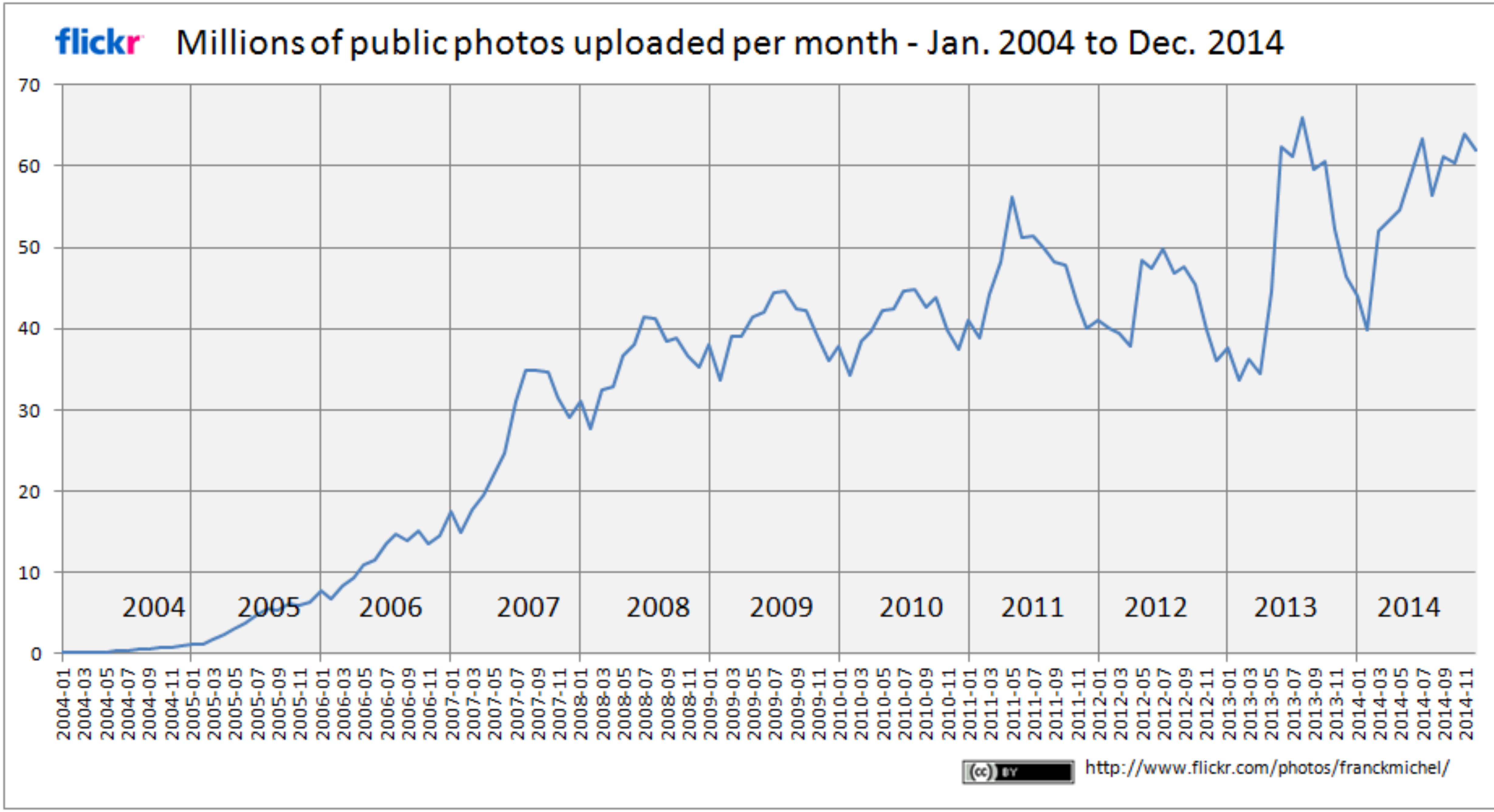
Popular Point & Shoot Cameras



Combien de photos sont-elles partagées *à chaque jour?*



Quelle est la taille de Flickr?



- API de Flickr reporte 4.25 milliards de photos en Décembre 2014

Credit: Franck_Michel (http://www.flickr.com/photos/franckmichel/)

Problèmes

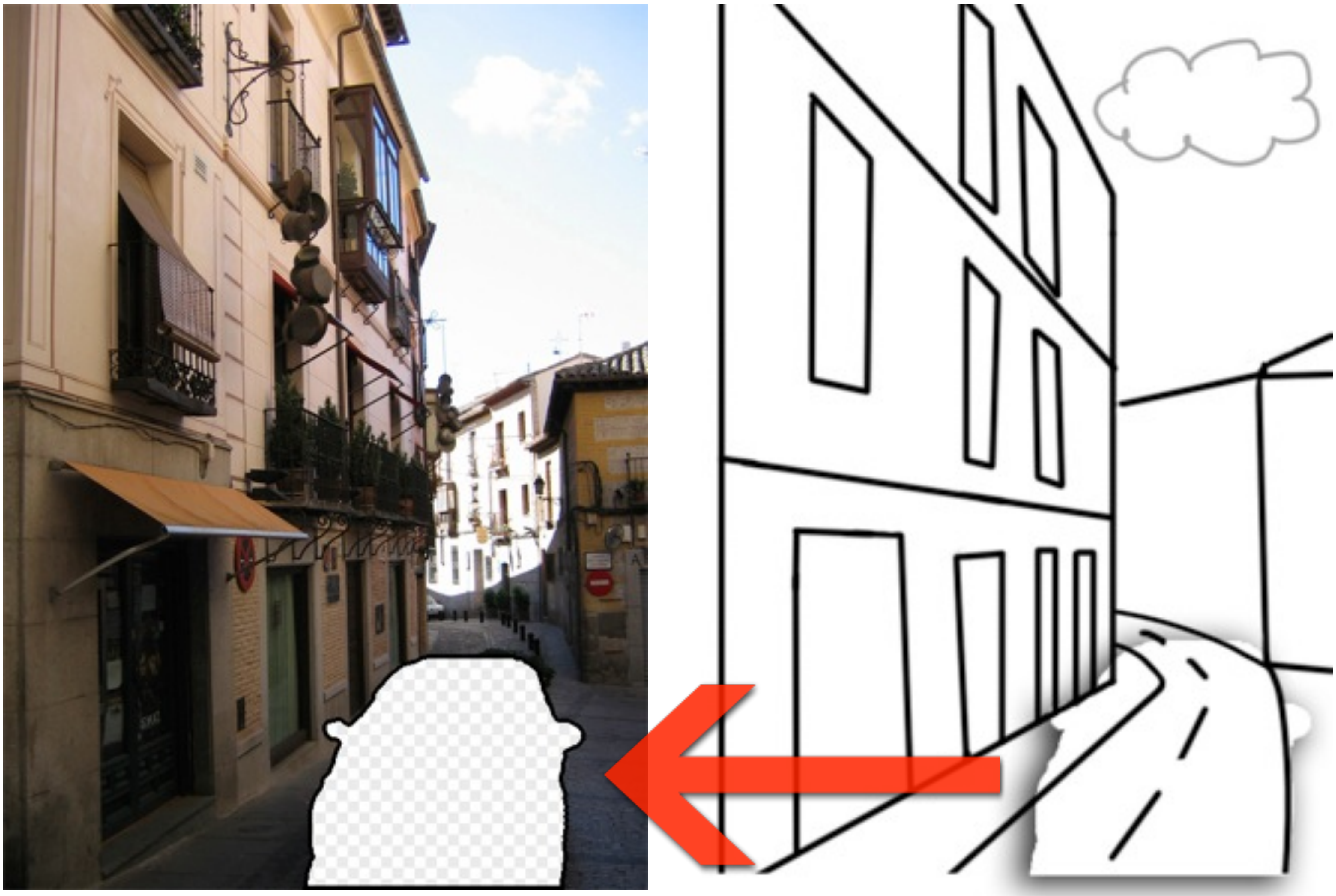
- Quel genre de photos y a-t-il sur Internet?
- Comment pouvons-nous y avoir accès?
- Qu’est-ce qu’on peut en faire?
    - Voyons un exemple d’application

[Hays and Efros. Scene Completion Using Millions of Photographs. SIGGRAPH 2007 and CACM October 2008.]

Diffusion

Efros and Leung

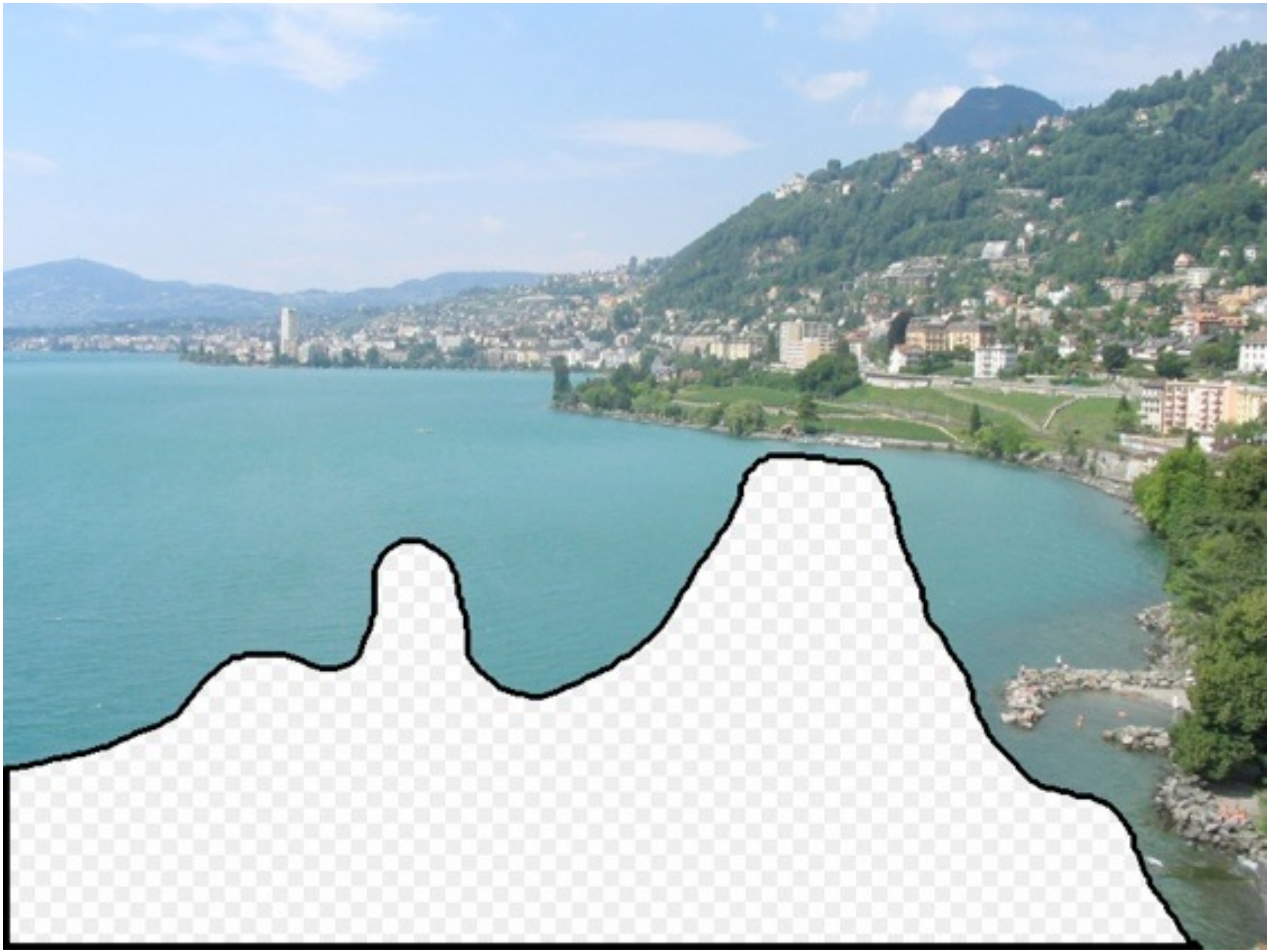
Compléter l'image par appariement de scènes



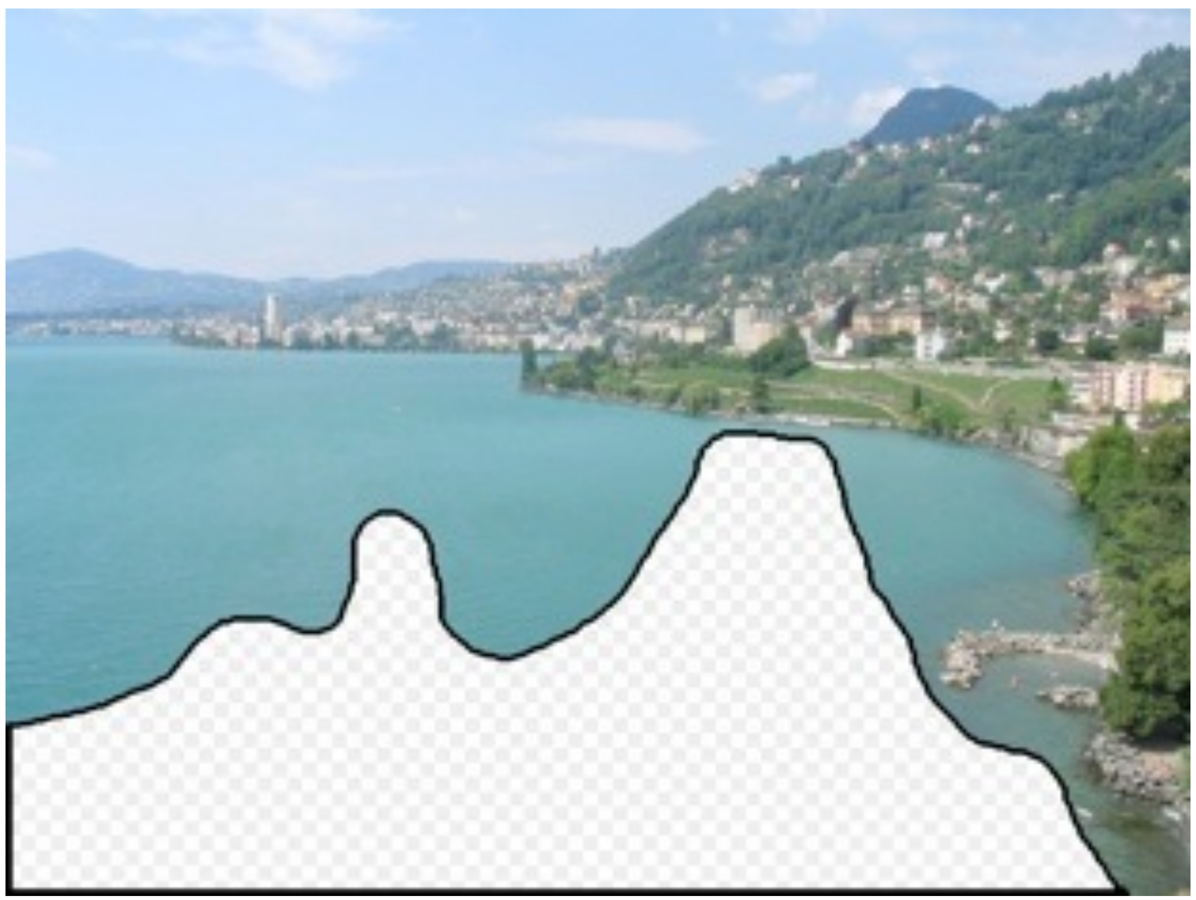
"Scene Completion"

