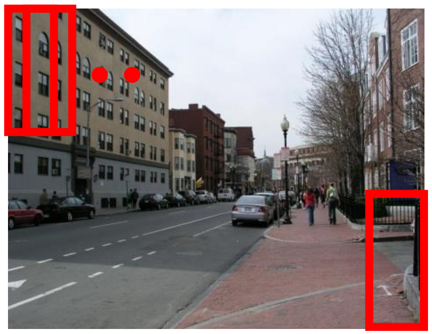
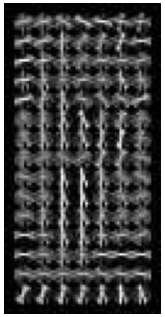
# Object Detection Wrapup

# Things to remember

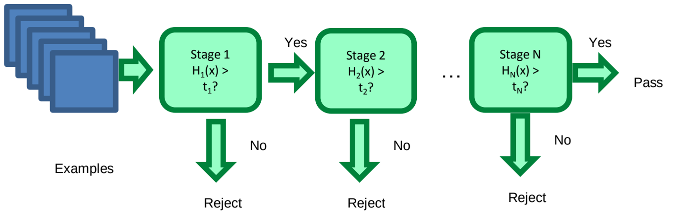
- Sliding window for search



- Features based on differences of intensity (gradient, wavelet, etc.)
  - Excellent results require careful feature design



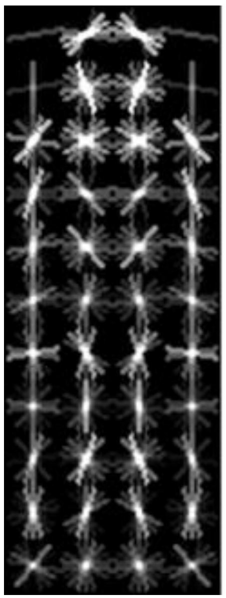
- Boosting for feature selection
- Integral images, cascade for speed



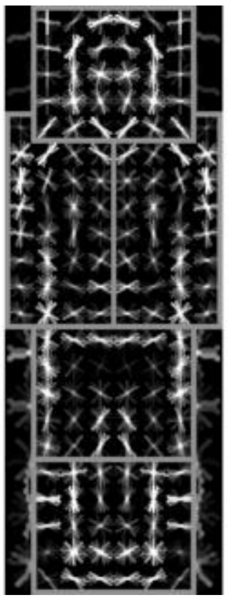

- Bootstrapping to deal with many, many negative examples

# Discriminative part-based models

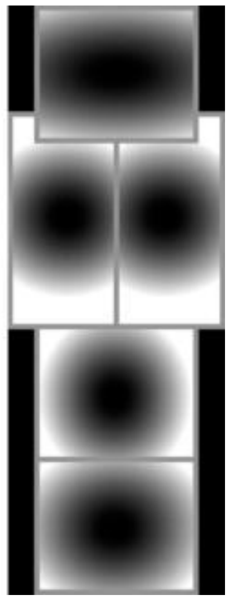
Root filter



Part filters



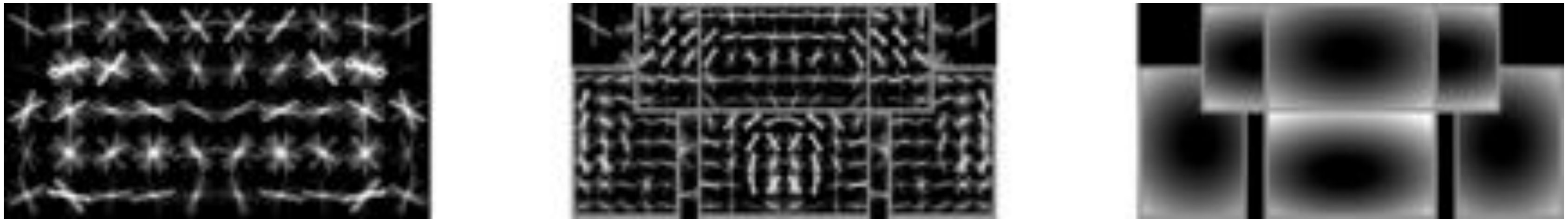
Deformation weights



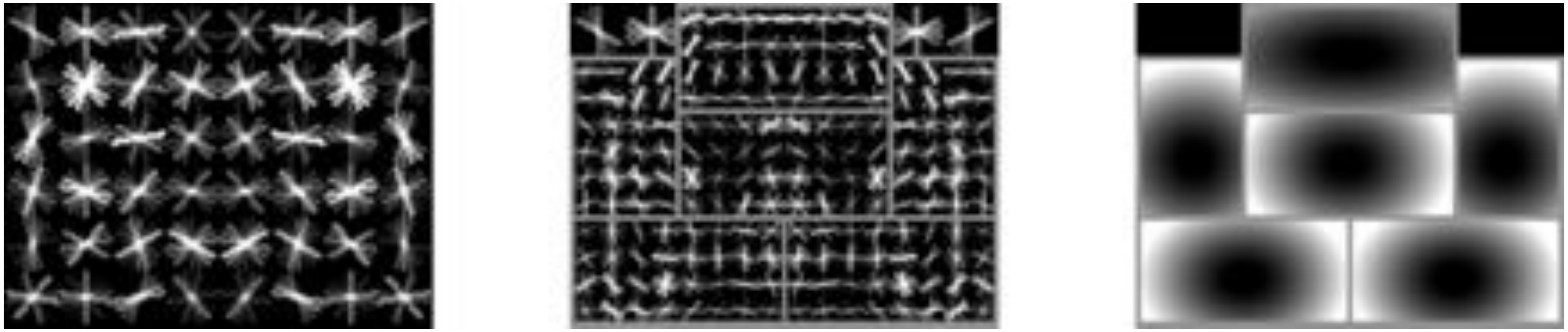
P. Felzenszwalb, R. Girshick, D. McAllester, D. Ramanan, [Object Detection with Discriminatively Trained Part Based Models](), PAMI 32(9), 2010

# Car model

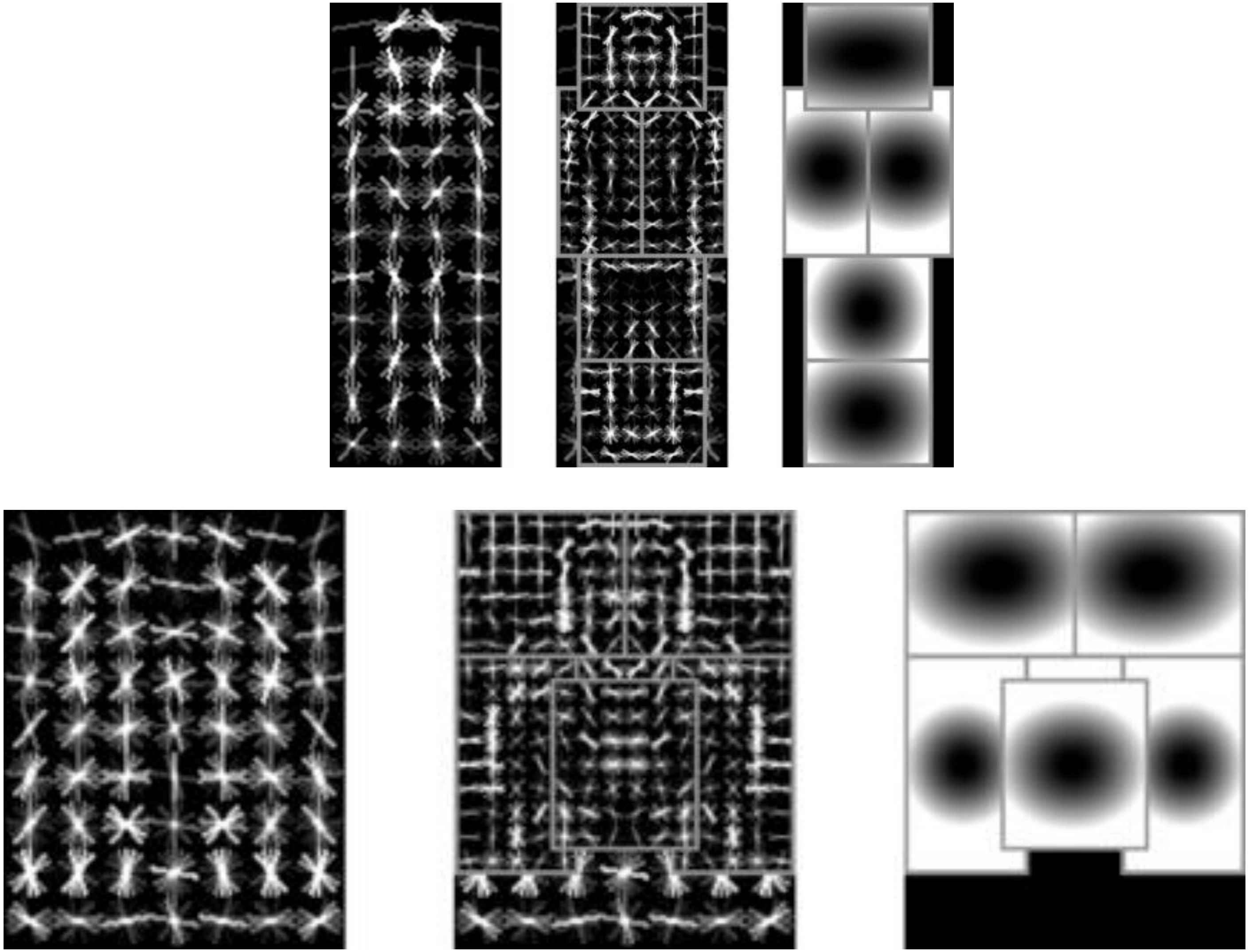
Component 1



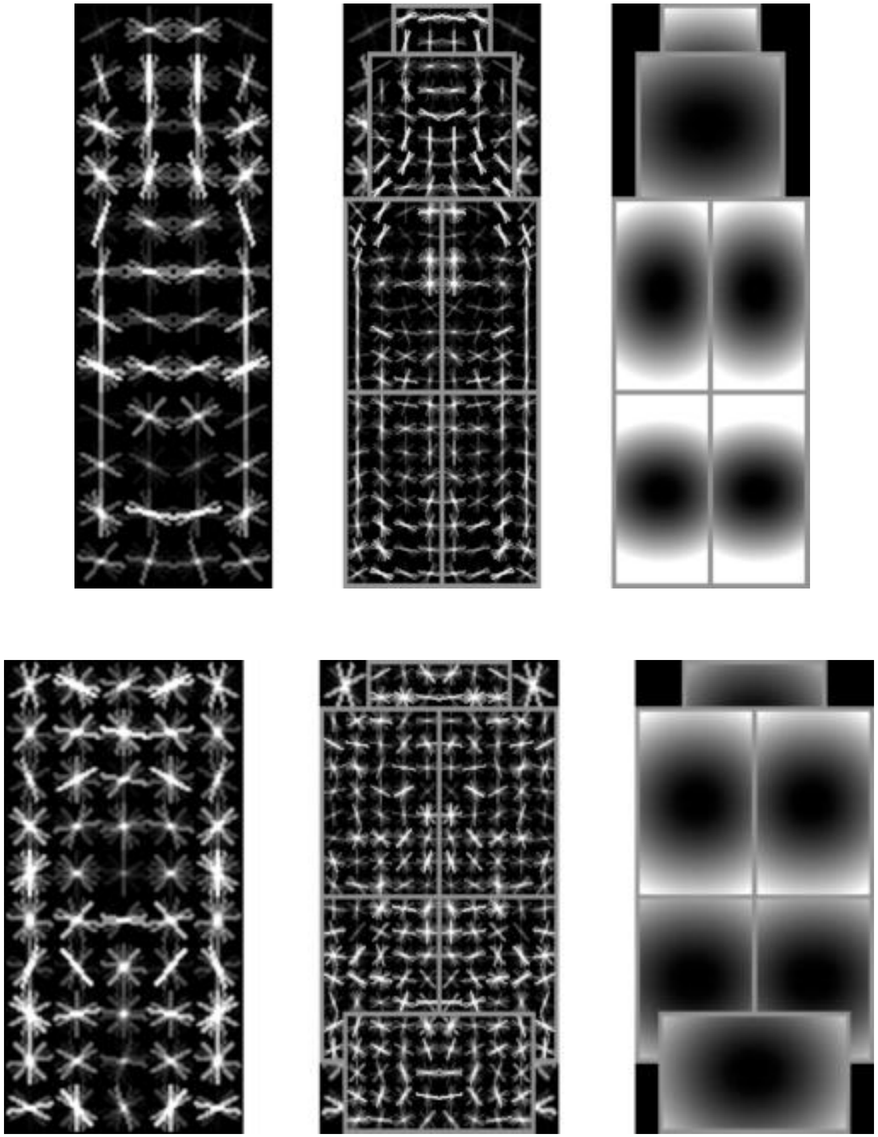
Component 2



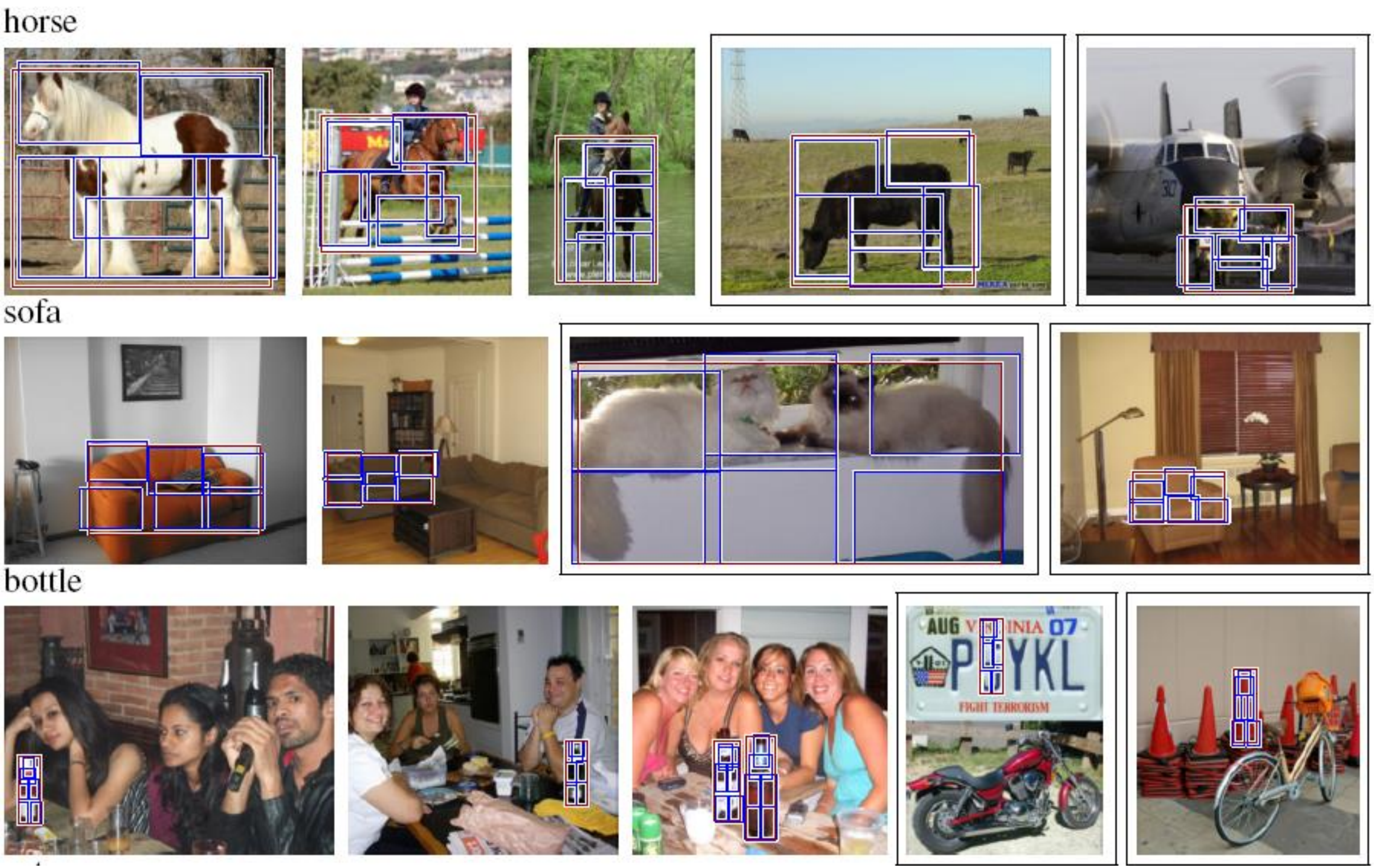
# Person model



# Bottle model

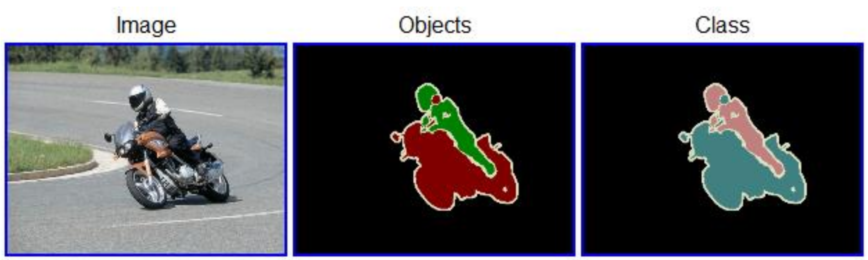


# More detections



# The PASCAL Visual Object Classes Challenge 2009 (VOC2009)

- Twenty object categories (aeroplane to TV/monitor)
- Three challenges:
  - Classification challenge (is there an X in this image?)
  - Detection challenge (draw a box around every X)
  - Segmentation challenge




Slides from Noah Snavely

# Dataset: Collection

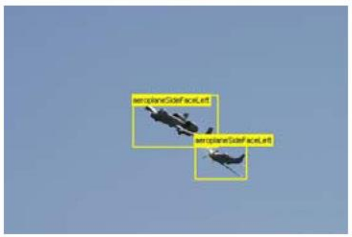
- Images downloaded from **flickr**
  - 500,000 images downloaded and random subset selected for annotation

# Dataset: Annotation

- Complete annotation of all objects
- Annotated over web with <u>written guidelines</u>
  - High quality (?)

