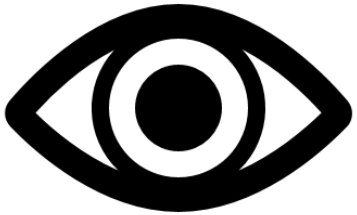


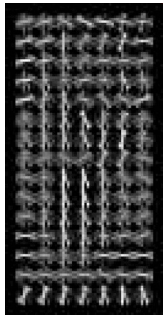
Advanced Image Processing

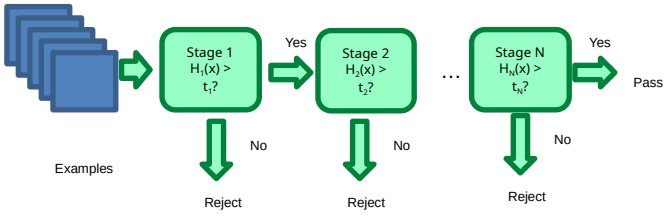
Big Data

SYDE 671

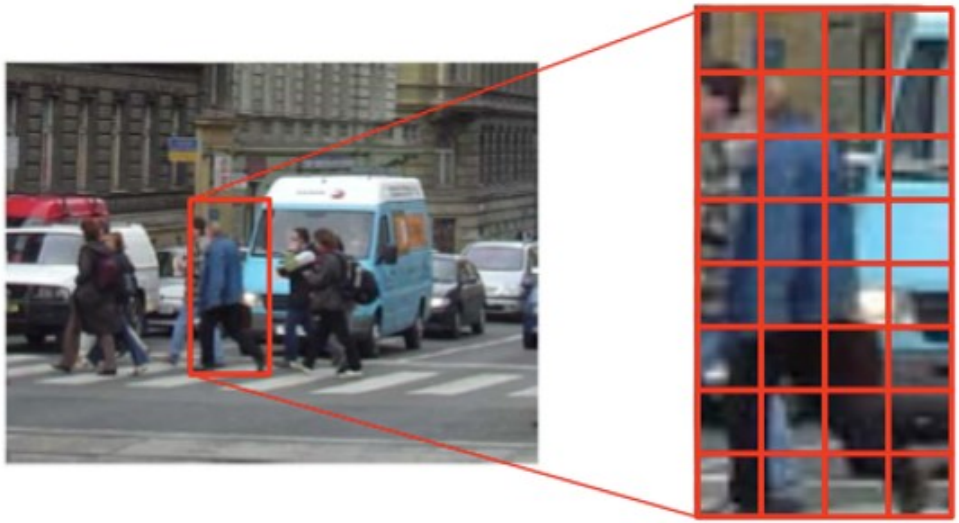
Object detection

- Sliding window for search
- Features based on differences of intensity (gradient, wavelet, etc.)
- Boosting for feature selection
- Integral images, cascade for speed
- Bootstrapping to deal with many, many negative examples





Starting point: sliding window classifiers

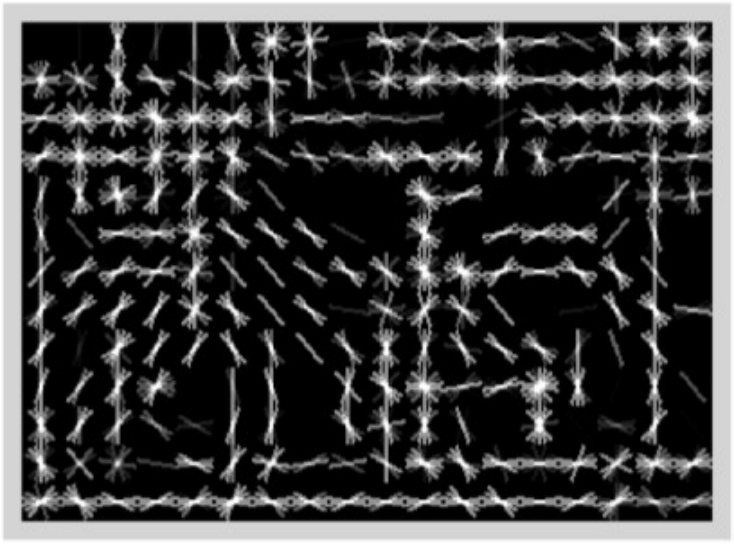


Feature vector

$x = [\ldots, \ldots, \ldots, \ldots]$

- Detect objects by testing each subwindow
  - Reduces object detection to binary classification
  - Dalal & Triggs: HOG features + linear SVM classifier
  - Previous state of the art for detecting people

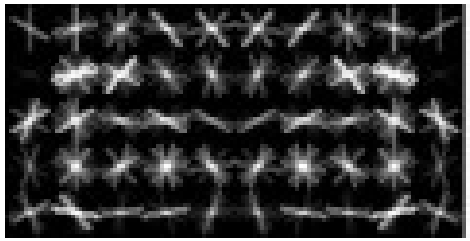
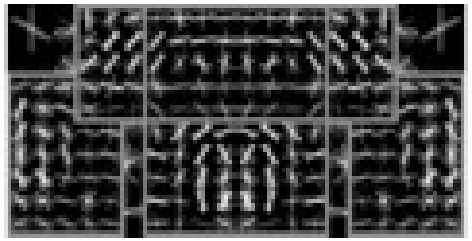
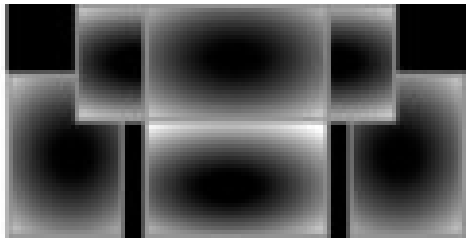
Histogram of Gradient (HOG) features



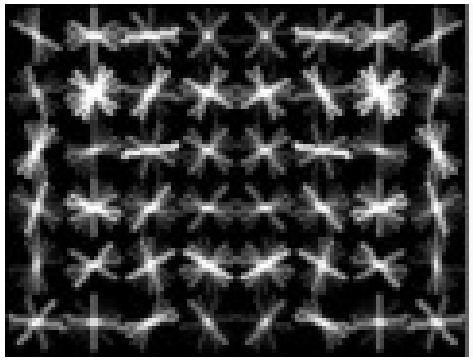
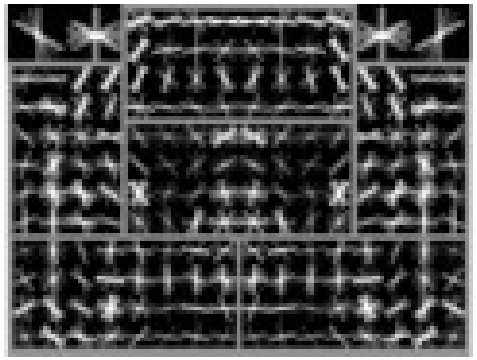
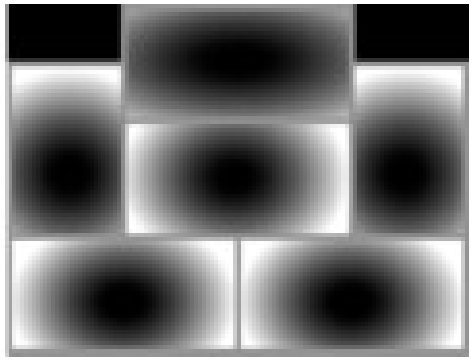
- Image is partitioned into 8x8 pixel blocks
- In each block we compute a histogram of gradient orientations
  - Invariant to changes in lighting, small deformations, etc.
- Compute features at different resolutions (pyramid)

Car model

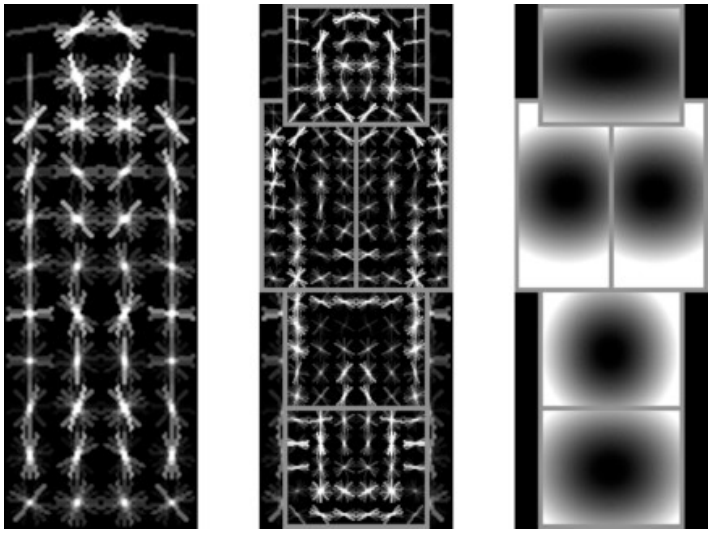
Component 1

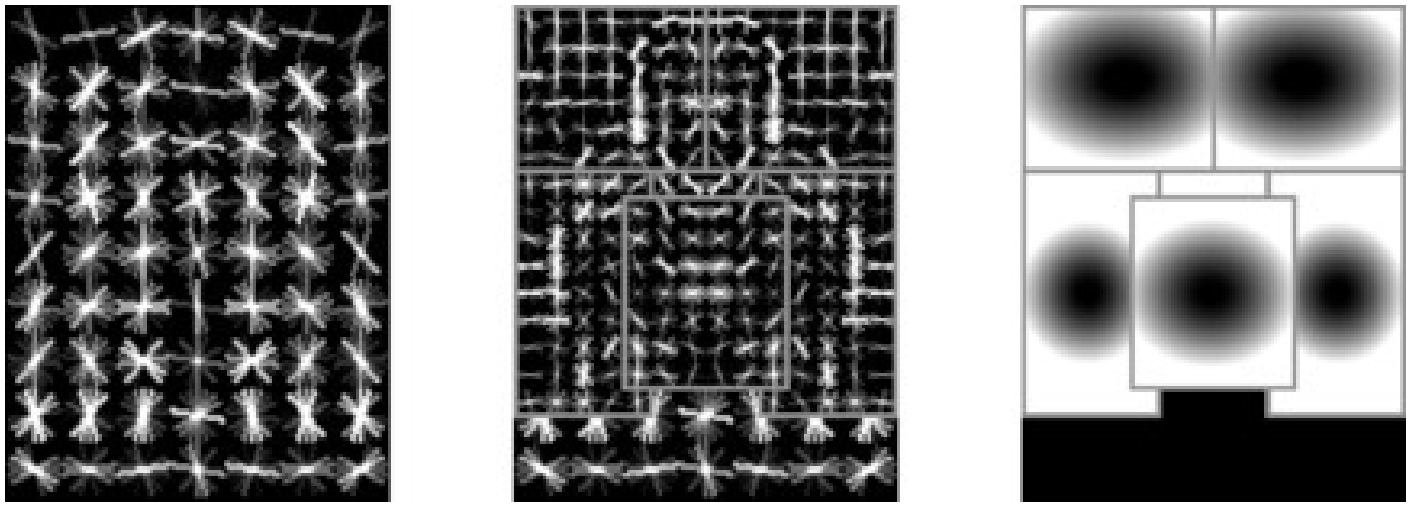




Component 2

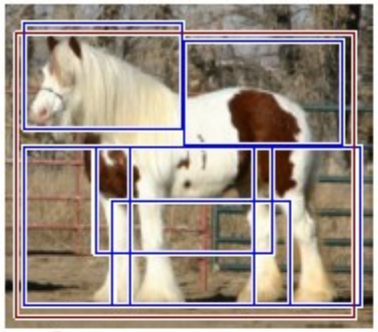
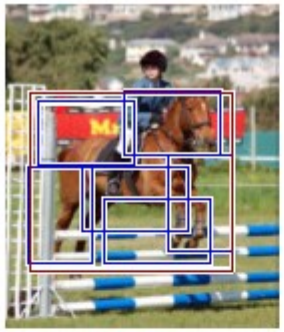
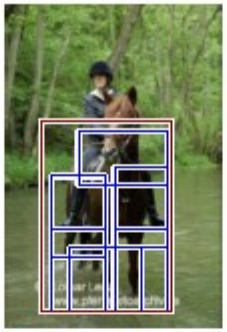
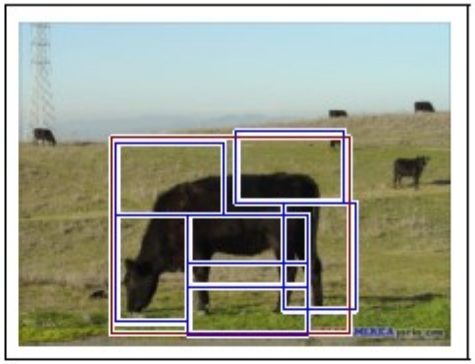
Person model



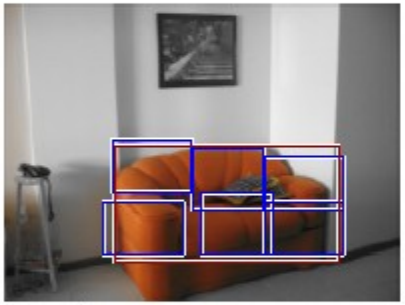


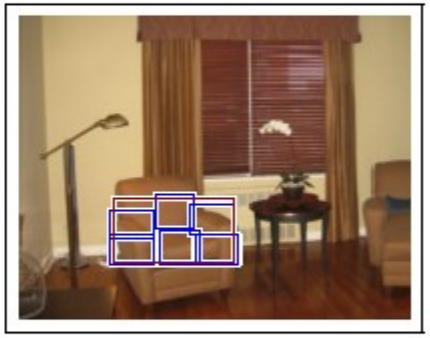
Good detections?

horse


sofa



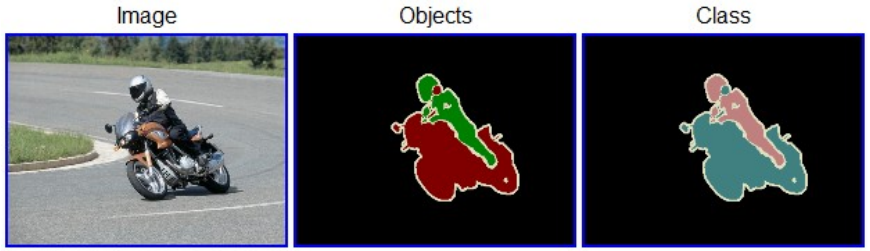
bottle




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



Dataset: Collection

- Images downloaded from **flickr**
  - 500,000 images downloaded and random subset selected for annotation
  - Queries
    - Keyword e.g. “car”, “vehicle”, “street”, “downtown”
    - Date of capture e.g. “taken 21-July”
      - Removes “recency” bias in flickr results
    - Images selected from random page of results
      - Reduces bias toward particular flickr users

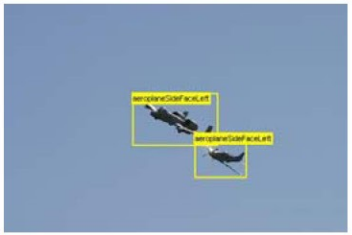
Dataset: Annotation

- "Complete" annotation of all objects
- Annotated over web with written guidelines
  - High quality (?)

20 classes.
- Train / validation data has 11,530 images containing 27,450 ROI annotated objects and 6,929 segmentations.

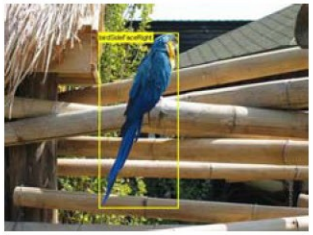
Examples

Aeroplane

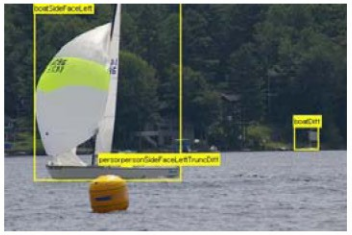


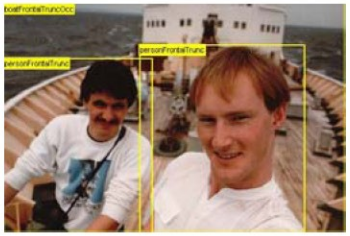
Bicycle

Bird



Boat





Bottle

Bus

Car

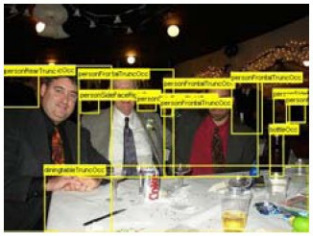
Cat

Chair

Cow

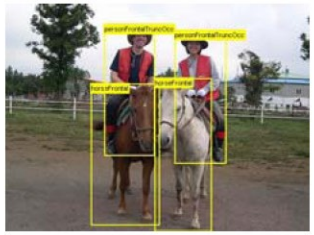
Examples

Dining Table



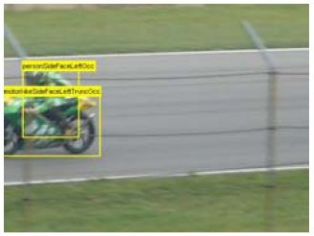
Dog

Horse

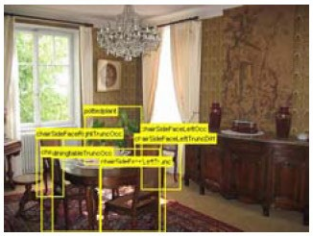


Motorbike

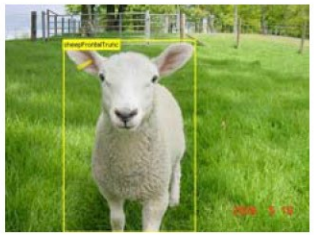
Person



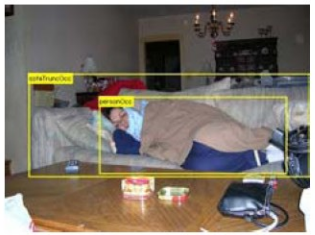
Potted Plant



Sheep

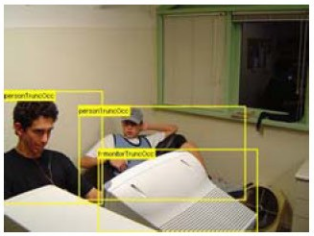


Sofa



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
- VOC2008: 21 Methods, 11 Groups
- Overwhelmingly "bag of visual words" methods with multiple features e.g. SIFT, color
- Multiple submissions of methods with small variations e.g. different features or classifier architectures

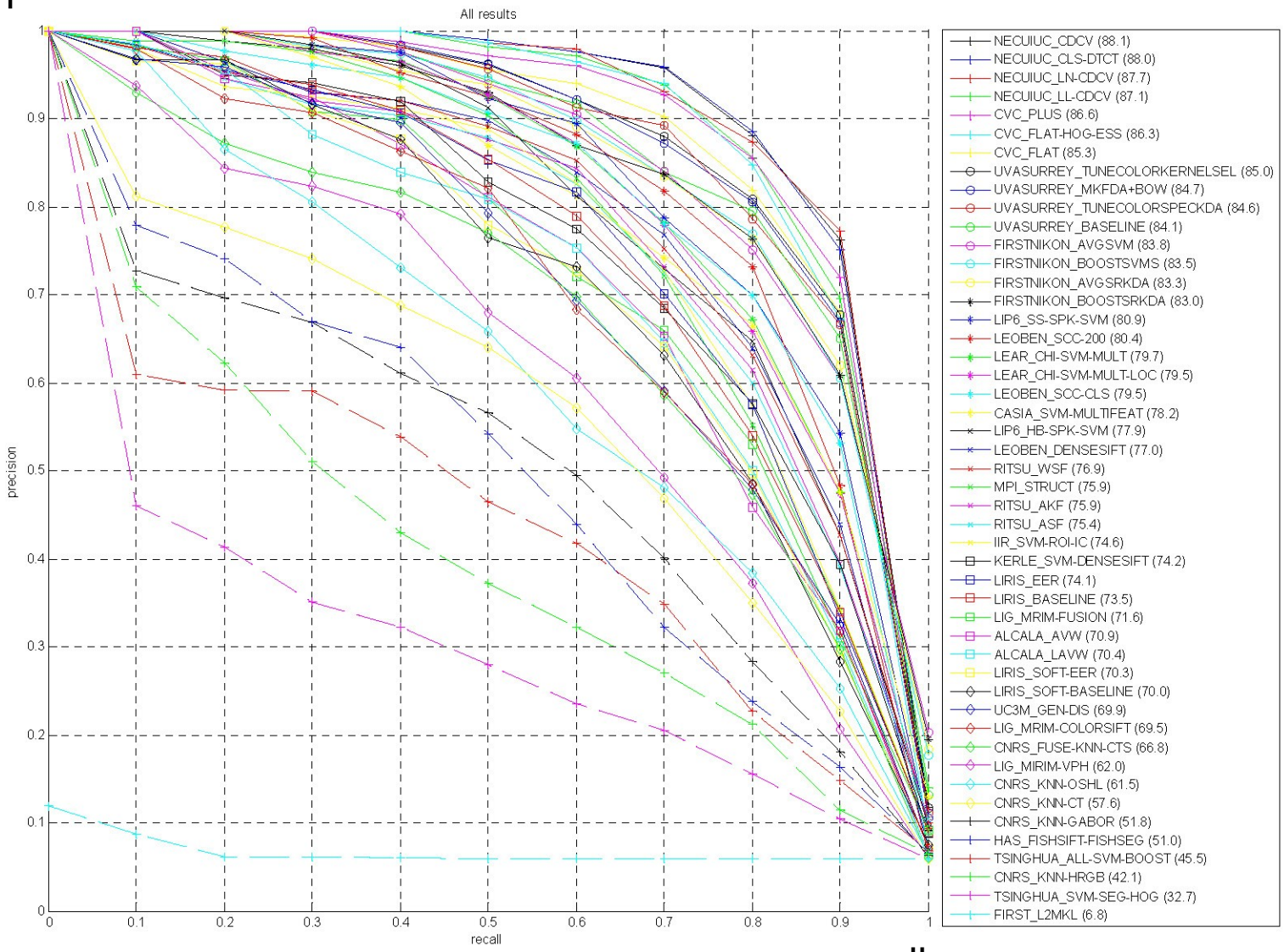
Results: AP by Method and Class

	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

Precision/Recall: Aeroplane (All)