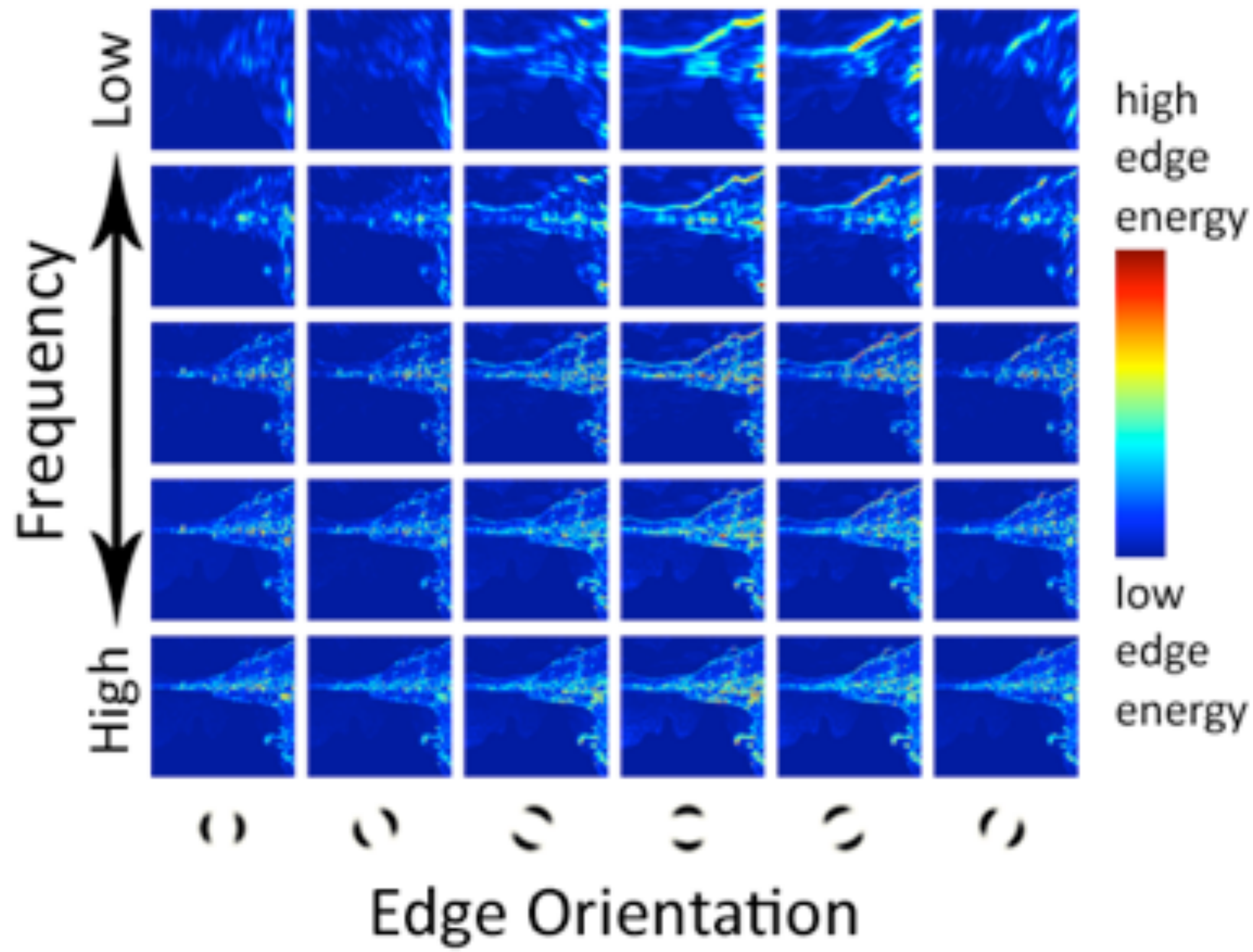
Algorithme

Appariement de scènes

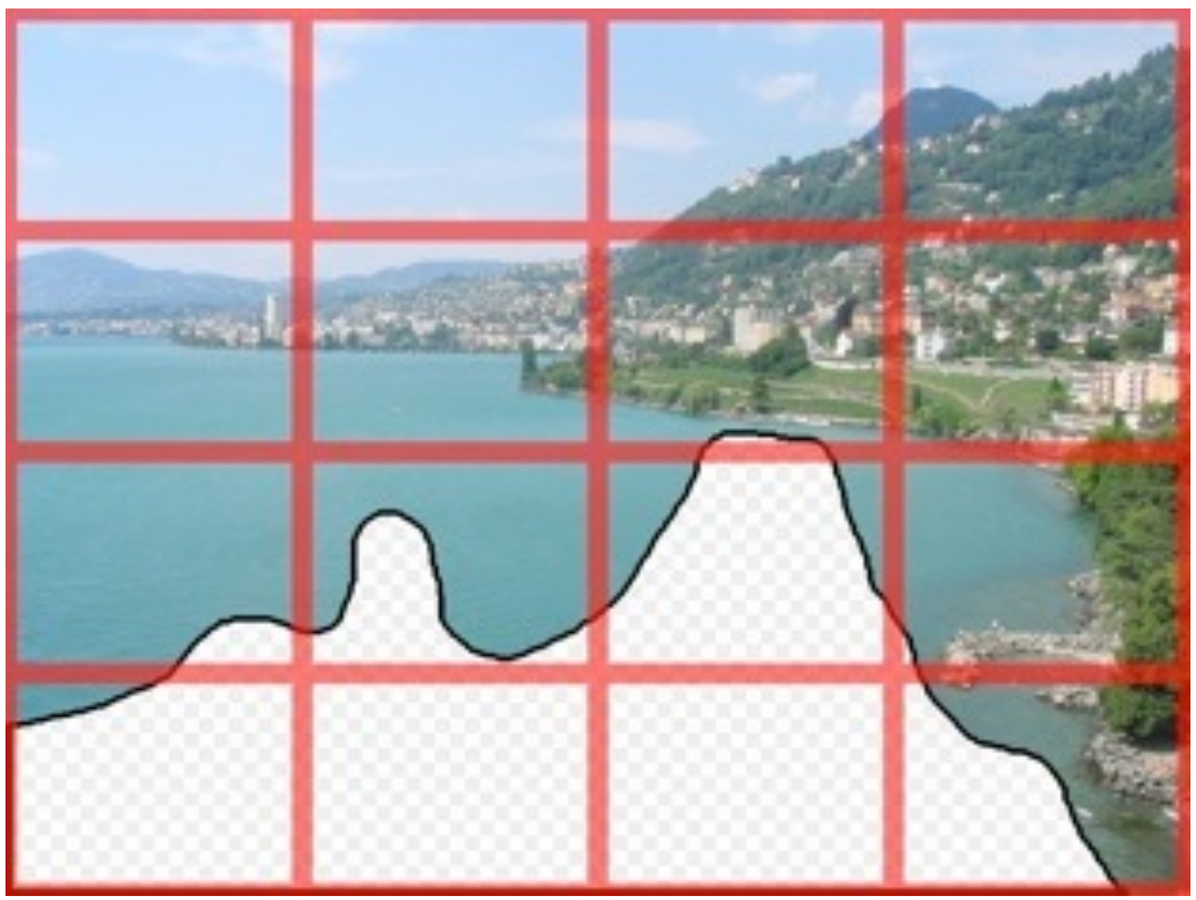


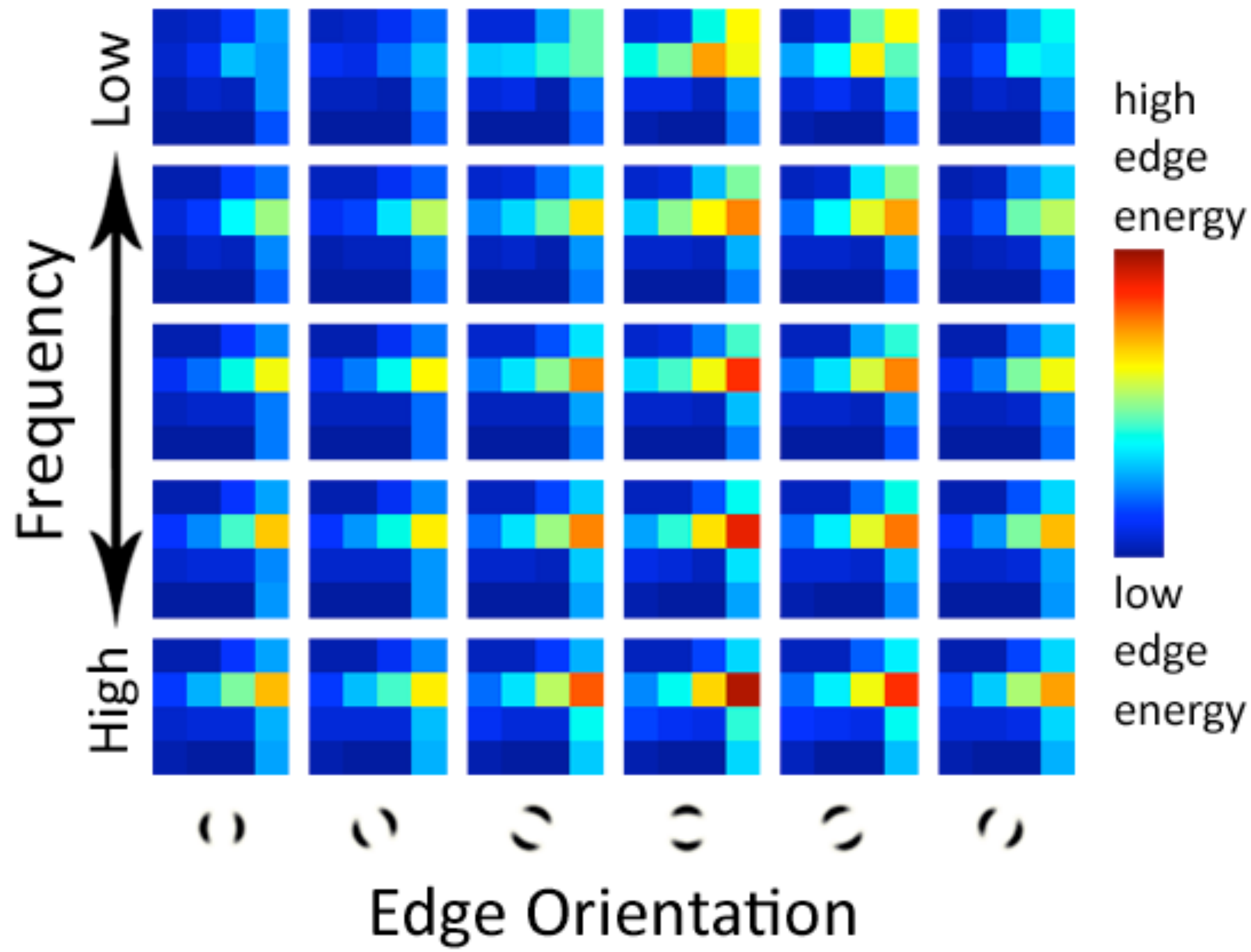
Descripteur de scène





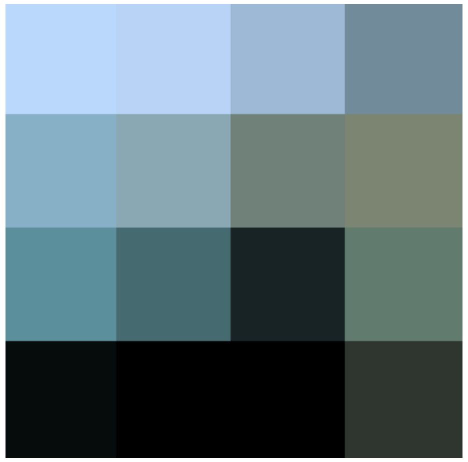
Descripteur de scène



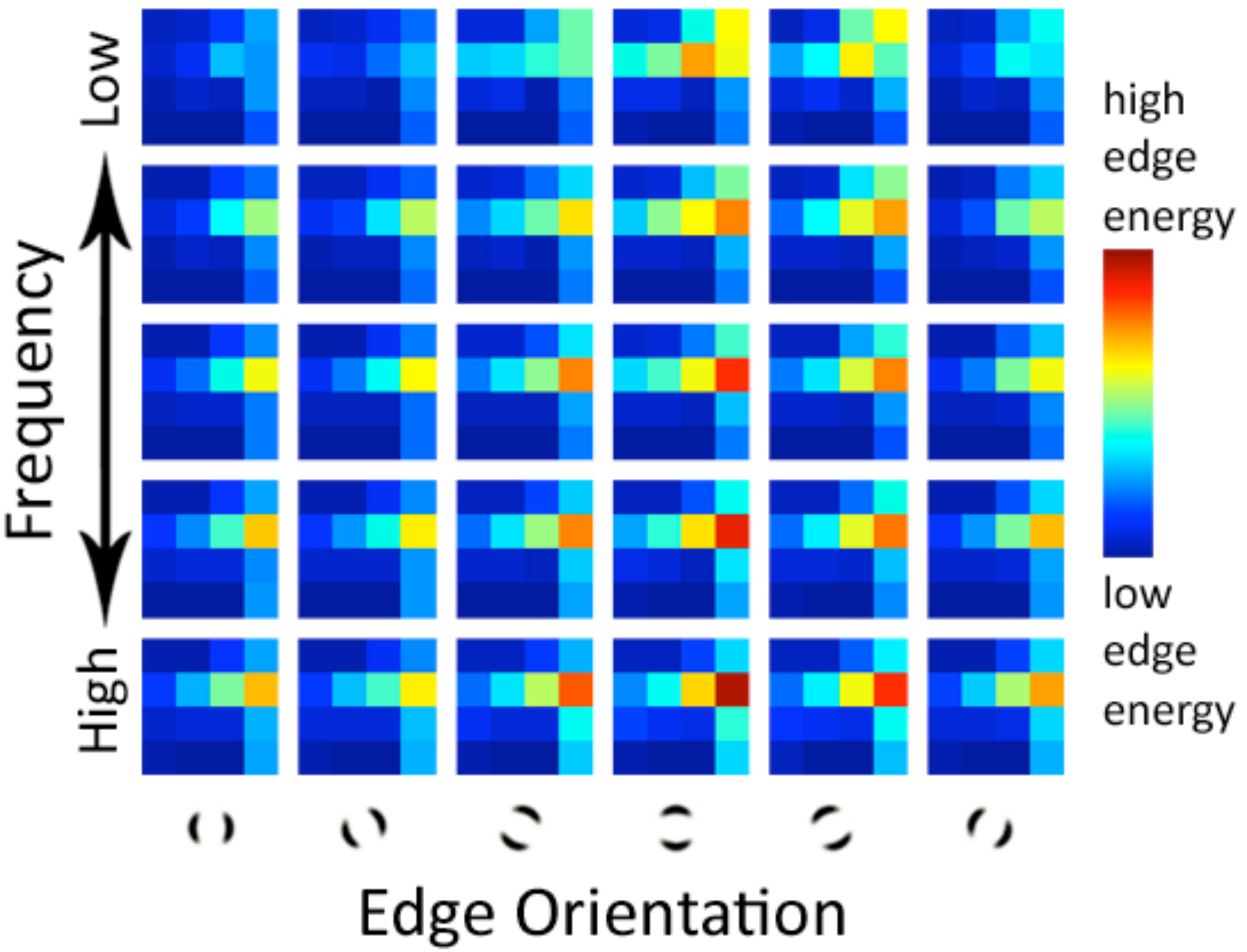


Scene Gist Descriptor
(Oliva and Torralba 2001)

Descripteur de scène

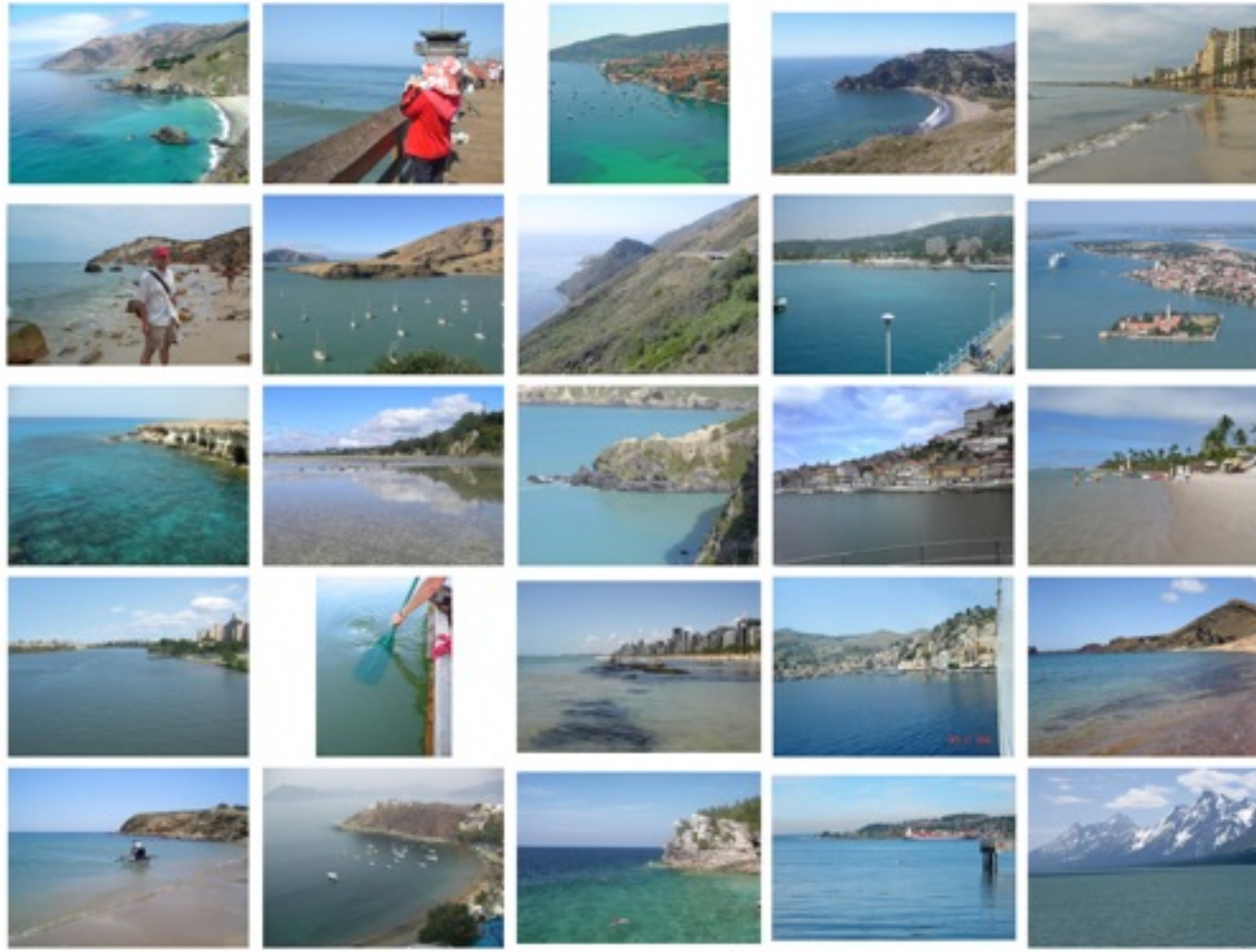


+



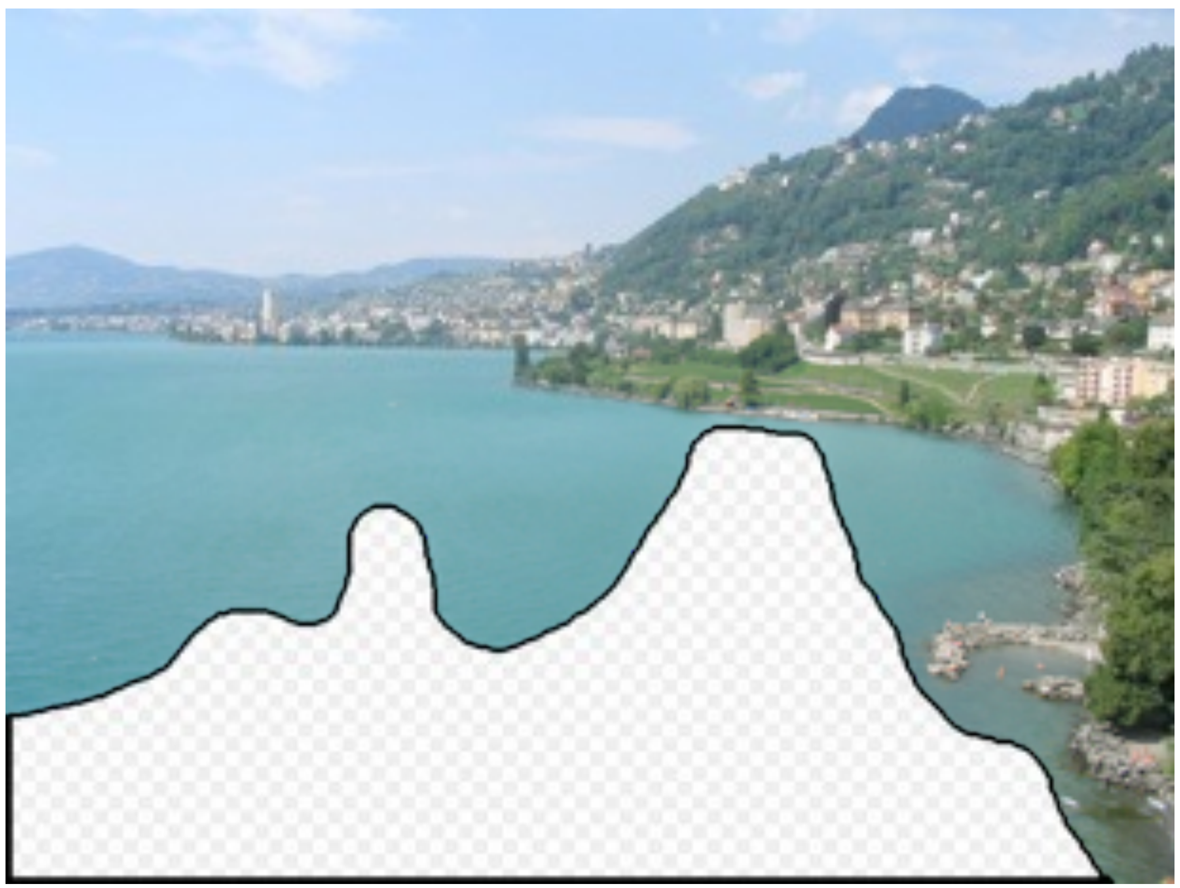
Descripteur nommé "gist"
(Oliva and Torralba 2001)

2 millions d’images de Flickr



… 200 total

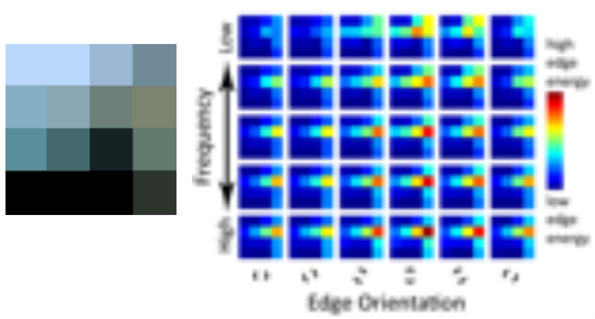
Appariement local



Graph cut + Poisson blending

Ordonner les résultats

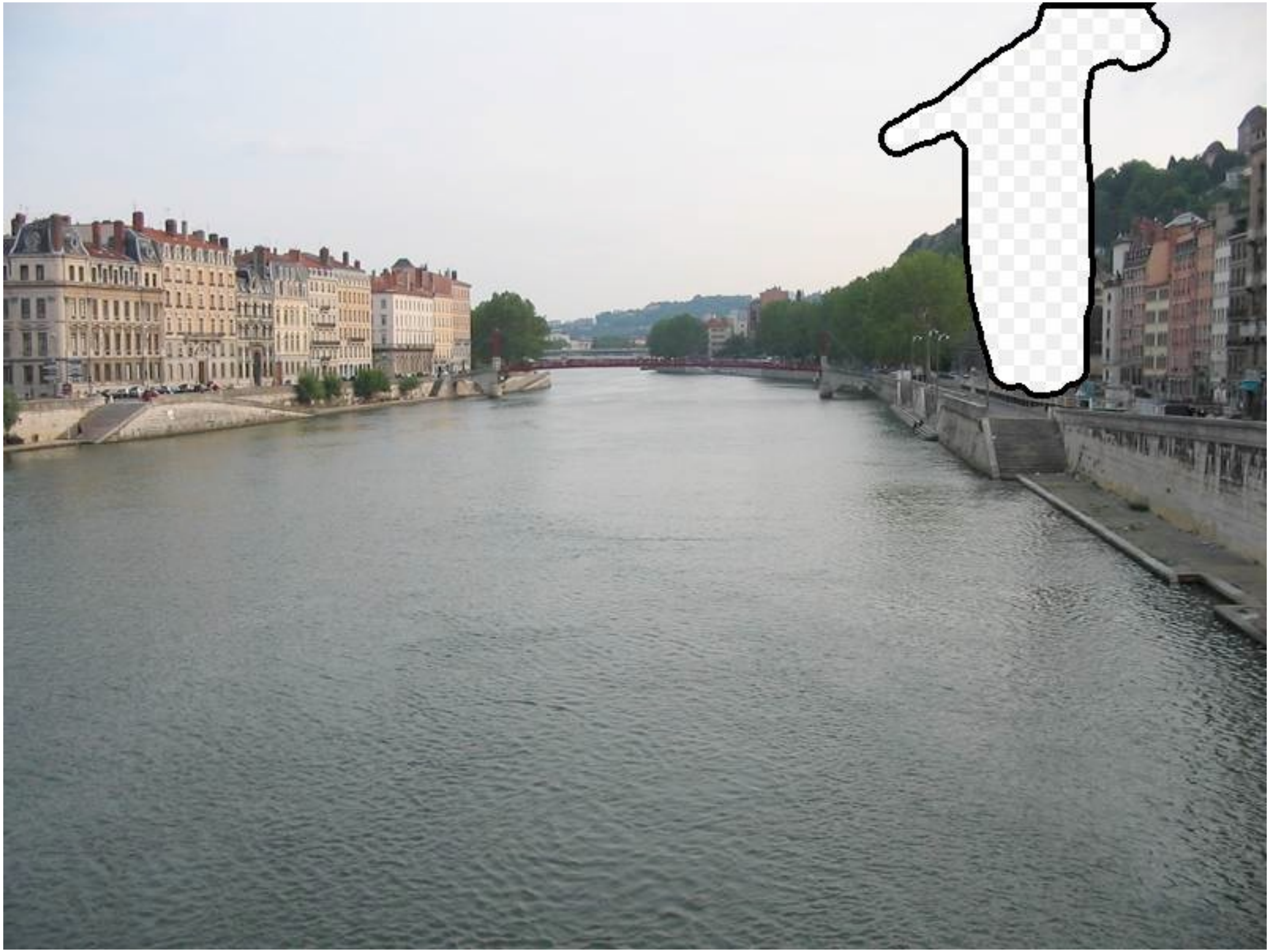
Score final est la somme de:



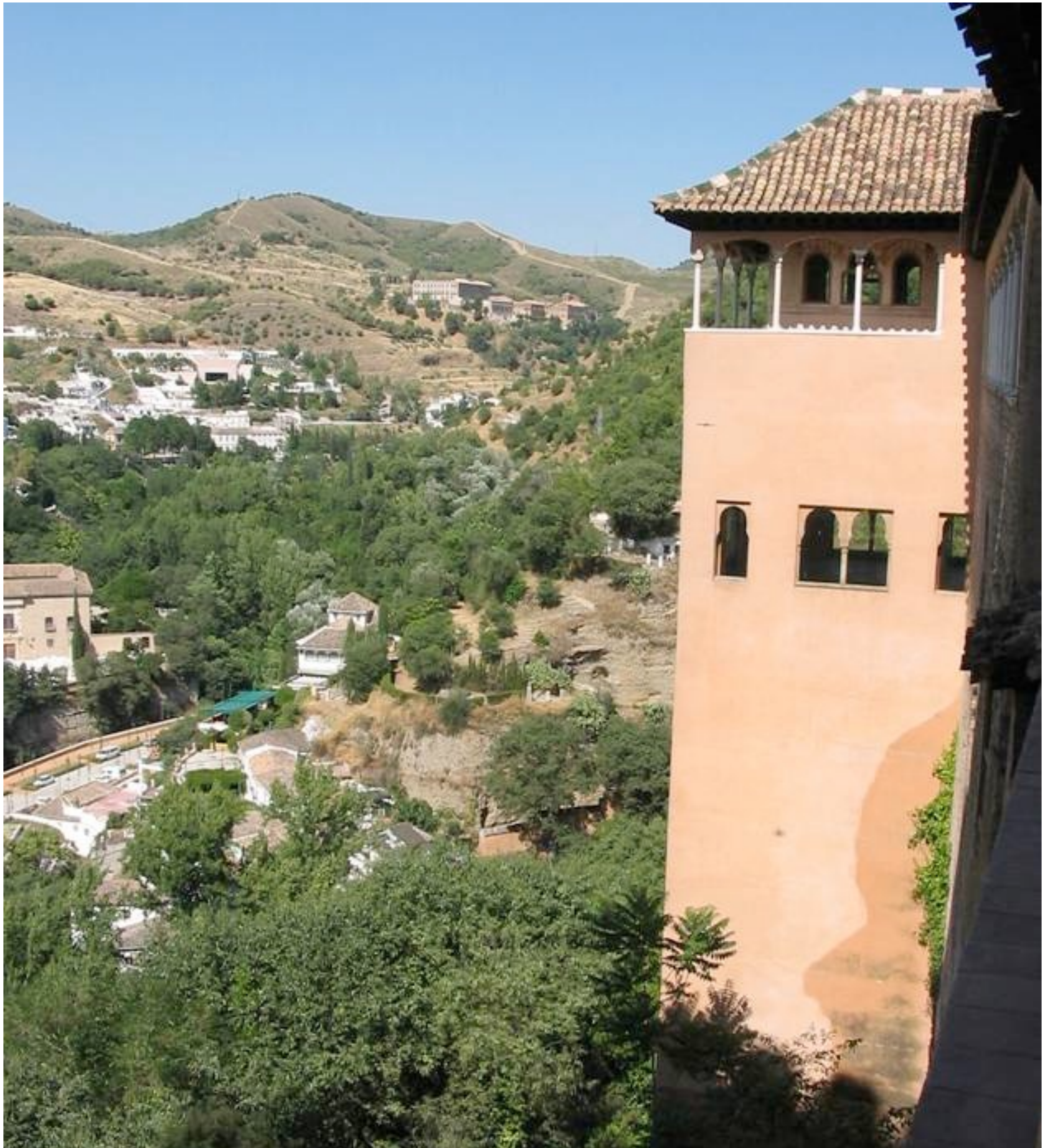
L'appariement de scènes

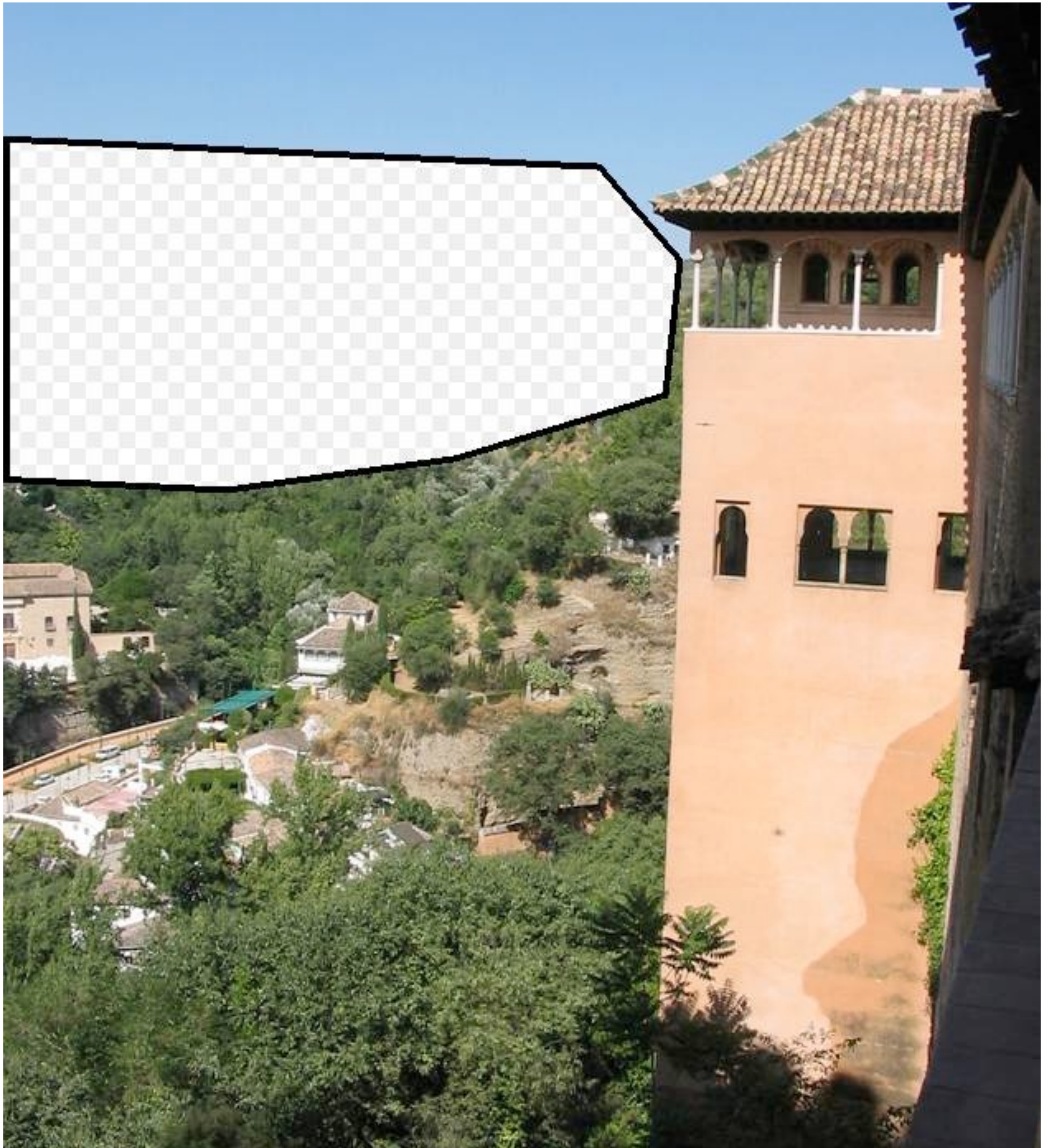
L'appariement local
(color + texture)