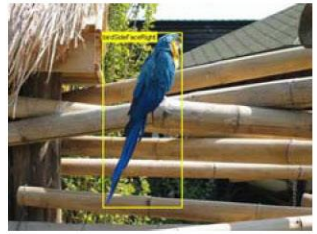
# Examples

### Aeroplane

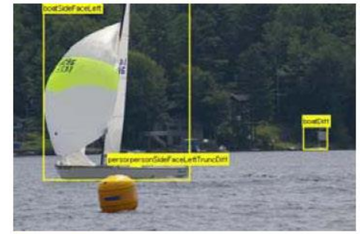


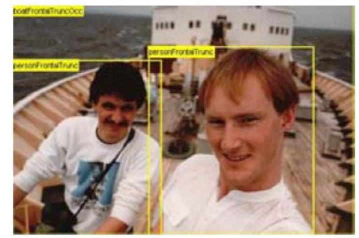
### Bicycle

### Bird

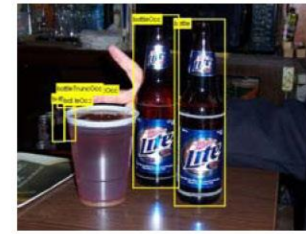


### Boat





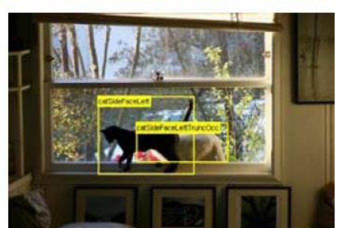
### Bottle



### Bus


### Car

### Cat

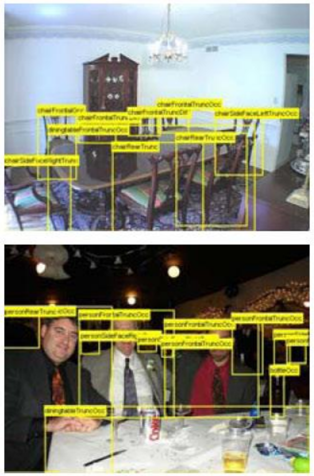


### Chair

### Cow

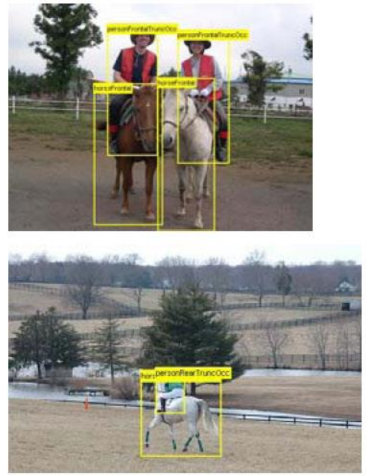
# Examples

Dining Table



Dog

Horse

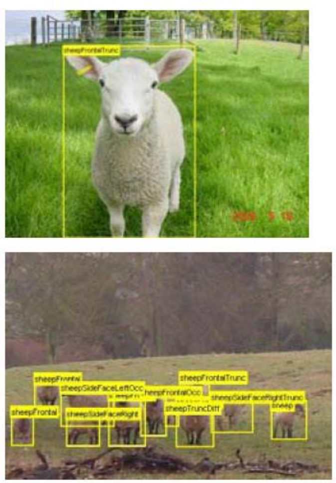


Motorbike

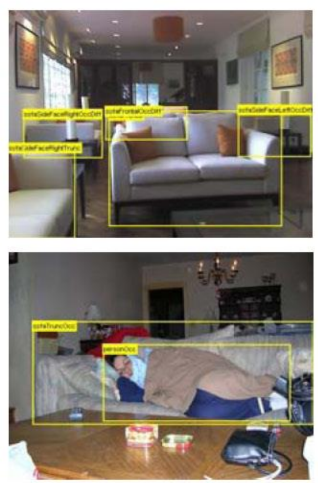
Person

Potted Plant

Sheep



Sofa



Train

TV/Monitor

# Classification Challenge

- Predict whether at least one object of a given class is present in an image

is there a cat?

# Participation

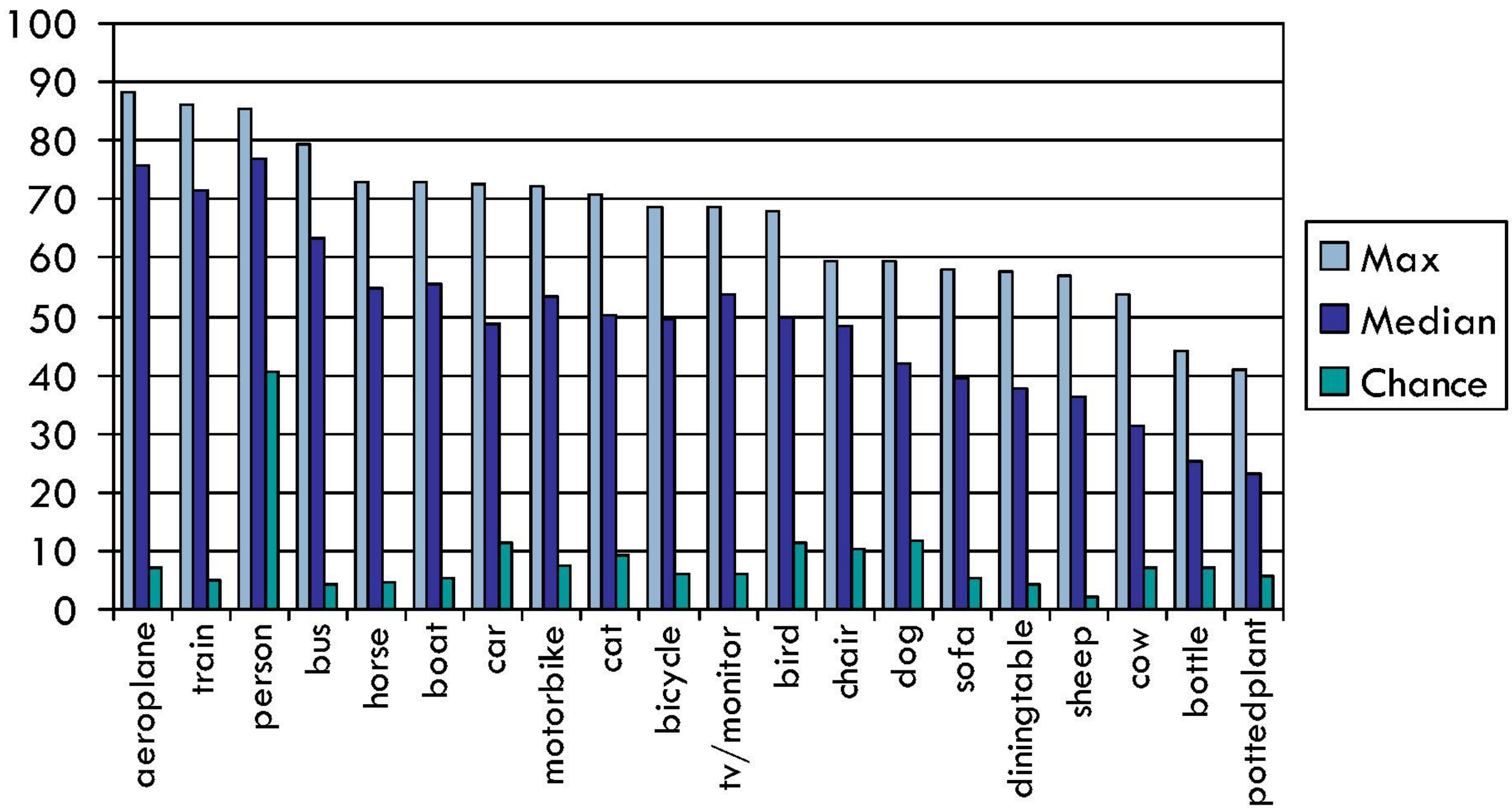
- 48 Methods, 20 Groups

# Results: AP by Method and Class

| | aero plane | bicycle | bird | boat | bottle | bus | car | cat | chair | cow | dining table | dog | horse | motor bike | person | potted plant | sheep | sofa | train | tv/ monitor |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CVC_FLAT | 85.3 | 57.8 | 66.0 | 66.1 | 36.2 | 70.6 | 60.6 | 63.5 | 55.1 | 44.6 | 53.4 | 49.1 | 64.4 | 66.8 | 84.8 | 37.4 | 44.1 | 47.9 | 81.9 | 67.5 |
| CVC_FLAT-HOG-ESS | 86.3 | 60.7 | 66.4 | 65.3 | 41.0 | 71.7 | 64.7 | 63.9 | 55.5 | 40.1 | 51.3 | 45.9 | 65.2 | 68.9 | 85.0 | 40.8 | 49.0 | 49.1 | 81.8 | 68.6 |
| CVC_PLUS | 86.6 | 58.4 | 66.7 | 67.3 | 34.8 | 70.4 | 60.0 | 64.2 | 52.5 | 43.0 | 50.8 | 46.5 | 64.1 | 66.8 | 84.4 | 37.5 | 45.1 | 45.4 | 82.1 | 67.0 |
| FIRSTNIKON_AVGSRKDA | 83.3 | 59.3 | 62.7 | 65.3 | 30.2 | 71.6 | 58.2 | 62.2 | 54.3 | 40.7 | 49.2 | 50.0 | 66.6 | 62.9 | 83.3 | 34.2 | 48.2 | 46.1 | 83.4 | 65.5 |
| FIRSTNIKON_AVGSVM | 83.8 | 58.2 | 62.6 | 65.2 | 32.0 | 69.8 | 57.7 | 61.1 | 54.5 | 44.0 | 50.3 | 49.6 | 64.6 | 61.7 | 83.2 | 33.4 | 46.5 | 48.0 | 81.6 | 65.3 |
| FIRSTNIKON_BOOSTSRKDA | 83.0 | 59.2 | 61.4 | 64.6 | 33.2 | 71.1 | 57.5 | 61.0 | 54.8 | 40.7 | 48.3 | 50.0 | 65.5 | 63.4 | 82.8 | 32.8 | 47.0 | 47.1 | 83.3 | 64.6 |
| FIRSTNIKON_BOOSTSVMS | 83.5 | 56.8 | 61.8 | 65.5 | 33.2 | 69.7 | 57.3 | 60.5 | 54.6 | 43.1 | 48.3 | 50.3 | 64.3 | 62.4 | 82.3 | 32.9 | 46.9 | 48.4 | 82.0 | 64.2 |
| LEAR_CHI-SVM-MULT-LOC | 79.5 | 55.5 | 54.5 | 63.9 | 43.7 | 70.3 | 66.4 | 56.5 | 54.4 | 38.8 | 44.1 | 46.2 | 58.5 | 64.2 | 82.2 | 39.1 | 41.3 | 39.8 | 73.6 | 66.2 |
| NECUIUC_CDCV | 88.1 | 68.0 | 68.0 | 72.5 | 41.0 | 78.9 | 70.4 | 70.4 | 58.1 | 53.4 | 55.7 | 59.3 | 73.1 | 71.3 | 84.5 | 32.3 | 53.3 | 56.7 | 86.0 | 66.8 |
| NECUIUC_CLS-DTCT | 88.0 | 68.6 | 67.9 | 72.9 | 44.2 | 79.5 | 72.5 | 70.8 | 59.5 | 53.6 | 57.5 | 59.0 | 72.6 | 72.3 | 85.3 | 36.6 | 56.9 | 57.9 | 85.9 | 68.0 |
| NECUIUC_LL-CDCV | 87.1 | 67.4 | 65.8 | 72.3 | 40.9 | 78.3 | 69.7 | 69.7 | 58.5 | 50.1 | 55.1 | 56.3 | 71.8 | 70.8 | 84.1 | 31.4 | 51.5 | 55.1 | 84.7 | 65.2 |
| NECUIUC_LN-CDCV | 87.7 | 67.8 | 68.1 | 71.1 | 39.1 | 78.5 | 70.6 | 70.7 | 57.4 | 51.7 | 53.3 | 59.2 | 71.6 | 70.6 | 84.0 | 30.9 | 51.7 | 55.9 | 85.9 | 66.7 |
| UVASURREY_BASELINE | 84.1 | 59.2 | 62.7 | 65.4 | 35.7 | 70.6 | 59.8 | 61.3 | 56.7 | 45.3 | 52.4 | 50.6 | 66.1 | 66.6 | 83.7 | 34.8 | 47.2 | 47.7 | 80.8 | 65.9 |
| UVASURREY_MKFDA+BOW | 84.7 | 63.9 | 66.1 | 67.3 | 37.9 | 74.1 | 63.2 | 64.0 | 57.1 | 46.2 | 54.7 | 53.5 | 68.1 | 70.6 | 85.2 | 38.5 | 47.2 | 49.3 | 83.2 | 68.1 |
| UVASURREY_TUNECOLORKERNELSEL | 85.0 | 62.8 | 65.1 | 66.5 | 37.6 | 73.5 | 62.1 | 62.0 | 57.4 | 45.1 | 54.5 | 52.5 | 67.7 | 69.8 | 84.8 | 39.1 | 46.8 | 49.9 | 82.9 | 68.1 |
| UVASURREY_TUNECOLORSPECKDA | 84.6 | 62.4 | 65.6 | 67.2 | 39.4 | 74.0 | 63.4 | 62.8 | 56.7 | 43.8 | 54.7 | 52.7 | 67.3 | 70.6 | 85.0 | 38.8 | 46.9 | 50.0 | 82.2 | 66.2 |