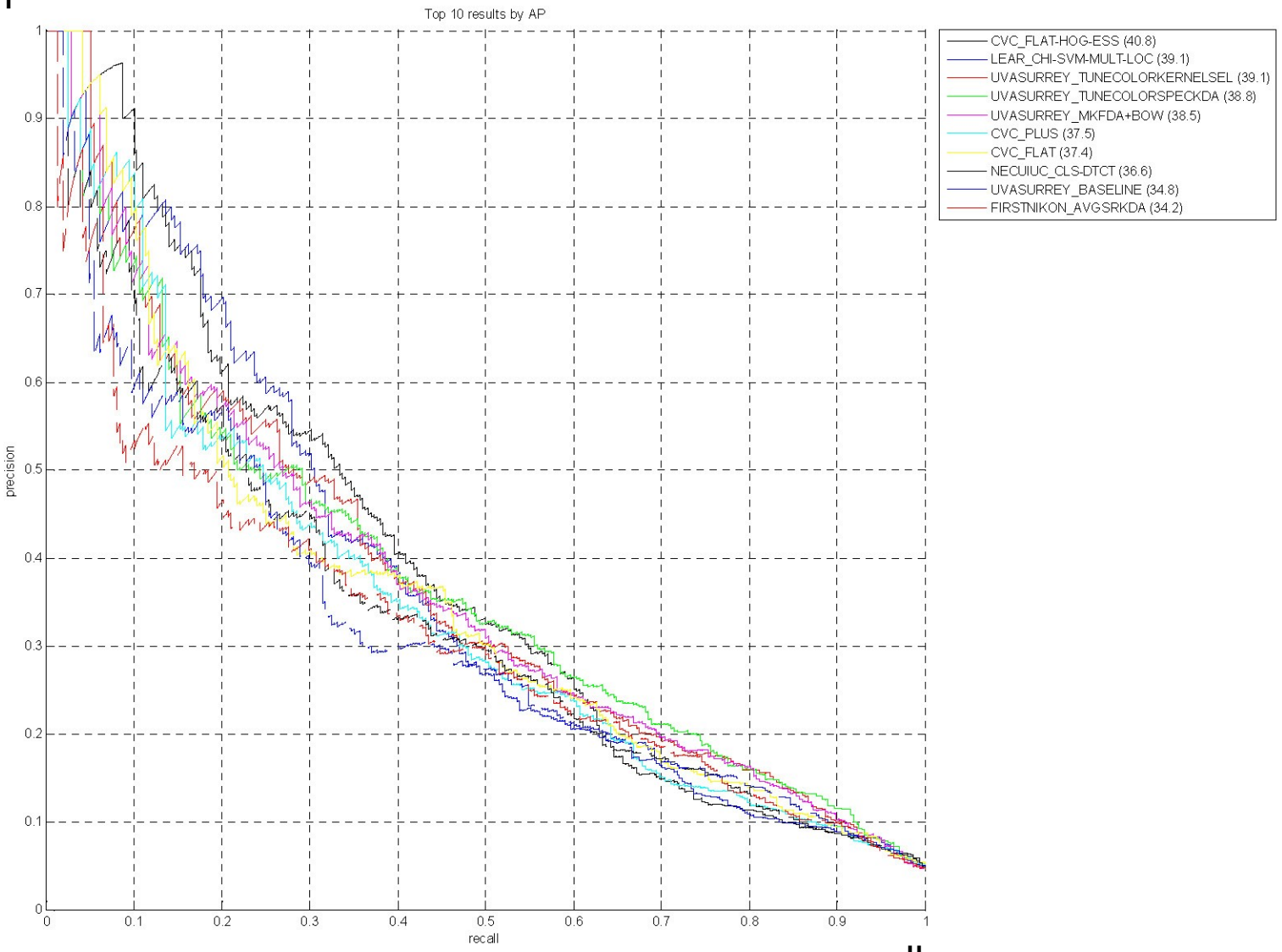
precision



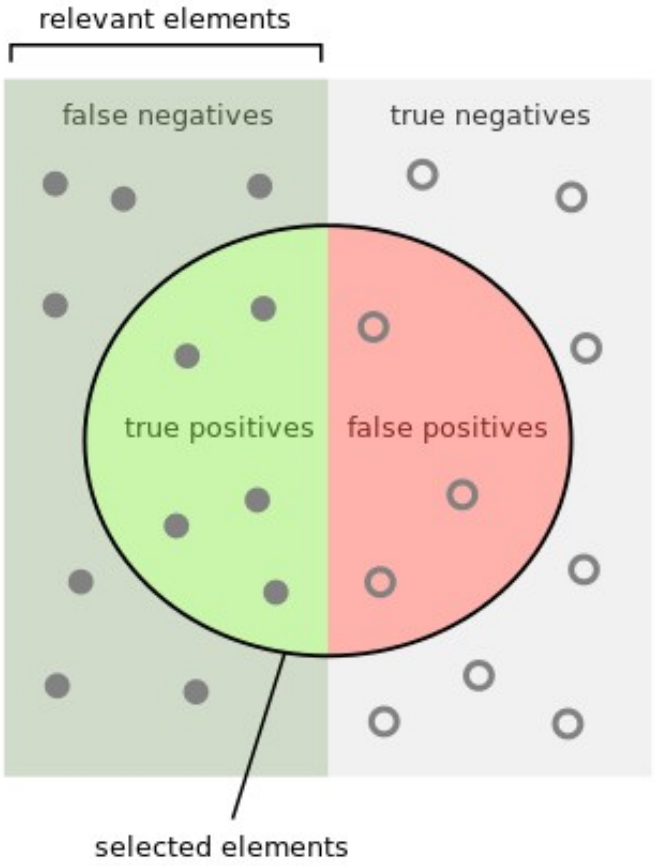
recall

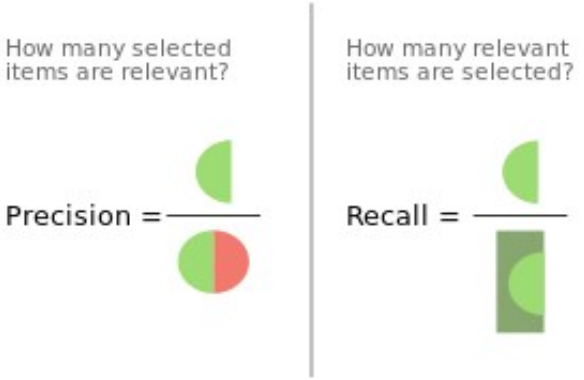
Precision/Recall: Potted plant (Top 10 by AP)

precision



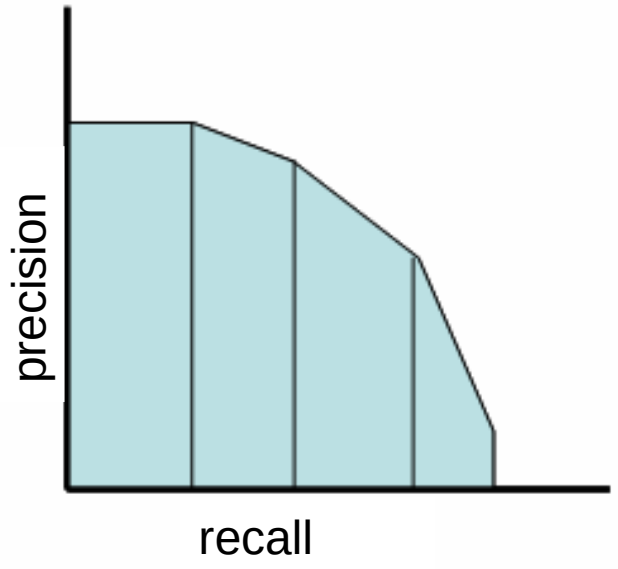
recall





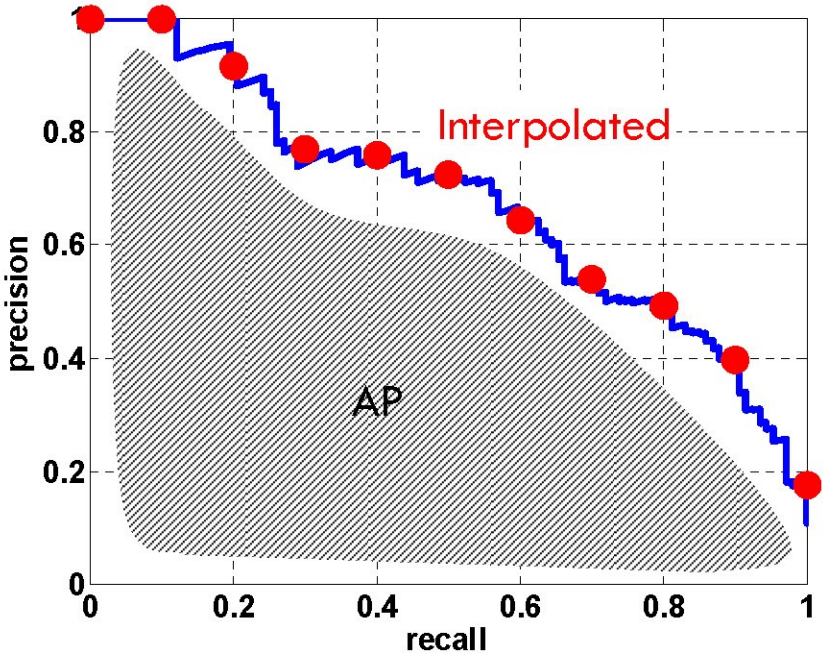
Set threshold on ‘detection’ to create one pair of precision / recall values.

Vary threshold across all values to generate precision / recall curves:



Evaluation

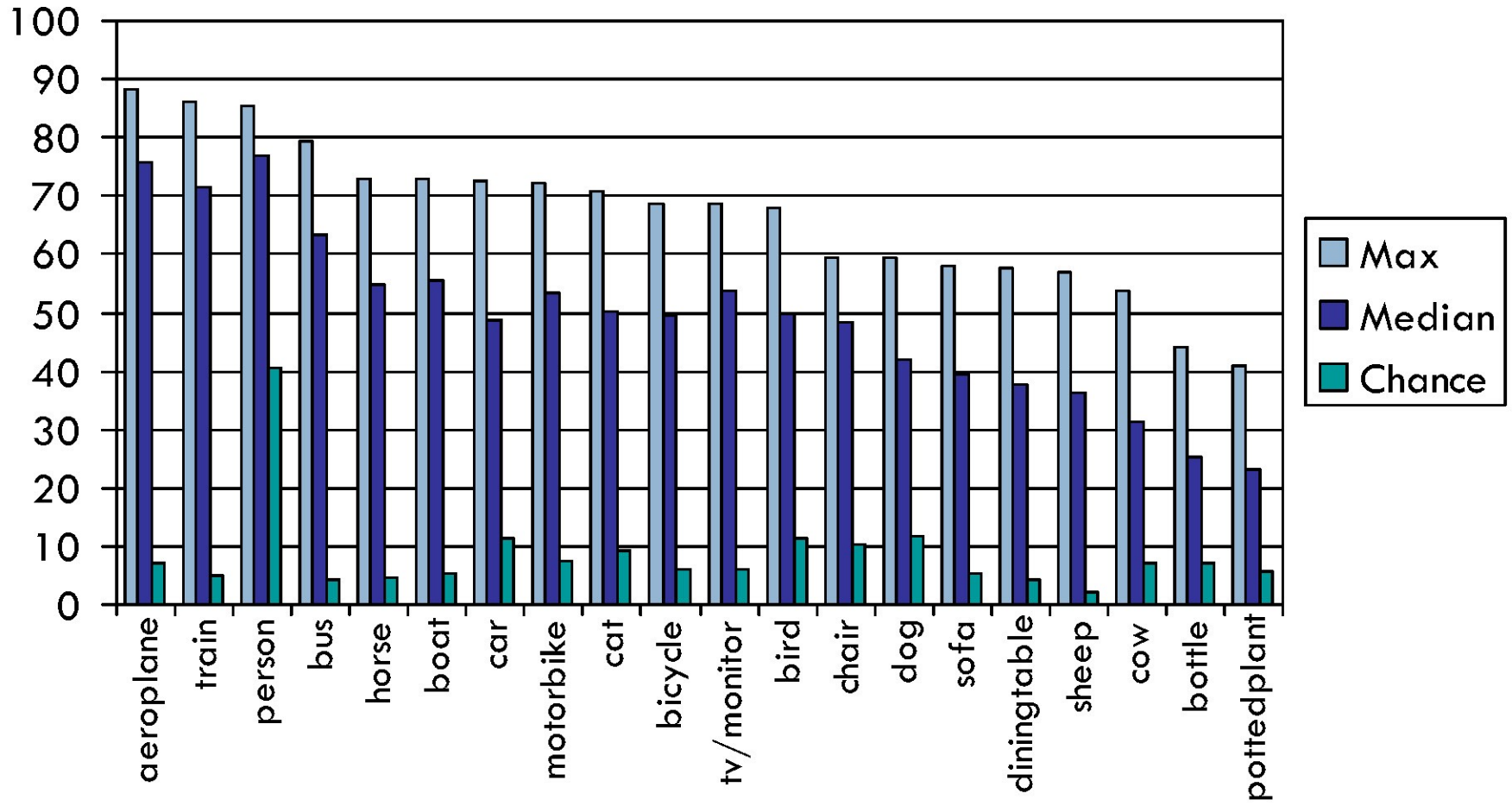
- Average Precision [TREC] averages precision over the entire range of recall
  - Curve interpolated to reduce influence of "outliers"



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

AP = average precision

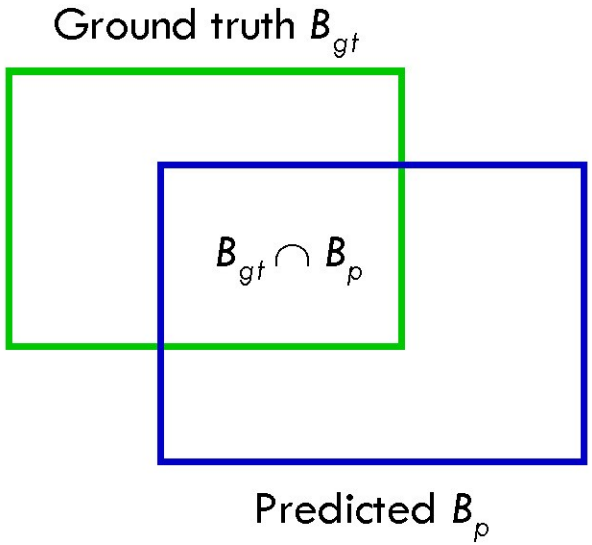
AP for Image classification



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

Evaluating Bounding Boxes

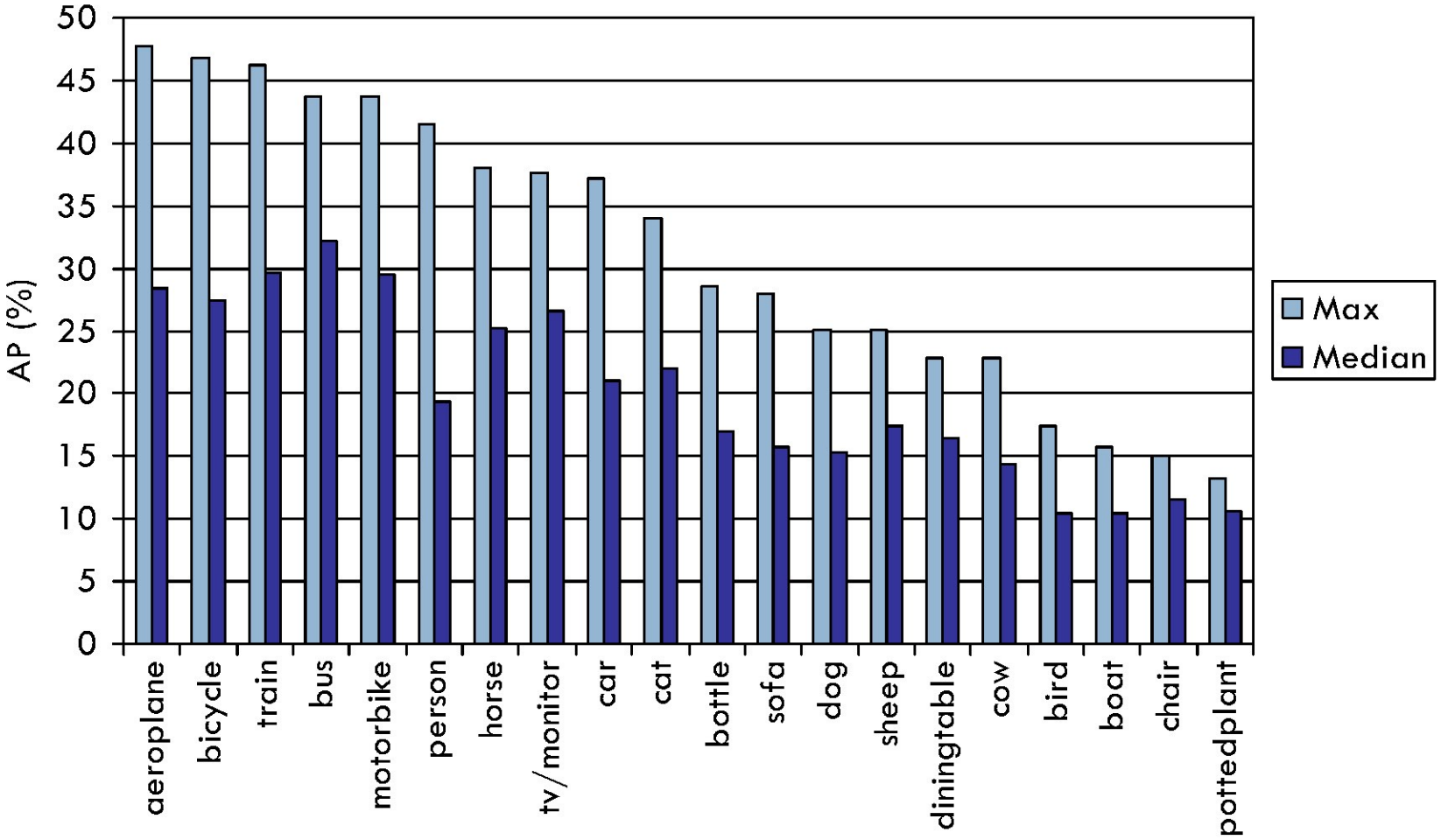
- Area of Overlap (AO) Measure



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

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

AP for Object detection

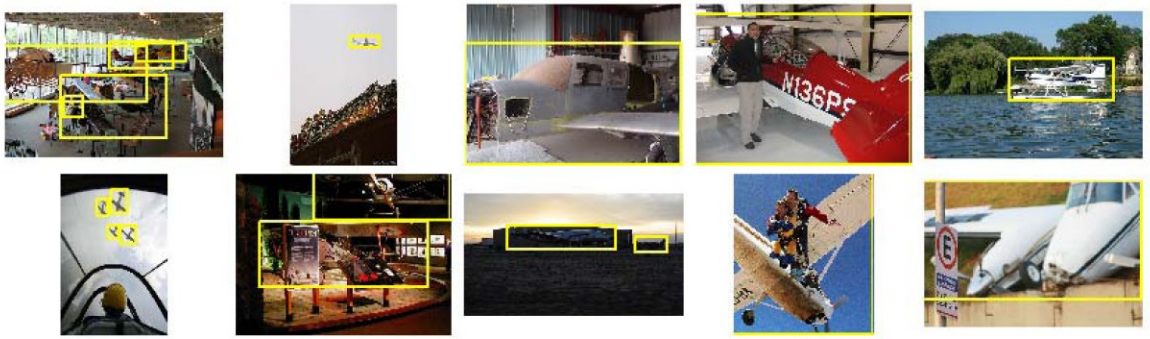


Chance essentially 0

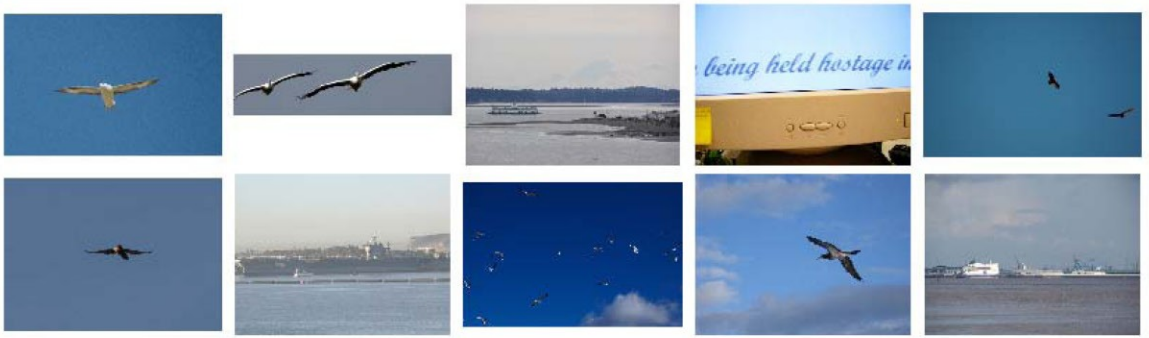
Ranked Images: Aeroplane

- Class images: Highest ranked

- Class images: Lowest ranked



- Non-class images: Highest ranked



- Context?