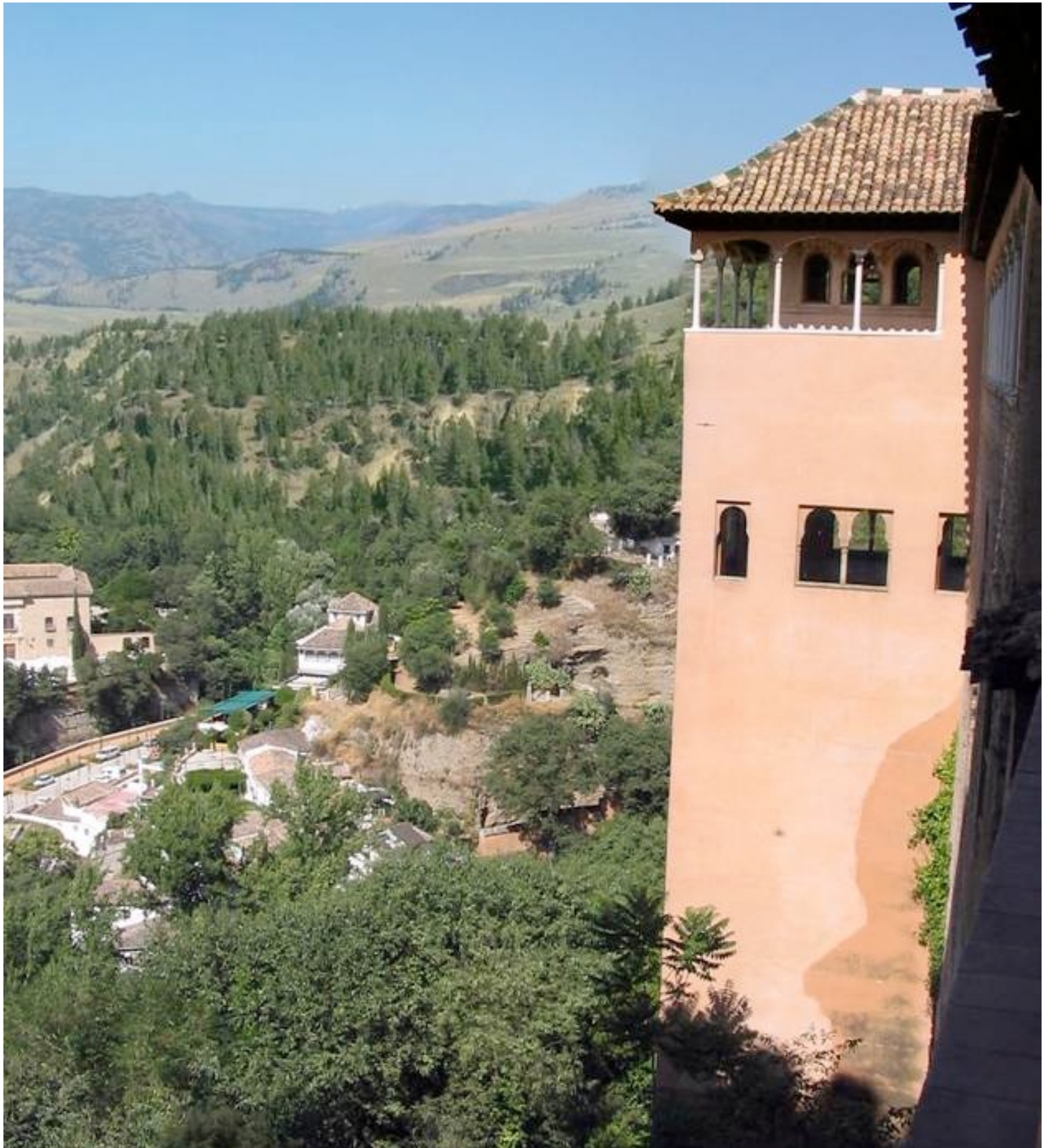
Le coût de la coupure de graphe



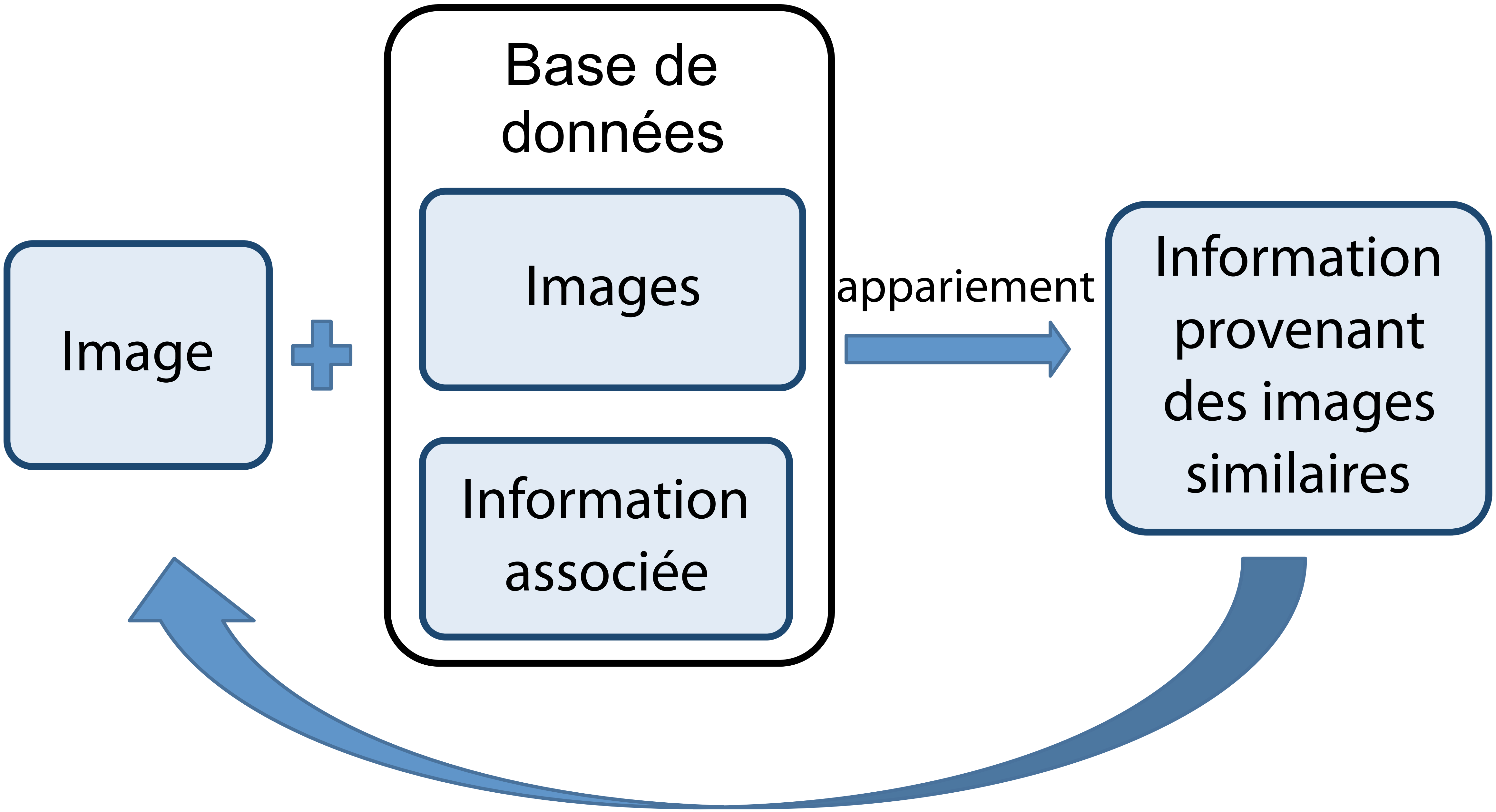
… 200 scenes



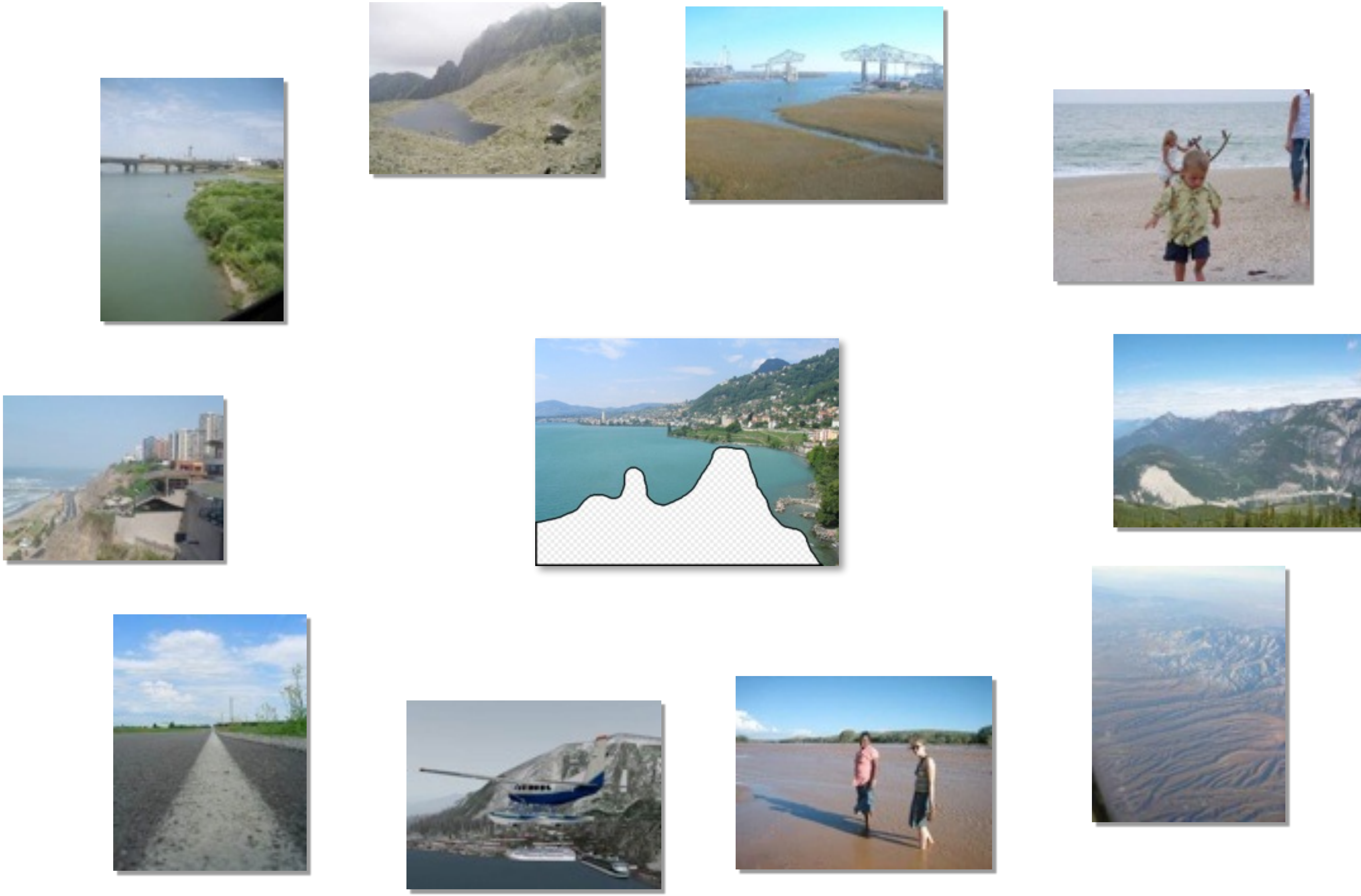


Utiliser beaucoup de données!

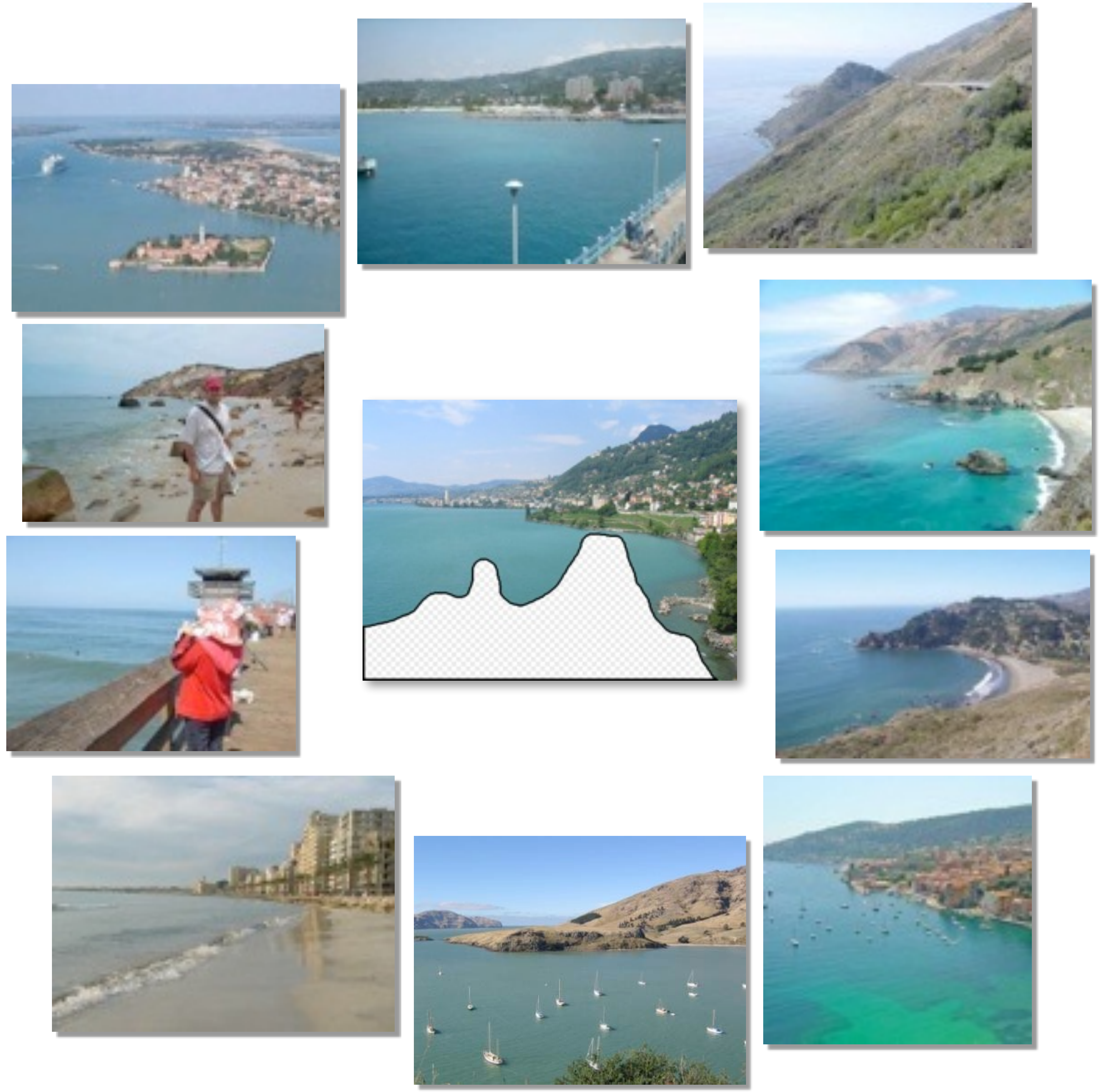


Truc: si vous avez assez d'images, la base de données devrait contenir des images suffisamment similaires, faciles à trouver!

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

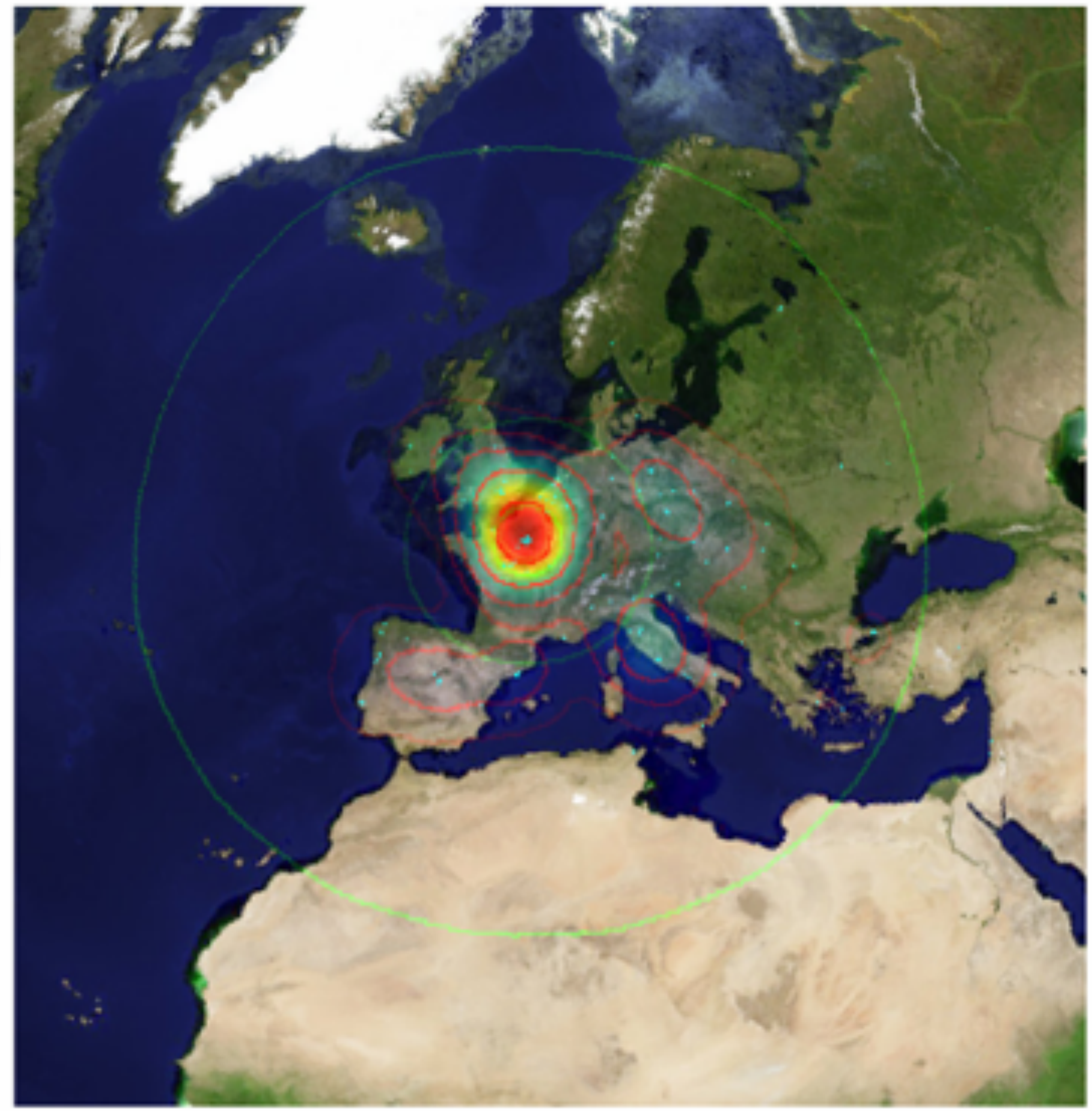
- Apparier des portions de l'image
- Déterminer ce qu'il faut apparier

im2gps (Hays & Efros, CVPR 2008)

6 millions d’images avec GPS

Quelle information géographique est disponible dans une image?

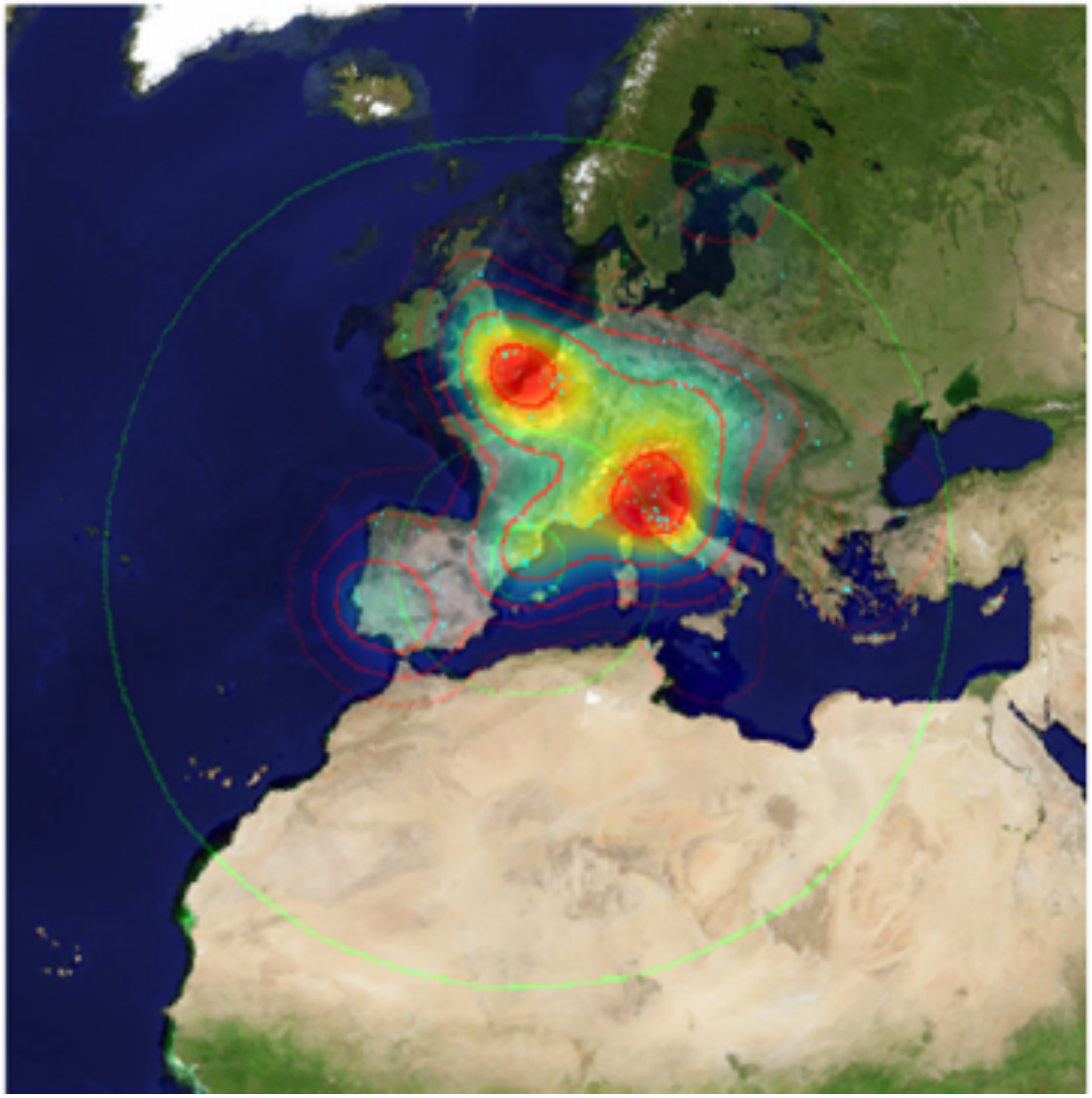

Paris
Paris
Paris
Paris
Paris
Paris
Paris
Madrid
Rome
Paris
Cuba
Paris
Paris
Poland
Paris
Paris



Exemples


Madrid
england
France
Paris
Croatia
heidelberg
Macau
Malta
Cairo
Italy
Italy
Italy
Latvia
europe
Barcelona
Austria