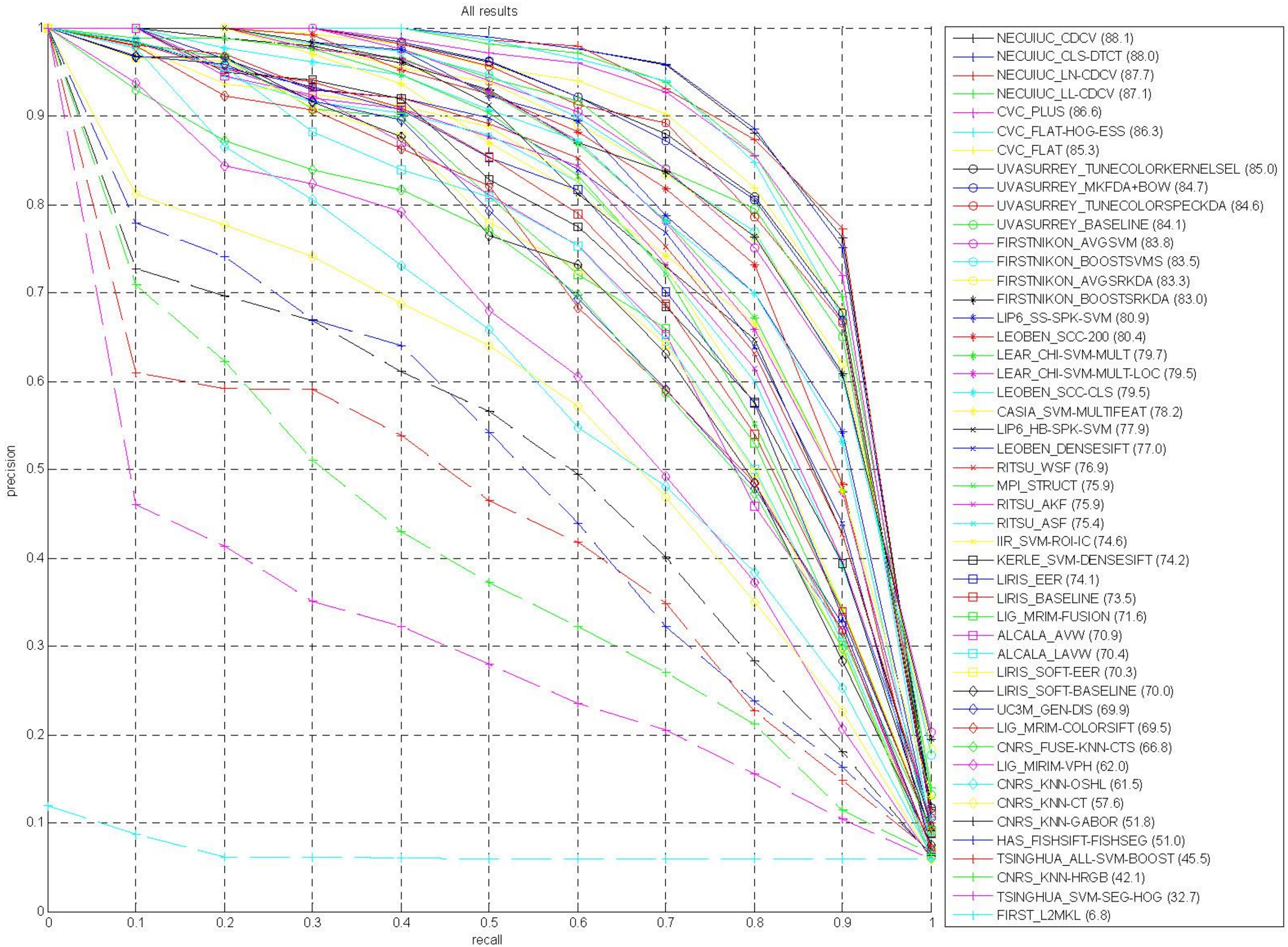
- Only methods in 1st, 2nd or 3rd place by group shown
- Groups: CVC, FIRST/Nikon, NEC/UIUC, UVA/Surrey

# AP by Class

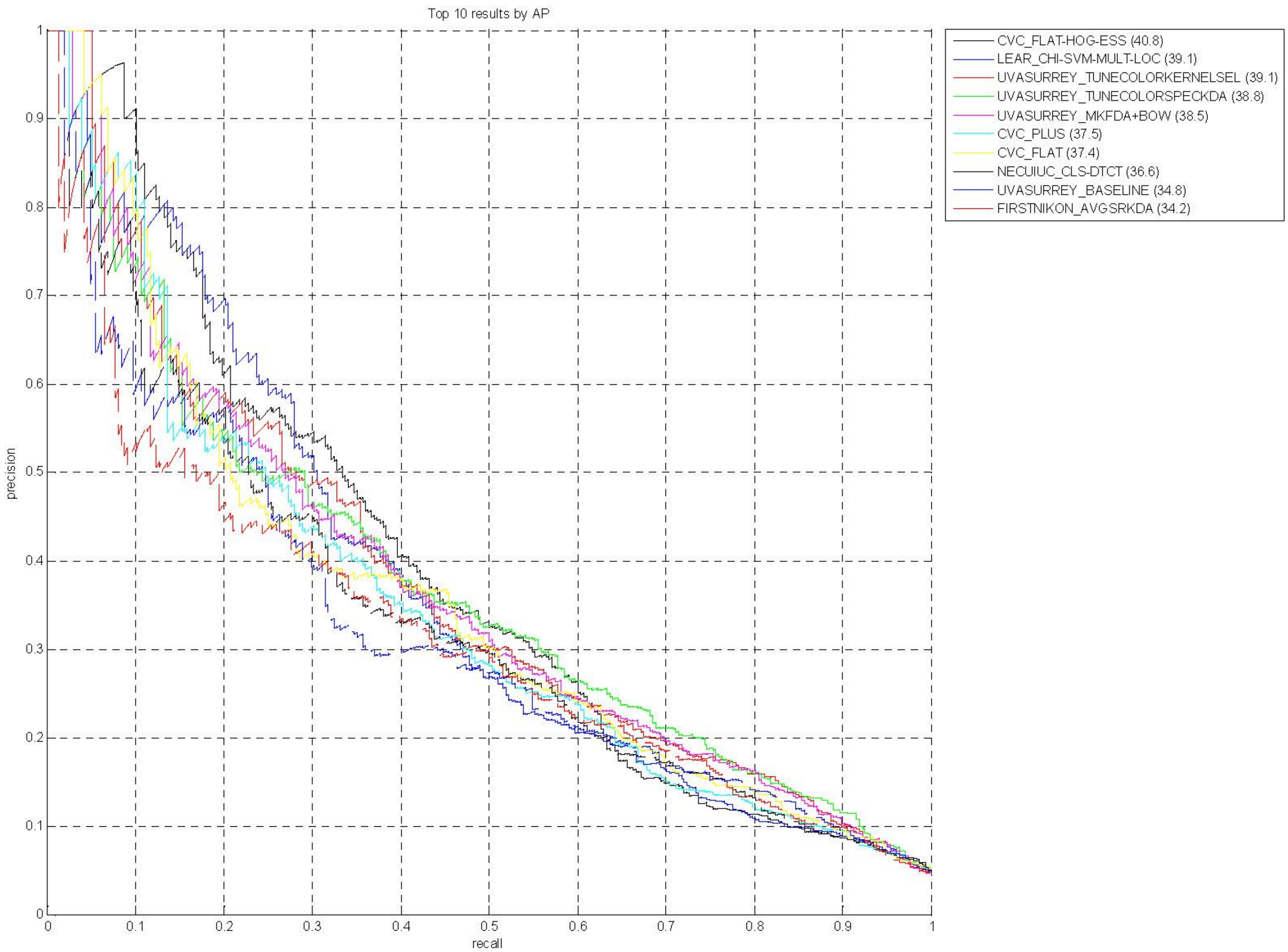



- Max AP: 88.1% (aeroplane) ... 40.8% (potted plant)

# Precision/Recall: Aeroplane (All)



# Precision/Recall: Potted plant (Top 10 by AP)

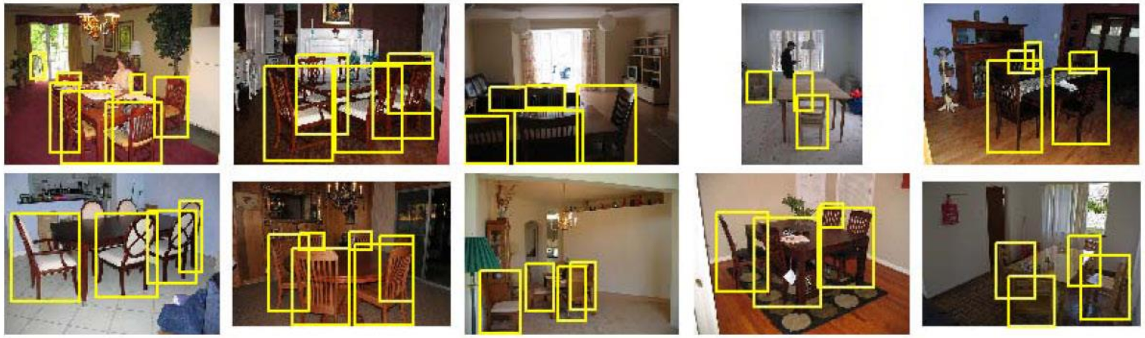


# Ranked Images: Aeroplane

- Class images: Highest ranked

# Ranked Images: Chair

- Class images: Highest ranked

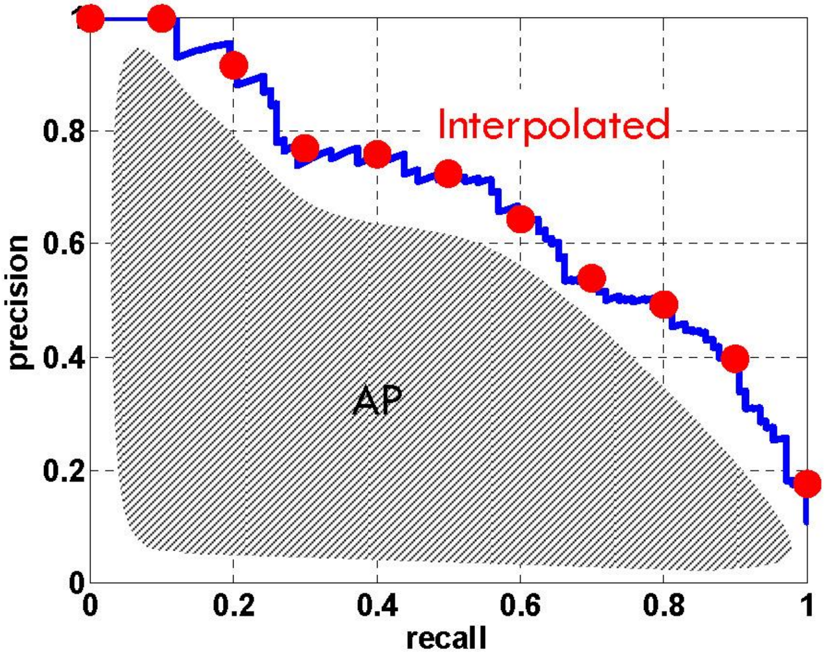


# Detection Challenge

- Predict the bounding boxes of all objects of a given class in an image (if any)

# Evaluation

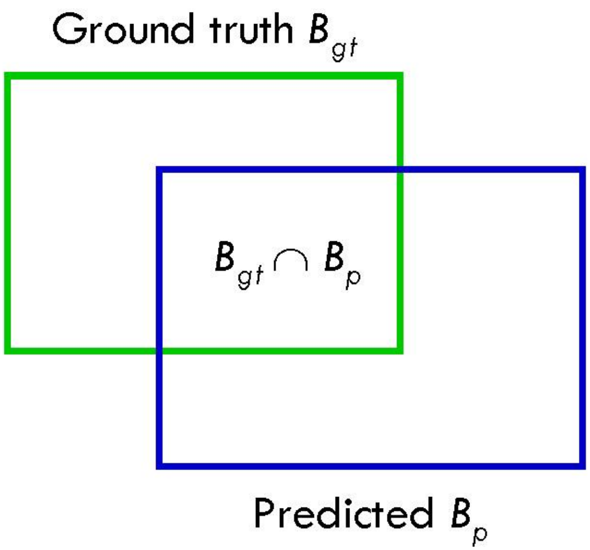
- Average Precision [TREC] averages precision over the entire range of recall
  - Curve interpolated to reduce influence of "outliers"




- A good score requires both high recall and high precision
- Application-independent
- Penalizes methods giving high precision but low recall