True Positives - Person

UoCTTI_LSVM-MDPM

MIZZOU_DEF-HOG-LBP

NECUIUC_CLS-DTCT

False Positives - Person

UoCTTI_LSVM-MDPM



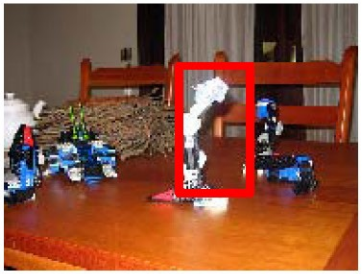


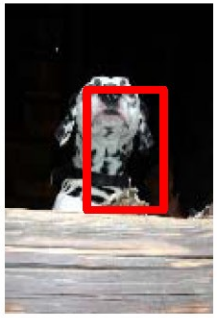
MIZZOU_DEF-HOG-LBP





NECUIUC_CLS-DTCT

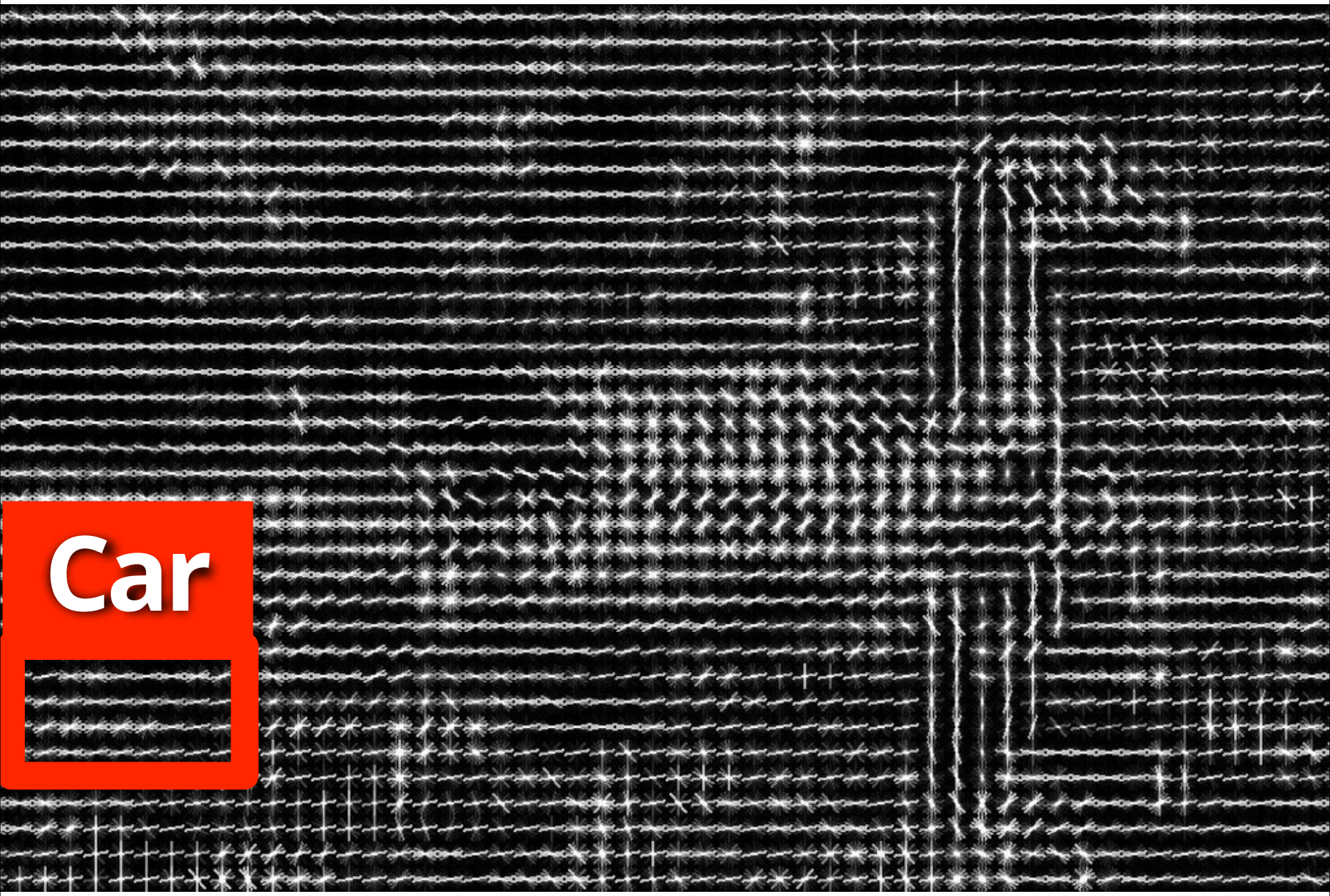






HOGgles (Vondrick et al. ICCV 2013)

Vondrick et

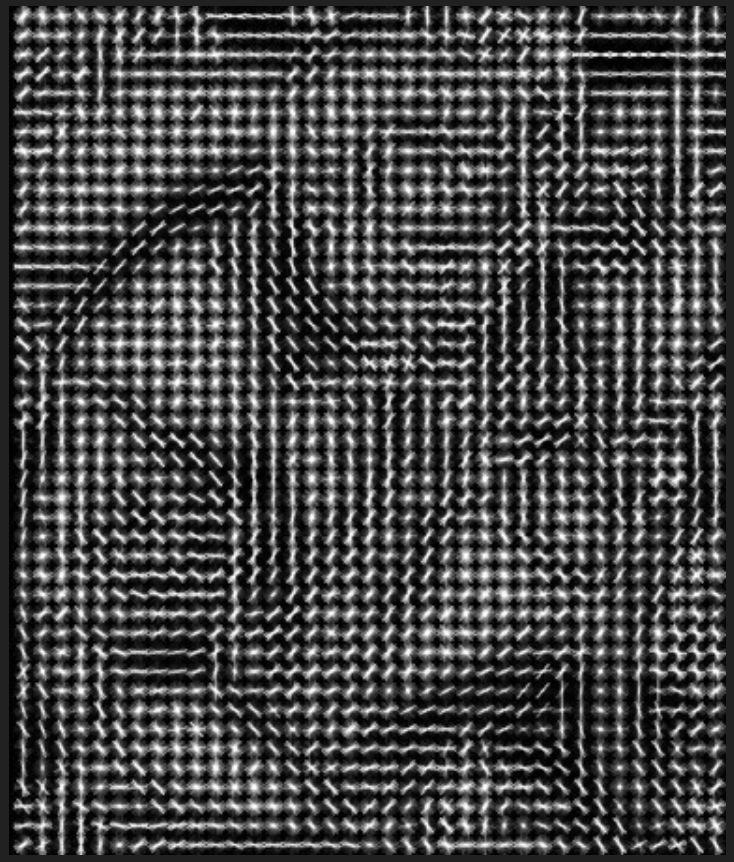

Car



Vondrick et

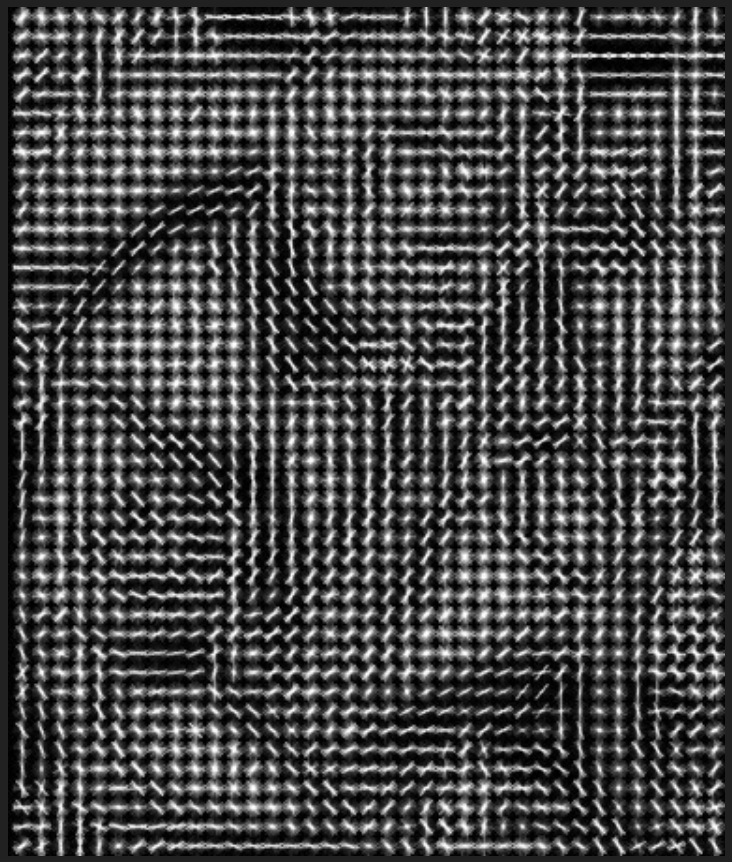
Vondrick et

What information is lost?



Vondrick et

What information is lost?



Vondrick et

How can we ‘invert’ lossy HOG?

- Gradient computation

- Oriented magnitude sum (via bins)
  - Loss of precision
  - Loss of specificity – any number of values can sum to the same total

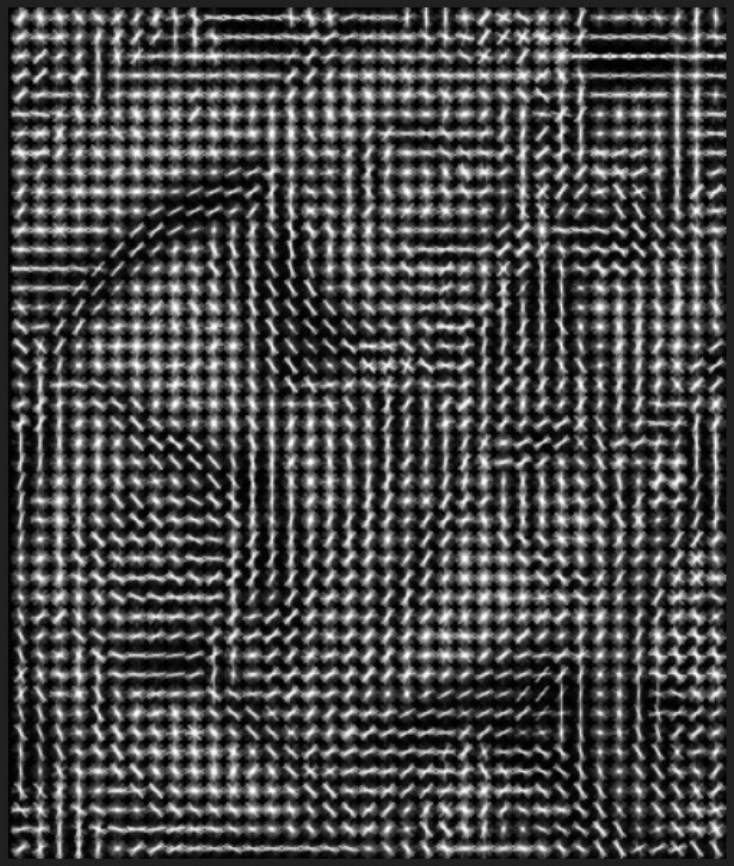
- Normalization
  - No way to unnormalize without knowing normalization factors

Many different image patches translate to the same HOG feature : (

What information is lost?

$x = input\ patch$
$y = HOG\ descriptor$
$\phi(x) = HOG\ transform$

$$\min_{x \in \mathbb{R}^d} ||\phi(x) - y||_2^2$$

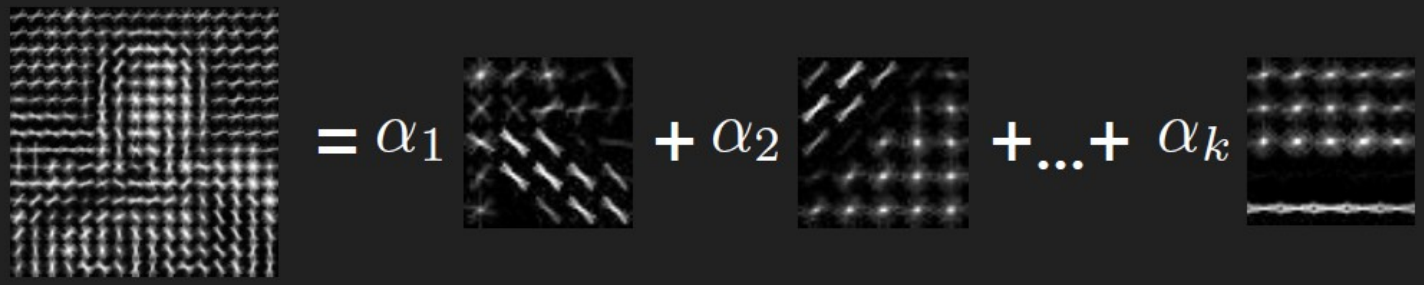


Hard to optimize!
Many-to-one = unconstrained!

The paper tries five approaches:
- Gradient descent
- Exemplar LDA
- Ridge regression
- Direct optimization
- Paired dictionary learning

Vondrick et

Method: Paired Dictionary

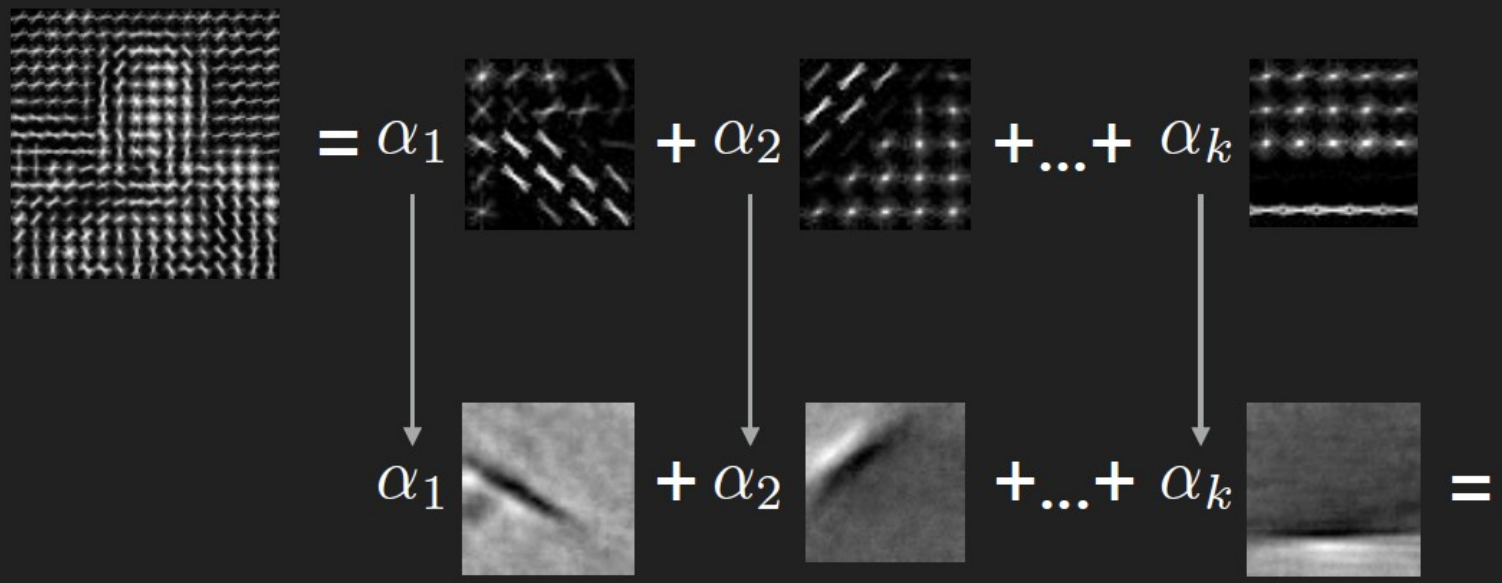


How to constrain (two parts):

1. Learn a basis over HOG windows

Vondrick et

Method: Paired Dictionary

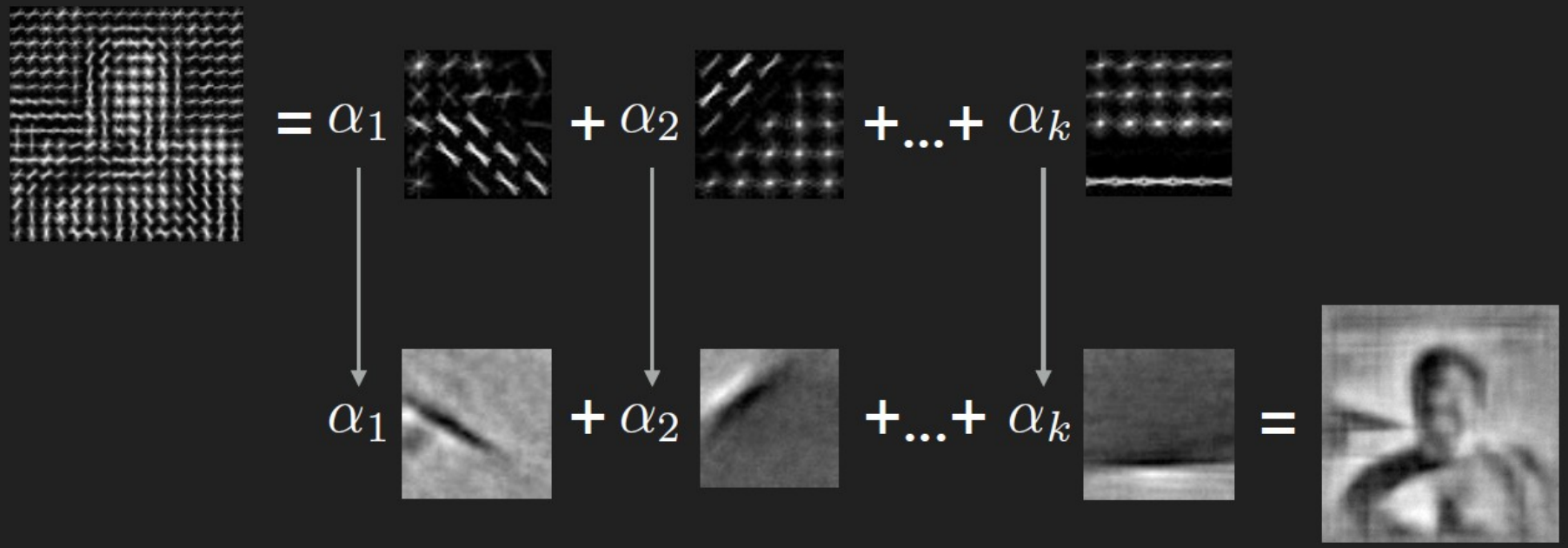


How to constrain (two parts):

1. Learn a basis over HOG windows
2. Simultaneously learn a basis over input windows, and *share the weights over the training data*

Vondrick et

Method: Paired Dictionary



Inference to invert HOG:

1. Transform HOG patch into basis vectors
2. Take weights and apply to input basis

Vondrick et

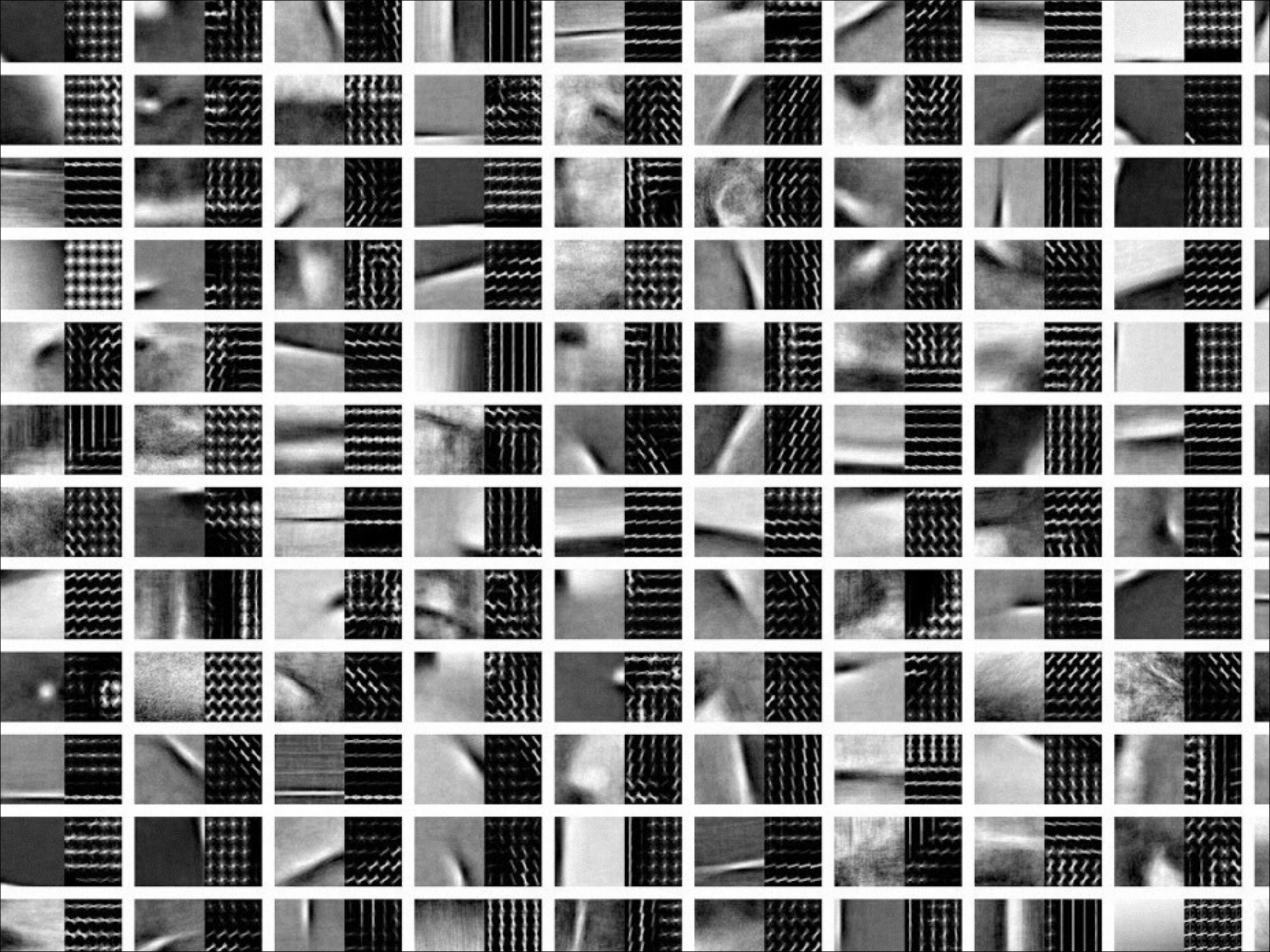
Paired Dictionary Learning

$$\arg\min_{U,V,\alpha} \sum_{i=1}^{N} ||x_i - U\alpha_i||_2^2 + ||y_i - V\alpha_i||_2^2$$