Votes



Philippines

Houston

Thailand

Houston

Maldives

Philippines

NewZealand

Bermuda

Palau

Mexico2

Brazil

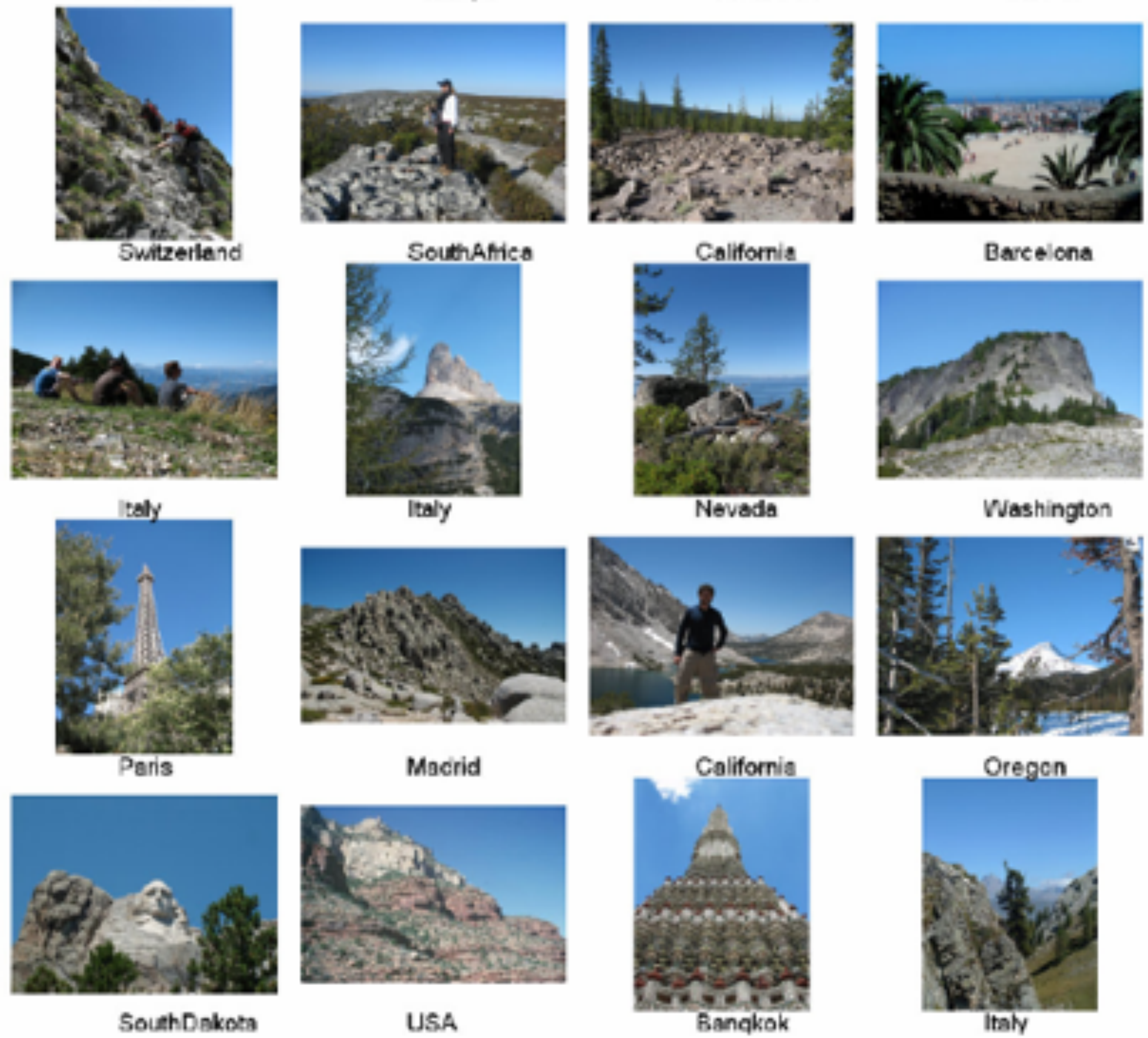
Mendoza

Brazil

Thailand

Arkansas

Hawaii

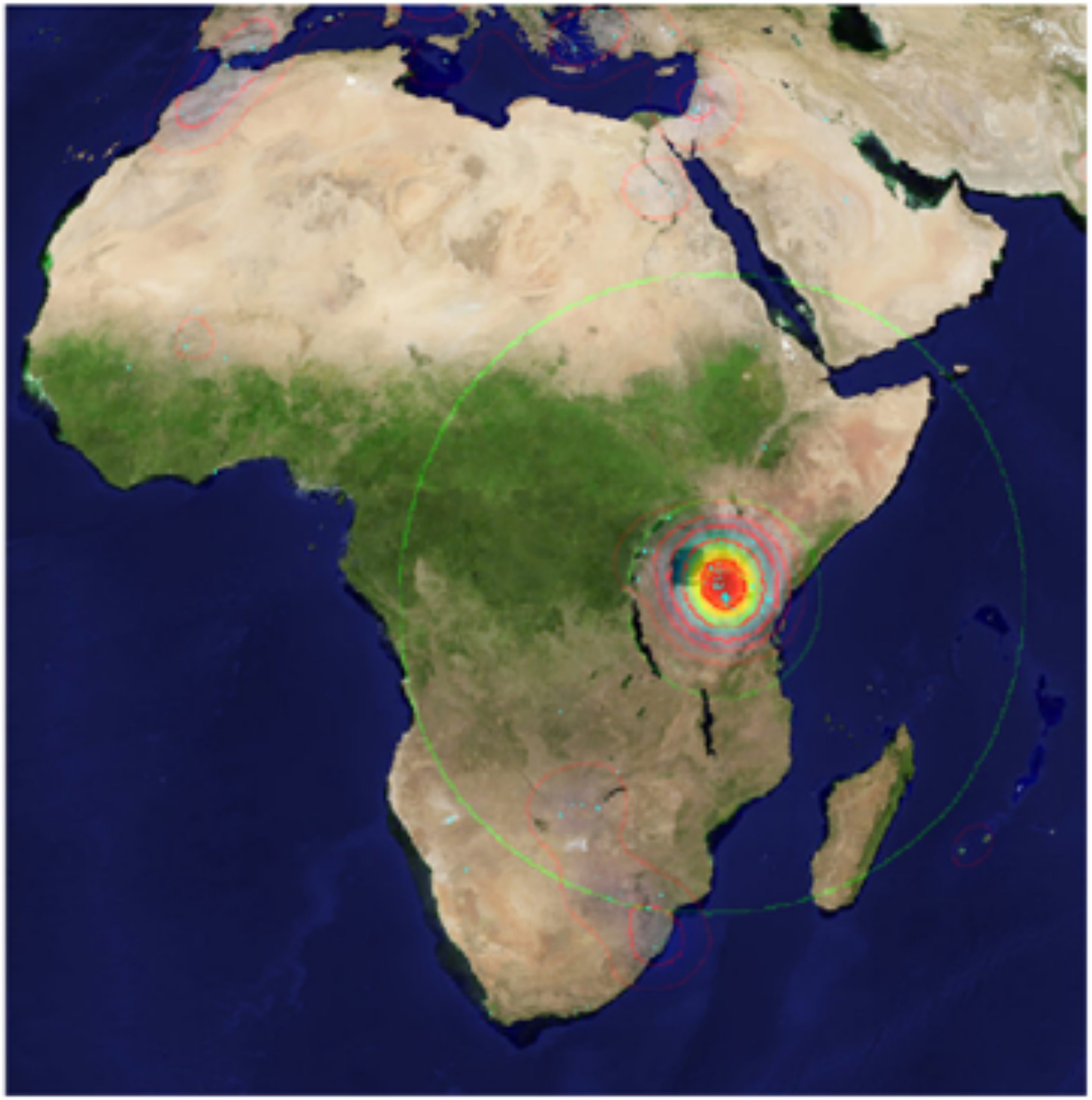

Switzerland
SouthAfrica
California
Barcelona
Italy
Italy
Nevada
Washington
Paris
Madrid
California
Oregon
SouthDakota
USA
Bangkok
Italy



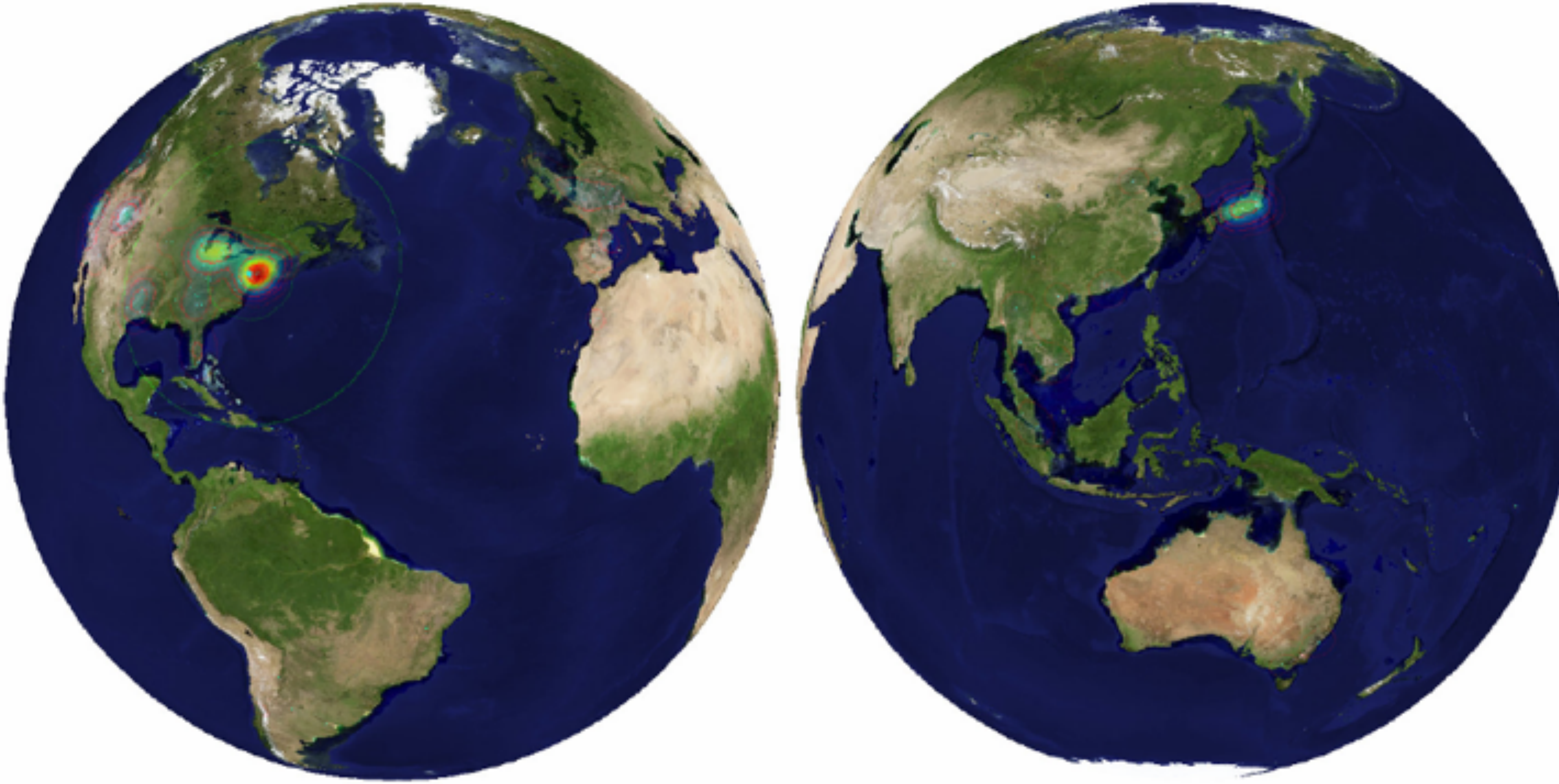
USA
Utah
Arizona
Utah
Utah
Utah
Tunisia
Kenya
Utah
LosAngeles
Burundi
NewMexico
Utah
Utah
Utah
Mendoza

USA
Utah
Arizona
Utah
Utah
Utah
Tunisia
Kenya
Utah
LosAngeles
Burundi
NewMexico
Utah
Utah
Utah
Mendoza

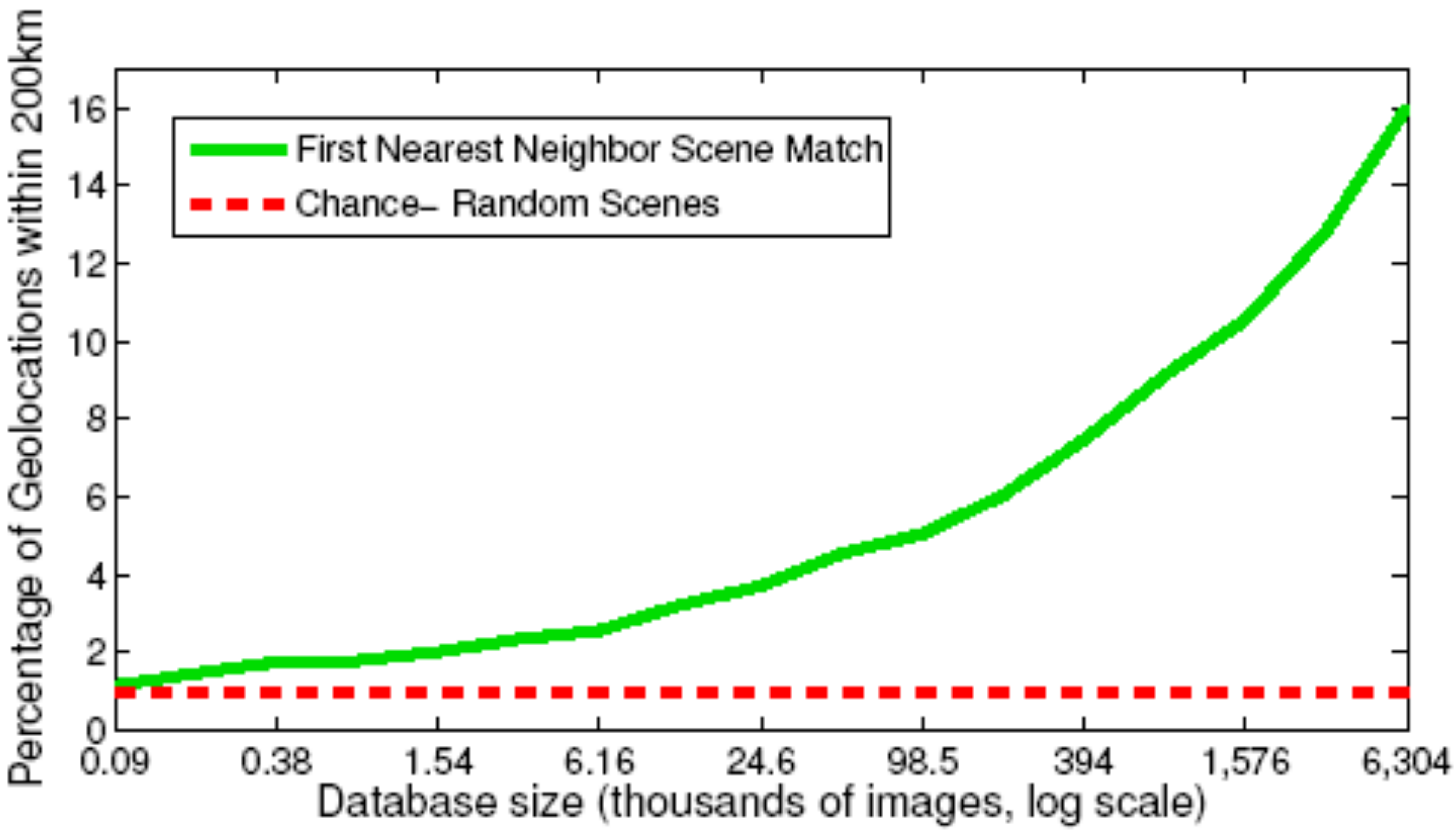
California
Oklahoma
SouthAfrica
Zambia
Kenya
Hyderabad
Mongolia
SouthAfrica
Kenya
Kenya
Zambia
Ethiopia
Nevada
africa
Morocco
Tennessee




Toronto
Florida
NewYork
Boston
Boston
Oregon
Oregon
Oregon
NewYork
Barcelona
Oregon
Chicago
Ohio
Philadelphia
NewYorkCity
Boston



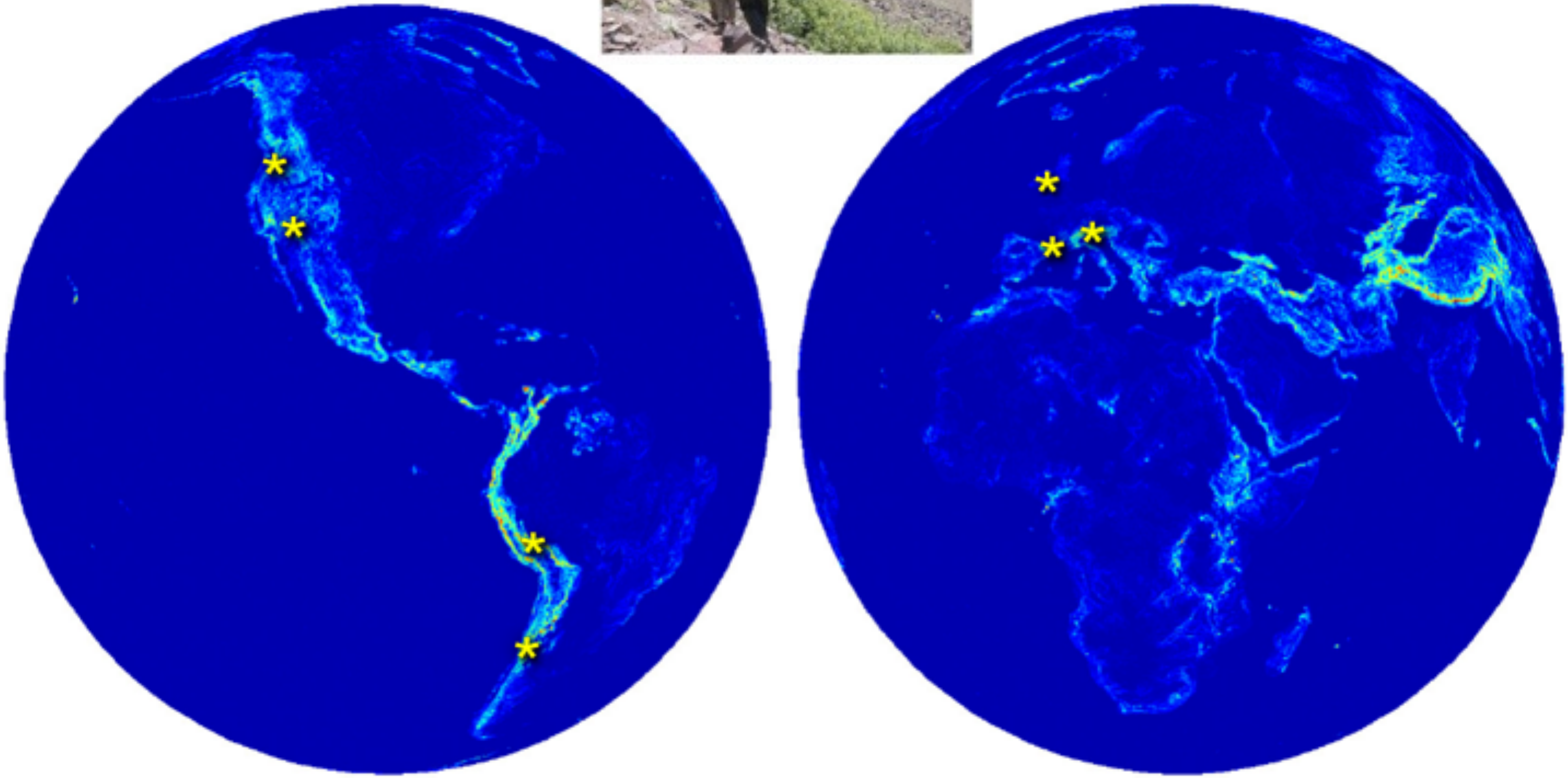
L'importance des données



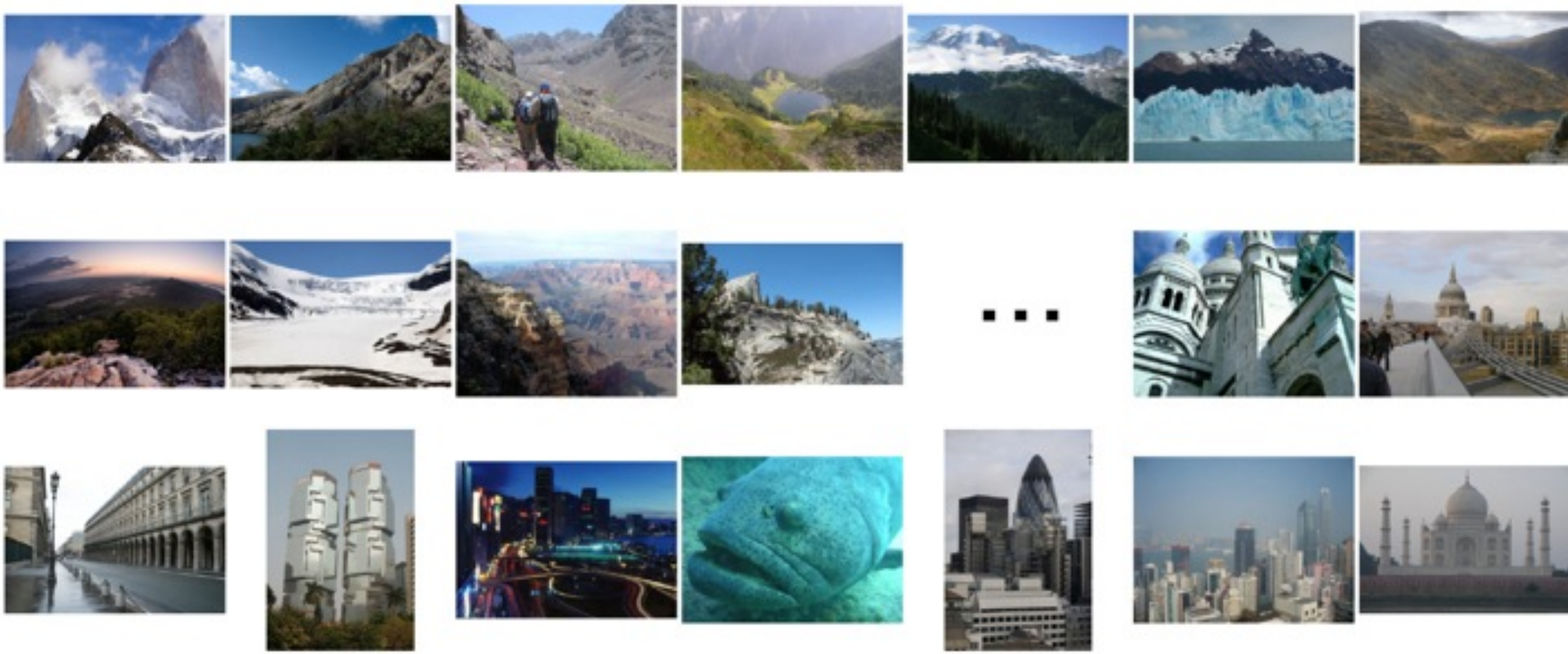
Data-driven categories

Argentina
Andorra
Andorra
Iceland
Idaho
Switzerland
Argentina
Bolivia
Nevada
Hawaii
Hawaii
Egypt
China
Arizona
Peru
Oregon

Elevation gradient = 112 m / km



Elevation gradient magnitude ranking



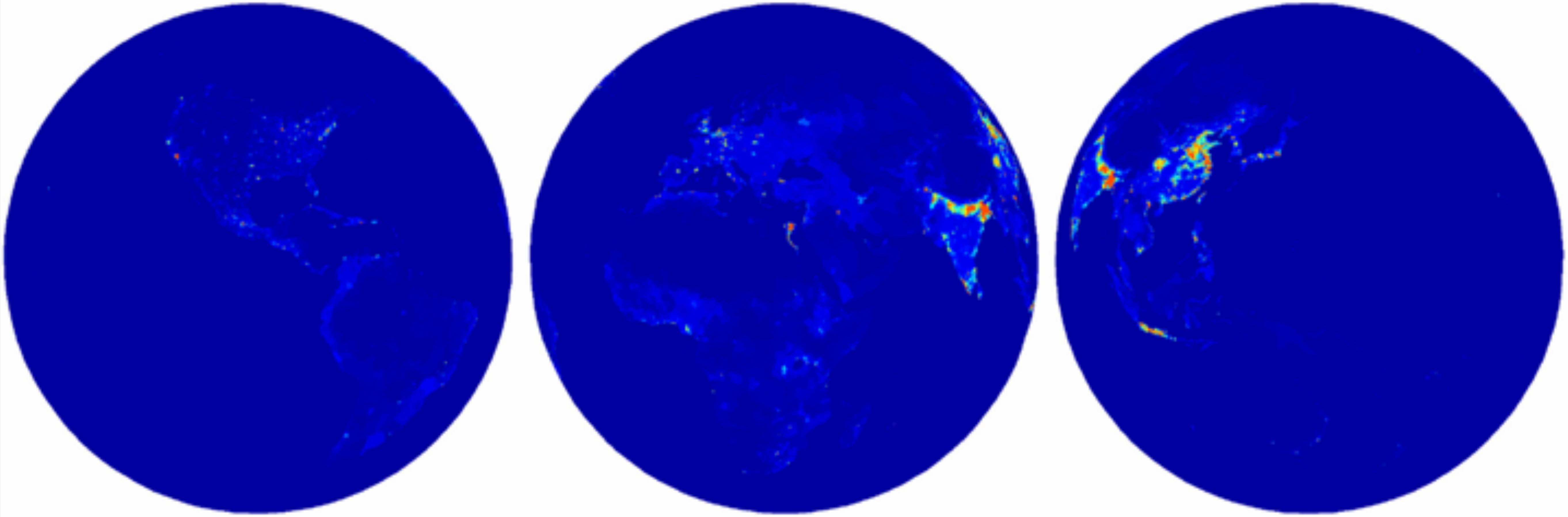


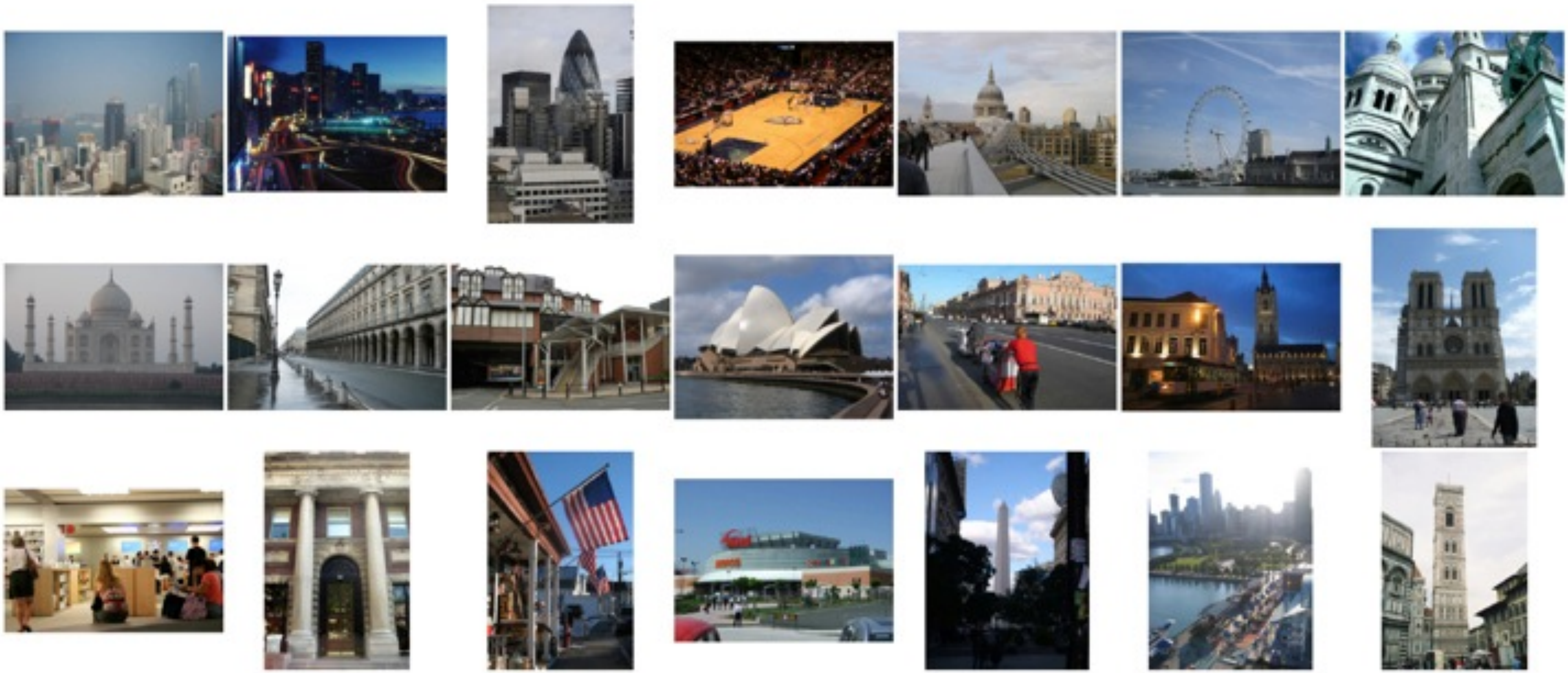
Figure 2. Global population density map.