# Evaluating Bounding Boxes

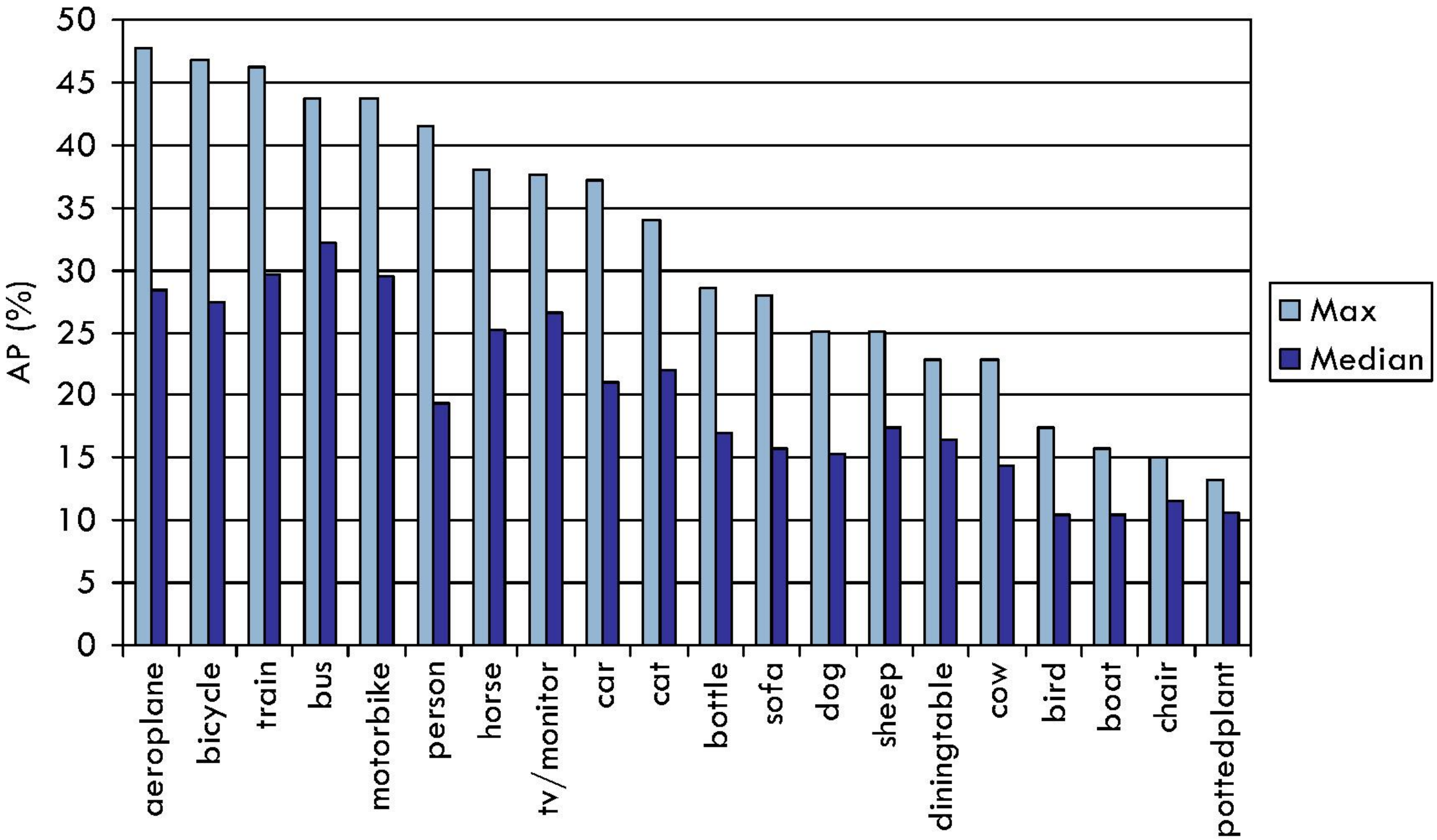
- Area of Overlap (AO) Measure




$$AO(B_{gt}, B_p) = \frac{|B_{gt} \bigcap B_p|}{|B_{gt} \bigcup B_p|}$$

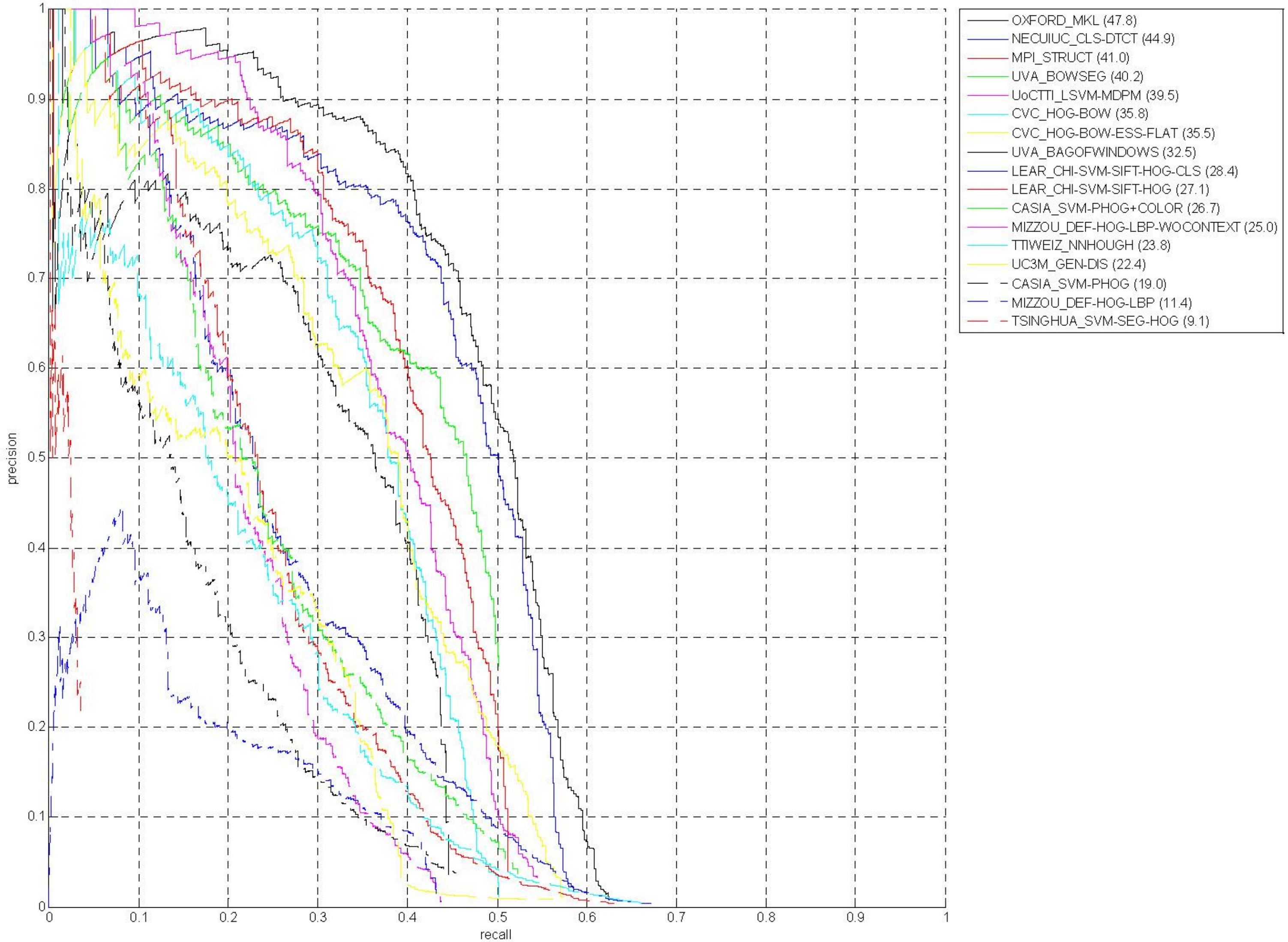
- Need to define a threshold *t* such that $AO(B_{gt}, B_p)$ implies a correct detection: 50%

# AP by Class

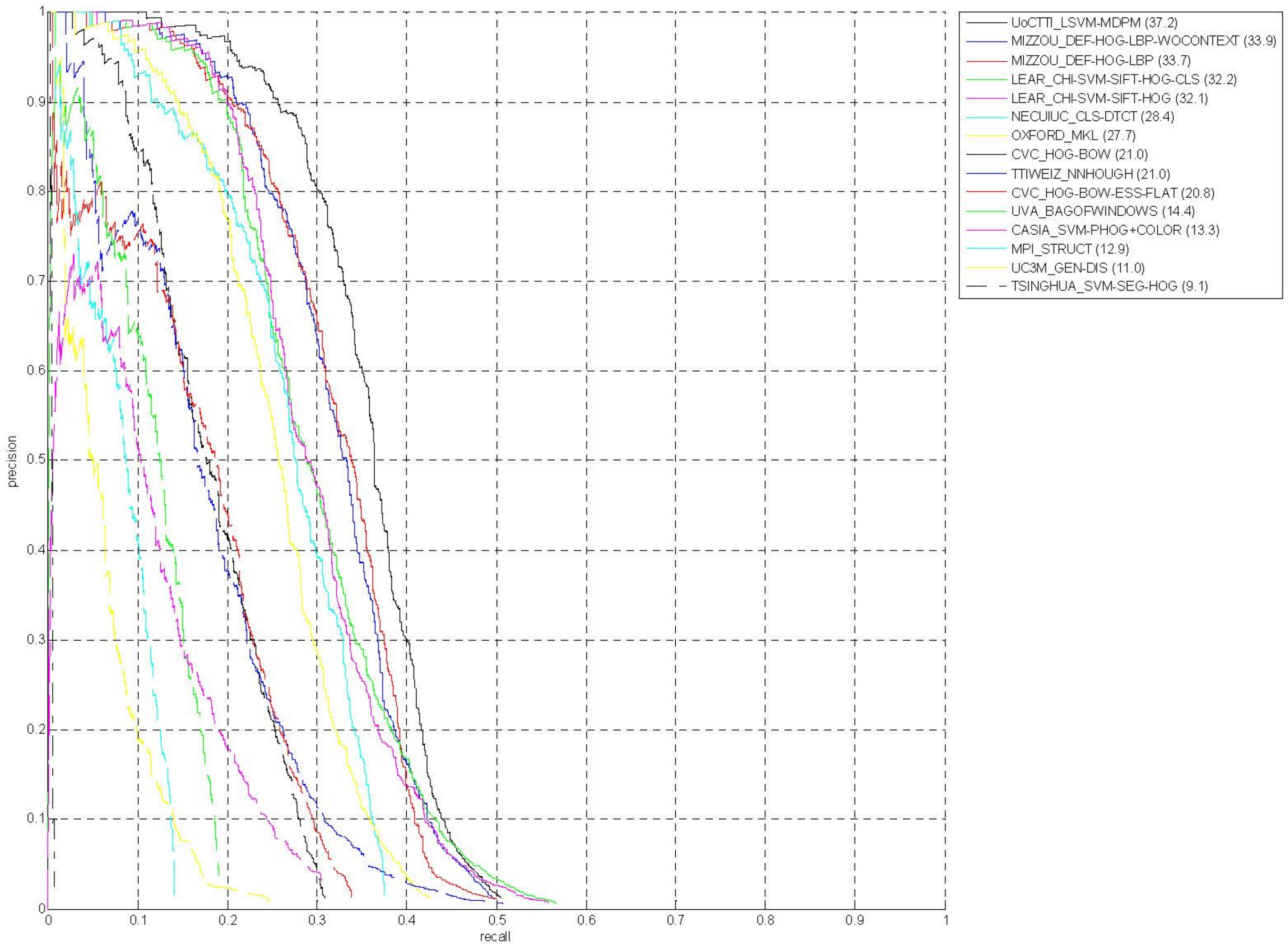



Chance essentially 0

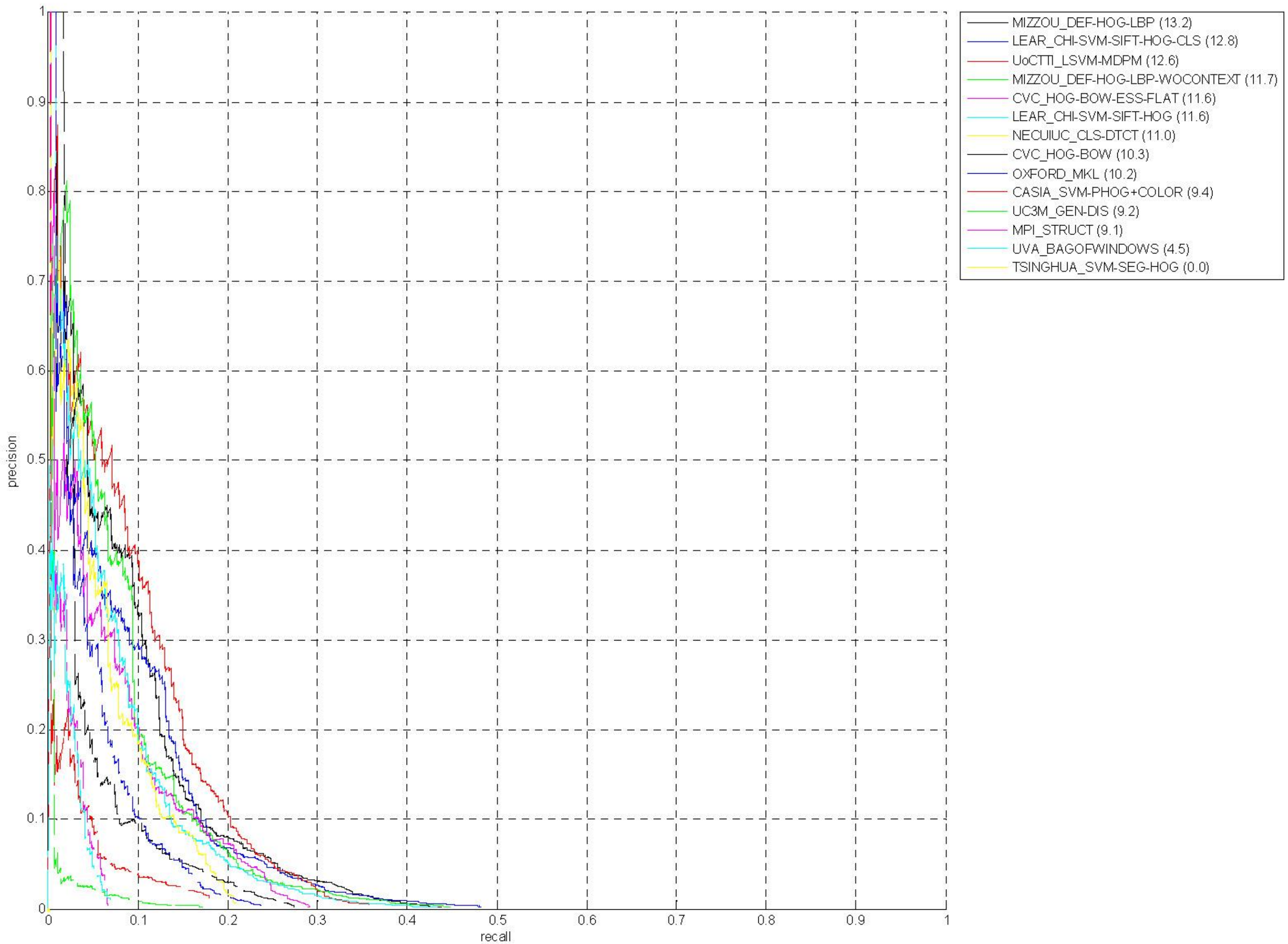
# Precision/Recall - Aeroplane



# Precision/Recall - Car



# Precision/Recall – Potted plant



# True Positives - Person

UoCTTI_LSVM-MDPM

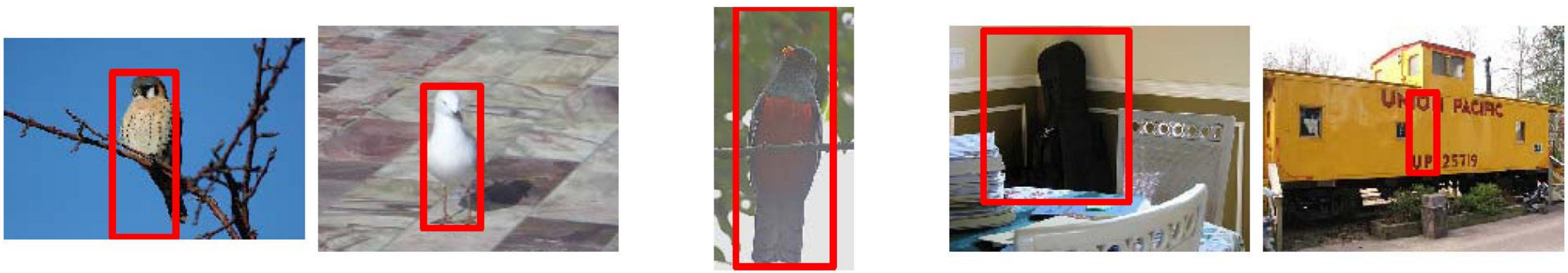
MIZZOU_DEF-HOG-LBP

NECUIUC_CLS-DTCT

# False Positives - Person

UoCTTI_LSVM-MDPM

MIZZOU_DEF-HOG-LBP



NECUIUC_CLS-DTCT

# “Near Misses” - Person

UoCTTI_LSVM-MDPM


MIZZOU_DEF-HOG-LBP

NECUIUC_CLS-DTCT

# True Positives - Bicycle

UoCTTI_LSVM-MDPM

OXFORD_MKL

NECUIUC_CLS-DTCT

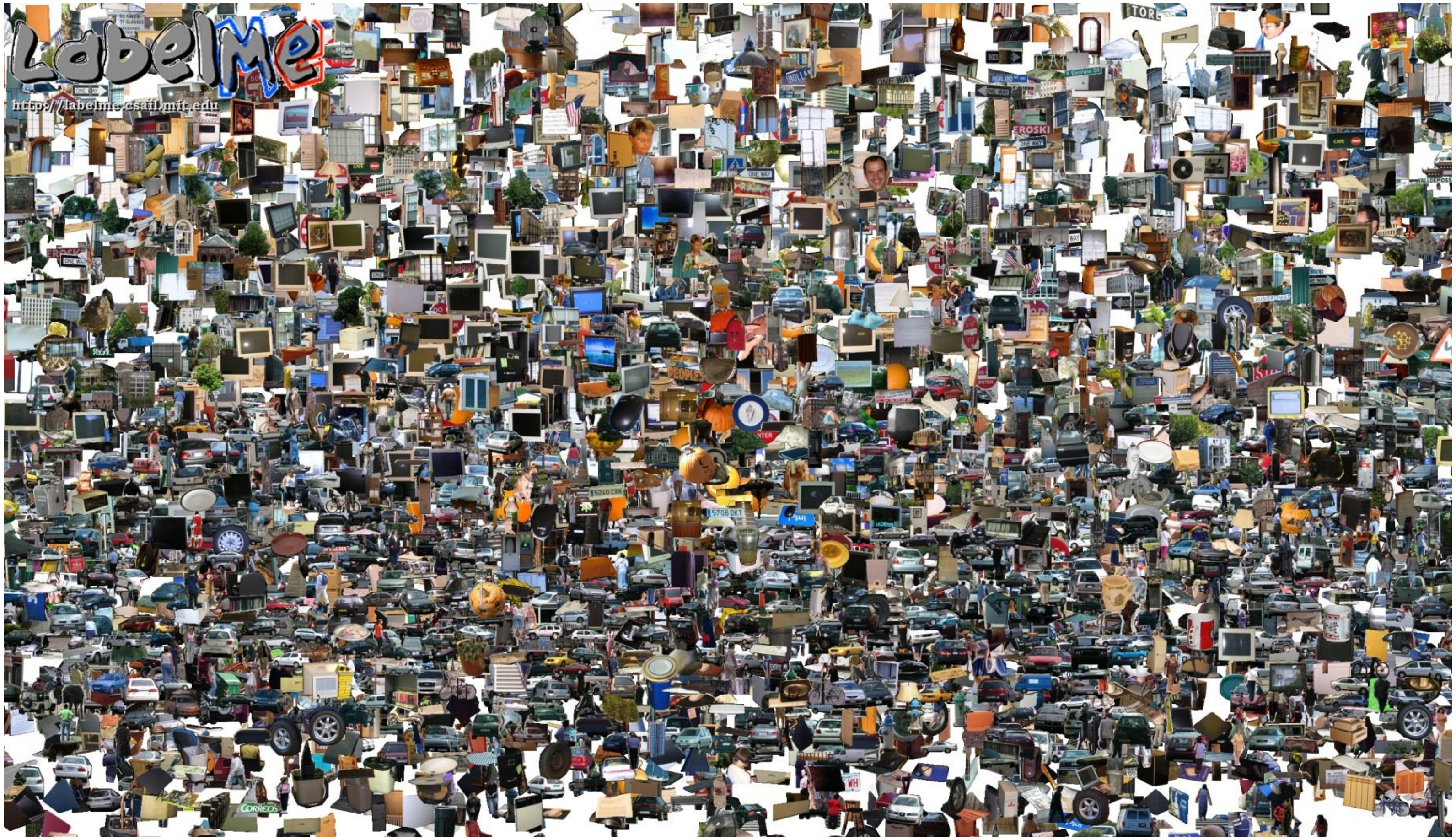
# False Positives - Bicycle

UoCTTI_LSVM-MDPM

OXFORD_MKL

NECUIUC_CLS-DTCT

# Opportunities of Scale




Computer Vision

James Hays

Many slides from James Hays, Alyosha Efros, and Derek Hoiem

Graphic from Antonio Torralba

# Computer Vision so far

- The geometry of image formation
  - Ancient / Renaissance
- Signal processing / Convolution
  - 1800, but really the 50’s and 60’s
- Hand-designed Features for recognition, either instance-level or categorical
  - 1999 (SIFT), 2003 (Video Google), 2005 (Dalal-Triggs), 2006 (spatial pyramid)
- Learning from Data
  - 1991 (EigenFaces) but late 90’s to now especially