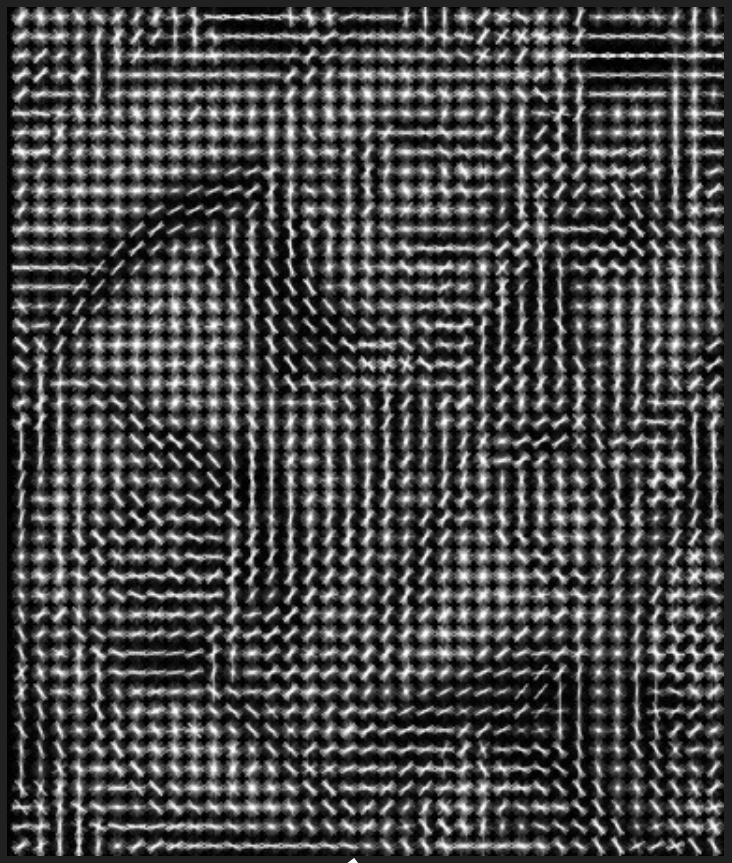
$$\text{s.t.} \quad ||\alpha_i||_1 \leq \lambda, \; ||U||_2^2 \leq \gamma_1, \; ||V||_2^2 \leq \gamma_2$$

Just sparse coding!

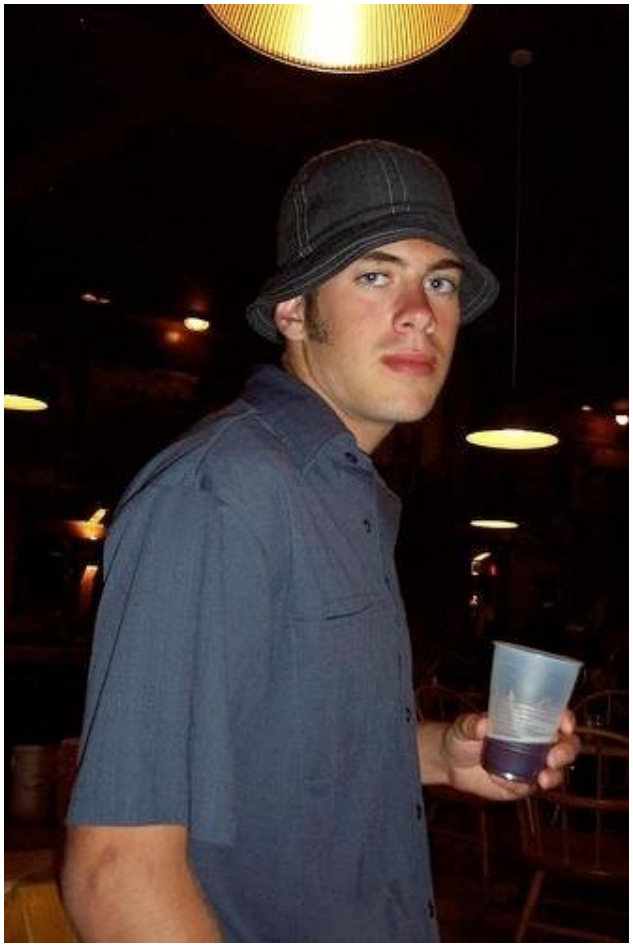
(Optimize using off the shelf solvers)



What information is lost?



Vondrick et

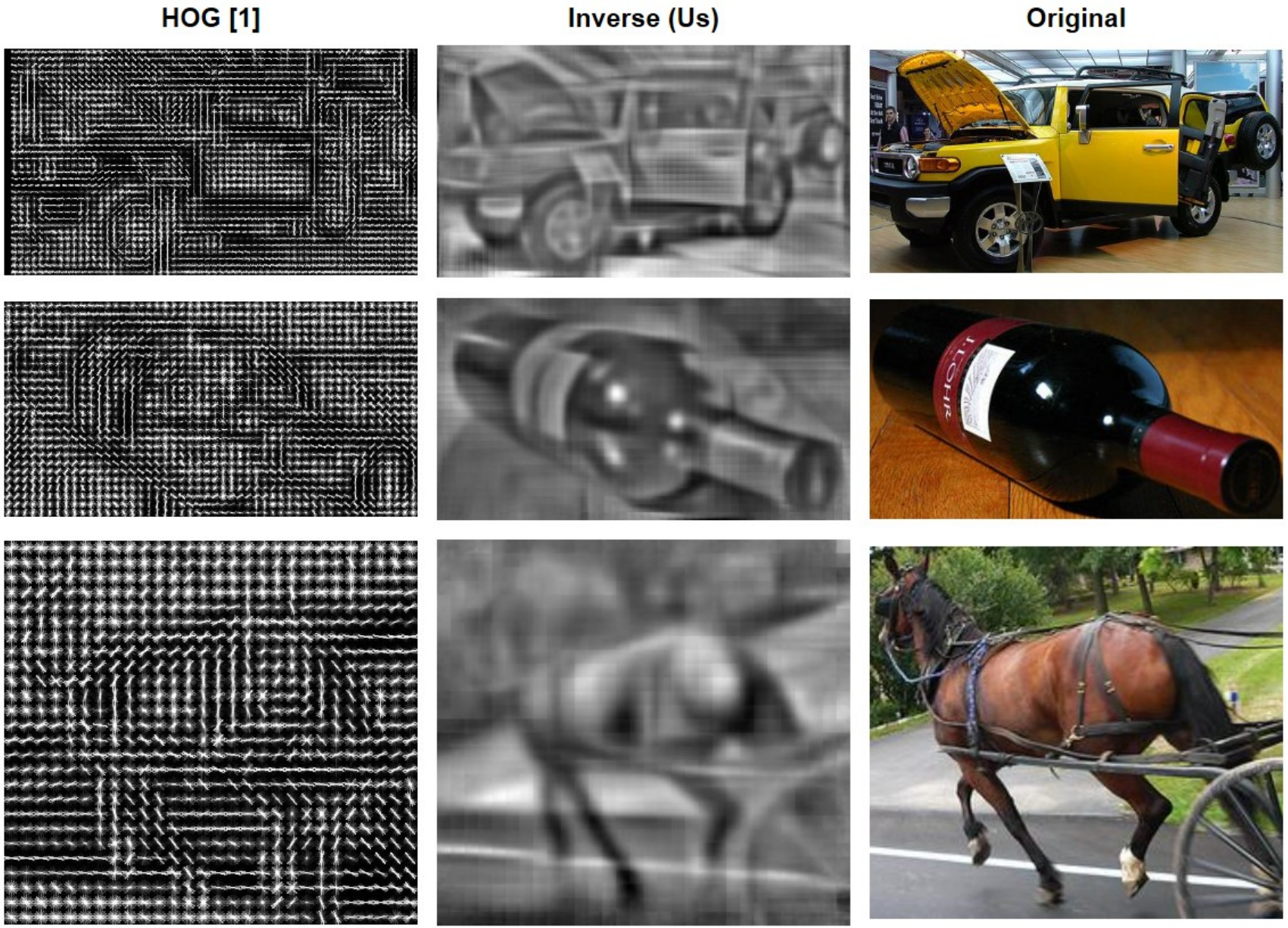


Human Vision

HOG Vision

Vondrick et al.

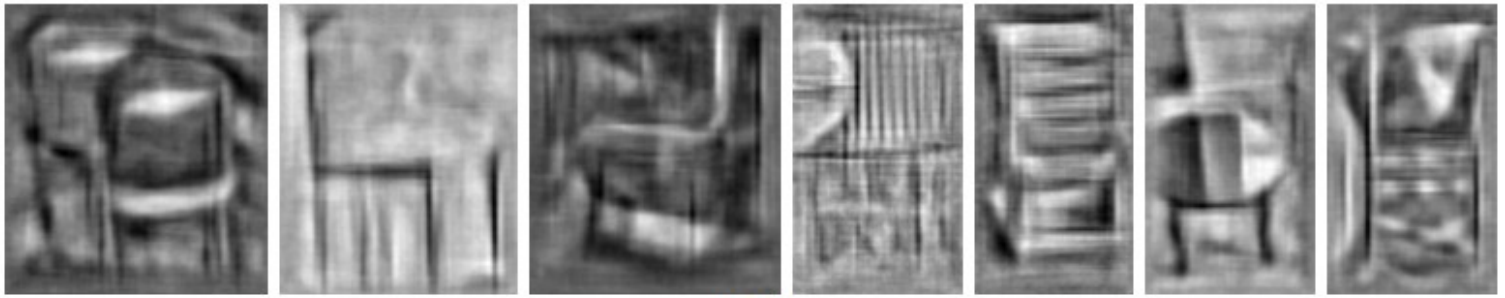
HOGgles (Vondrick et al. ICCV 2013)



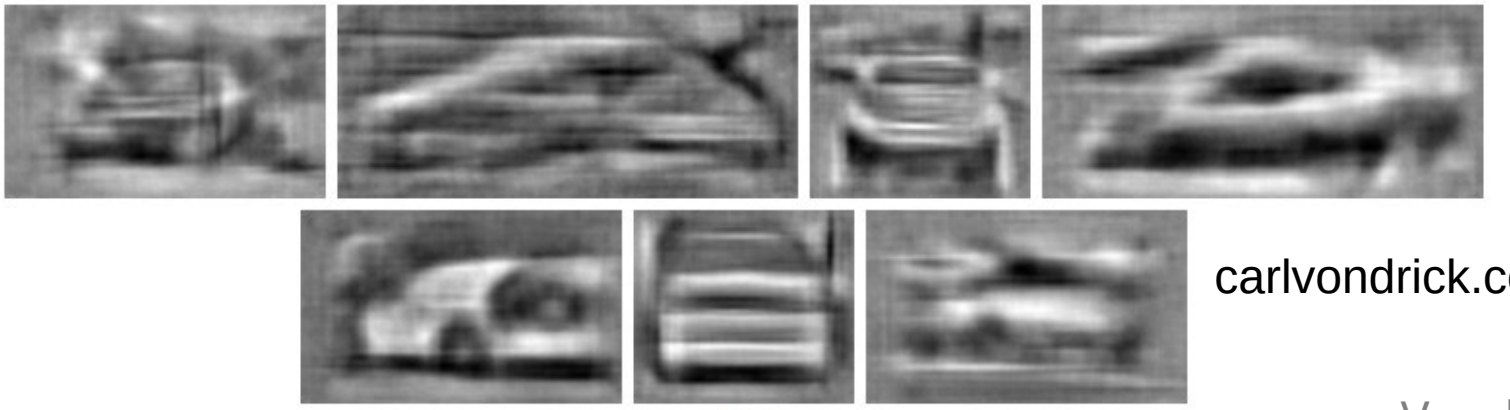
Visualizing Top Detections

We have visualized some high scoring detections from the deformable parts model. Can you guess which are false alarms? Click on the images below to reveal the corresponding RGB patch. You might be surprised!

Person



Chair



Car

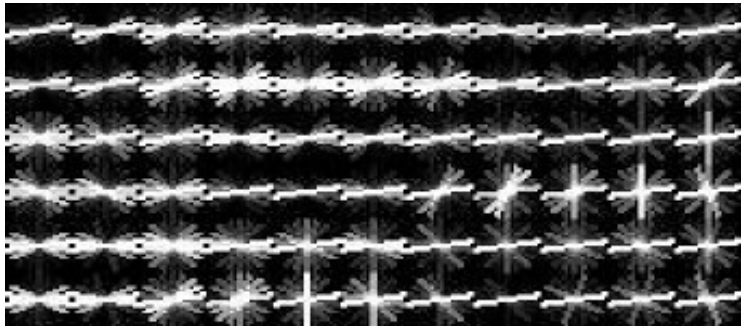
carlvondrick.com/ihog/

Vondrick et

Why did the detector fail?

Vondrick et

Why did the detector fail?



Vondrick et

Why did the detector fail?

Vondrick et

Recursive HOG!

Original x $\quad x' = \phi^{-1}(\phi(x)) \quad x'' = \phi^{-1}(\phi(x'))$

Figure 11: We recursively compute HOG and invert it with a paired dictionary. While there is some information loss, our visualizations still do a good job at accurately representing HOG features. $\phi(\cdot)$ is HOG, and $\phi^{-1}(\cdot)$ is the inverse.

Code Available

Try it on your projects!

```
ihog = invertHOG(feat);
```

https://github.com/cvondrick/ihog/blob/master/README.md

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)

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?

Short cuts to AI

With billions of images on the web, it’s often possible to find a close nearest neighbor.

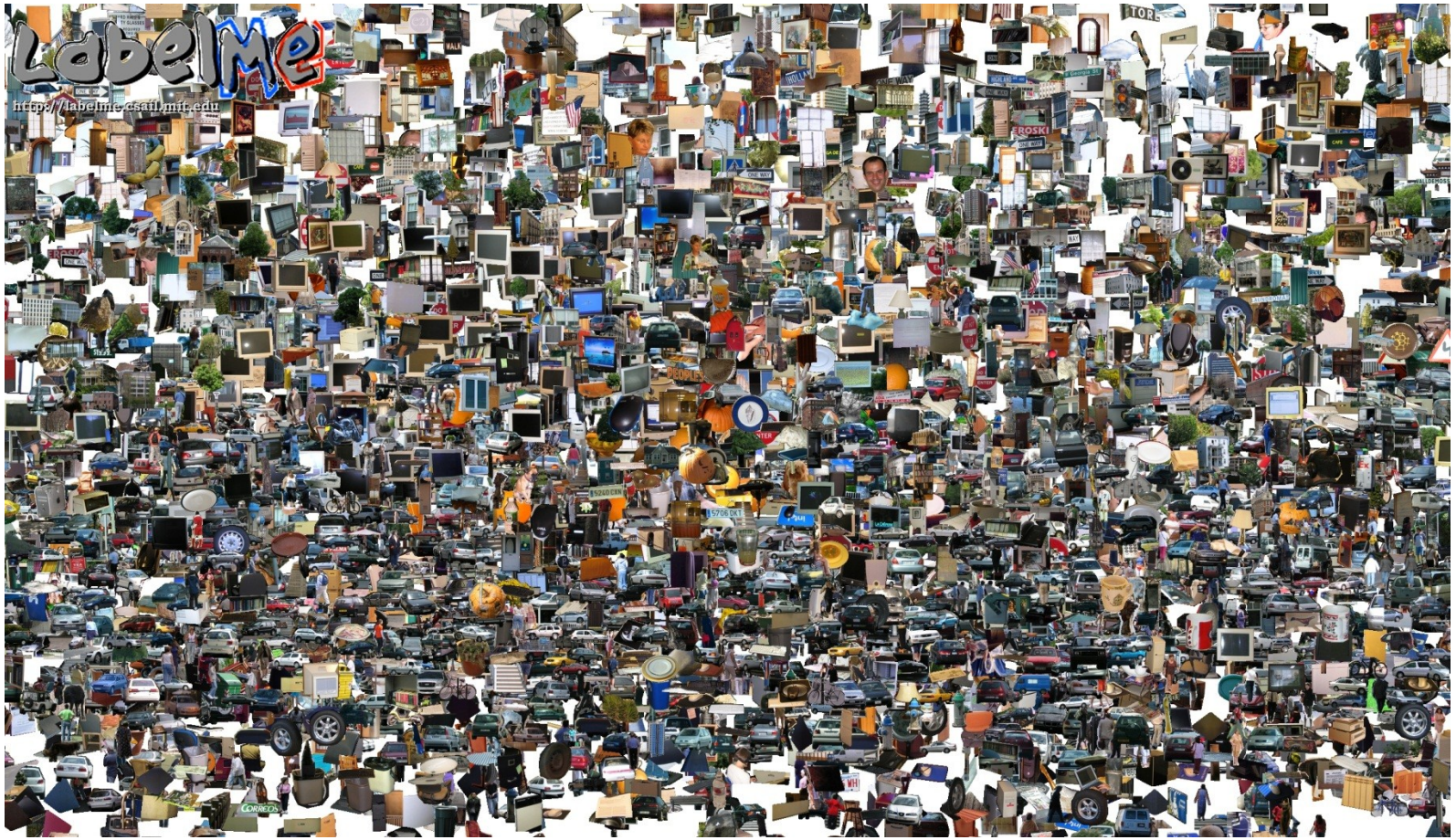
We can shortcut hard problems by “looking up” the answer, stealing the labels from our nearest neighbor.

So what is intelligence?

Weak AI: The simulation of a ‘mind’ is a model for the ‘mind’.

Strong AI: The simulation of a ‘mind’ is a ‘mind’.