Population density ranking

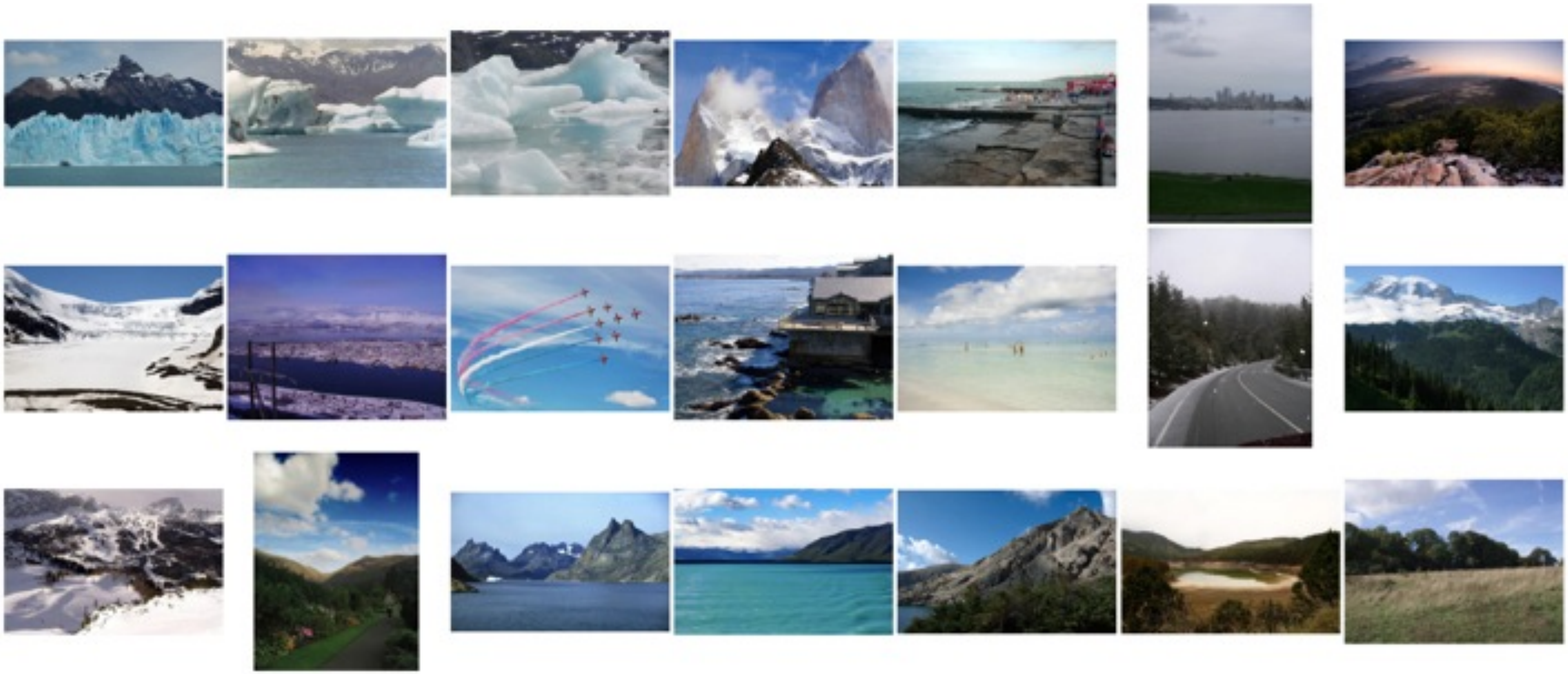
Figure 4. Global land cover classification map.

Barren or sparsely populated

Urban and built up

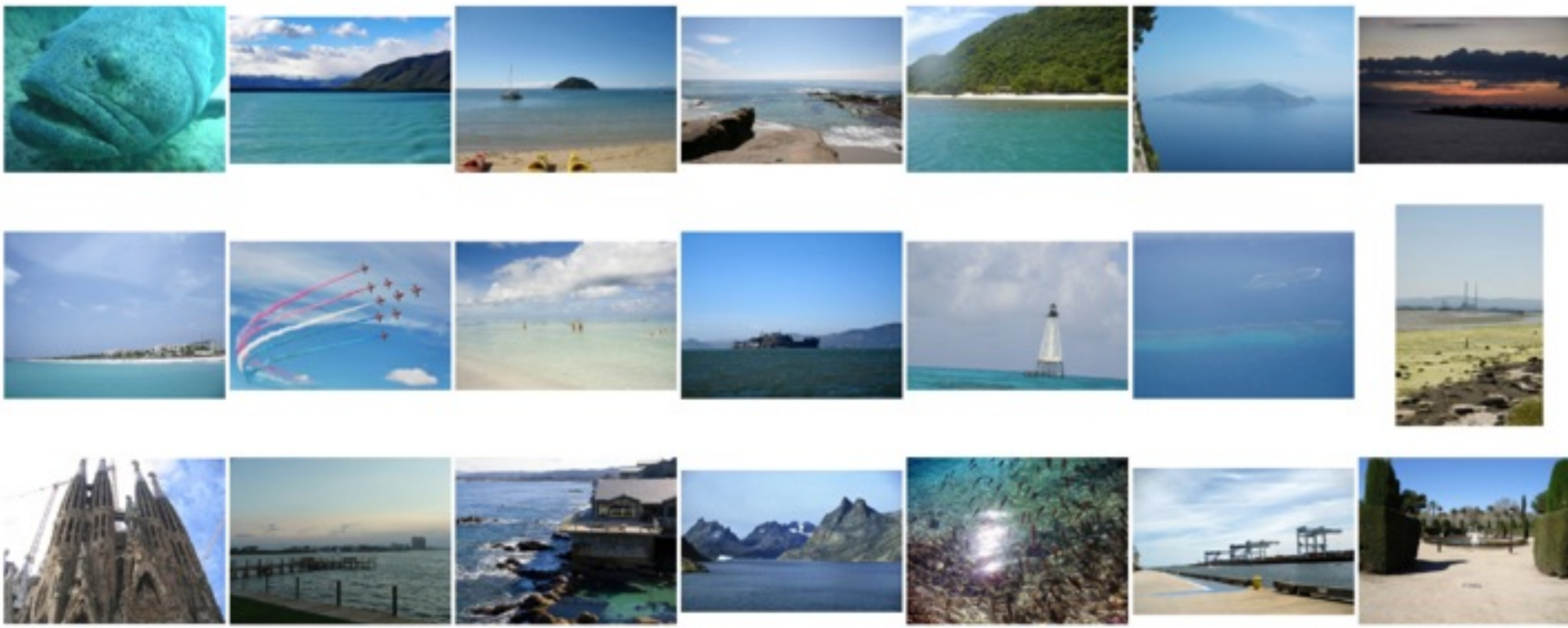


Snow and Ice



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

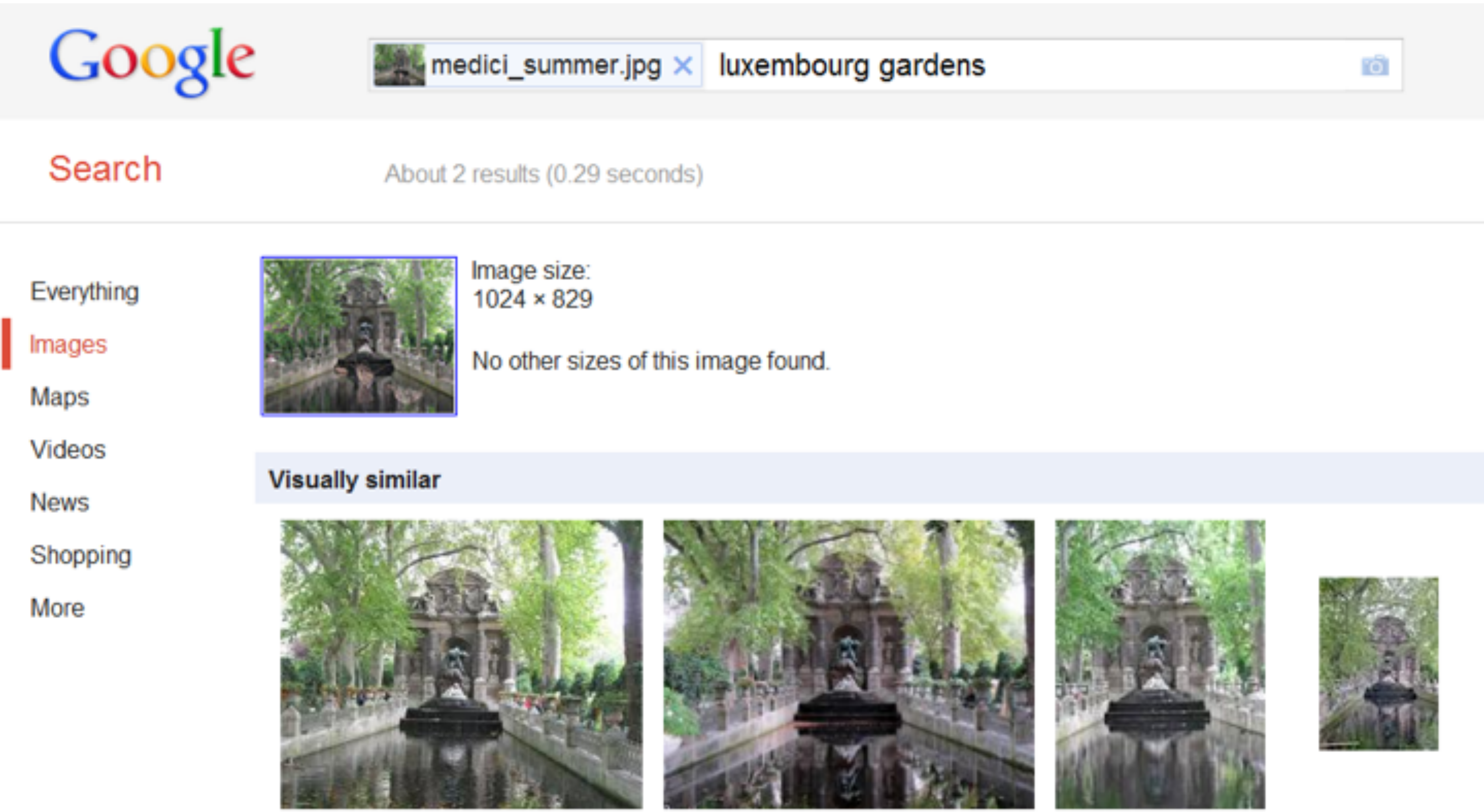
Google images

Search by image

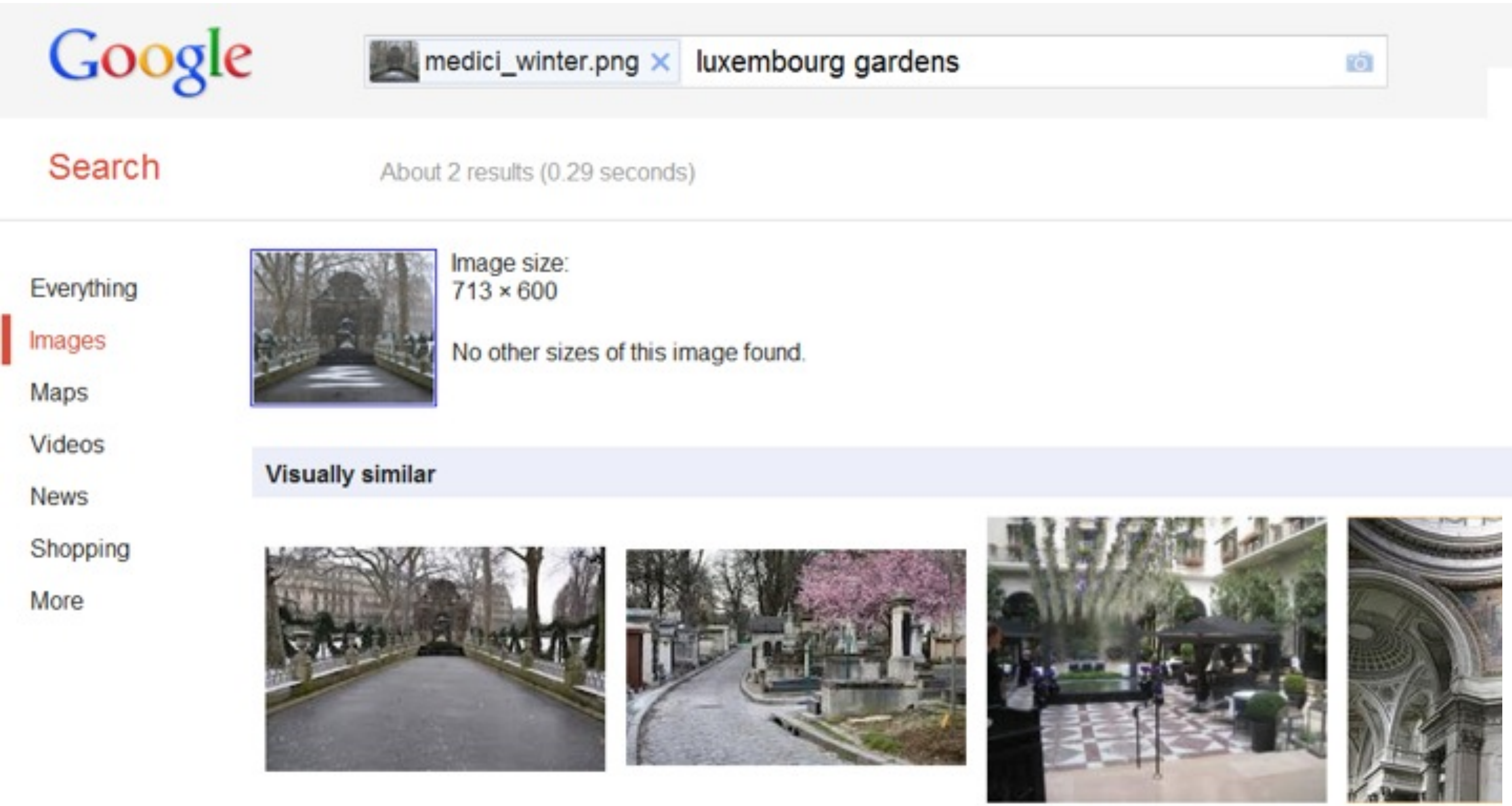
Drop image here

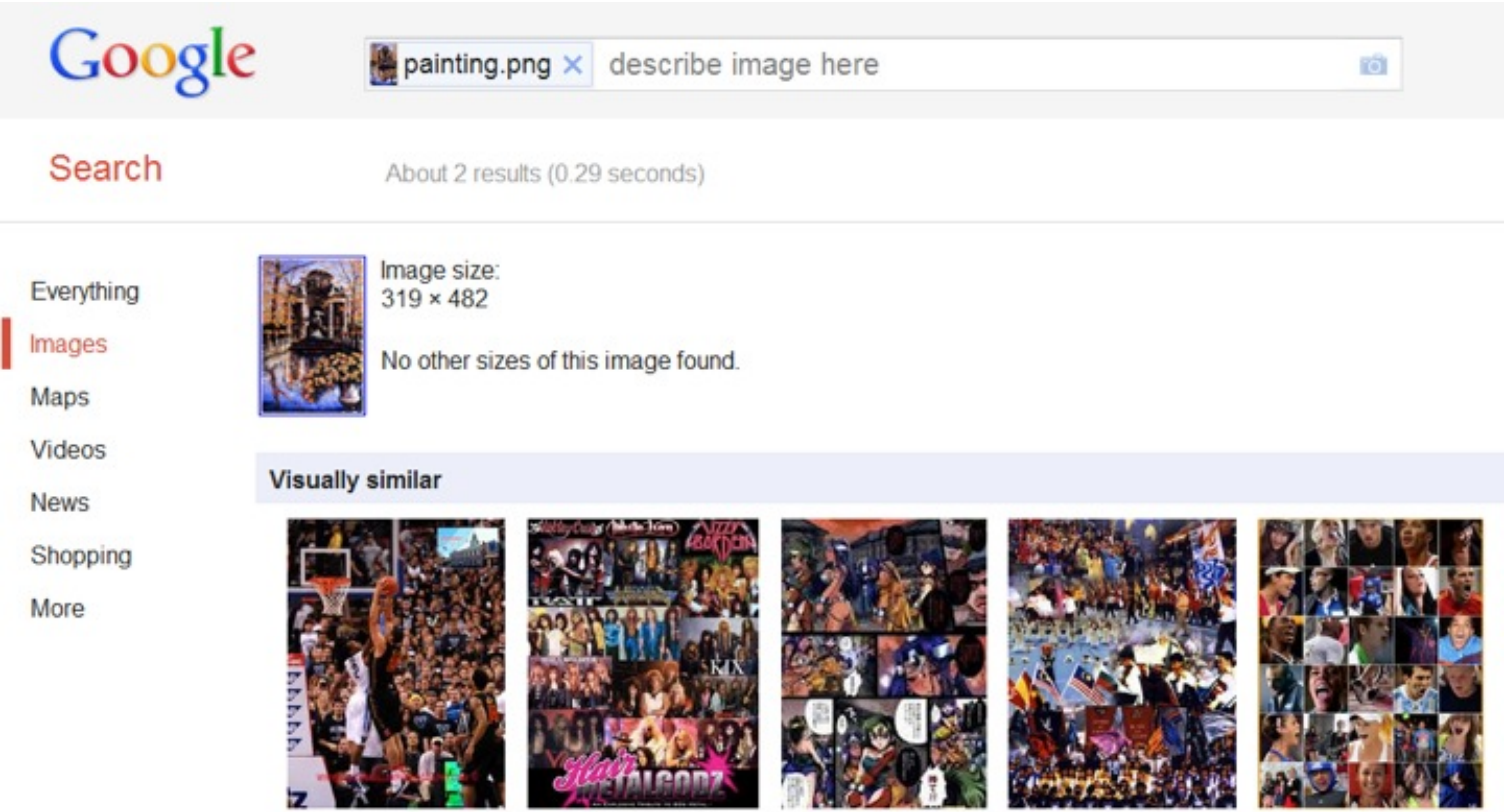
Move

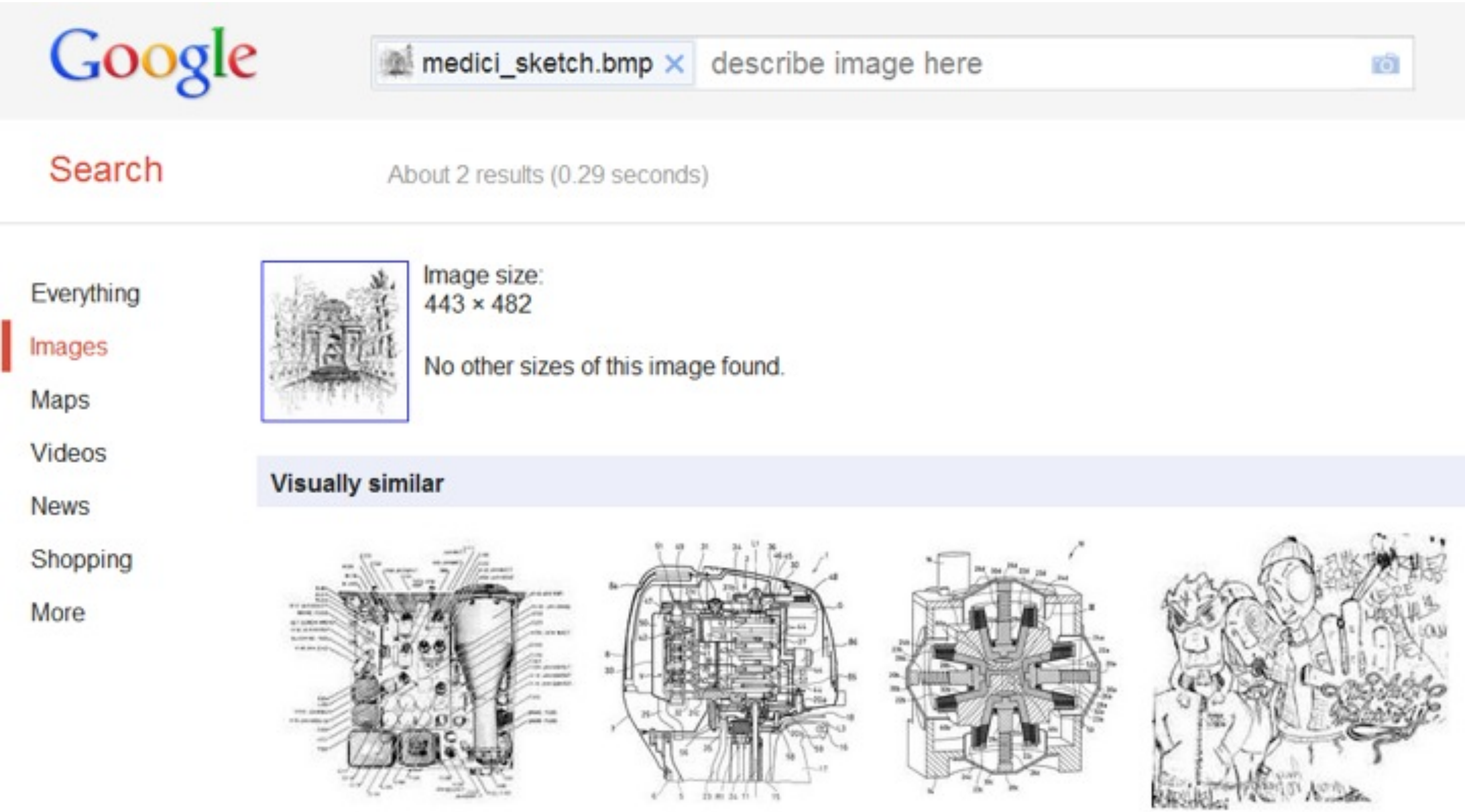
Watch a short video to learn more.


Google
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)


Google
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


Google
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


Google
medici_sketch.bmp
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?

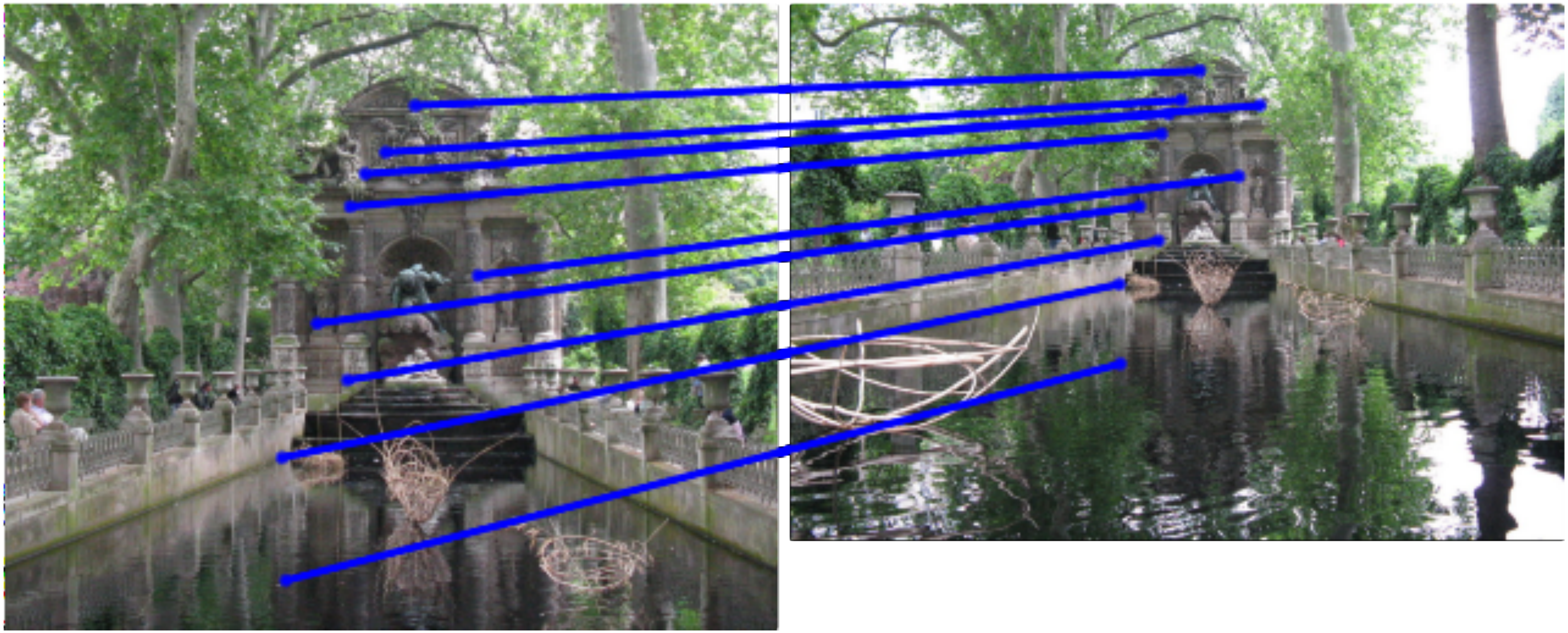



Comparer les images

SIFT
(représentation des gradients
autour des coins)

GIST
(représentation des gradients
dans l'image)