# What has changed in the last decade?

- The Internet
- Crowdsourcing
- Learning representations from the data these sources provide (deep learning)

# Opportunities of Scale: Data-driven methods

- Today's class
  - Scene completion
  - Im2gps

# Google and massive data-driven algorithms

A.I. for the postmodern world:

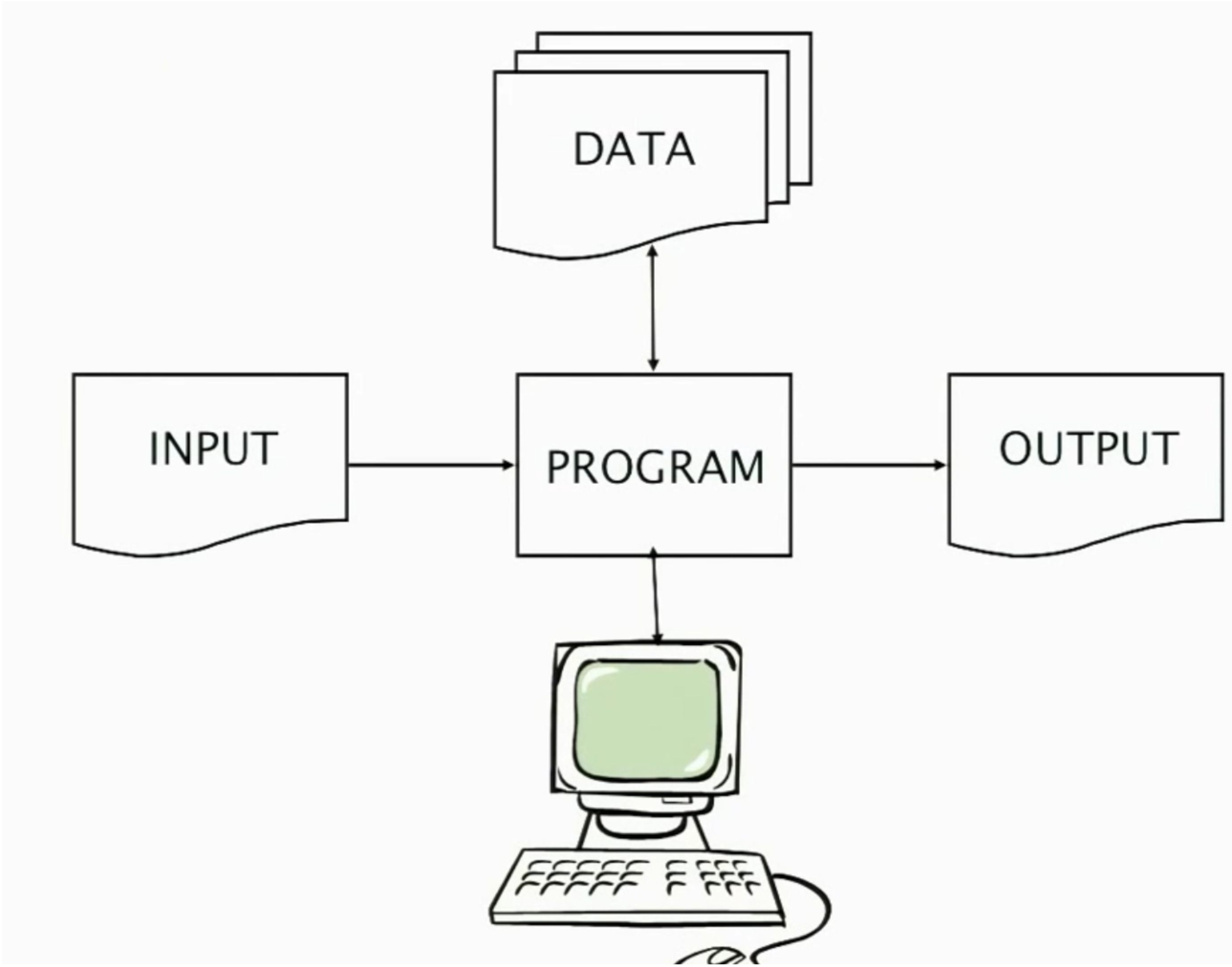
- all questions have already been answered…many times, in many ways
- Google is dumb, the "intelligence" is <u>in the data</u>

# The Unreasonable Effectiveness of Data

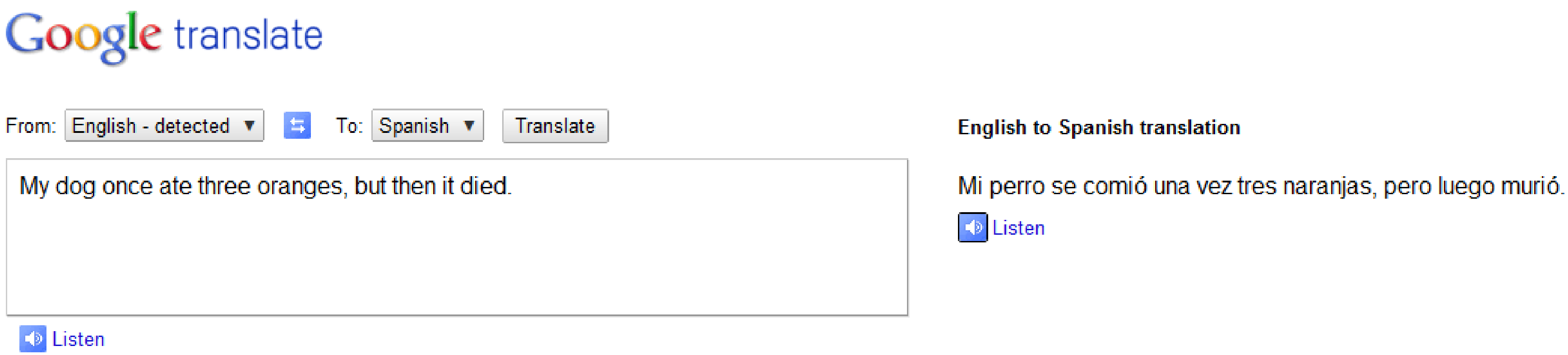
Peter Norvig
Google


Peter Norvig

The Unreasonable
Effectiveness of Data


DATA
INPUT
PROGRAM
OUTPUT

# Google Translate




http://ackuna.com/badtranslator

# Chinese Room, John Searle (1980)

If a machine can convincingly simulate an intelligent conversation, does it necessarily understand? In the experiment, Searle imagines himself in a room, acting as a computer by manually executing a program that convincingly simulates the behavior of a native Chinese speaker.

Most of the discussion consists of attempts to refute it. "The overwhelming majority," notes *BBS* editor Stevan Harnad,“ still think that the Chinese Room Argument is dead wrong." The sheer volume of the literature that has grown up around it inspired Pat Hayes to quip that the field of cognitive science ought to be redefined as "the ongoing research program of showing Searle's Chinese Room Argument to be false.

**Yann LeCun**

October 23 at 9:58pm ·

Questions from the piece:

Q1. Does the Chinese Room argument prove the impossibility of machine consciousness?
A1: Hell no. ... See More

## Can Machines Become Moral?

The question is heard more and more often, both from those who think that machines cannot become moral, and who think that to believe otherwise is a dangerous illusion, and from those who think that machines must become moral,...

BIGQUESTIONSONLINE.COM | BY DON HOWARD

You and 156 others 30 Comments 20 Shares

Like Comment Share

# Big Idea

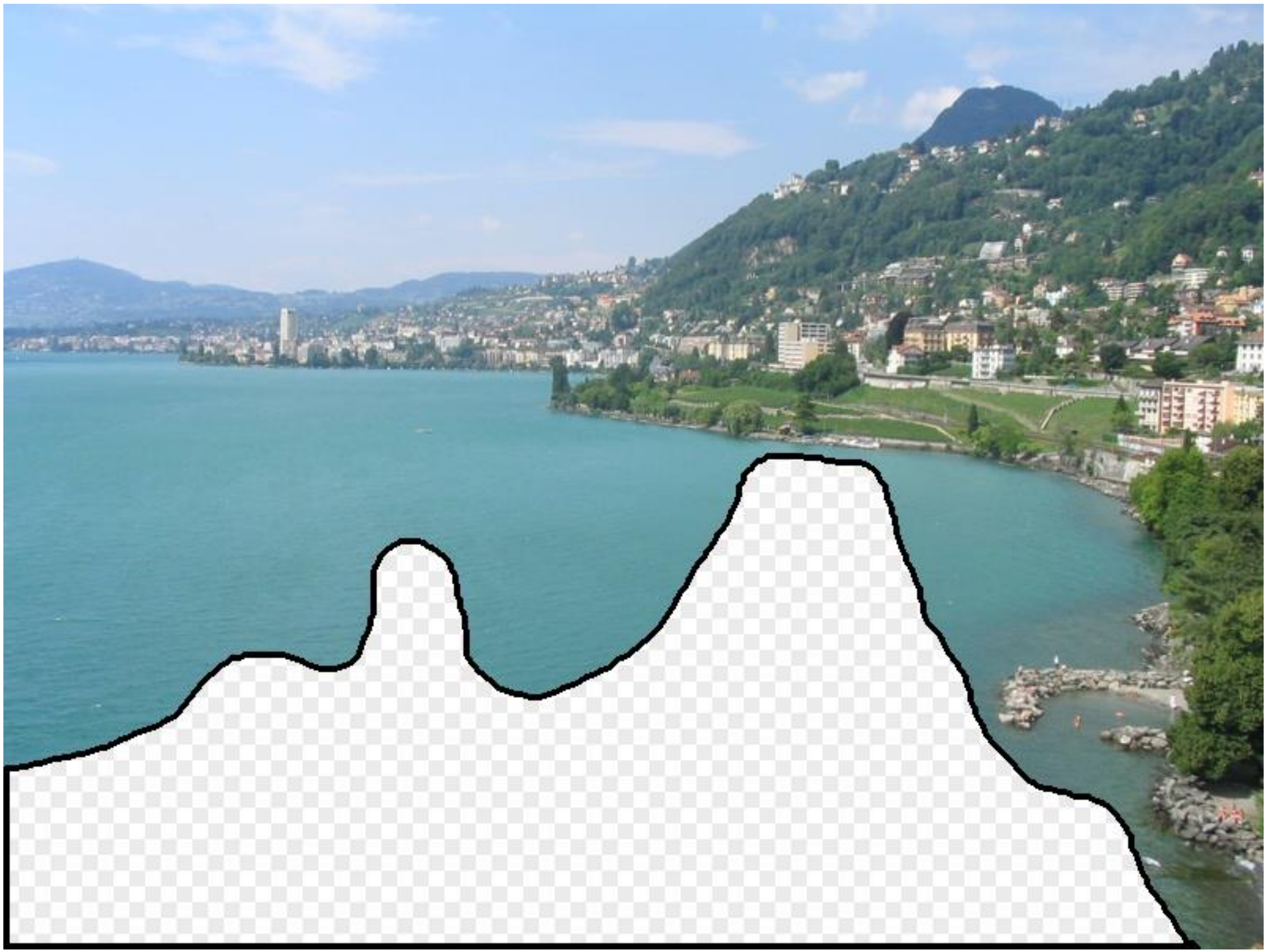
- Do we need computer vision systems to have strong AI-like reasoning about our world?
- What if invariance / generalization isn’t actually the core difficulty of computer vision?
- What if we can perform high level reasoning with brute-force, data-driven algorithms?

# Image Completion Example

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

http://graphics.cs.cmu.edu/projects/scene-completion/

# What should the missing region contain?



# Which is the original?

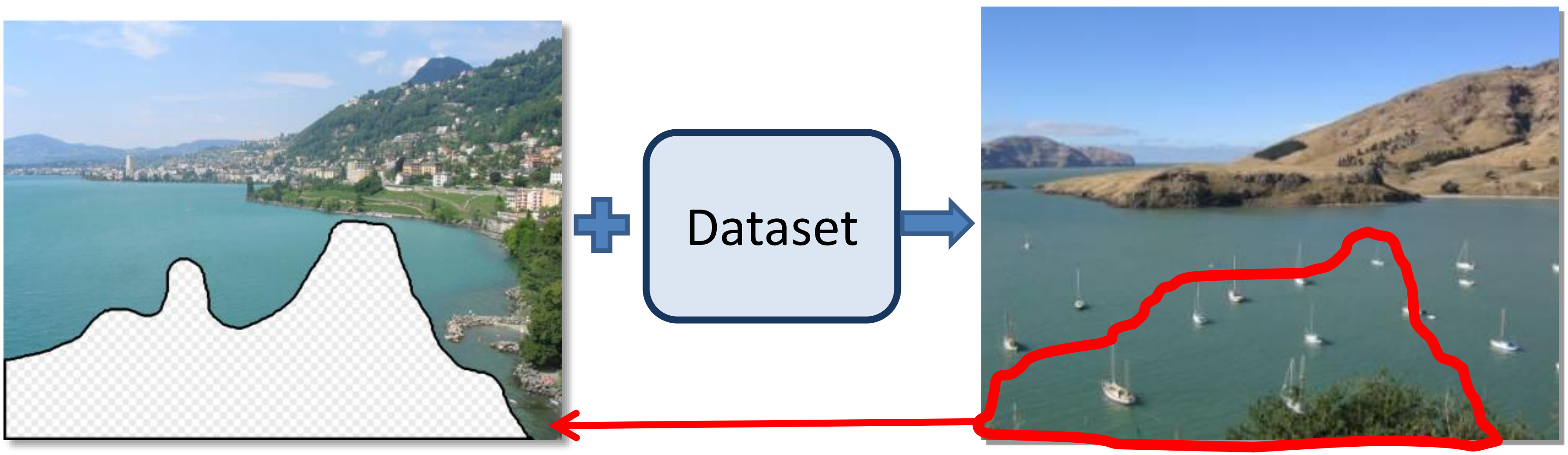
(a)

(b)