Opportunities of Scale



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

Graphic from Antonio Torralba

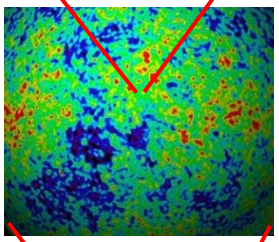
Powers of 10

Number of images on my hard drive: 10^6

Number of images seen during my first 10 years: 10^8
(3 images/second * 60 * 60 * 16 * 365 * 10 = 630,720,000)

Number of images seen by all humanity: 10^{20}
106,456,367,669 humans[1] * 60 years * 3 images/second * 60 * 60 * 16 * 365 =
1 from http://www.prb.org/Articles/2002/HowManyPeopleHaveEverLivedonEarth.aspx

Number of photons in the universe: 10^{88}

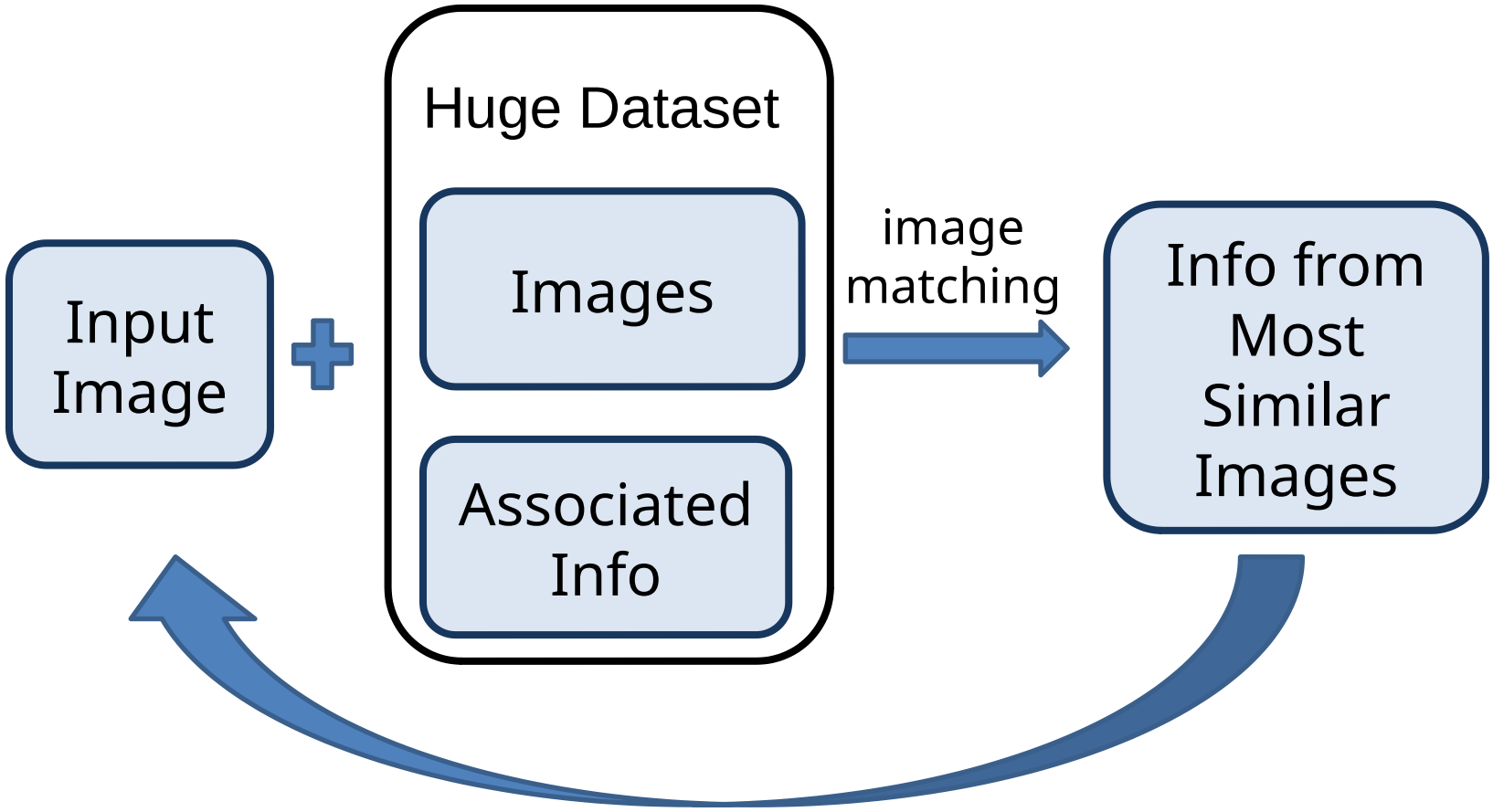


Number of all 32x32 images: 10^{7373}
$256^{32*32*3} \sim 10^{7373}$

Understanding scenes encompasses all kinds of knowledge

But not all scenes are so original

General Principal

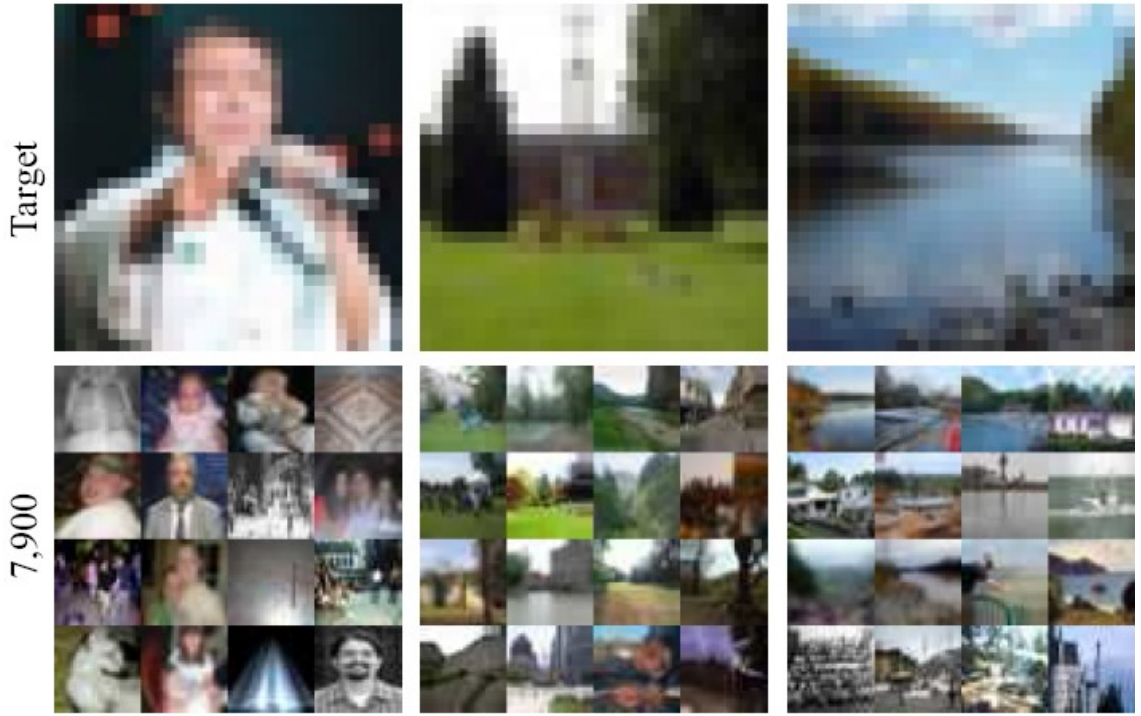


Hopefully, If you have enough images, the dataset will contain very similar images that you can find with simple matching methods.

Lots

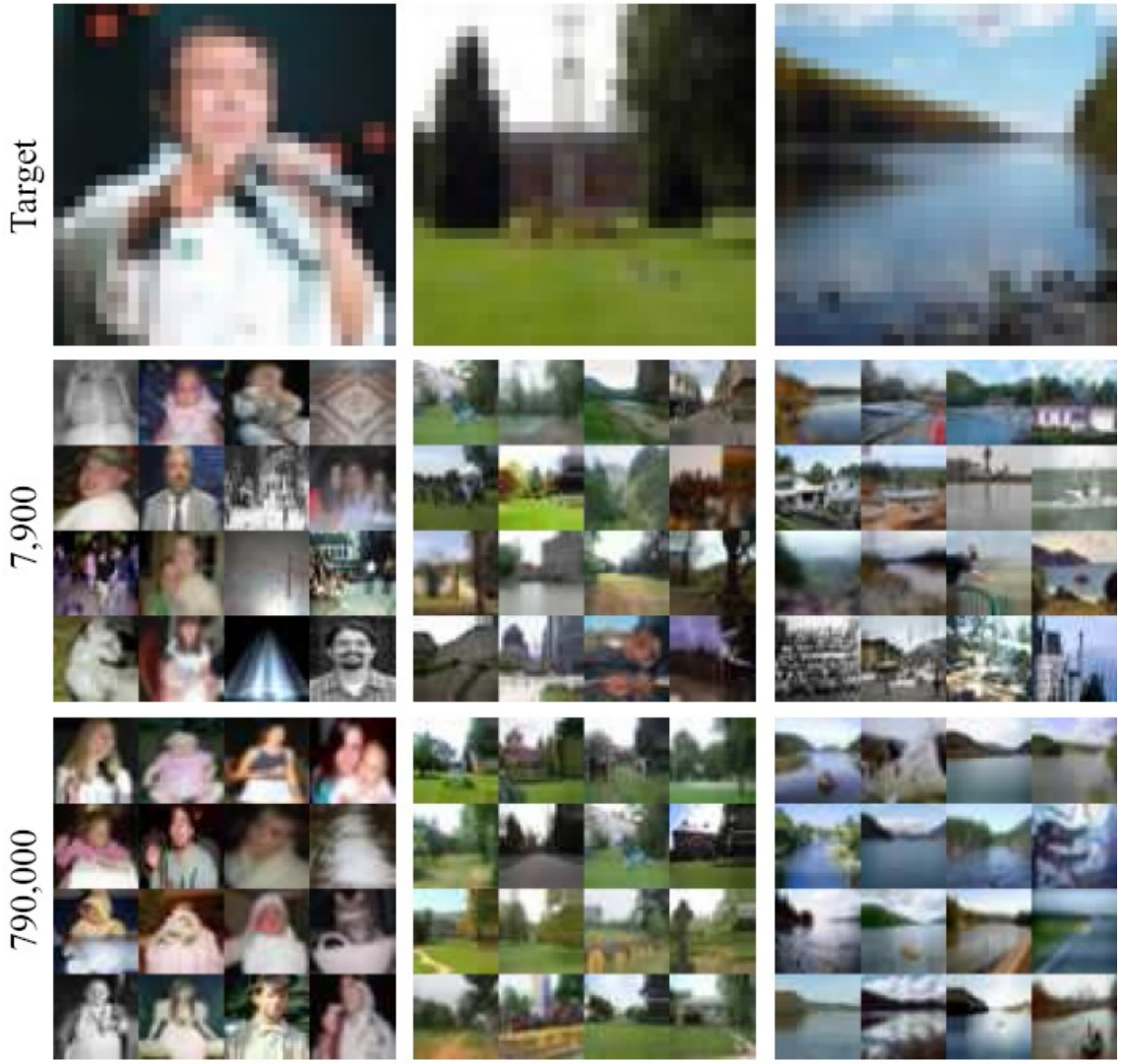
Of

Images



A. Torralba, R. Fergus, W.T.Freeman. PAMI 2008

Lots Of Images

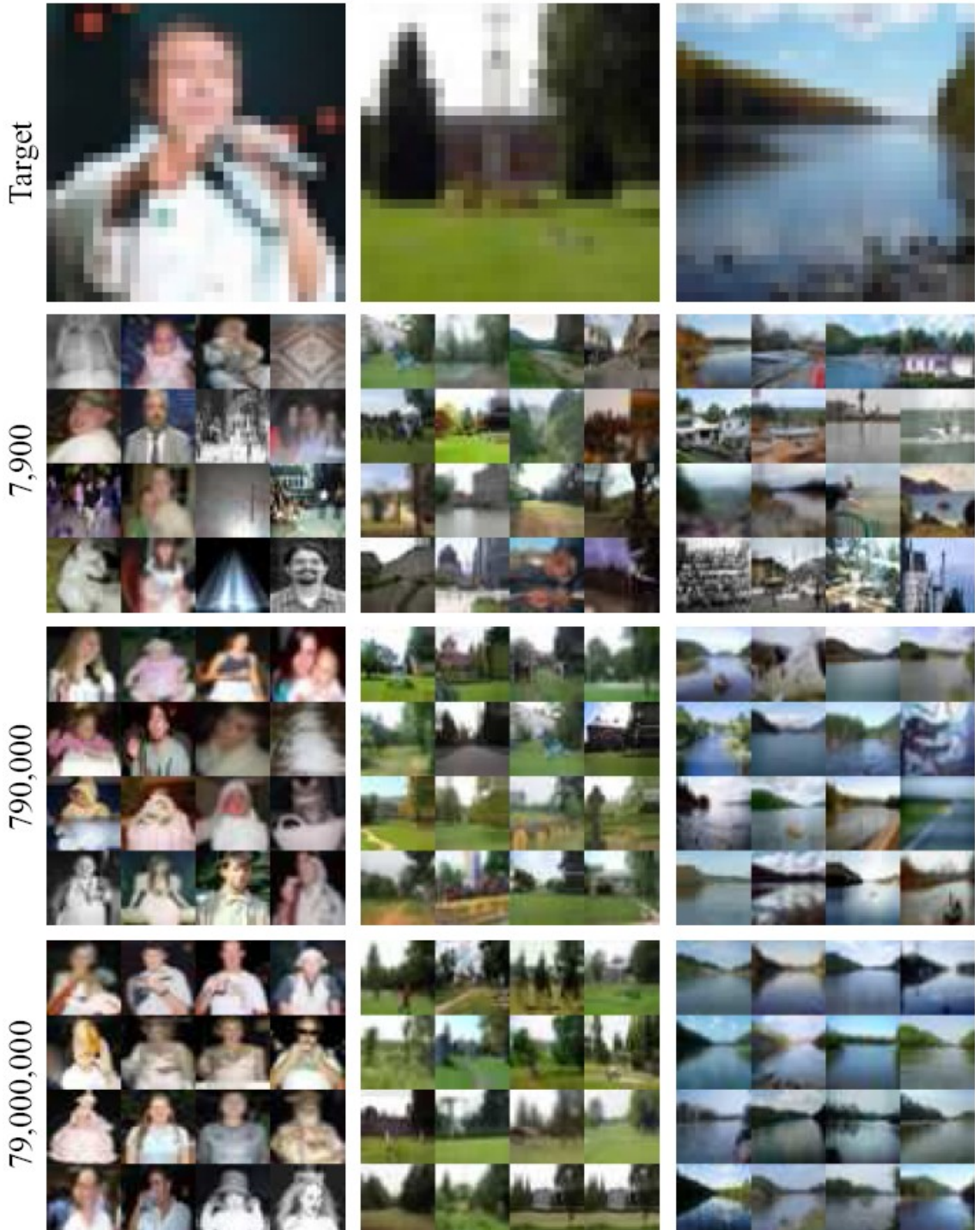


A. Torralba, R. Fergus, W.T.Freeman. PAMI 2008

Lots

Of

Images



Application: Automatic Colorization

Input

Color Transfer

Color Transfer

Matches (gray)

Matches (w/ color)

Avg Color of Match

Application: Automatic Colorization

Input

Color Transfer

Color Transfer

Matches (gray)

Matches (w/ color)

Avg Color of Match

How much can an image tell about its geographic location?

How much can an image tell about its geographic location?

6 million geo-tagged Flickr images

http://graphics.cs.cmu.edu/projects/im2gps/

im2gps (Hays & Efros, CVPR 2008)

Nearest Neighbors according to gist + bag of SIFT + color histogram + a few others