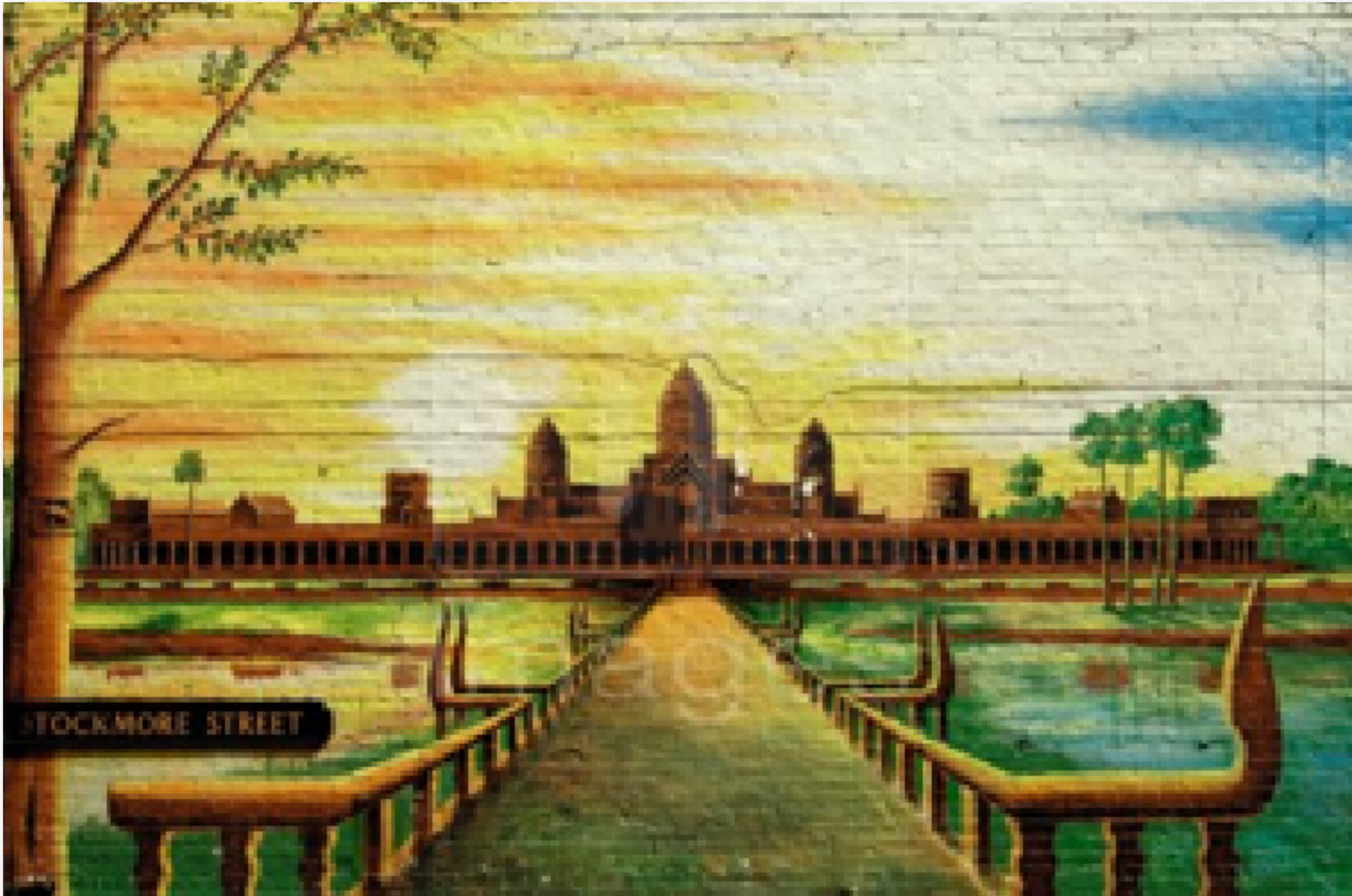
Exemple: appariement SIFT



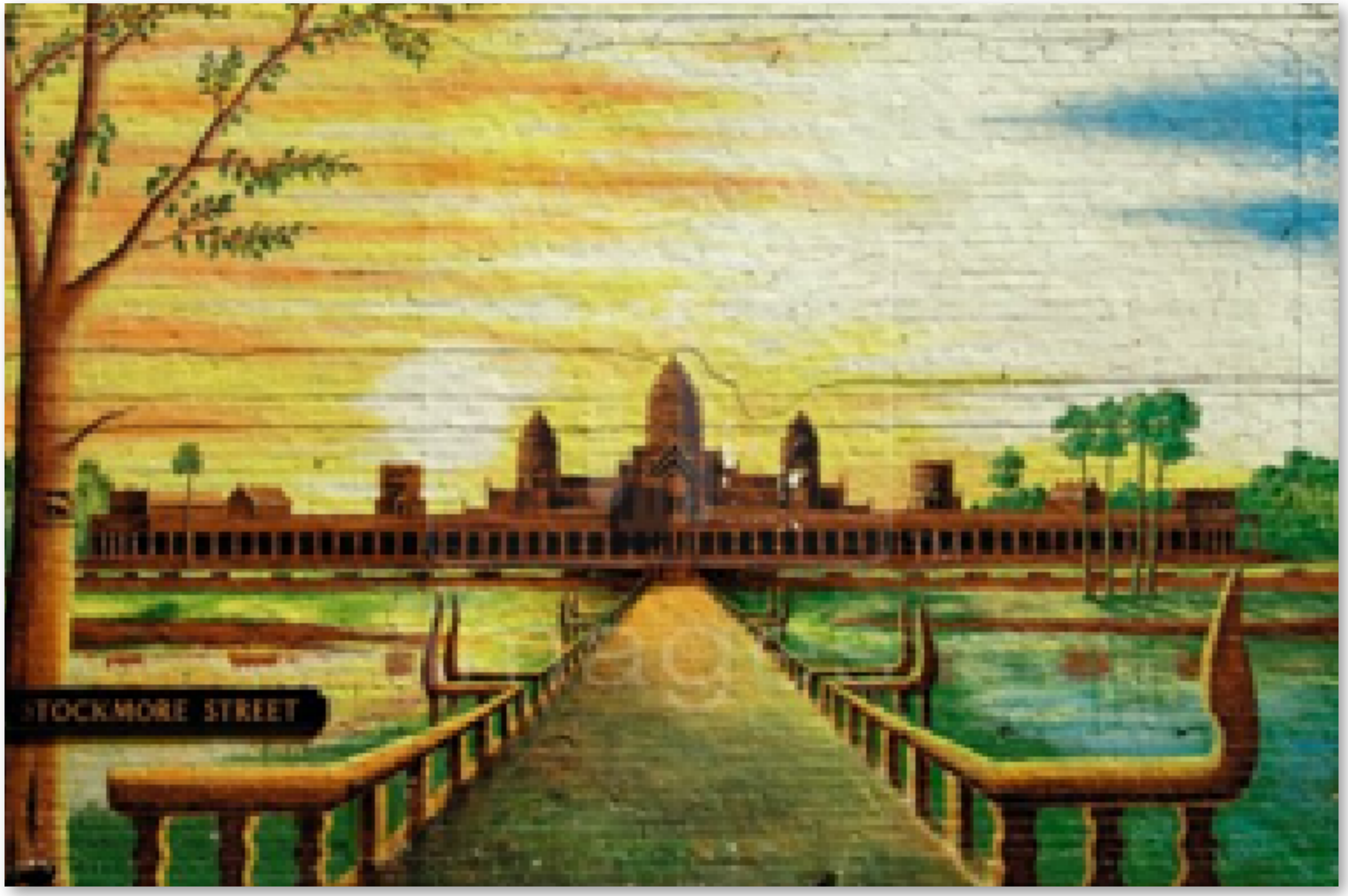
[SIFT: Lowe, 2004]

Exemple: appariement SIFT

[SIFT: Lowe, 2004]