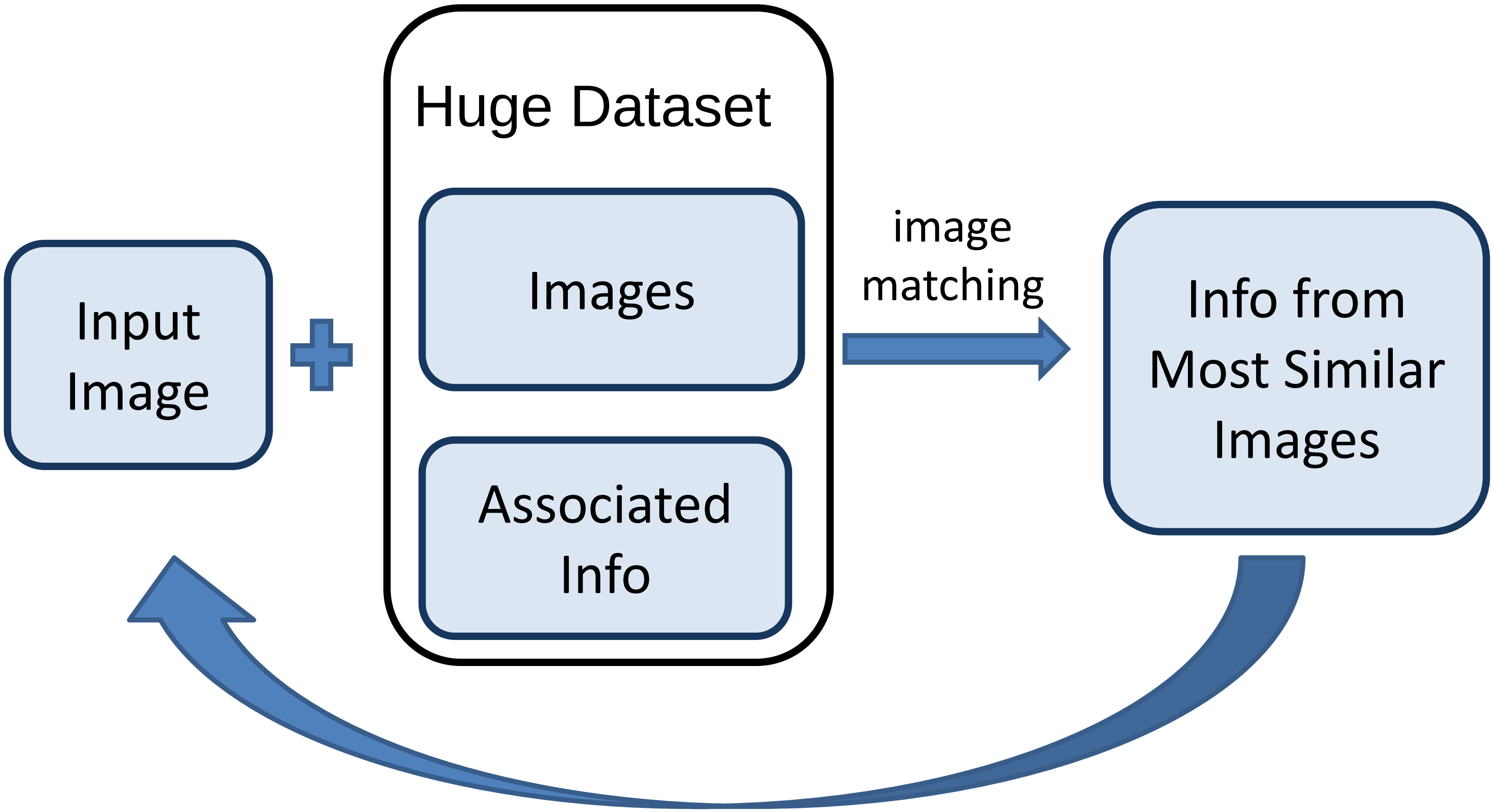
(c)

# How it works

- Find a similar image from a large dataset
- Blend a region from that image into the hole

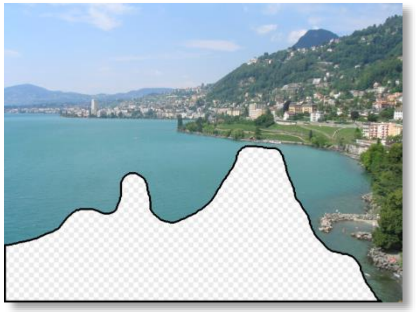


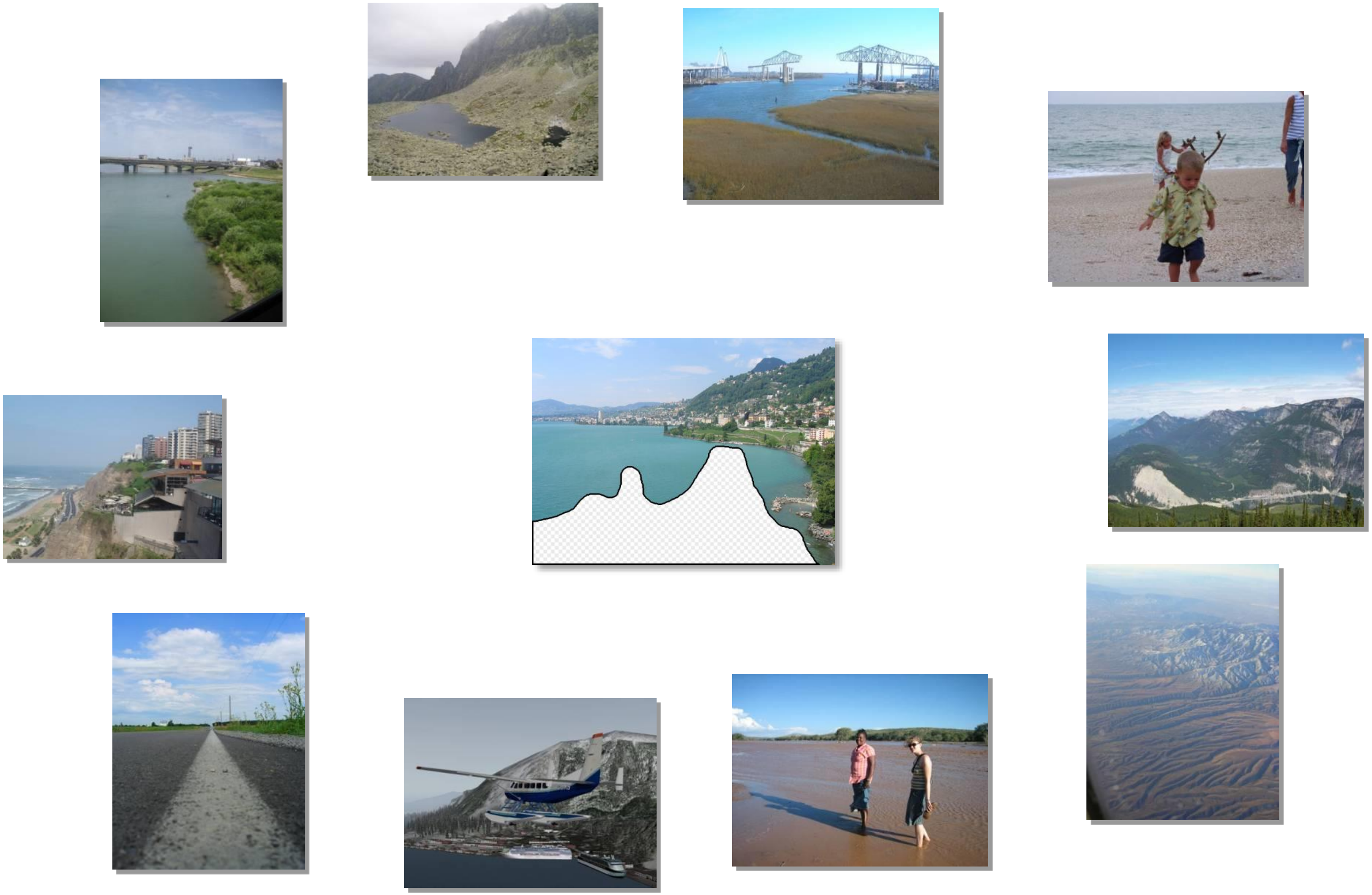
# General Principal



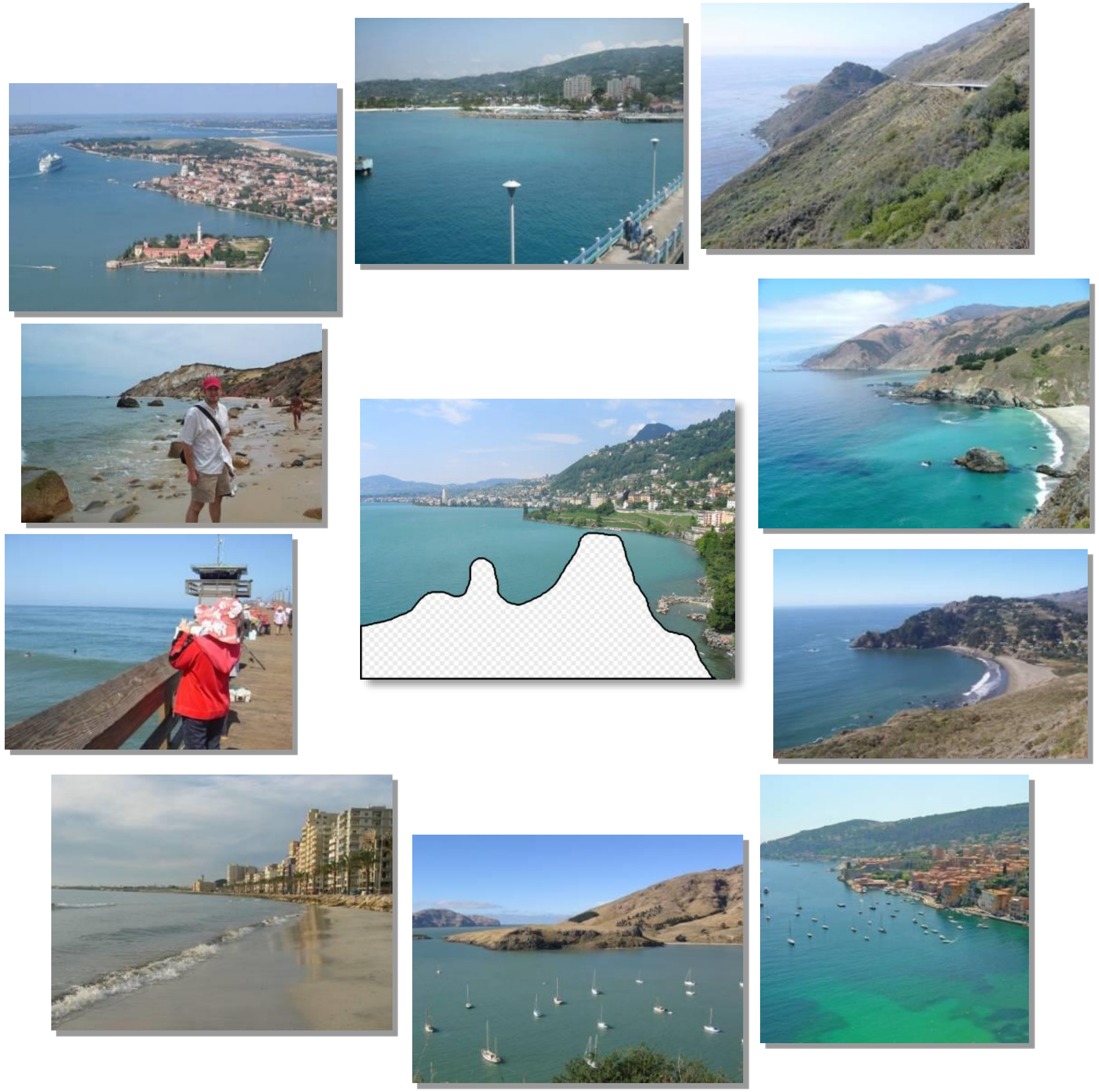

Hopefully, If you have enough images, the dataset will contain very similar images that you can find with simple matching methods.

# How many images is enough?





Nearest neighbors from a
collection of 20 thousand images



Nearest neighbors from a
collection of 2 million images

# Image Data on the Internet

- Flickr (as of Sept. 19th, 2010)
  - 5 billion photographs
  - 100+ million geotagged images
- Facebook (as of 2009)
  - 15 billion

http://royal.pingdom.com/2010/01/22/internet-2009-in-numbers/

# Image Data on the Internet

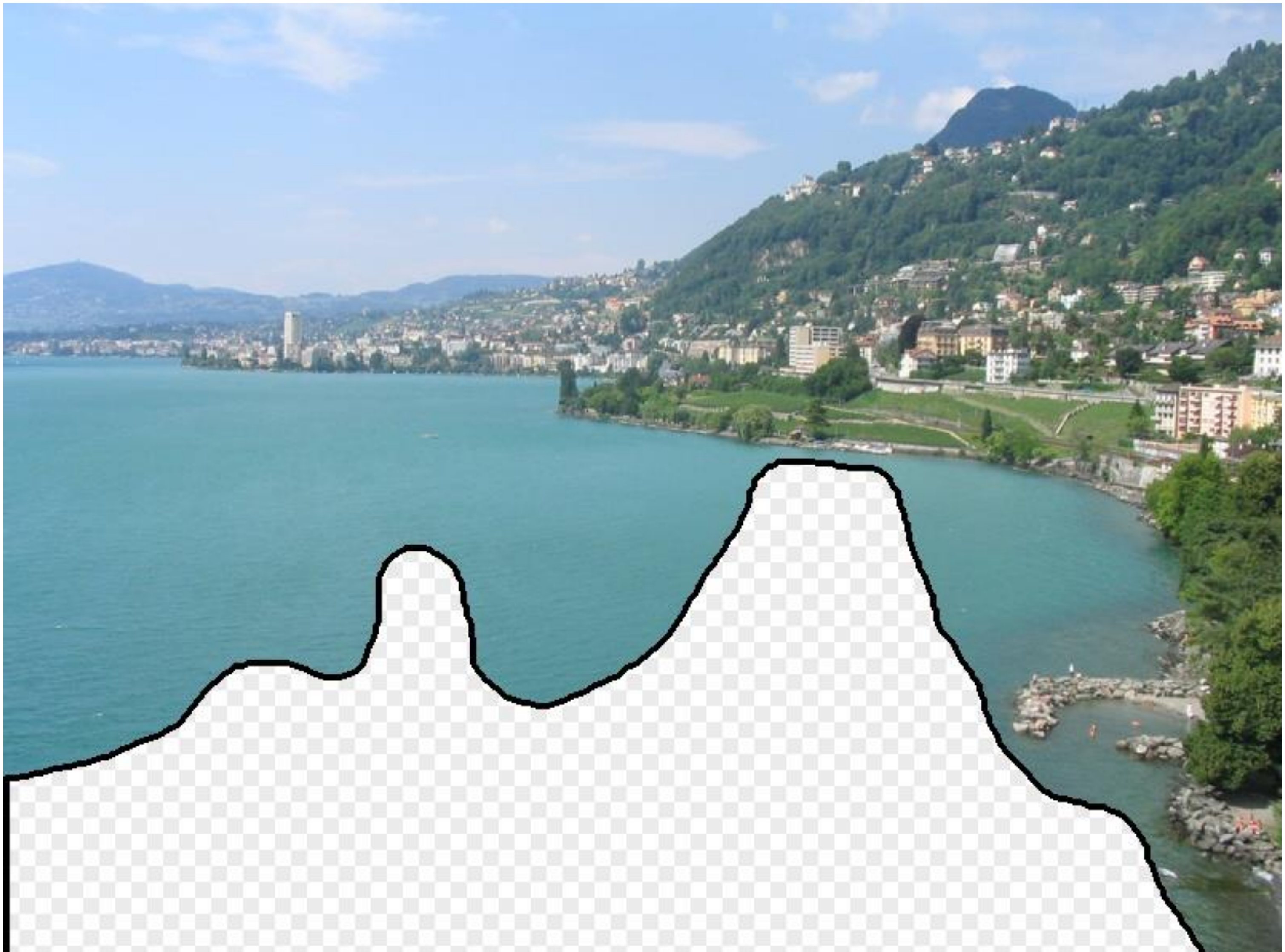
- Flickr (as of Nov 2013)
  - 10 billion photographs
  - 100+ million geotagged images
  - 3.5 million a day
- Facebook (as of Sept 2013)
  - 250 billion+
  - 300 million a day
- Instagram
  - 55 million a day

# Image completion: how it works

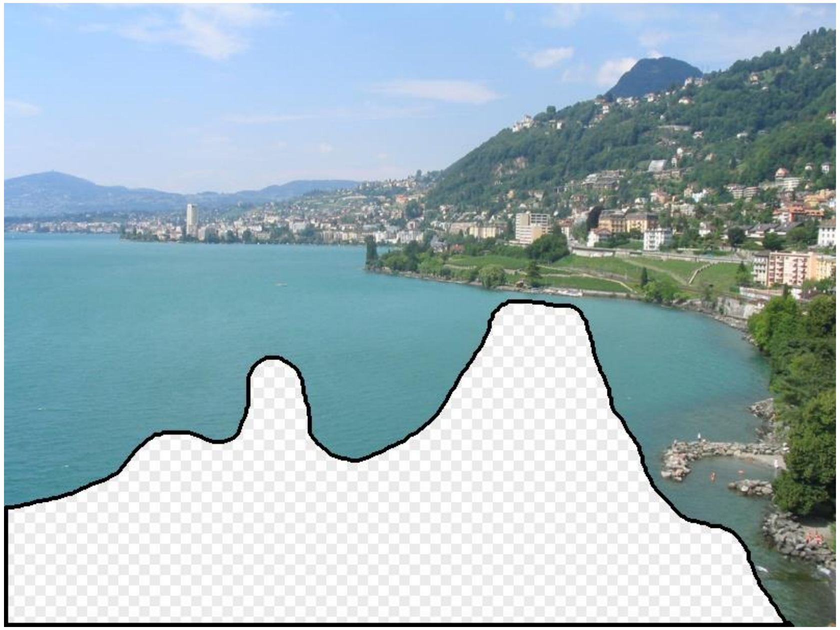
[Hays and Efros. Scene Completion Using Millions of Photographs. SIGGRAPH 2007 and CACM October 2008.]