Paris


Paris


Paris


Paris


Paris


Paris


Paris


Madrid


Rome


Paris


Cuba

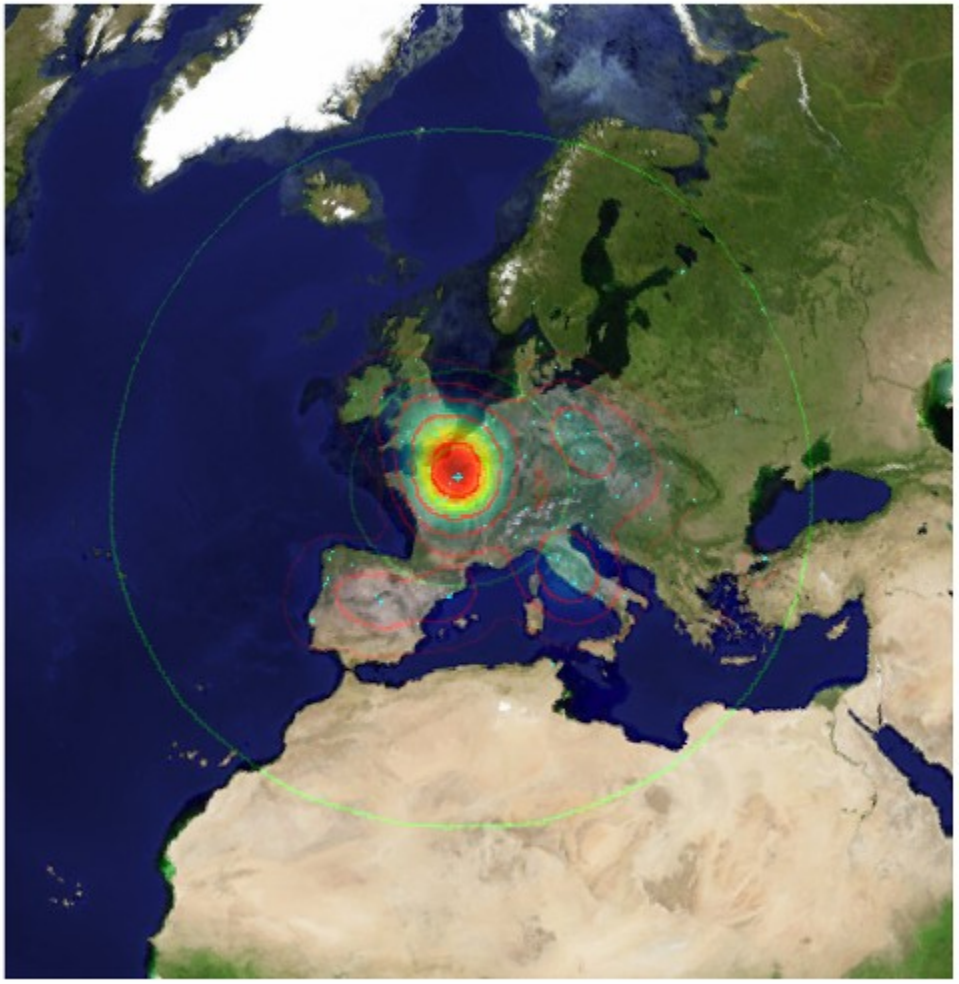

Paris


Paris


Poland


Paris


Paris



Im2gps

Example Scene Matches


Madrid


england


France


Paris


Croatia


heidelberg


Macau


Malta


Cairo


Italy


Italy


Italy

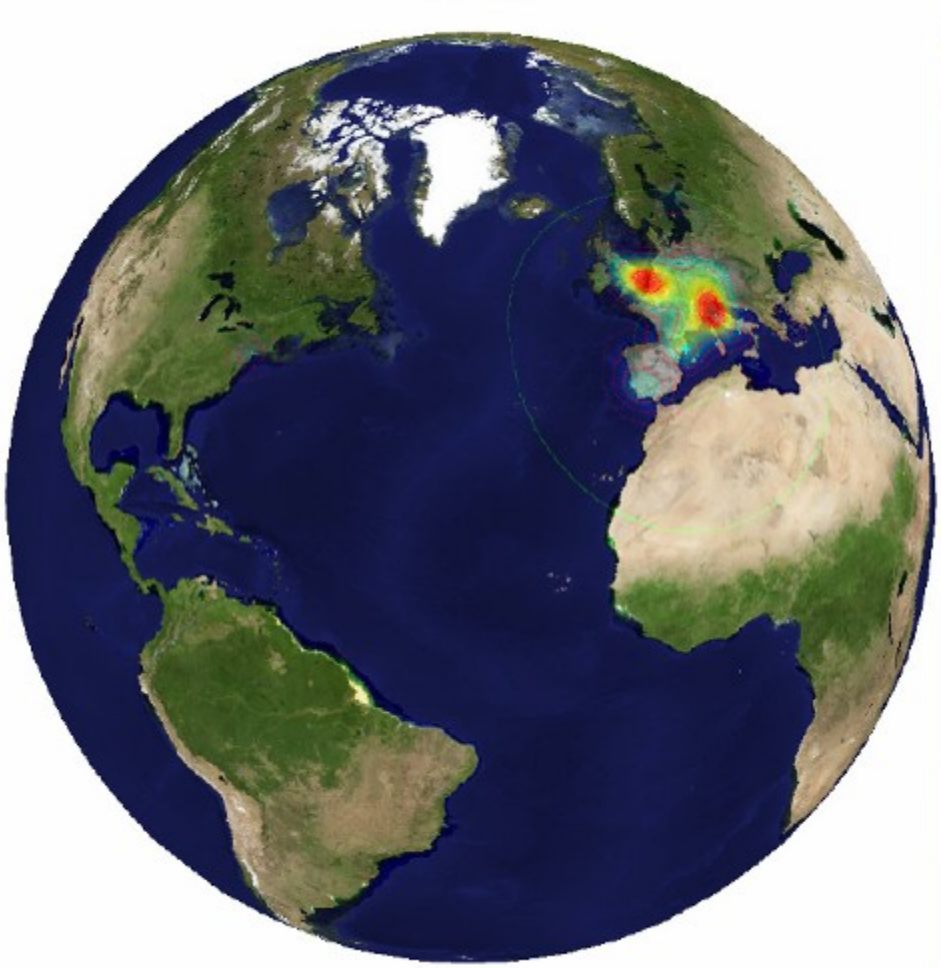

Latvia

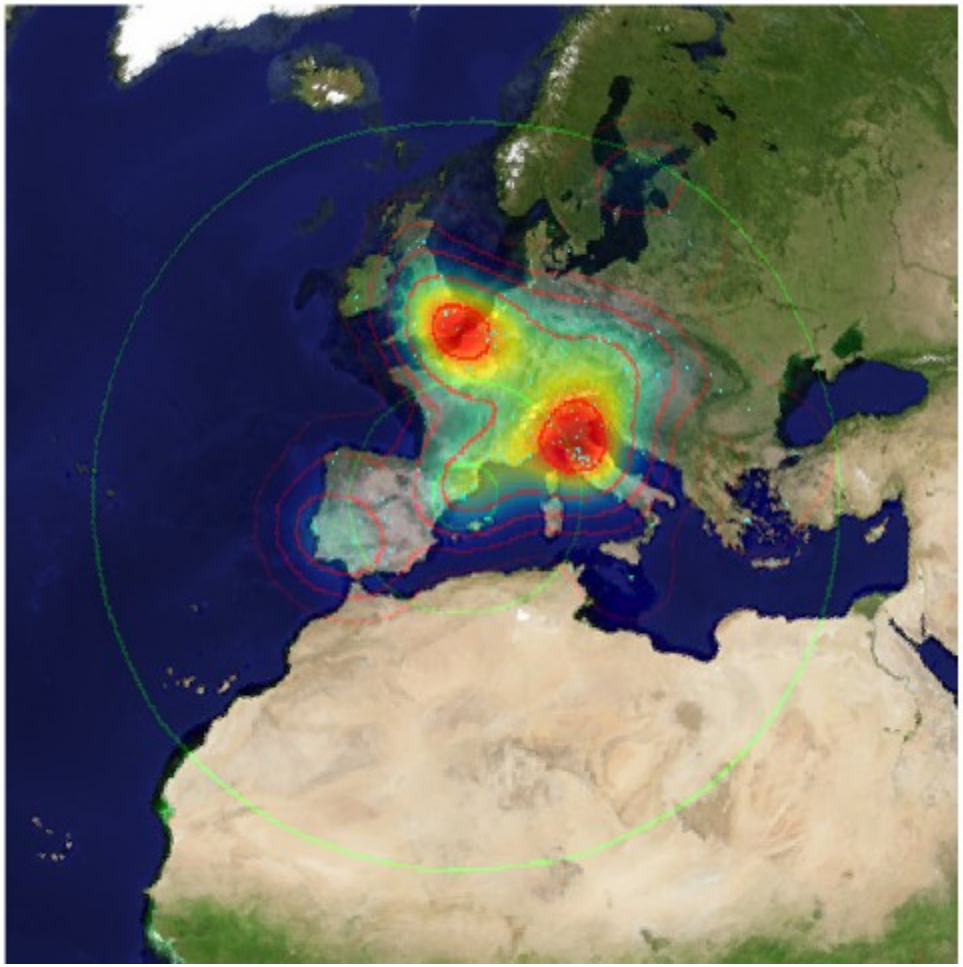

europe


Barcelona


Austria

Voting Scheme





im2gps

Philippines

Houston

Thailand

Houston

Maldives

Philippines

NewZealand

Bermuda

Palau

Mexico2

Brazil

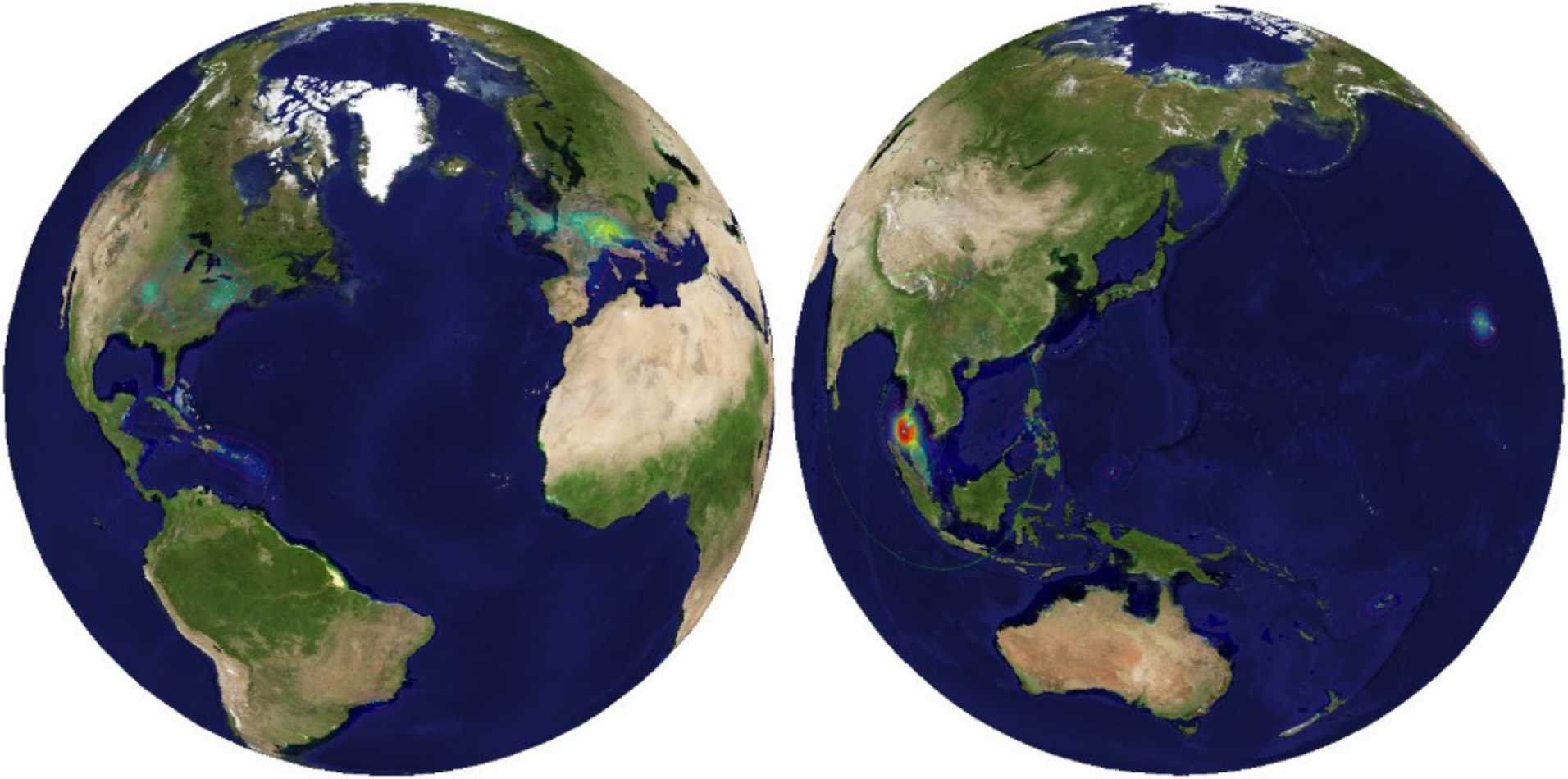
Mendoza

Brazil

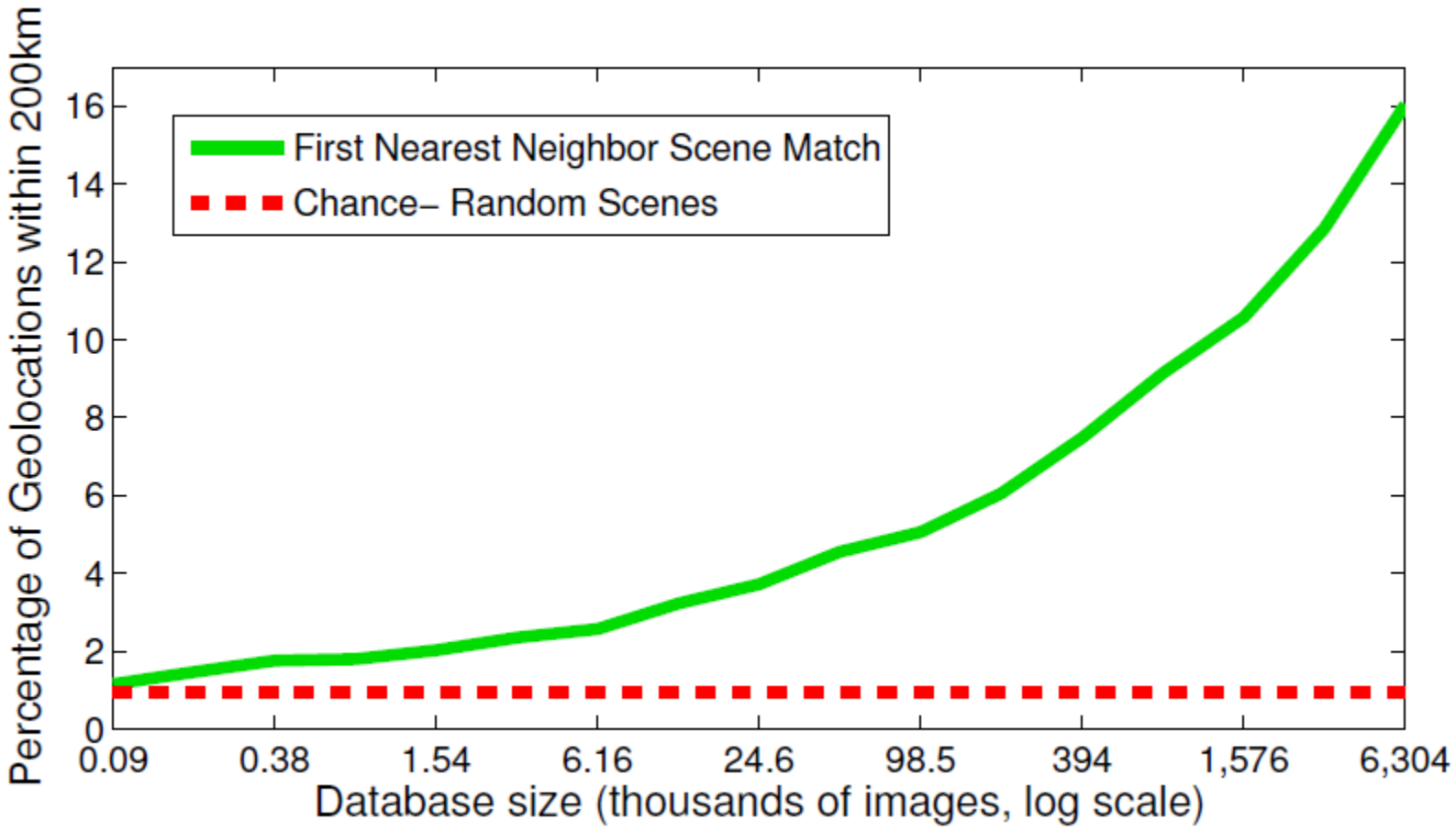
Thailand

Arkansas

Hawaii



Effect of Dataset Size



Where is This?

[Vesselova, Kalogerakis, Hertzmann, Hays, Efros. Image Sequence Geolocation. ICCV'09]

Where is This?

Where are These?

15:14,
June 18th, 2006

16:31,
June 18th, 2006

Where are These?

15:14,
June 18th, 2006

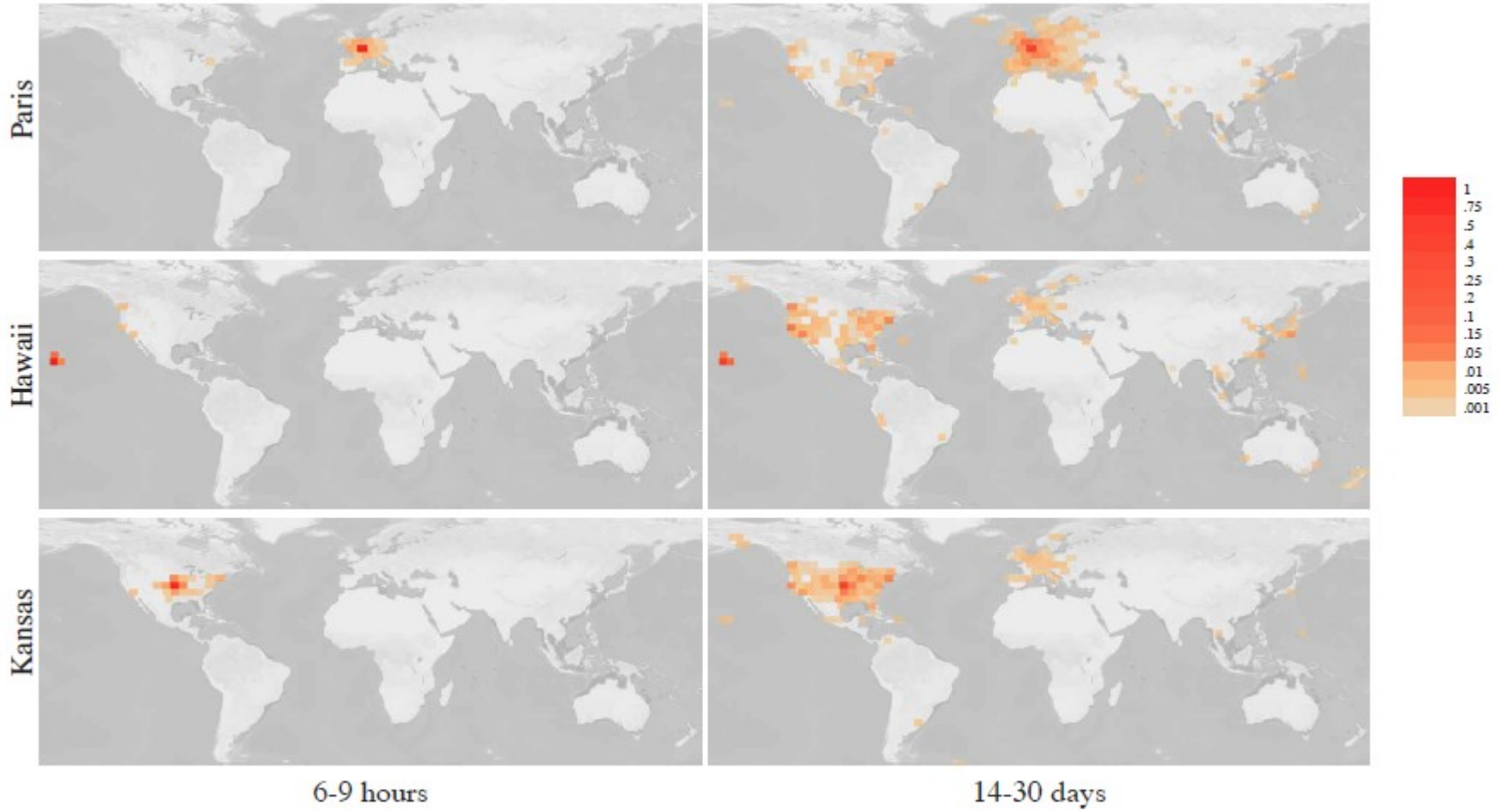
16:31,
June 18th, 2006

17:24,
June 19th, 2006

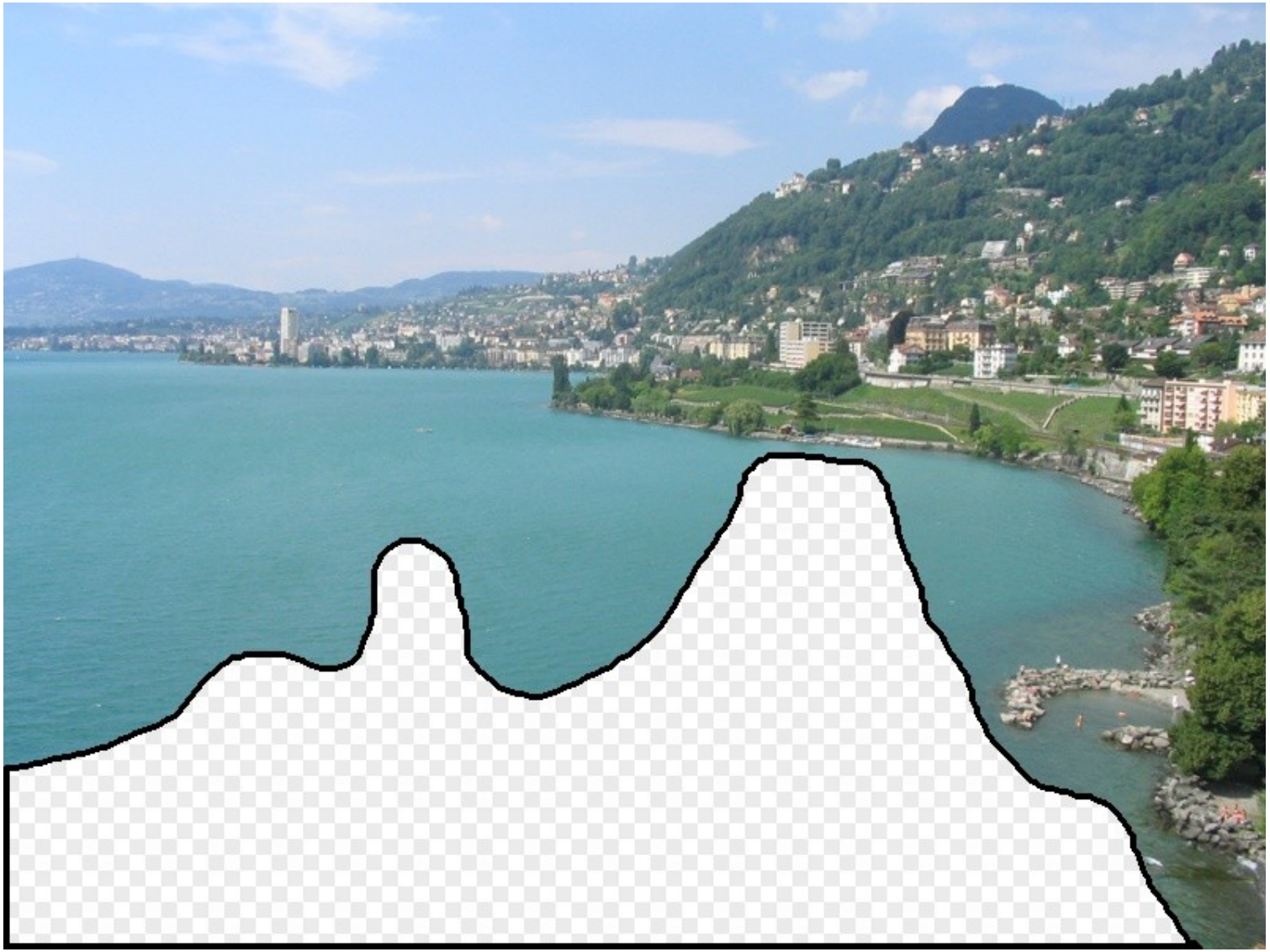
Results

https://github.com/lugiavn/revisiting-im2gps

- im2gps – 10% (geo-loc within 400 km)
- temporal im2gps – 56%



What should the missing region contain?



Which is the original?

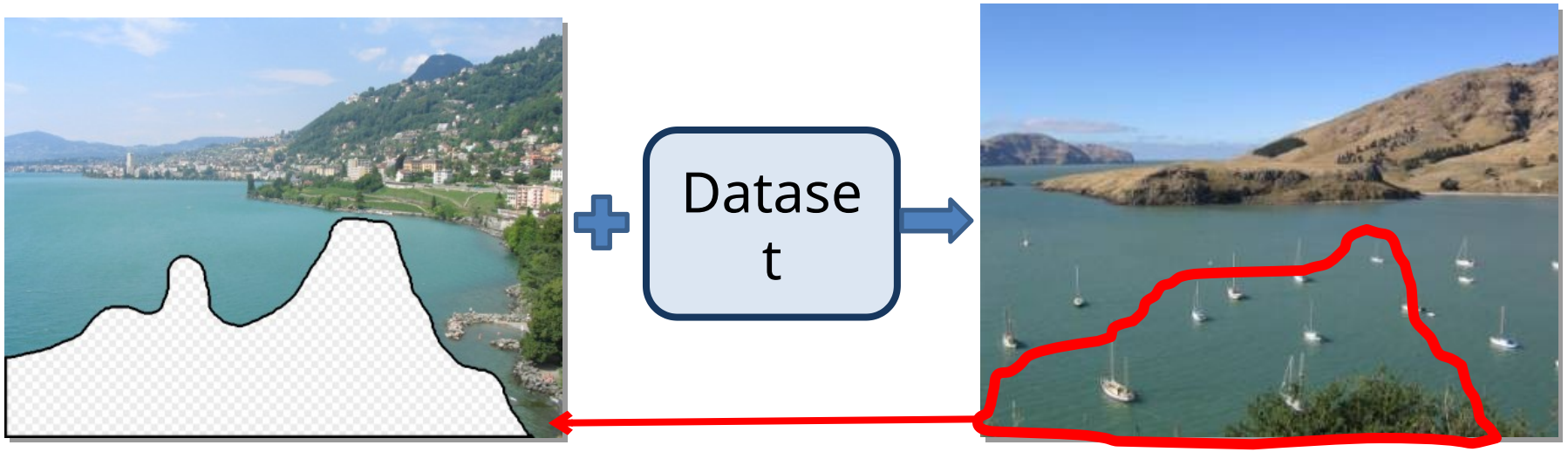
(a)

(b)

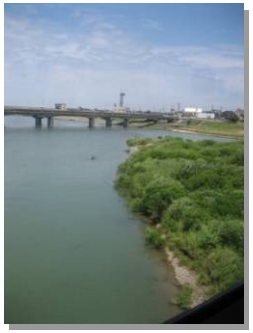
(c)

How it works

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

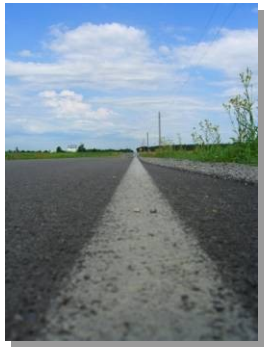


How many images is enough?