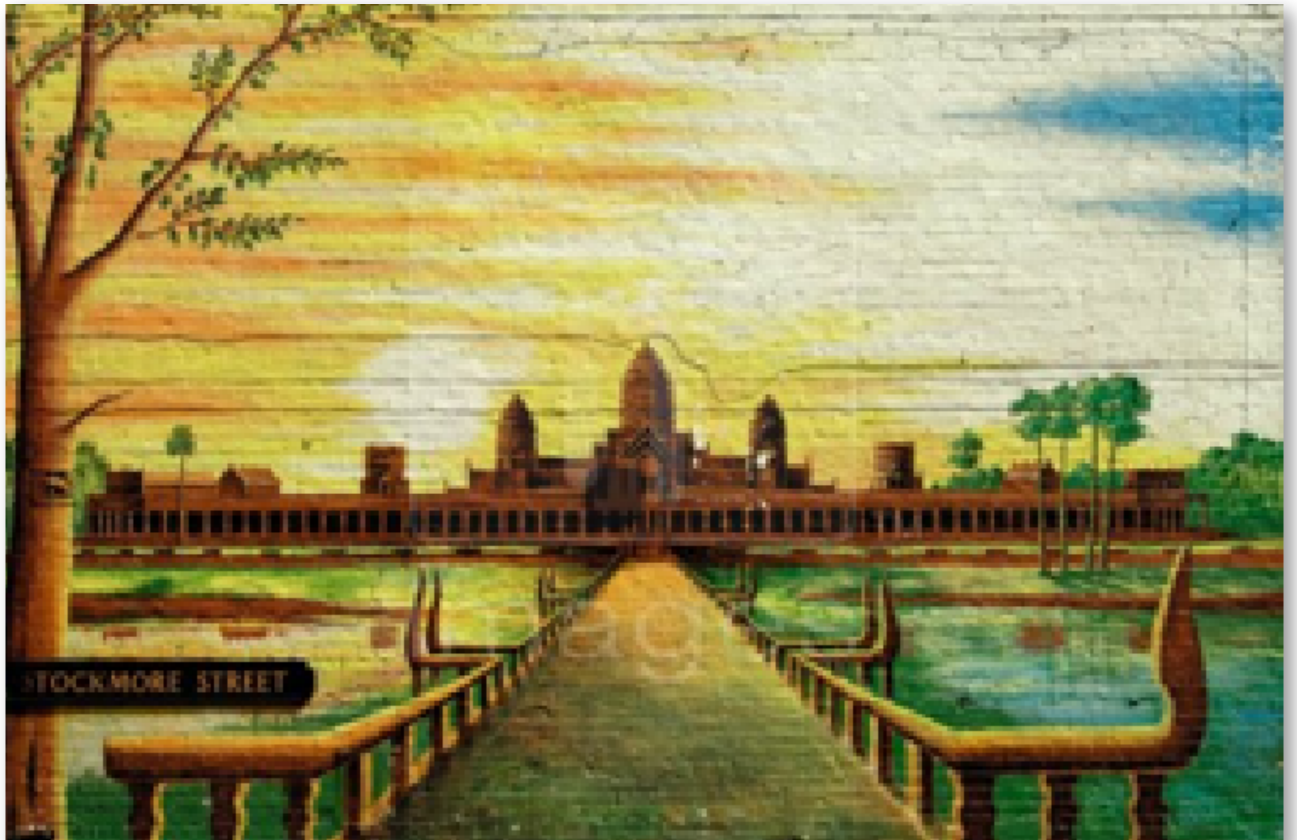

TOCKMORE STREET

Image



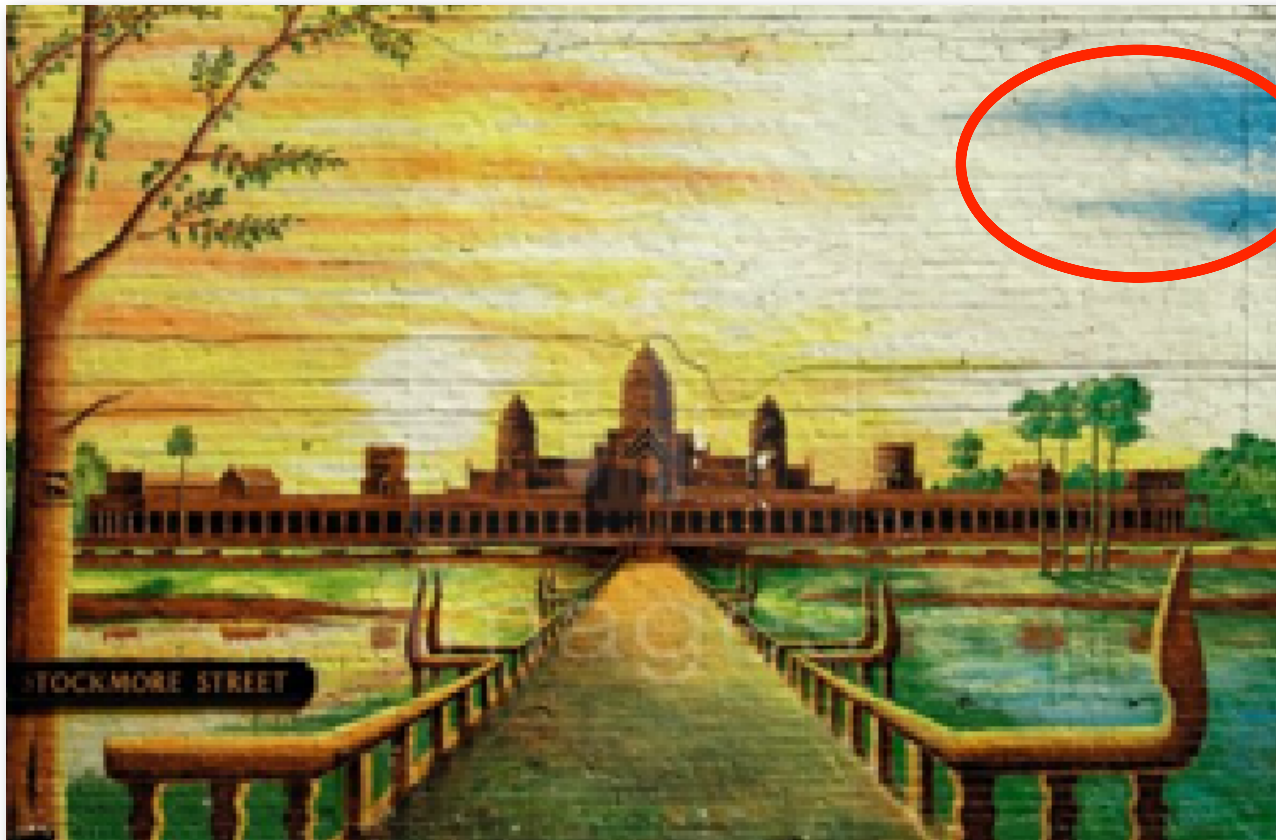
Plus proches voisins

Image



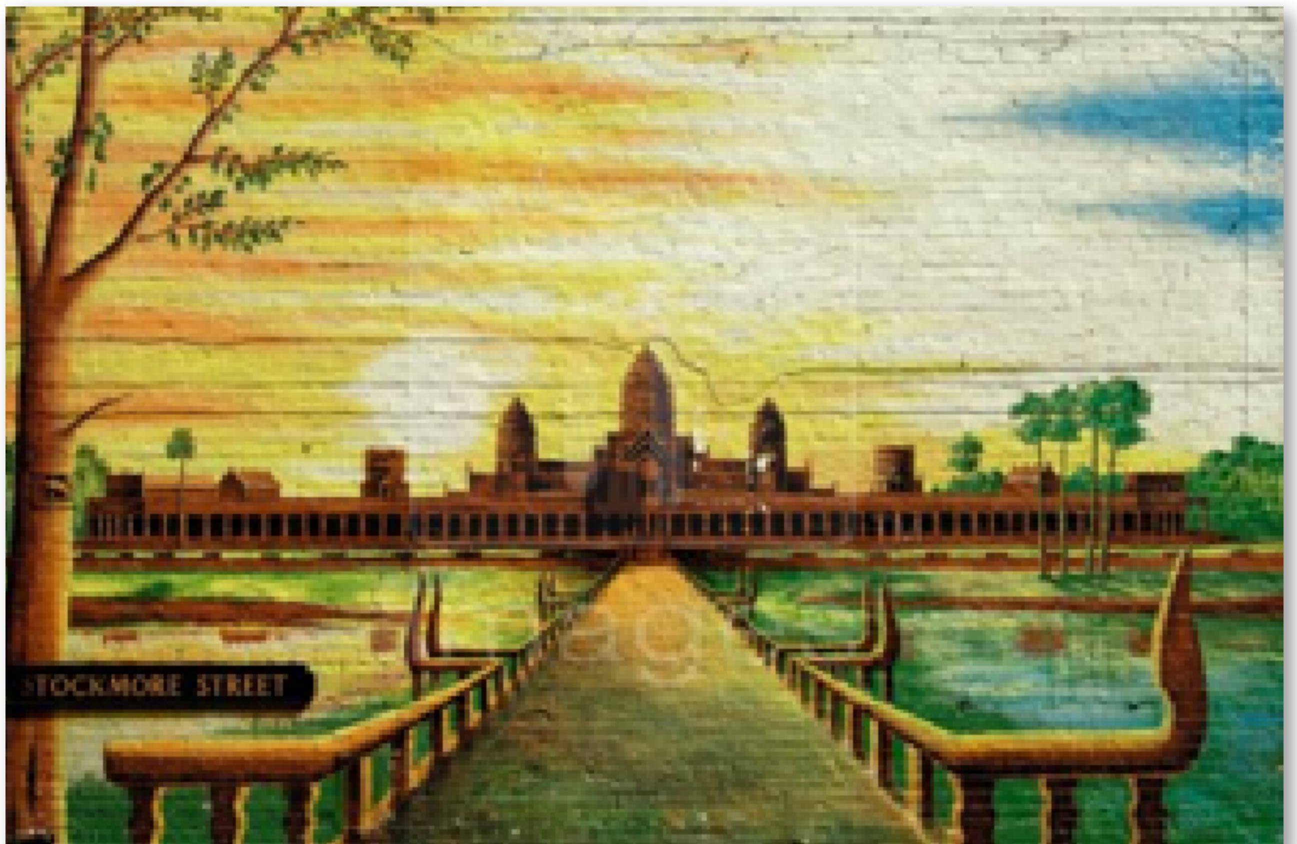
Plus proches voisins

Image



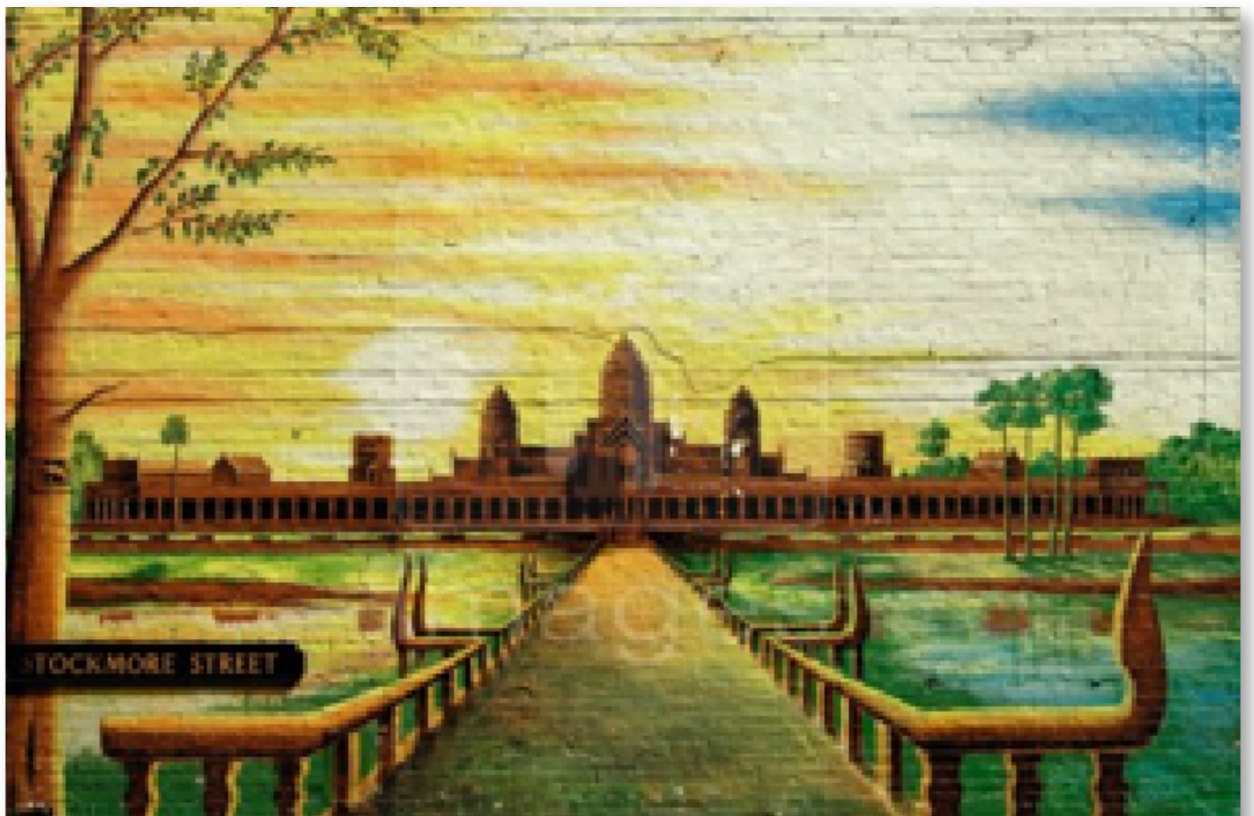
Plus proches voisins

Image

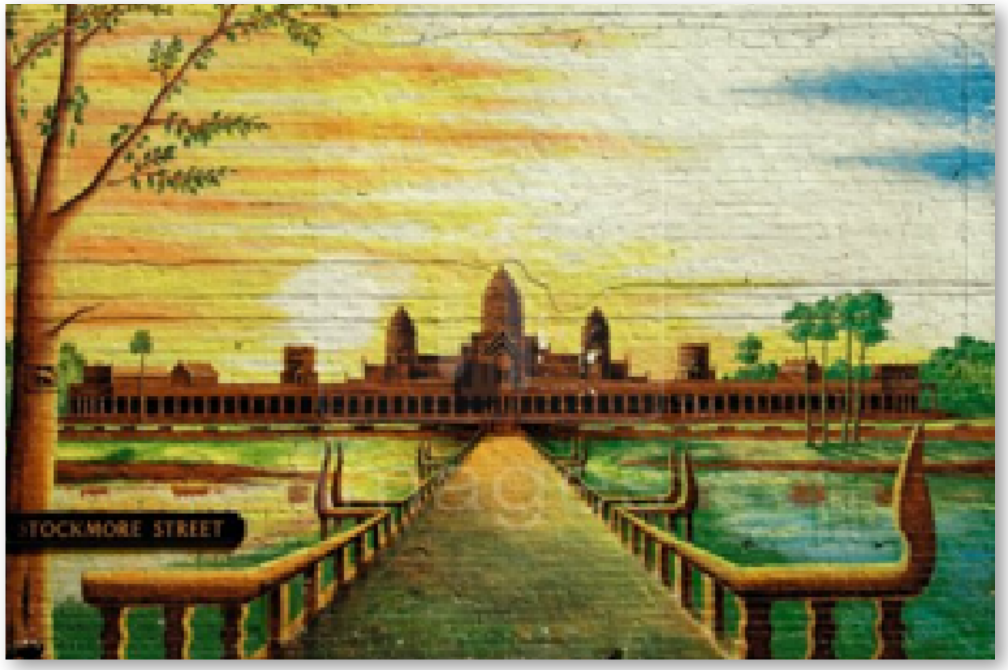


Parties importantes

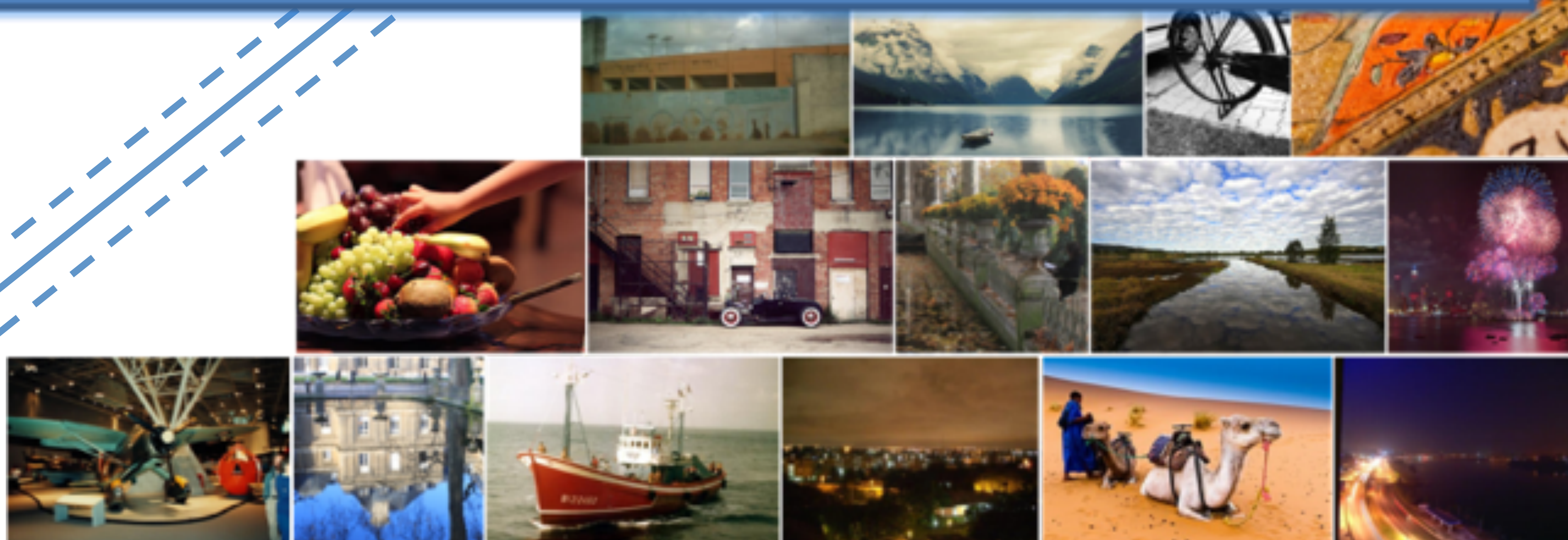
Image



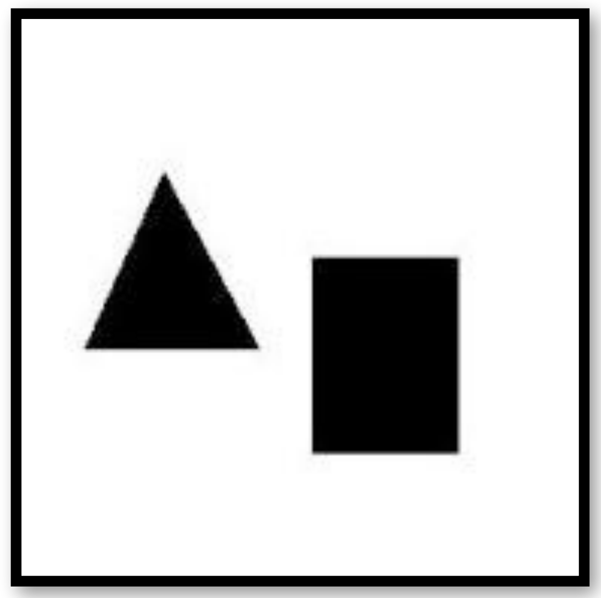
Plus proches voisins



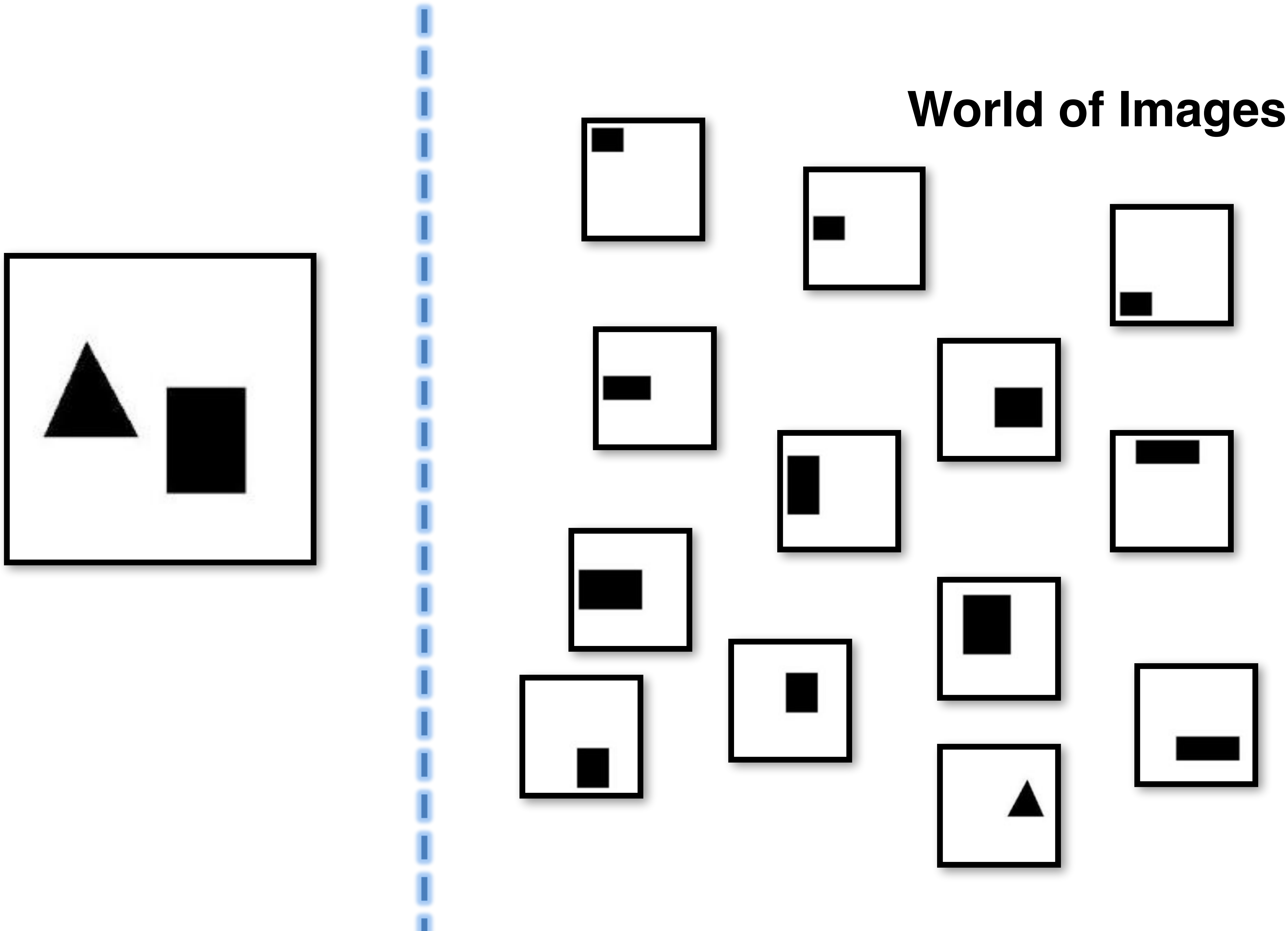
Utiliser les données pour déterminer ce qui est unique



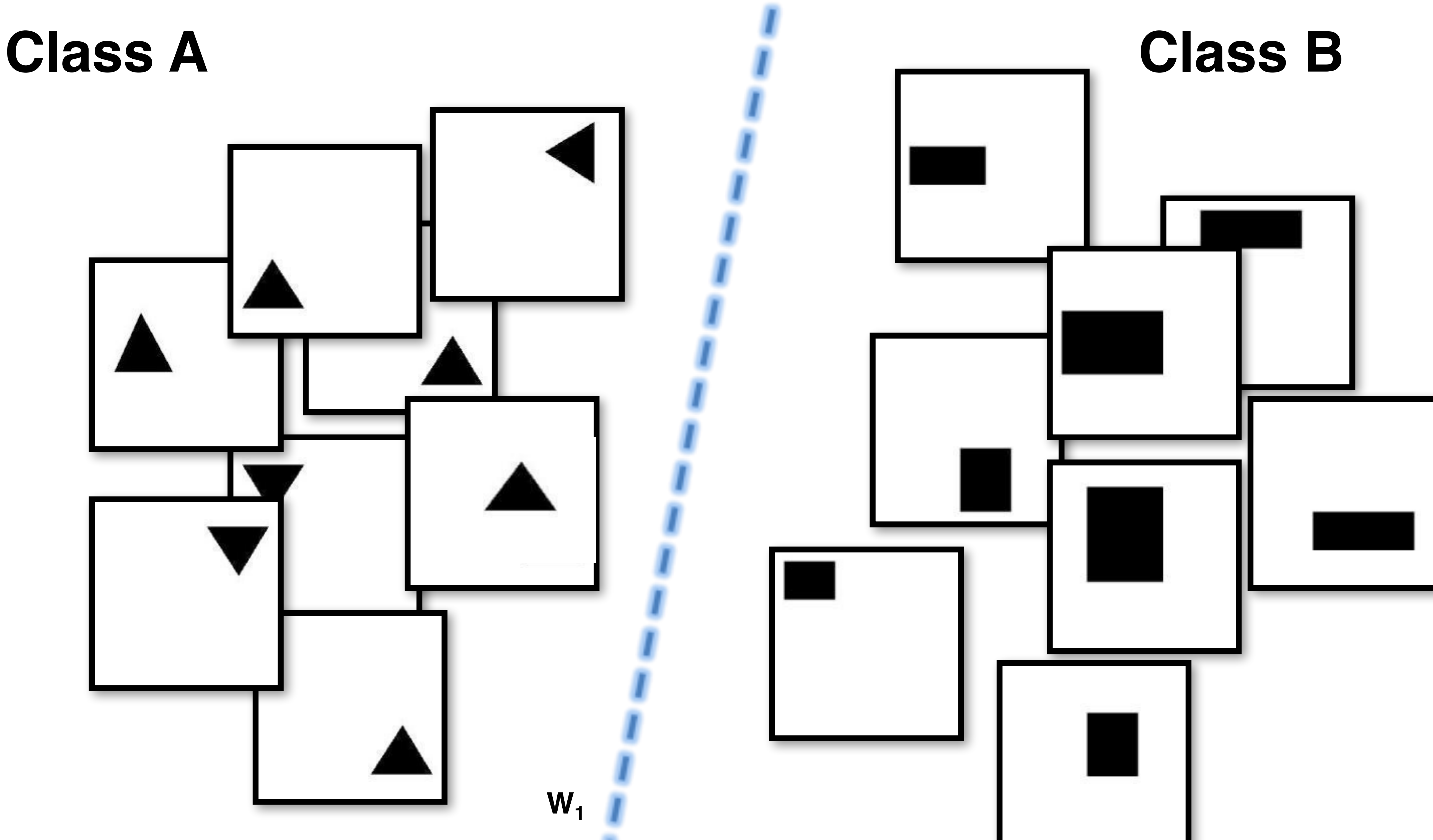
Qu’est-ce qui est unique?



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

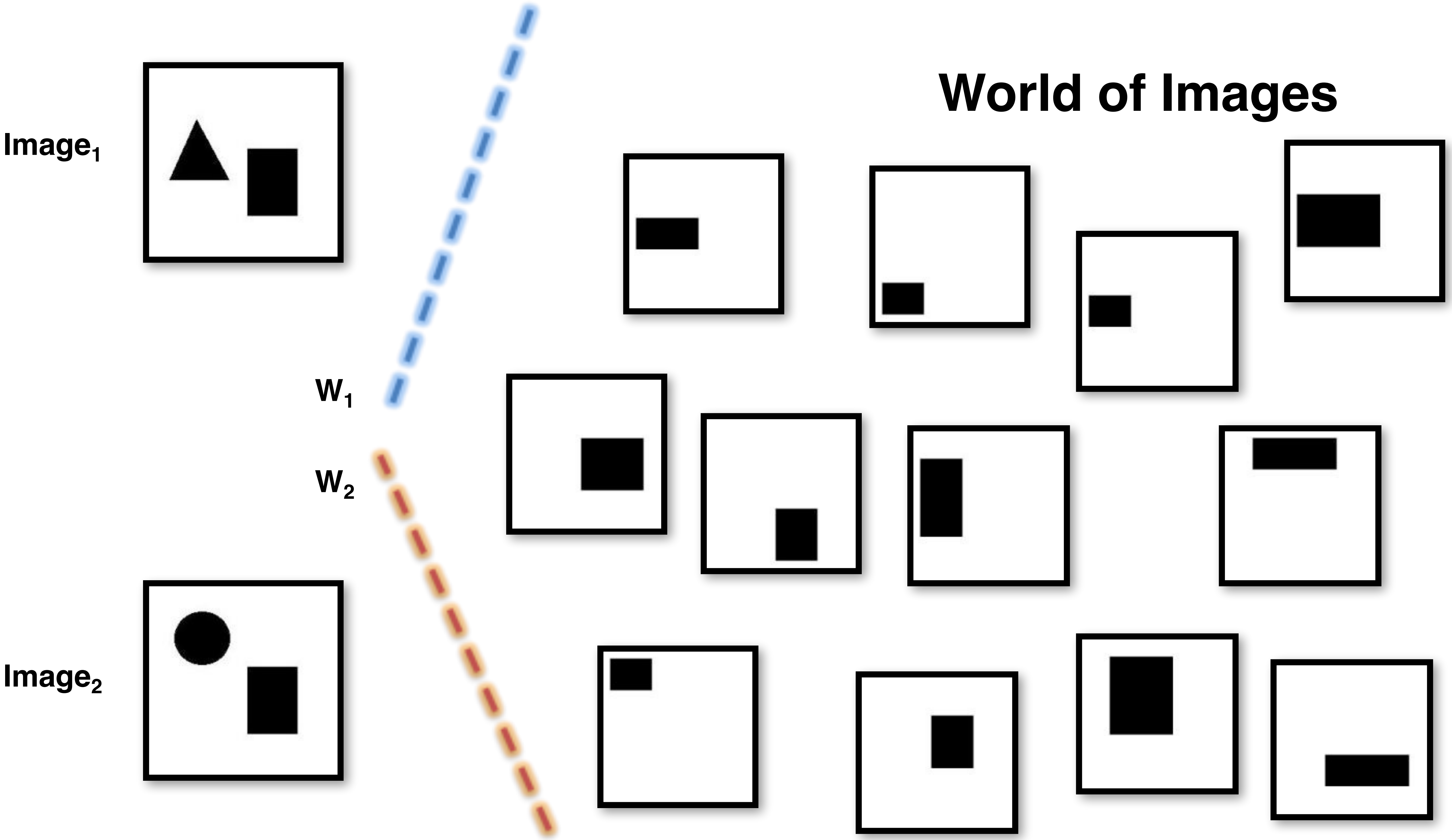


Support vector machine (SVM)



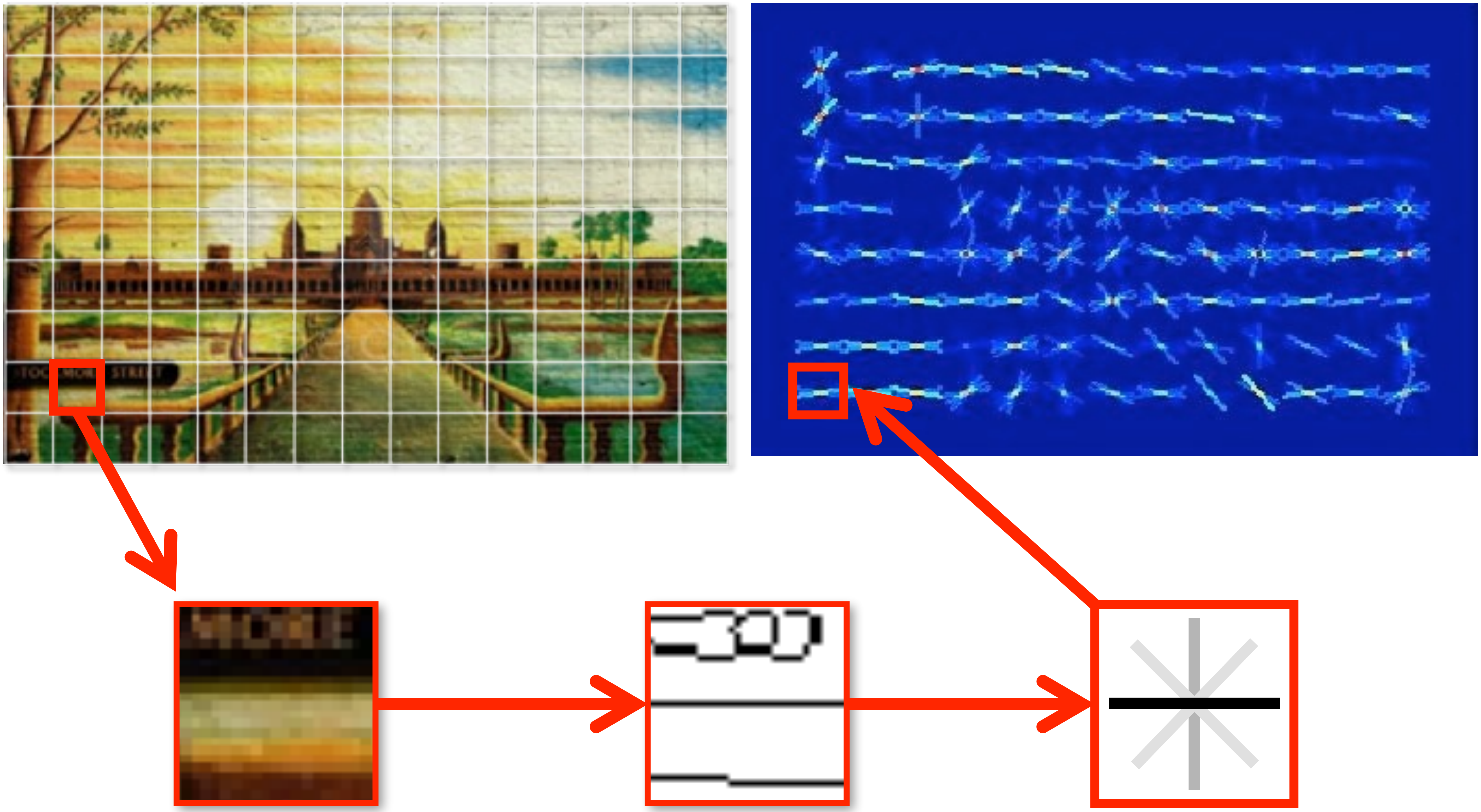
[Cortes and Vapnik, Machine Learning, 1995]

Per-exemplar SVM



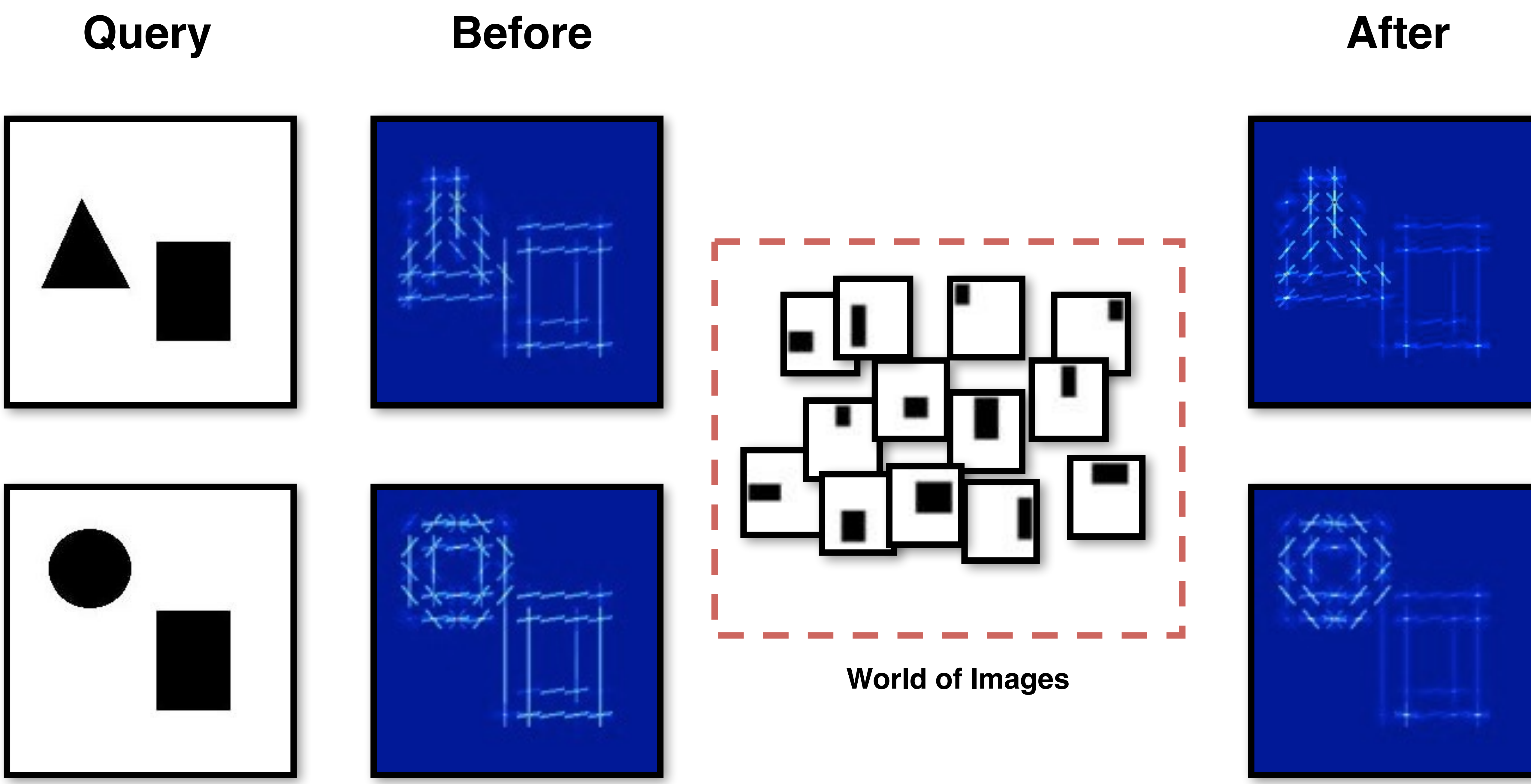
[Malisiewicz et al., ICCV, 2011]

Histogram of oriented gradients (HOG)

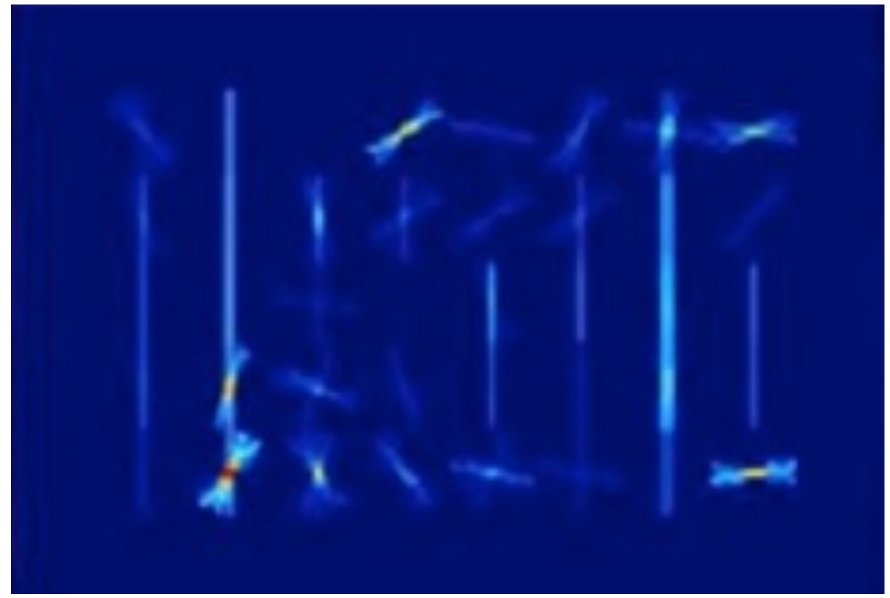


[Dalal and Triggs, CVPR, 2005]