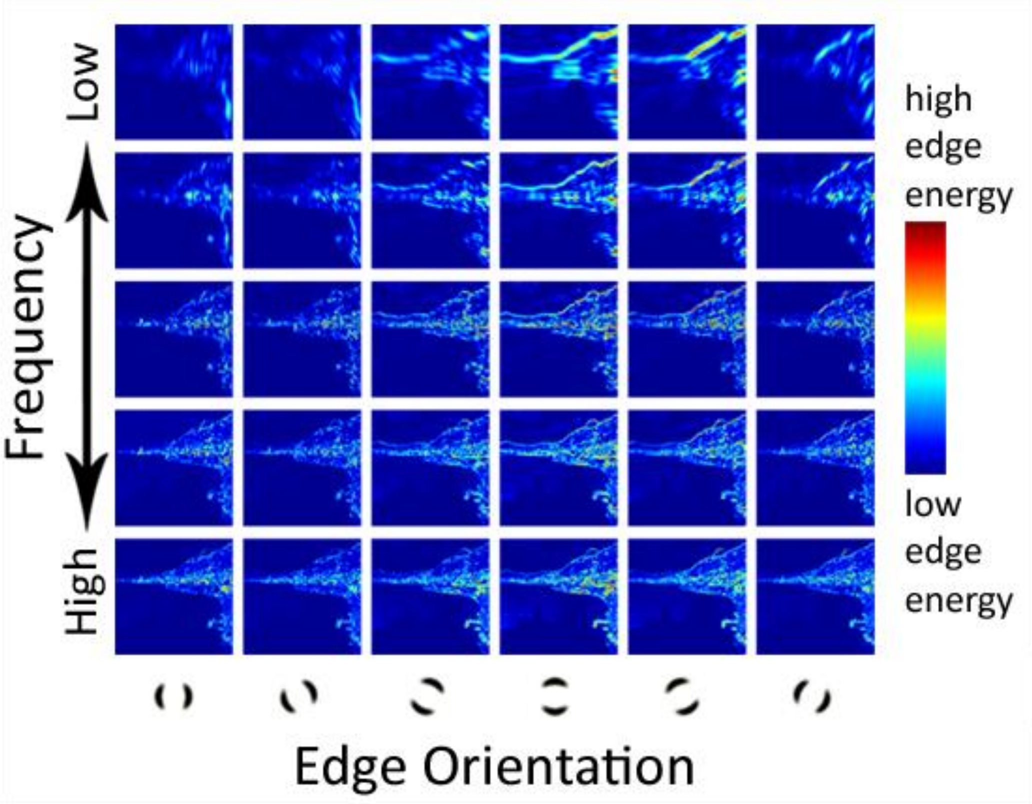
# The Algorithm

# Scene Matching



# Scene Descriptor





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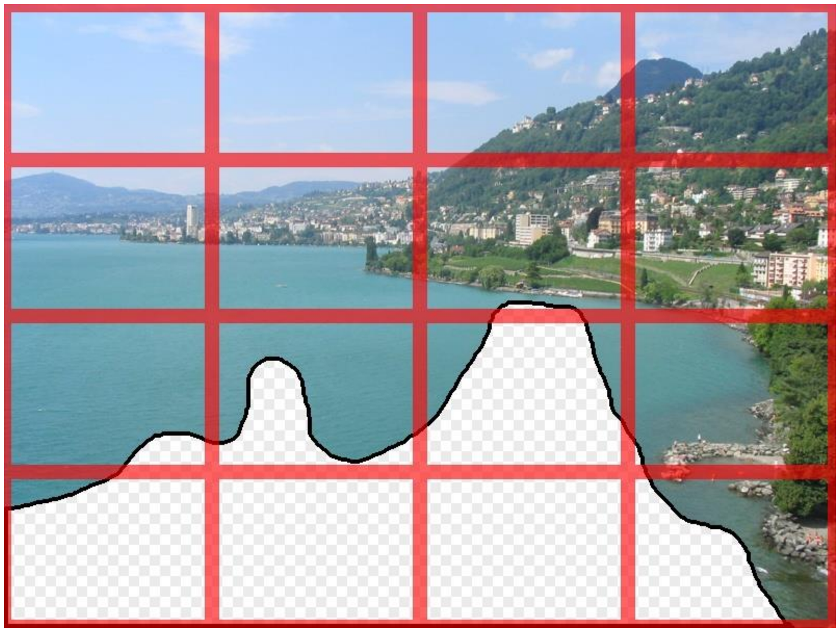

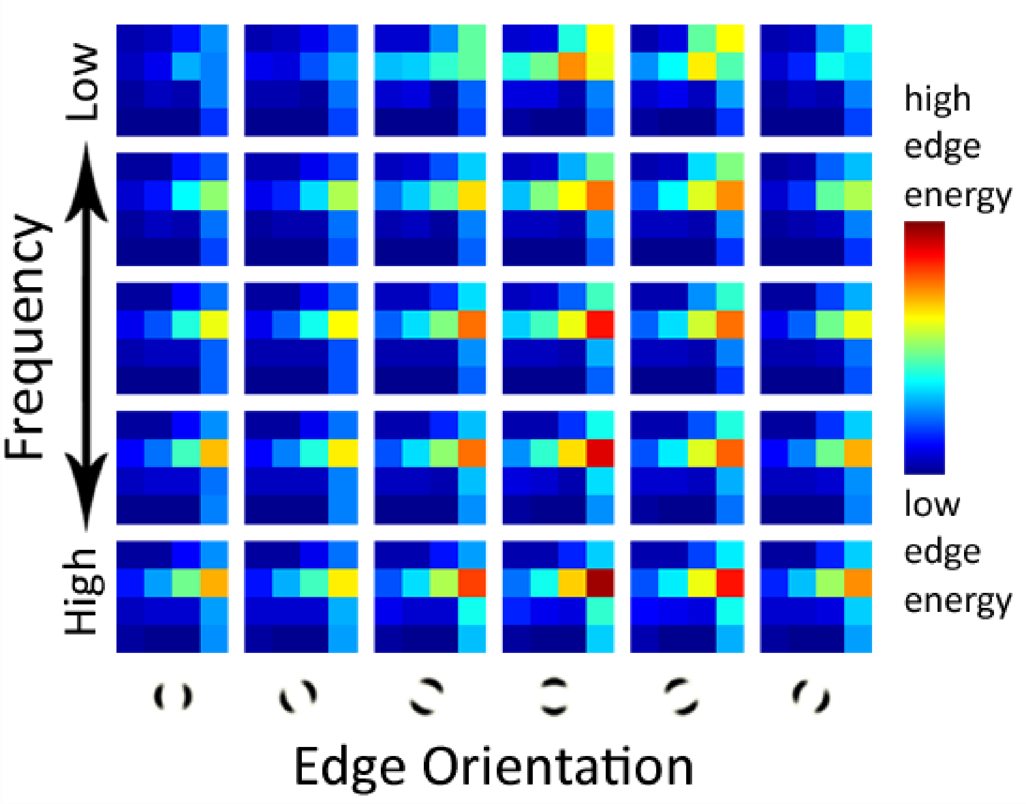


Scene Gist Descriptor
(Oliva and Torralba 2001)

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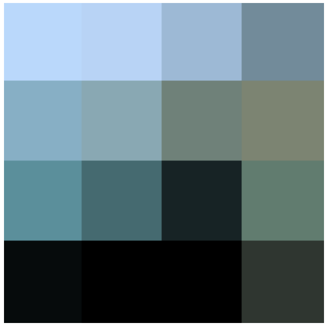
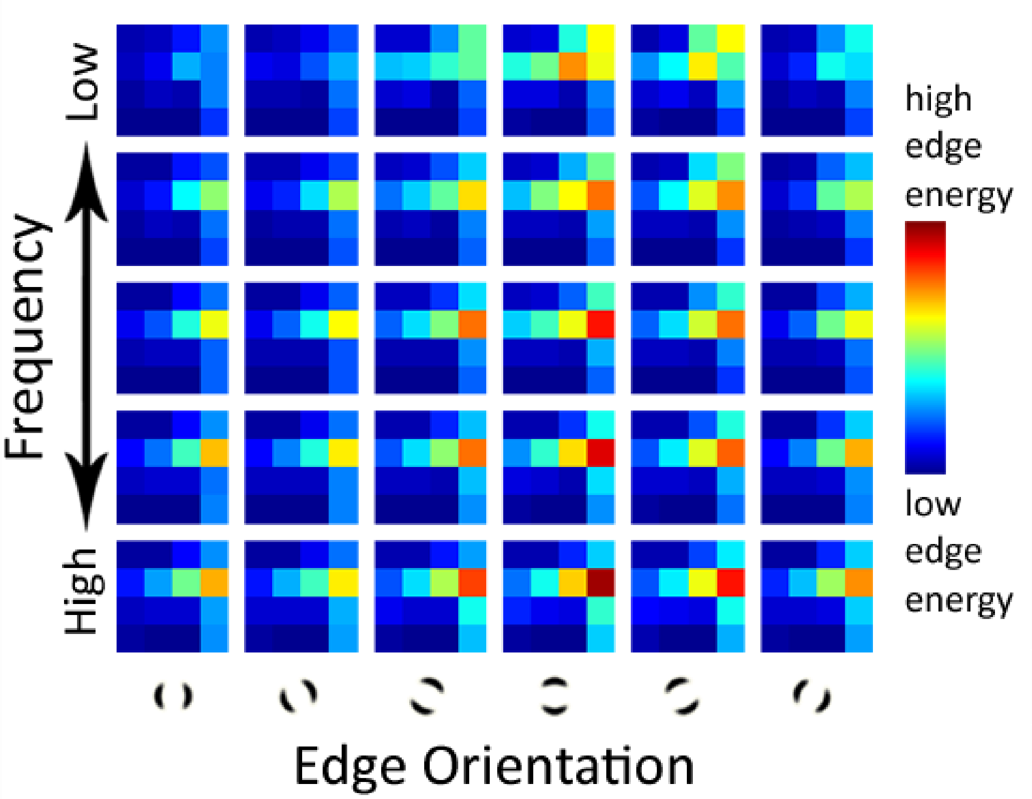
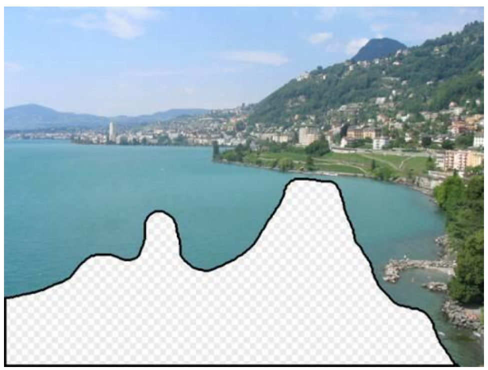


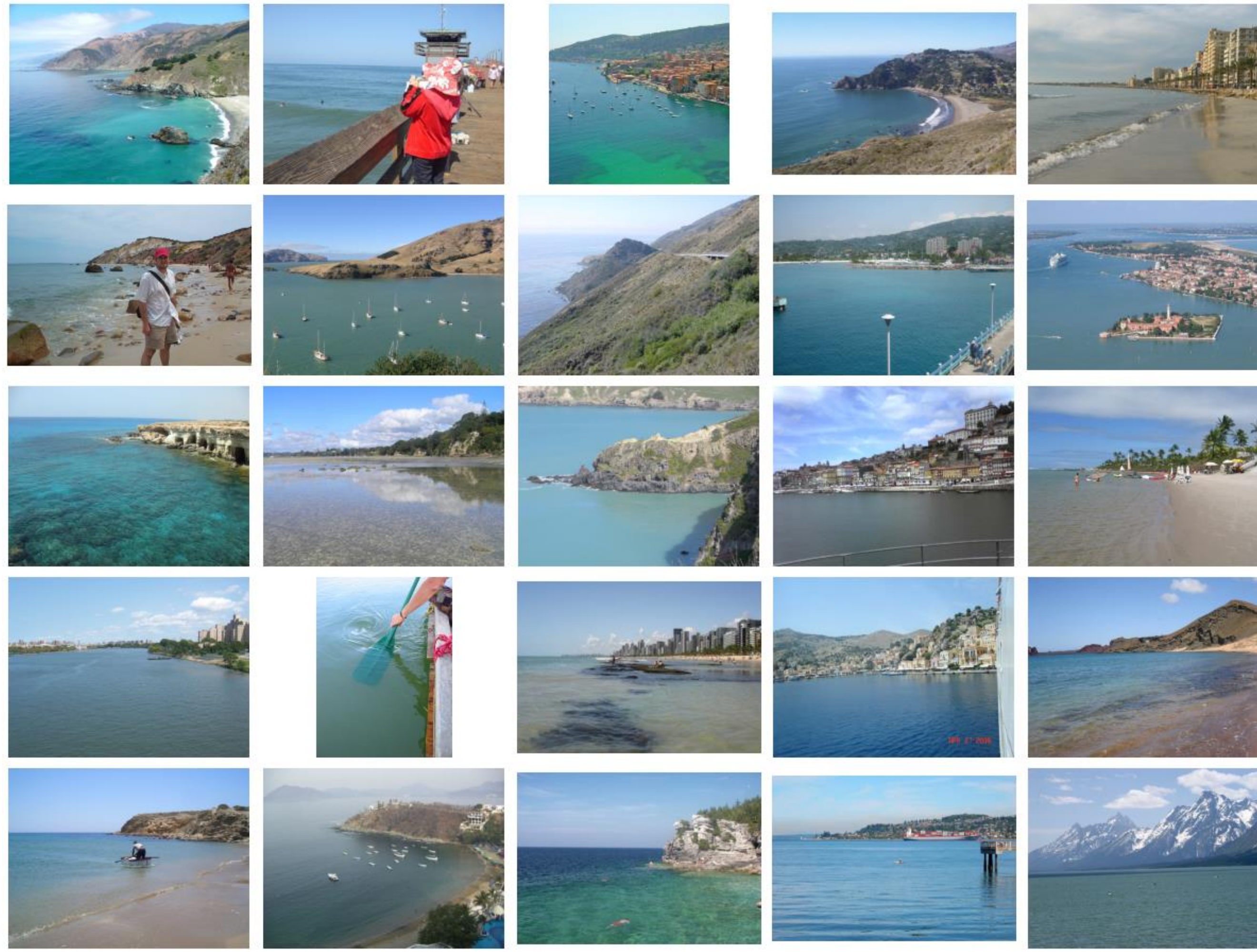
+




Scene Gist Descriptor
(Oliva and Torralba 2001)

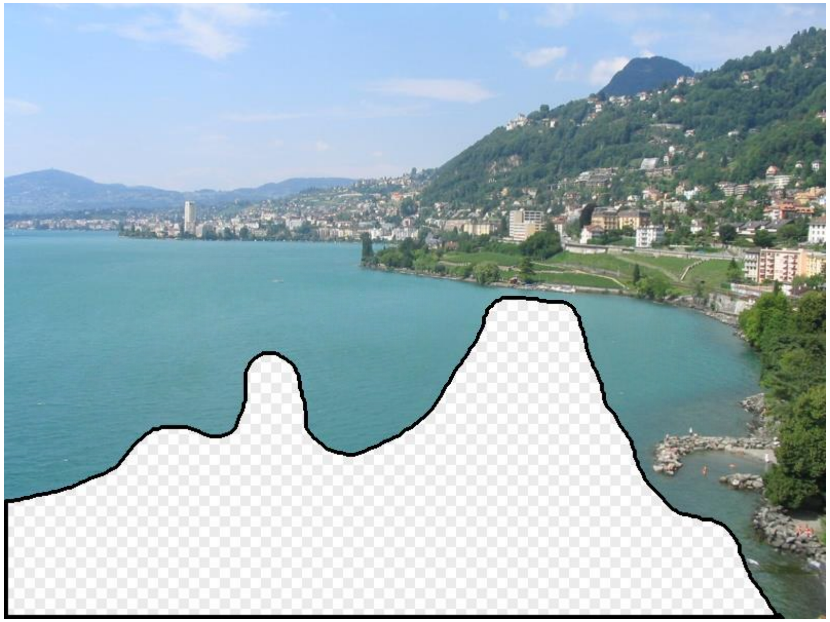

2 Million Flickr Images





... 200 total

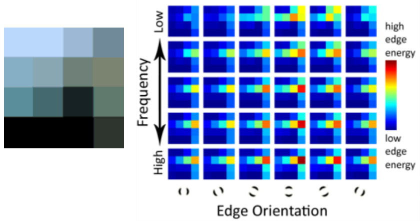
# Context Matching



Graph cut + Poisson blending

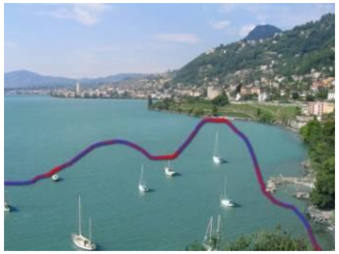
# Result Ranking

We assign each of the 200 results a score which is the sum of:

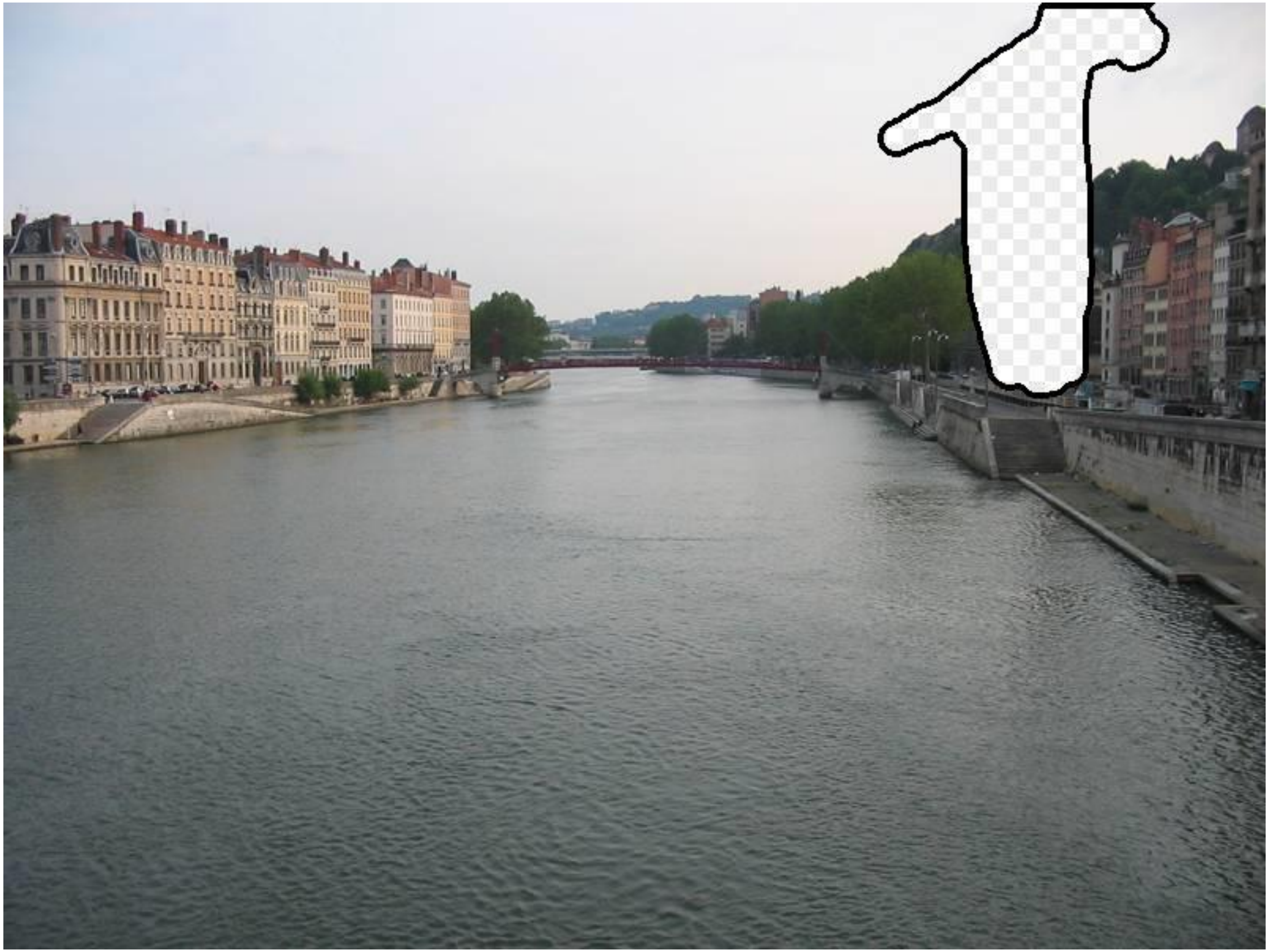


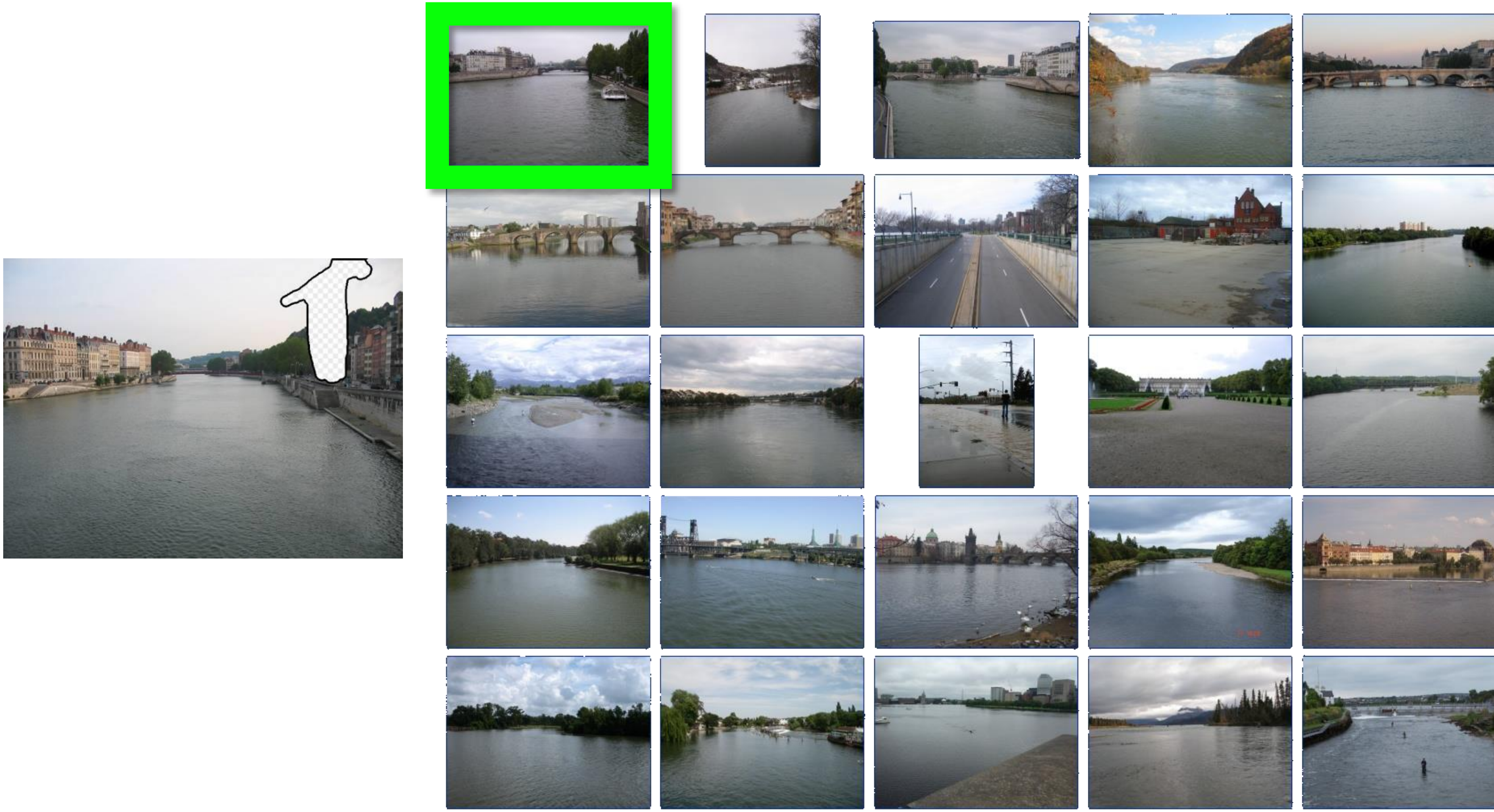

The scene matching distance

The context matching distance
(color + texture)

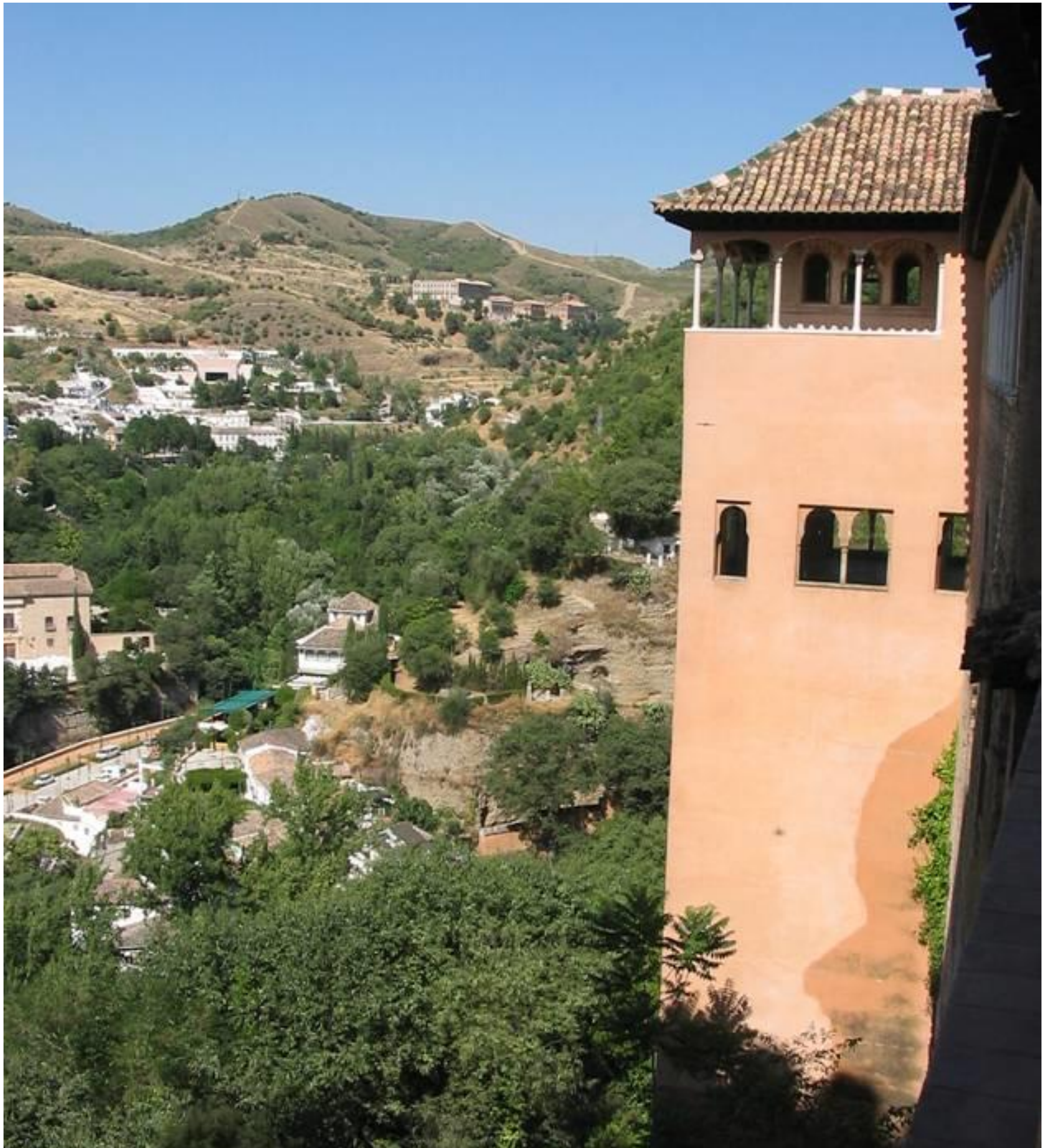


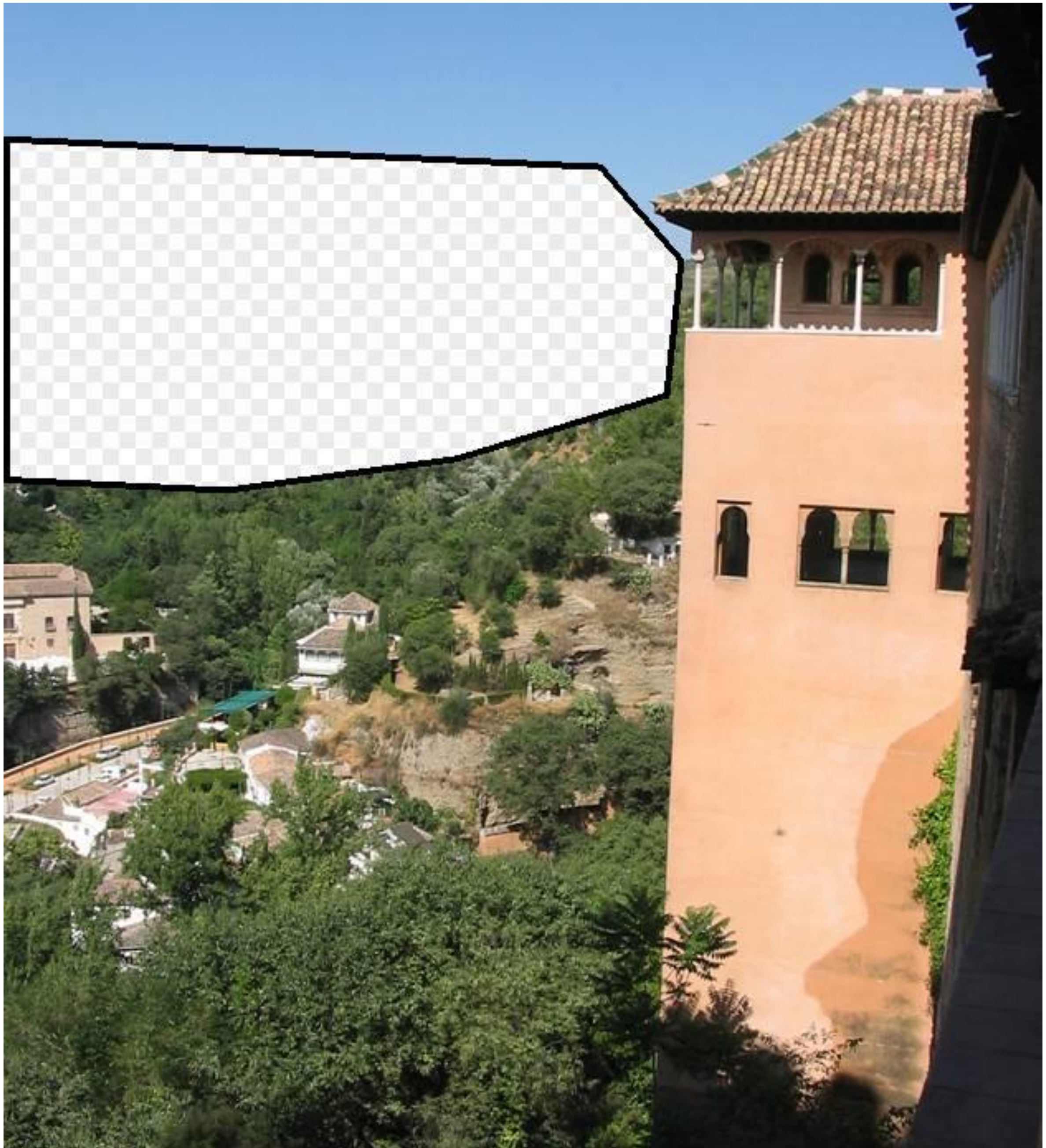
The graph cut cost





… 200 scene matches



# Which is the original?