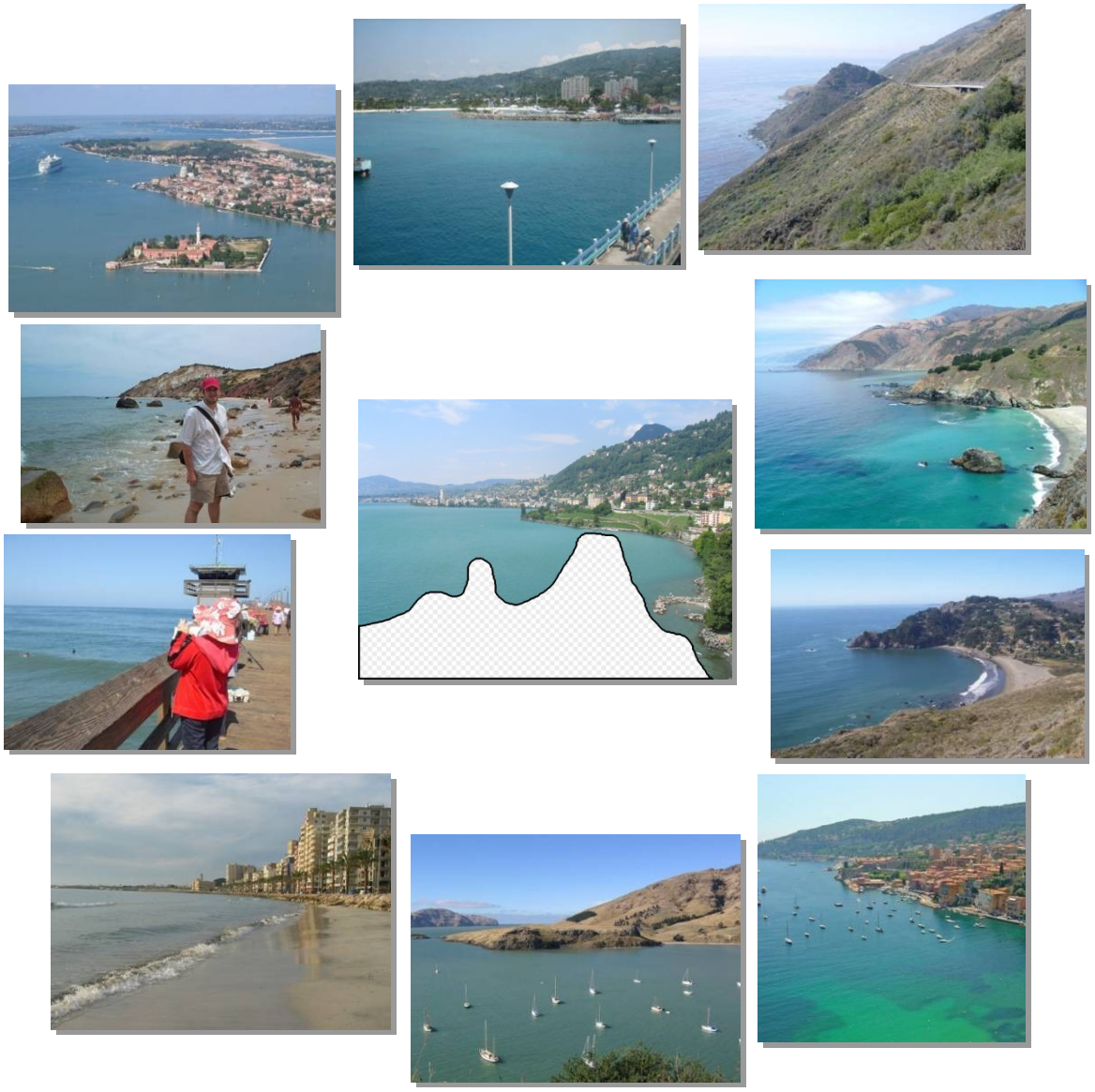







Nearest neighbors from a
collection of 20 thousand images



Nearest neighbors from a collection of 2 million images

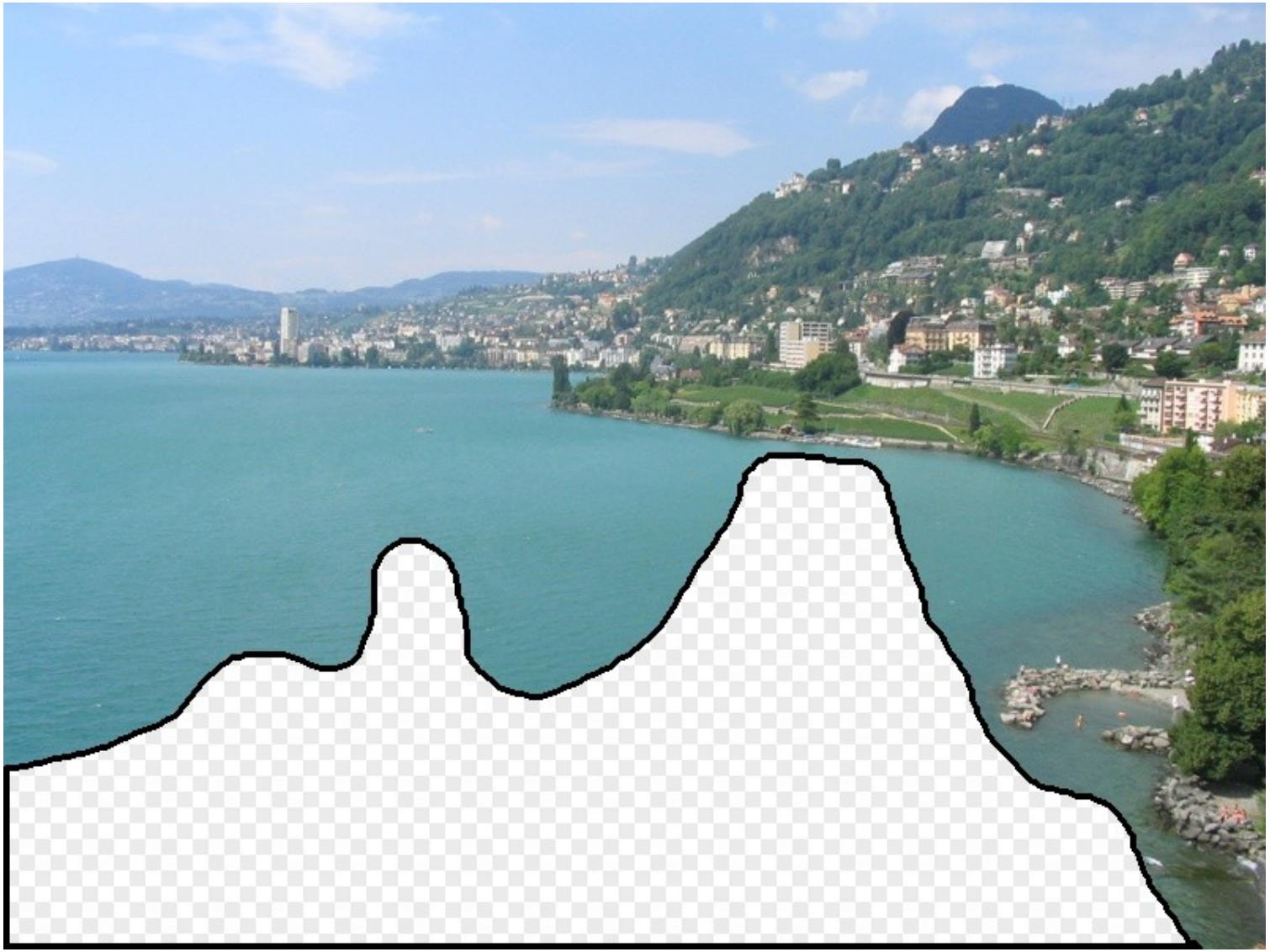
Image Data on the Internet

- Flickr (as of Nov 2015)
  - 10 billion photographs
  - 100+ million geotagged images
  - 3.5 million a day
- Facebook (as of Sept 2013)
  - 250 billion+
  - 300 million a day
- Instagram
  - 93 million a day

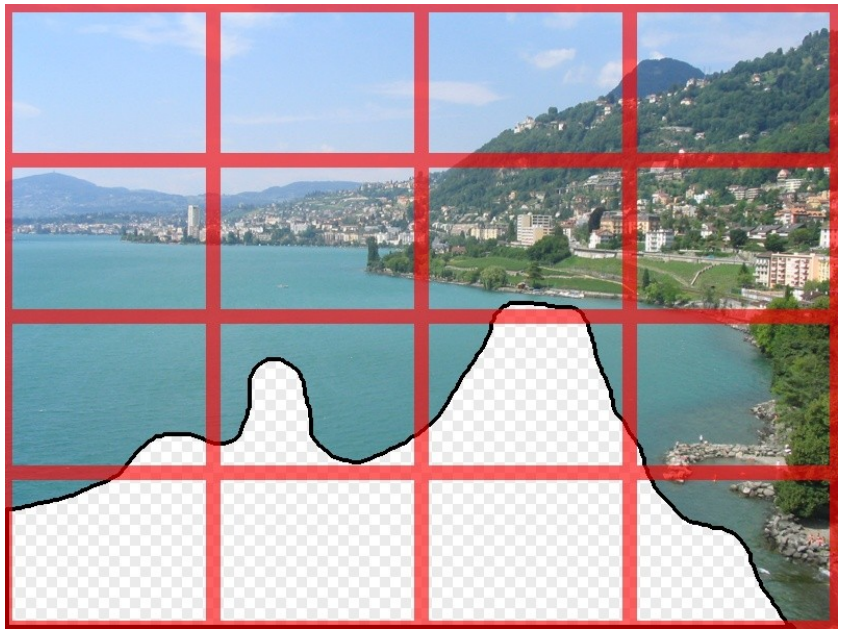
The Algorithm:

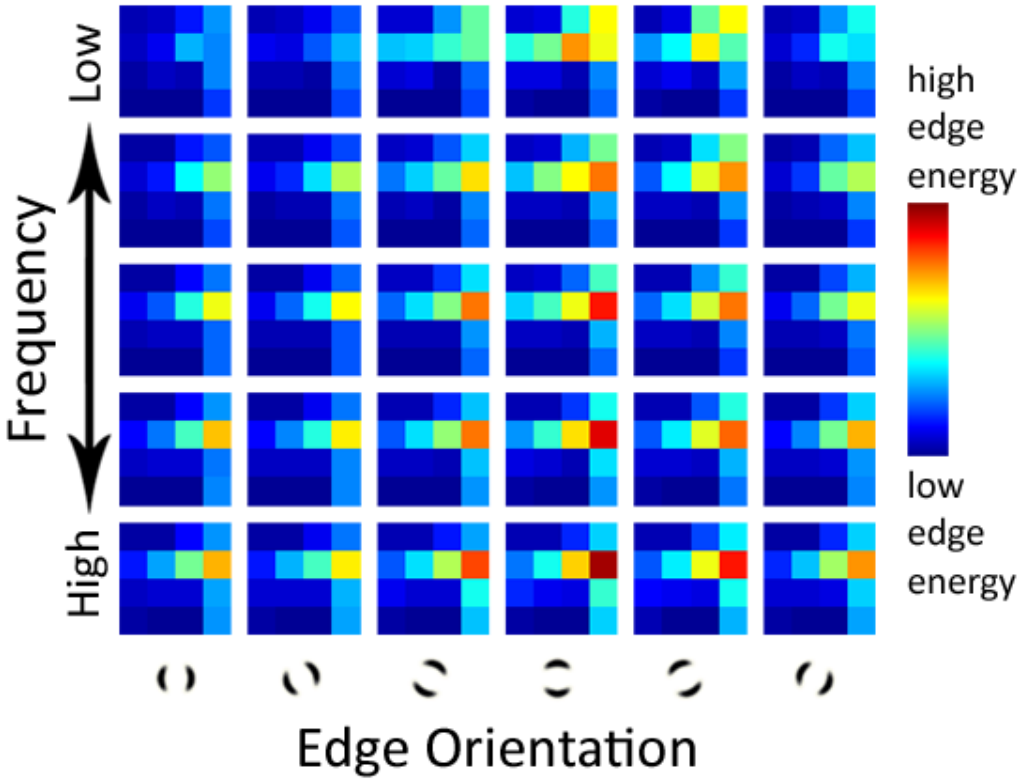
[Hays and Efros. Scene Completion Using Millions of Photographs. SIGGRAPH 2007 and CACM October 2008.]

Scene Matching



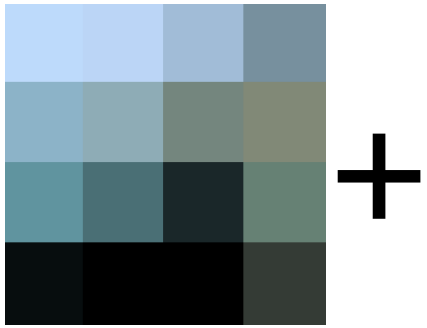
Scene Descriptor



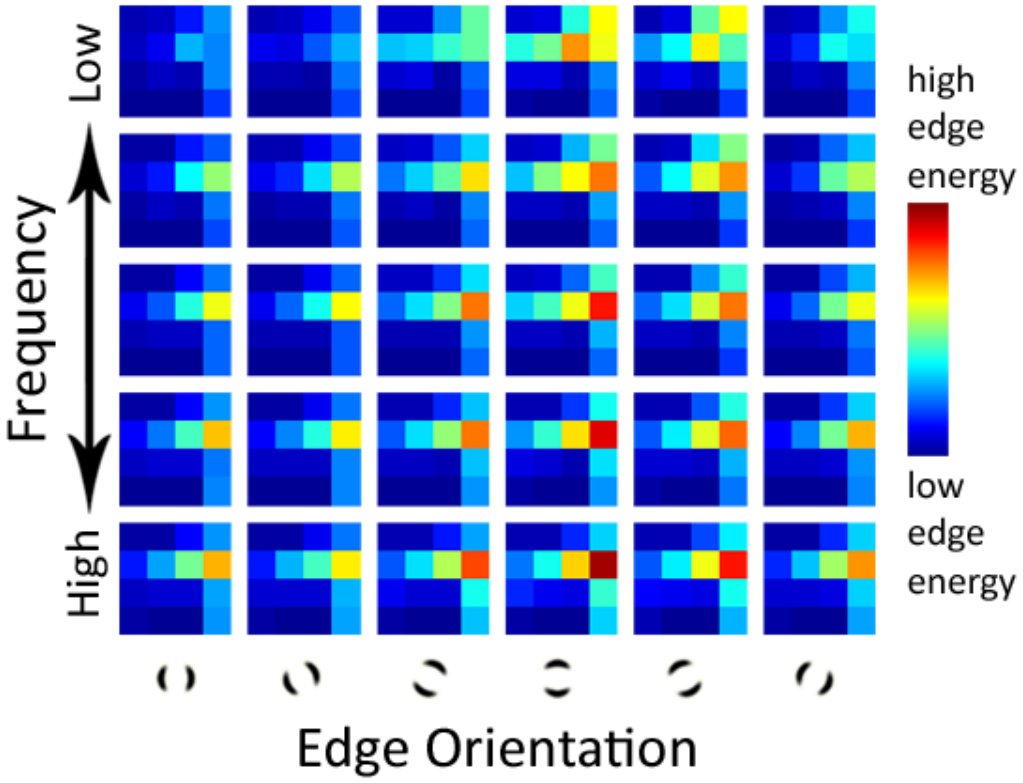


Scene Gist Descriptor
(Oliva and Torralba 2001)

Scene Descriptor

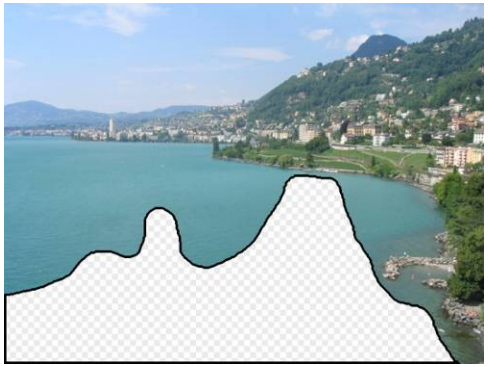


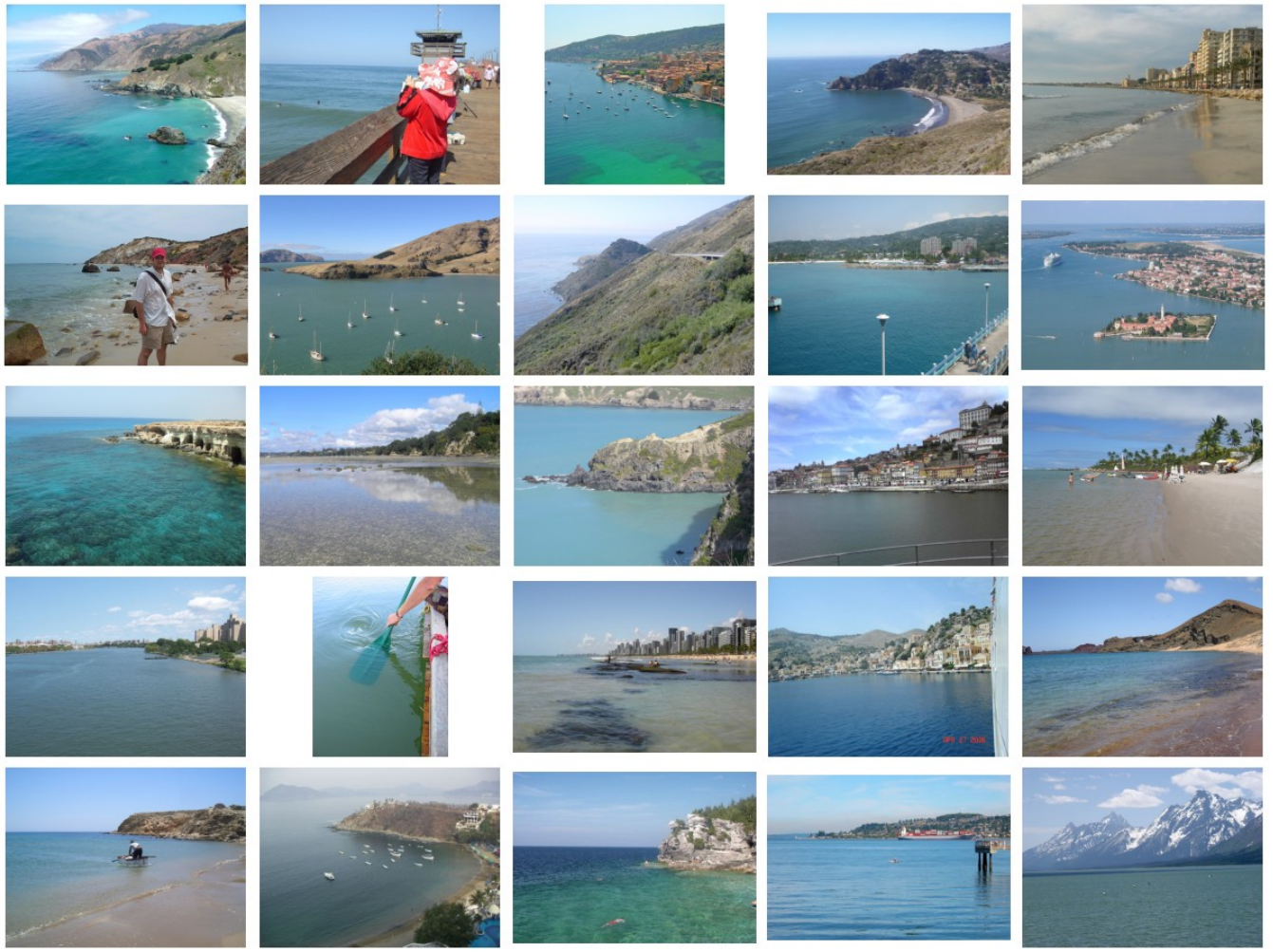
+



Scene Gist Descriptor
(Oliva and Torralba 2001)