Visualizer ce qui est unique

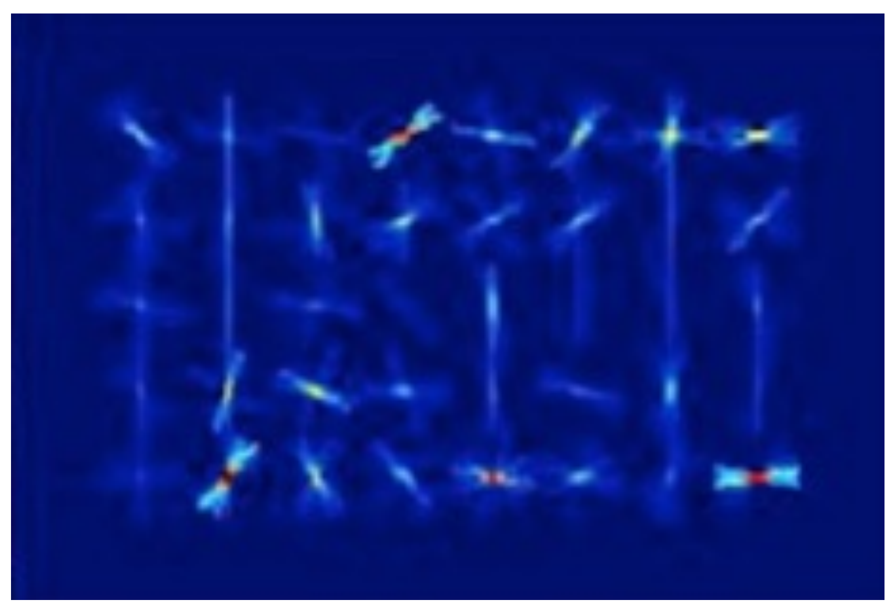


Input Query



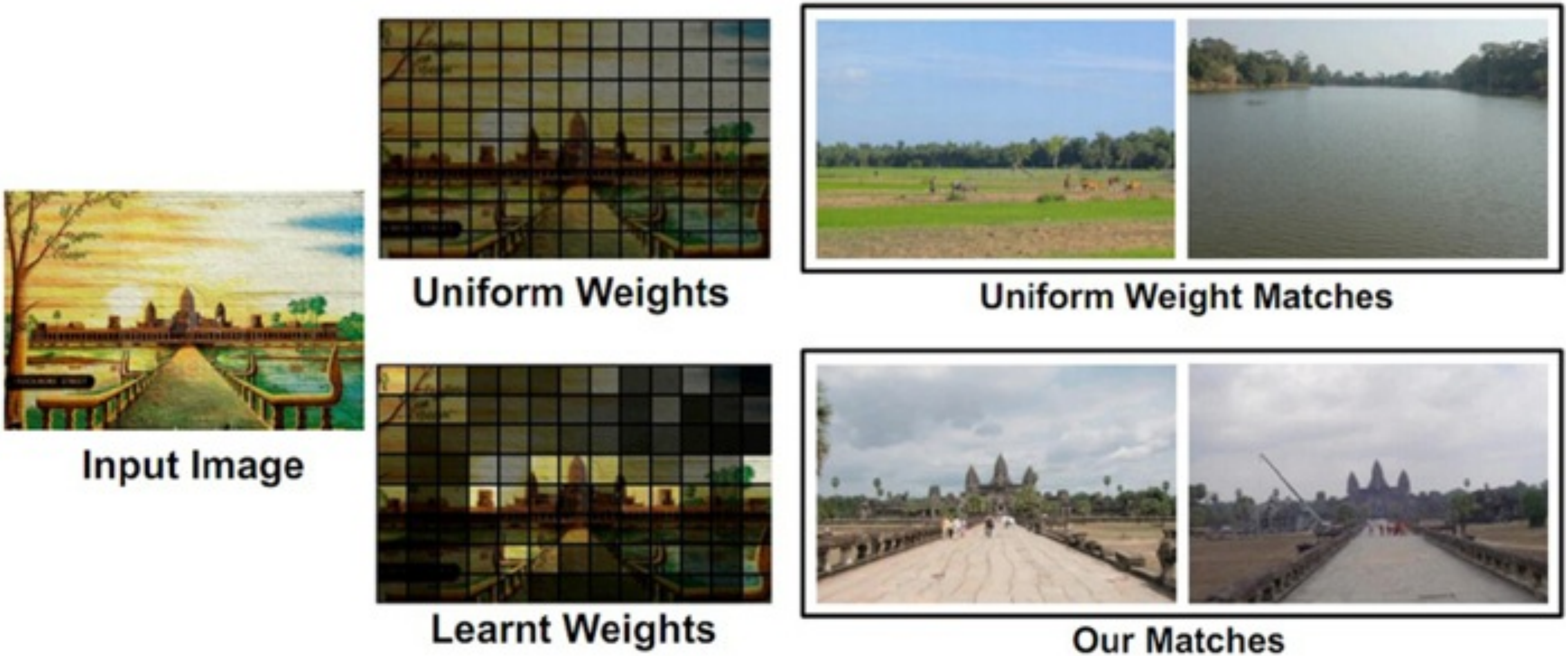
HOG

Top Match

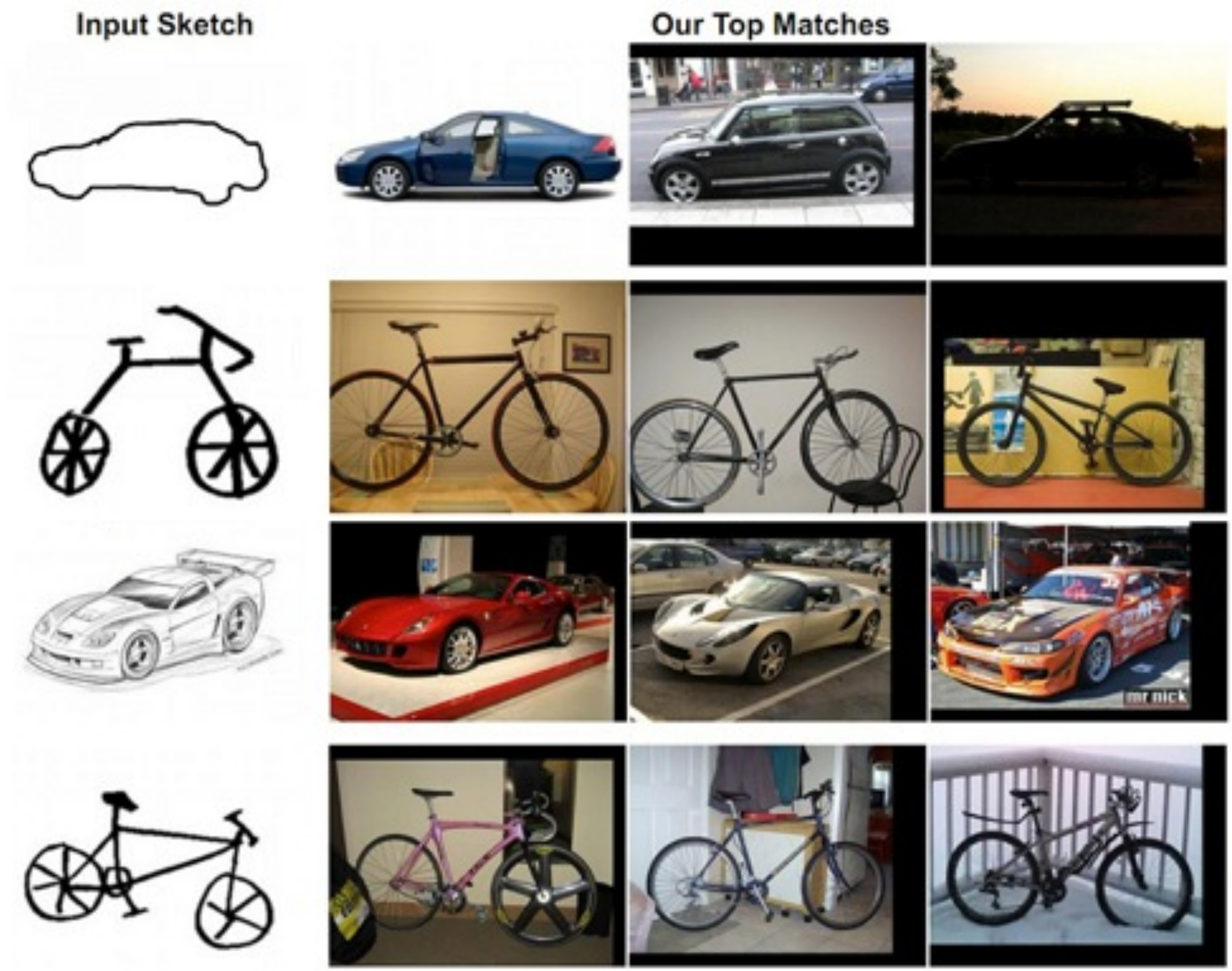


Learnt Weights

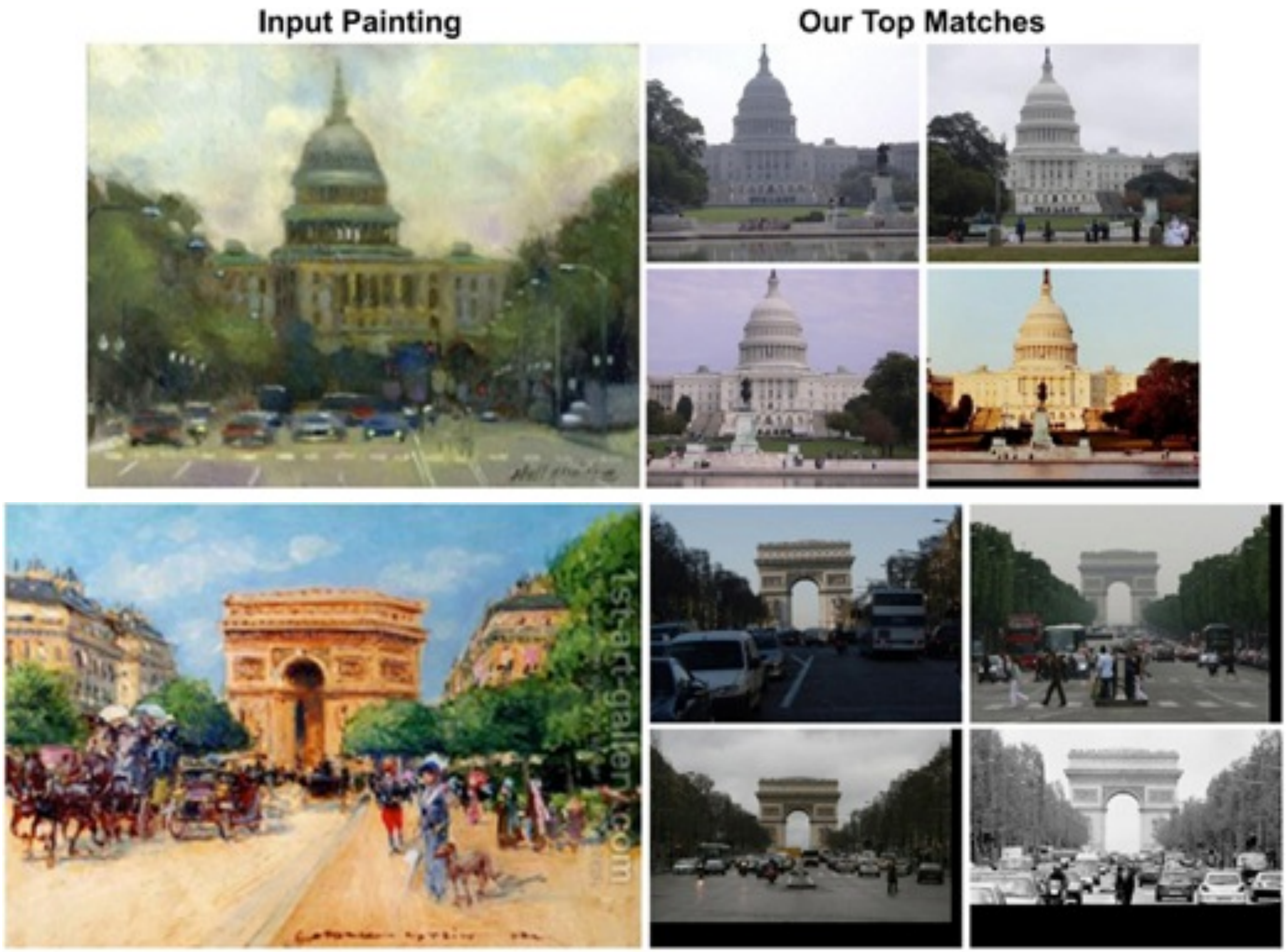
Top Match


Input Image
Uniform Weights
Learnt Weights
Uniform Weight Matches
Our Matches

Sketch based Image Retrieval



Painting based Image Retrieval



painting2gps

Results

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

Les Dangers des Données

Biais

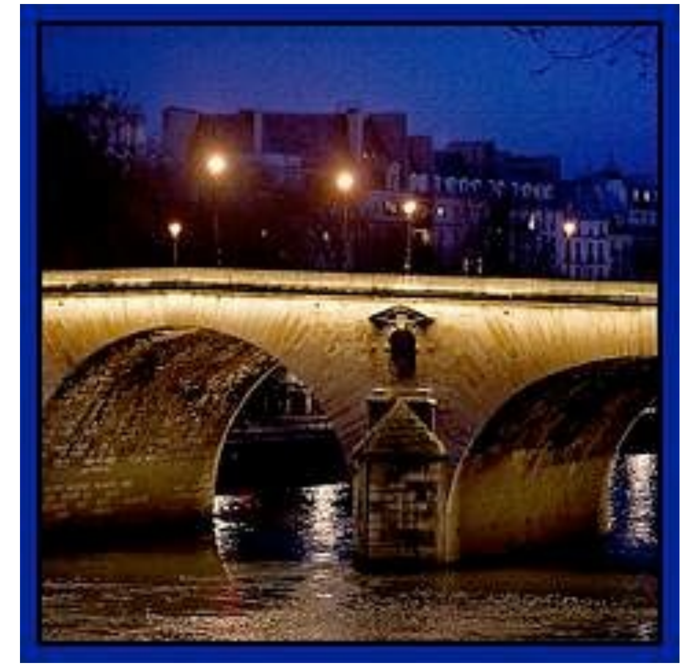
Internet contient un nombre énorme d'images (Flickr, YouTube, Picasa, etc.)

Les images ne sont pas échantillonnées aléatoirement

Plusieurs sources de biais:

- Échantillonnage
- Photographe
- Social

Flickr Paris



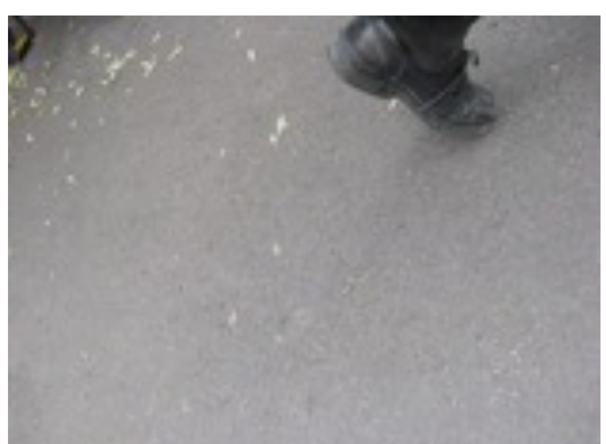
Vrai Paris



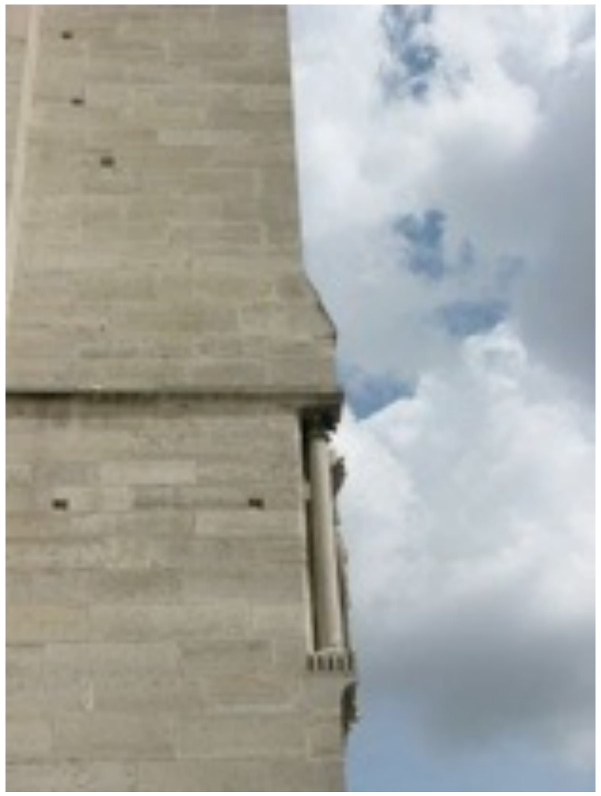






Vraie Notre Dame

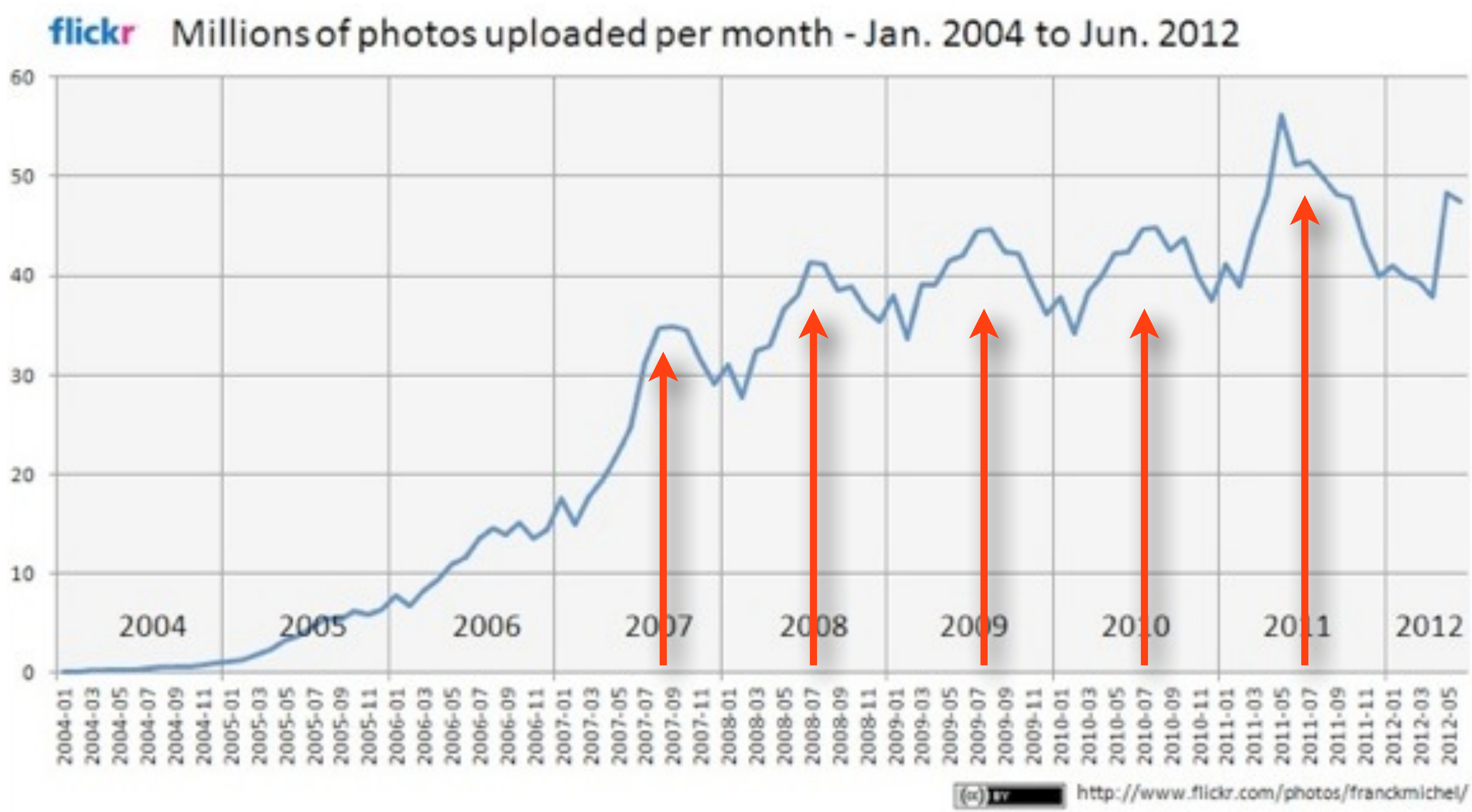


Biais d'échantillonnage

Nous aimons prendre des photos en vacances

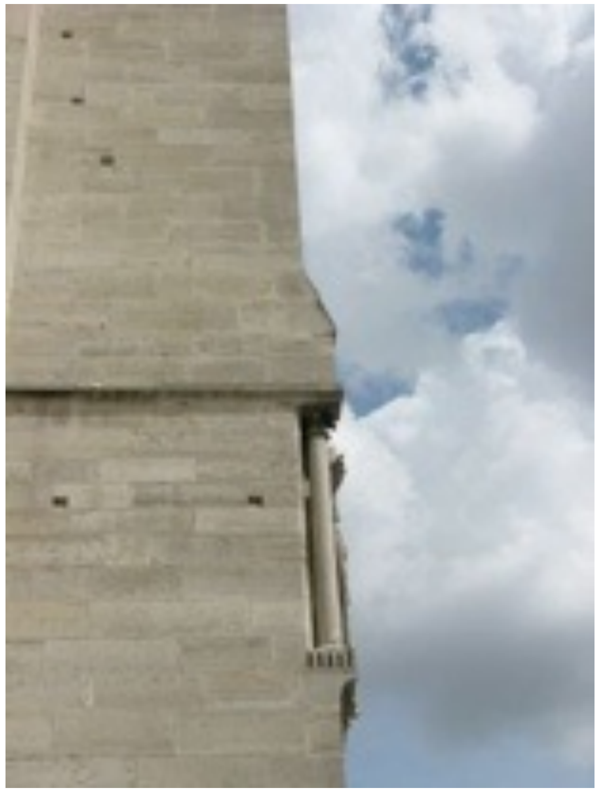
Biais d'échantillonnage

Nous aimons prendre des photos en vacances



Biais du photographe

Nous voulons que nos photos soient intéressantes, ou reconnaissables!



vs.

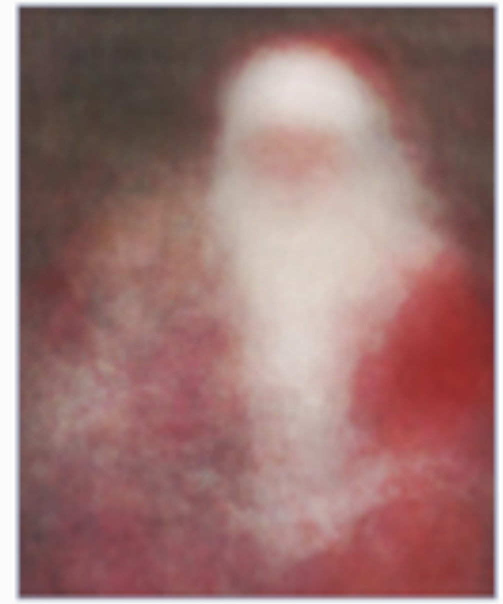
Biais du photographe

Conventions photographiques

vs.

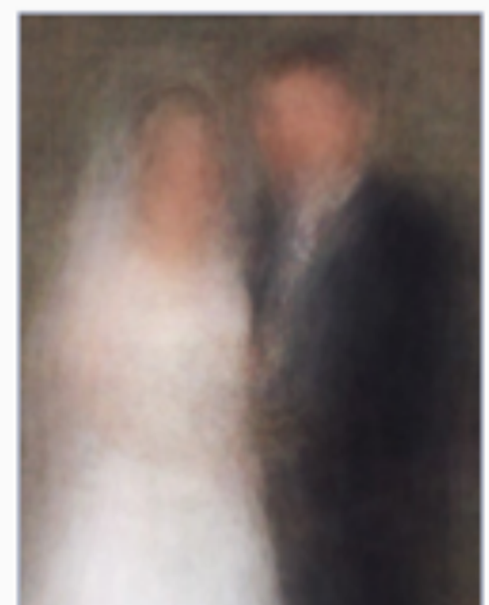
Biais social

Little Leaguer



Kids with Santa

The Graduate

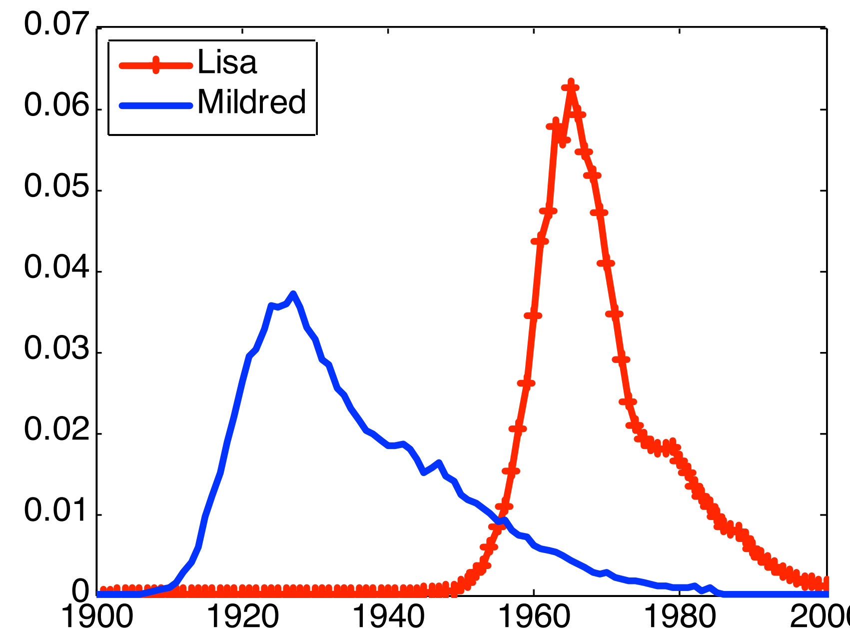


Newlyweds

“100 Special Moments” by Jason Salavon

Biais Social

Mildred and Lisa



Source: U.S. Social Security Administration

Gallagher et al CVPR 2008

Biais social

Limiter le biais

Street side
Google StreetView

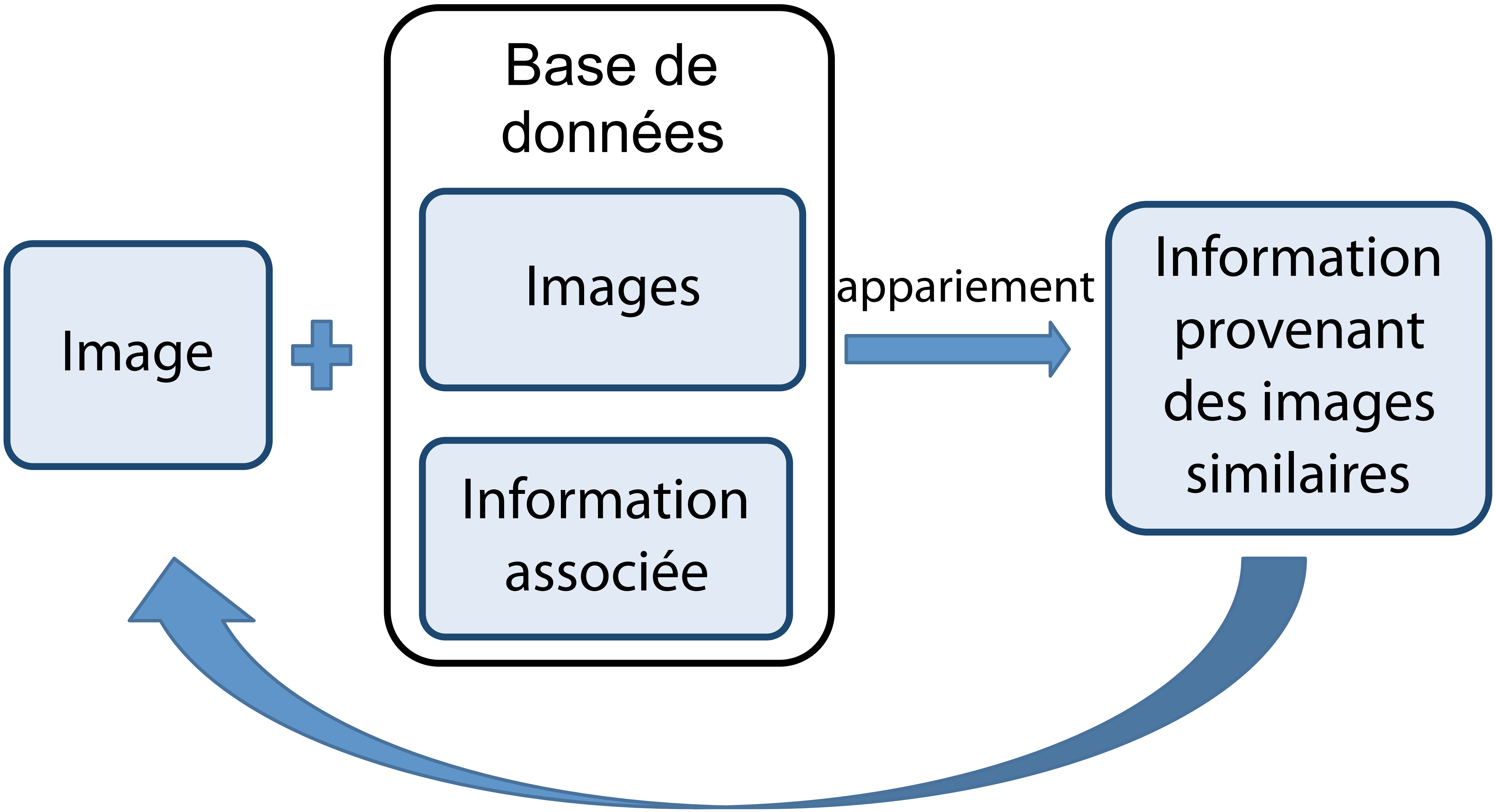
Satellite
google.com

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!