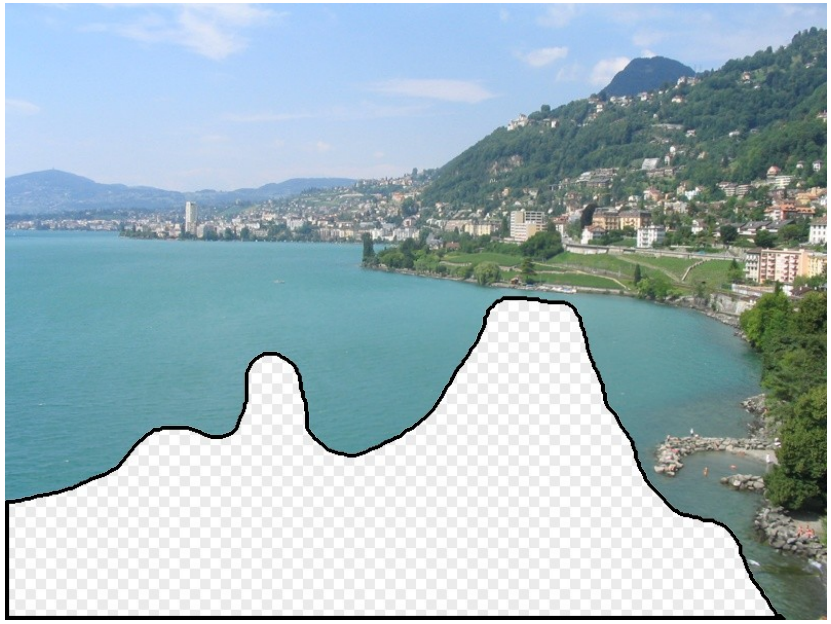

2 Million Flickr Images





... 200 total

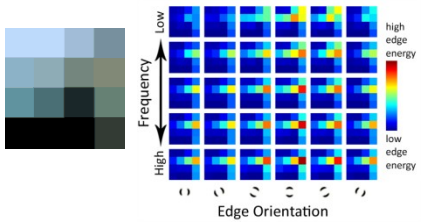
Context Matching




Graph cut + Poisson

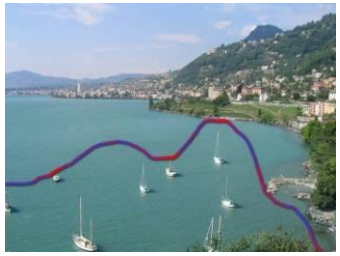
Result Ranking

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

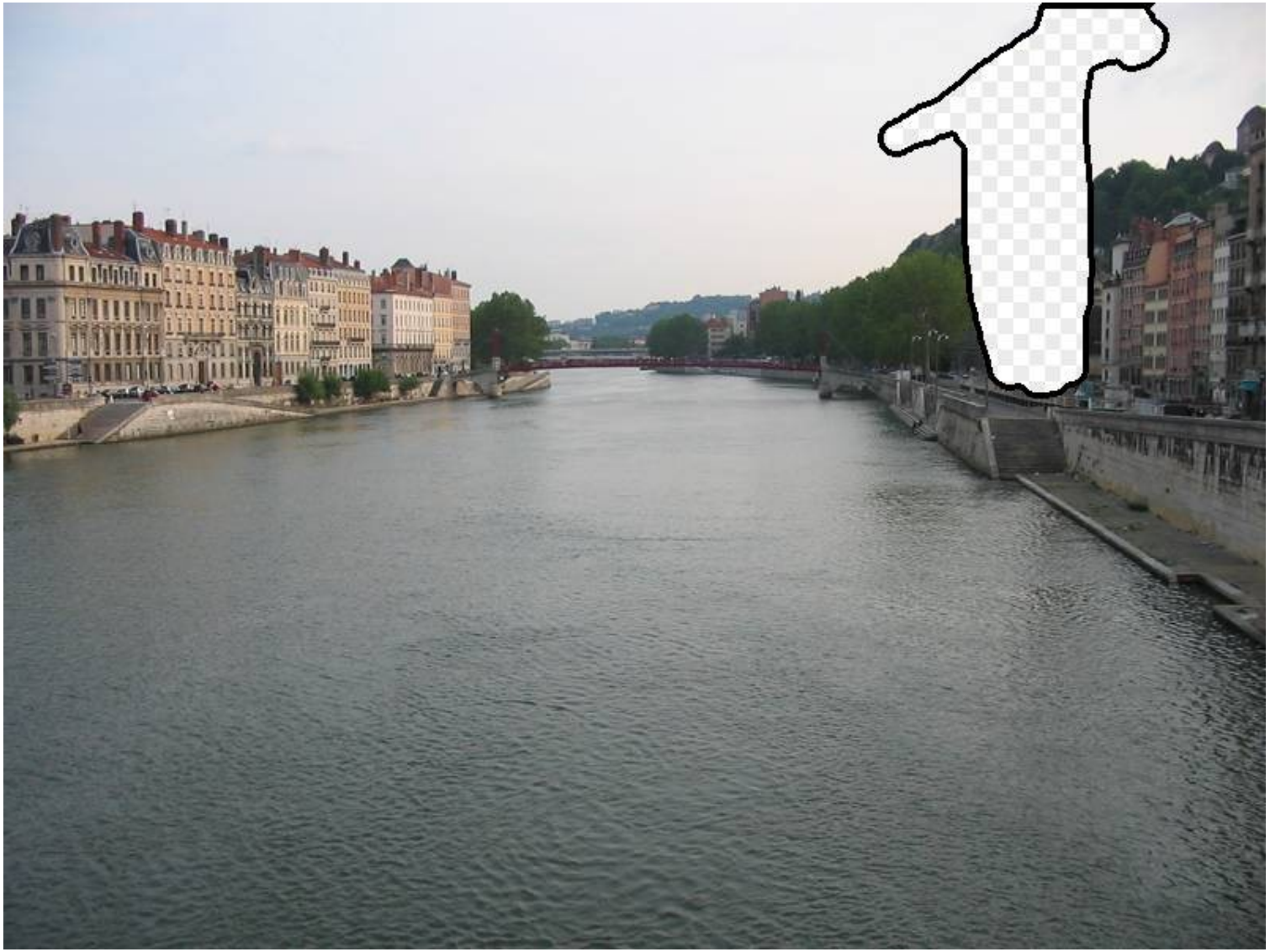


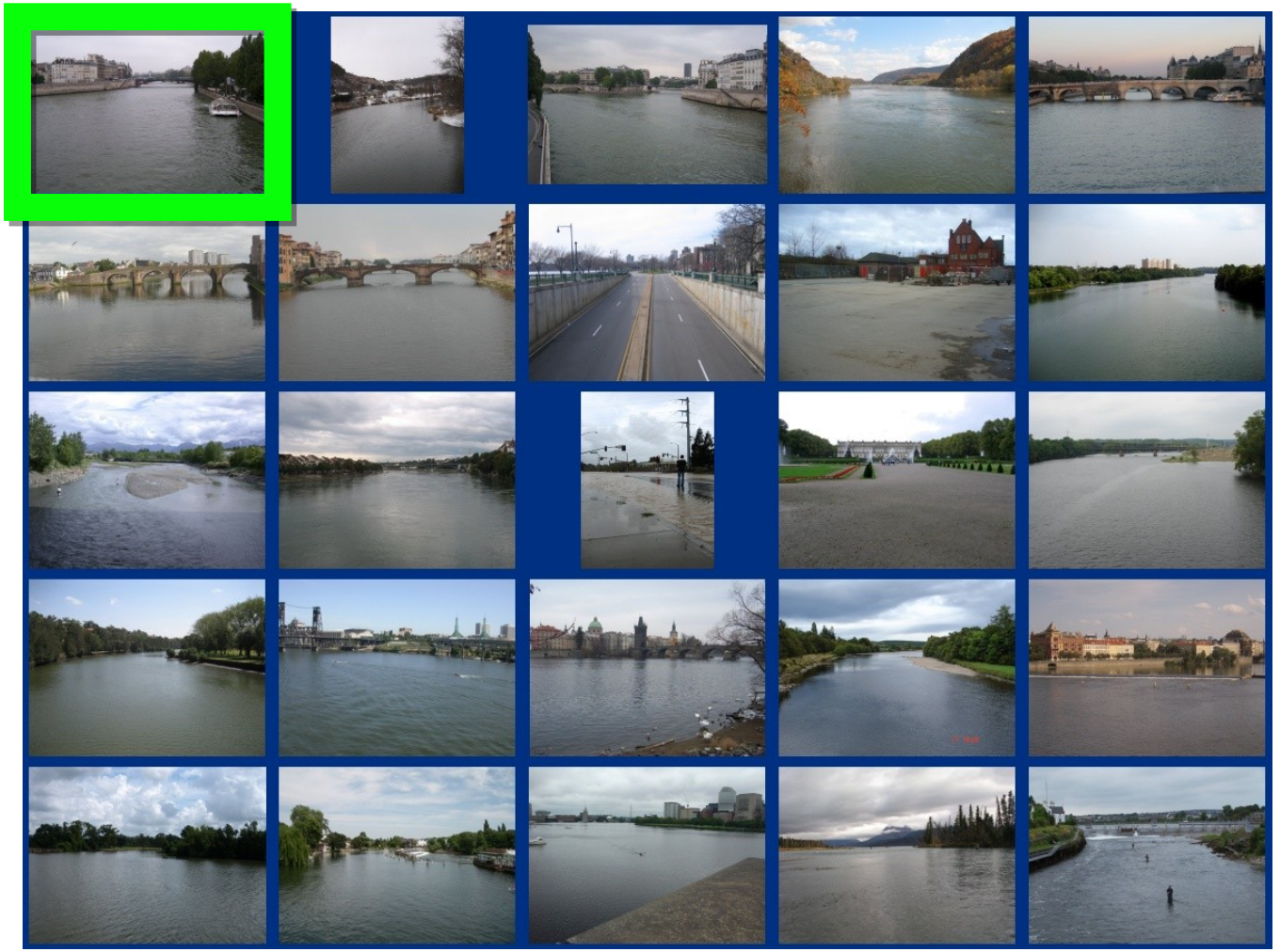
The scene matching distance

The context matching distance (color + texture)

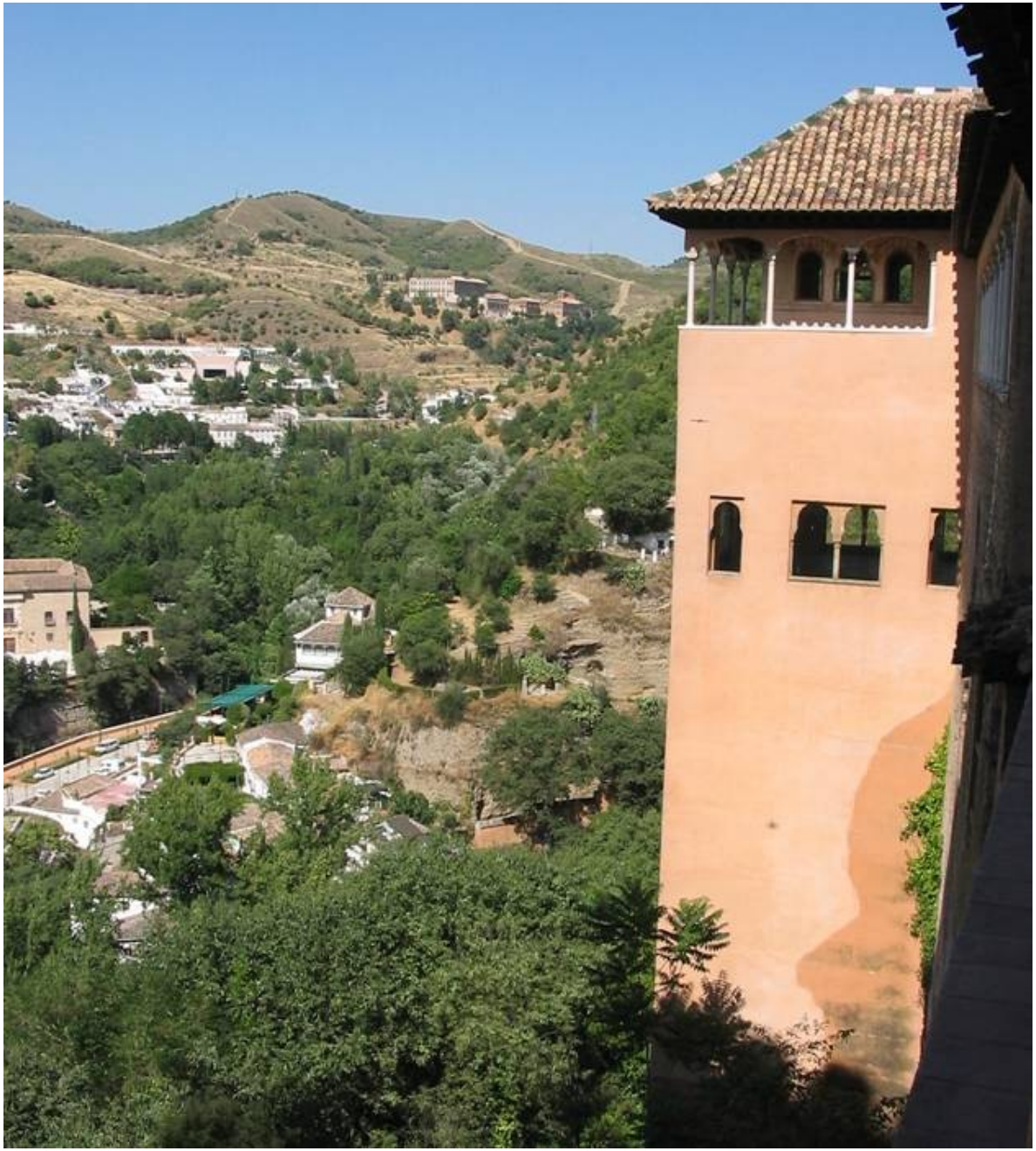


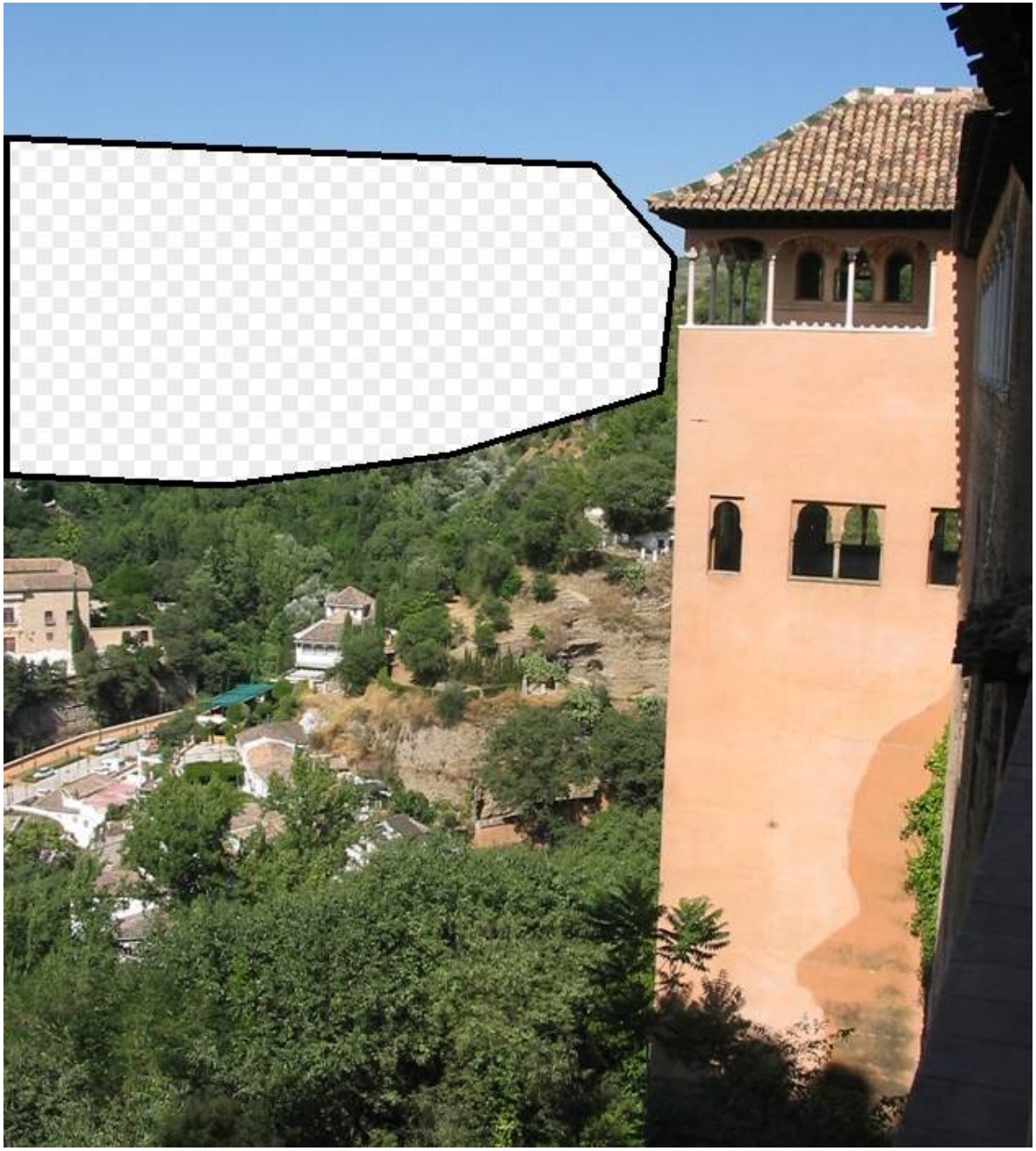
The graph cut cost





… 200 scene matches

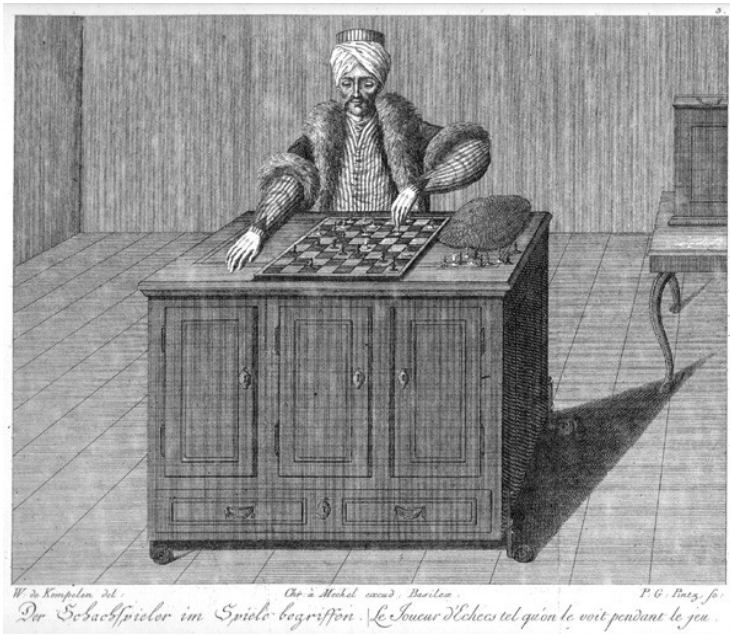




Which is the original?

Mechanical Turk

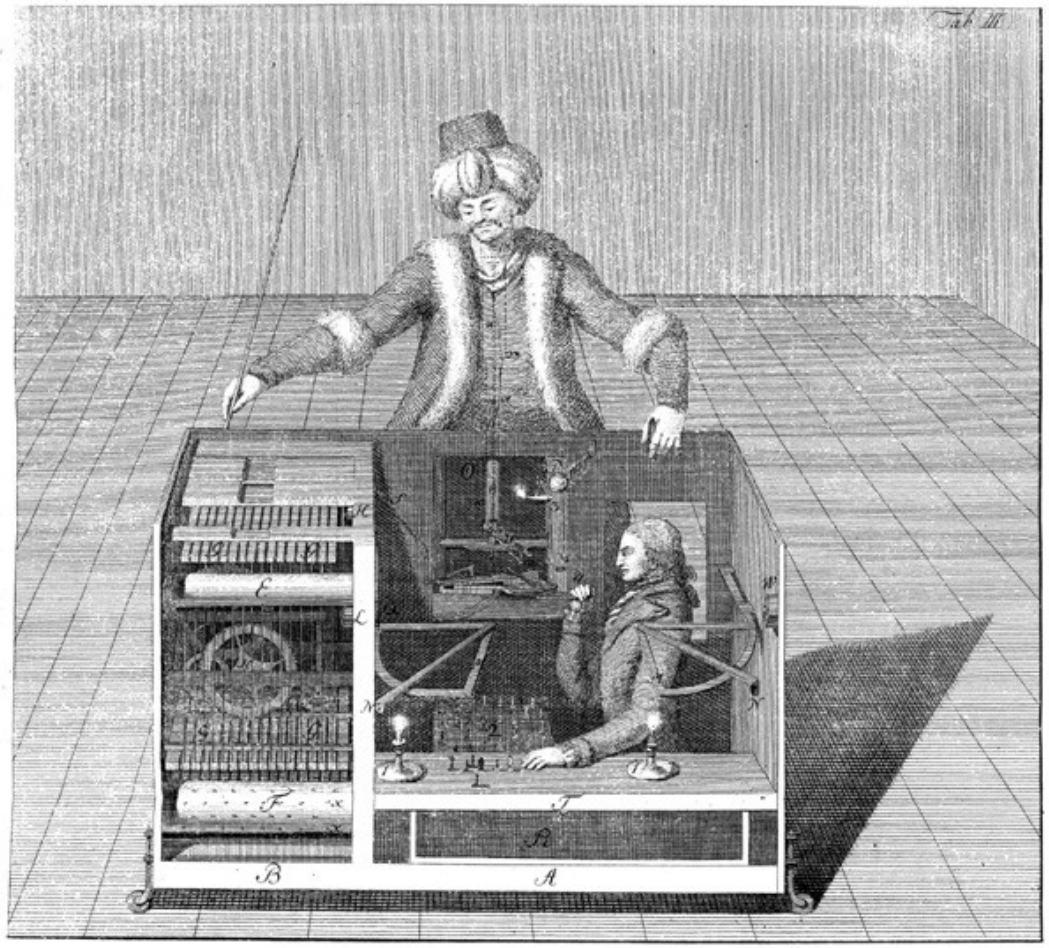
- von Kempelen, 1770 to 1854.
- Robotic chess player.
- Clockwork routines.
- Magnetic induction (not vision)



- Toured the world; played Napoleon Bonaparte and Benjamin Franklin.

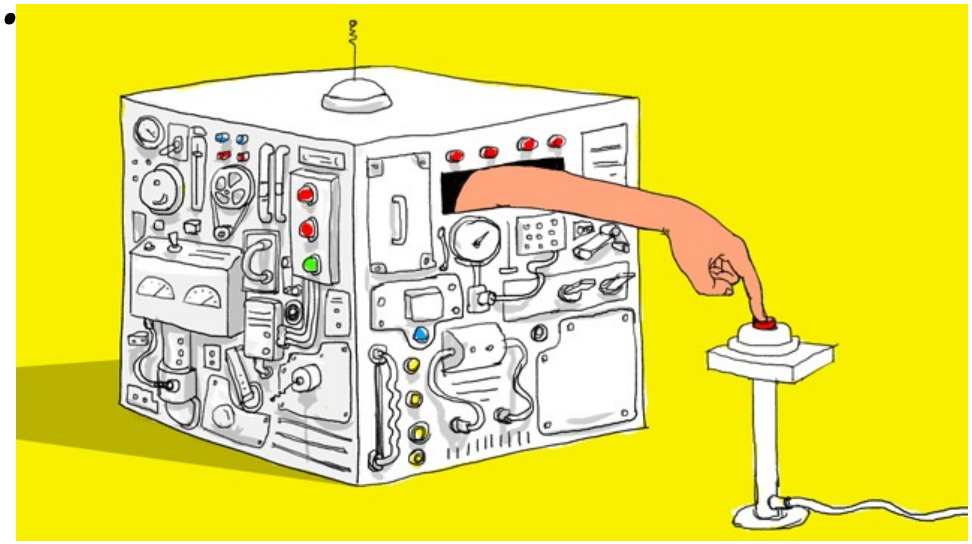
Mechanical Turk

- It was all a ruse!
- Ho ho ho.



Amazon Mechanical Turk

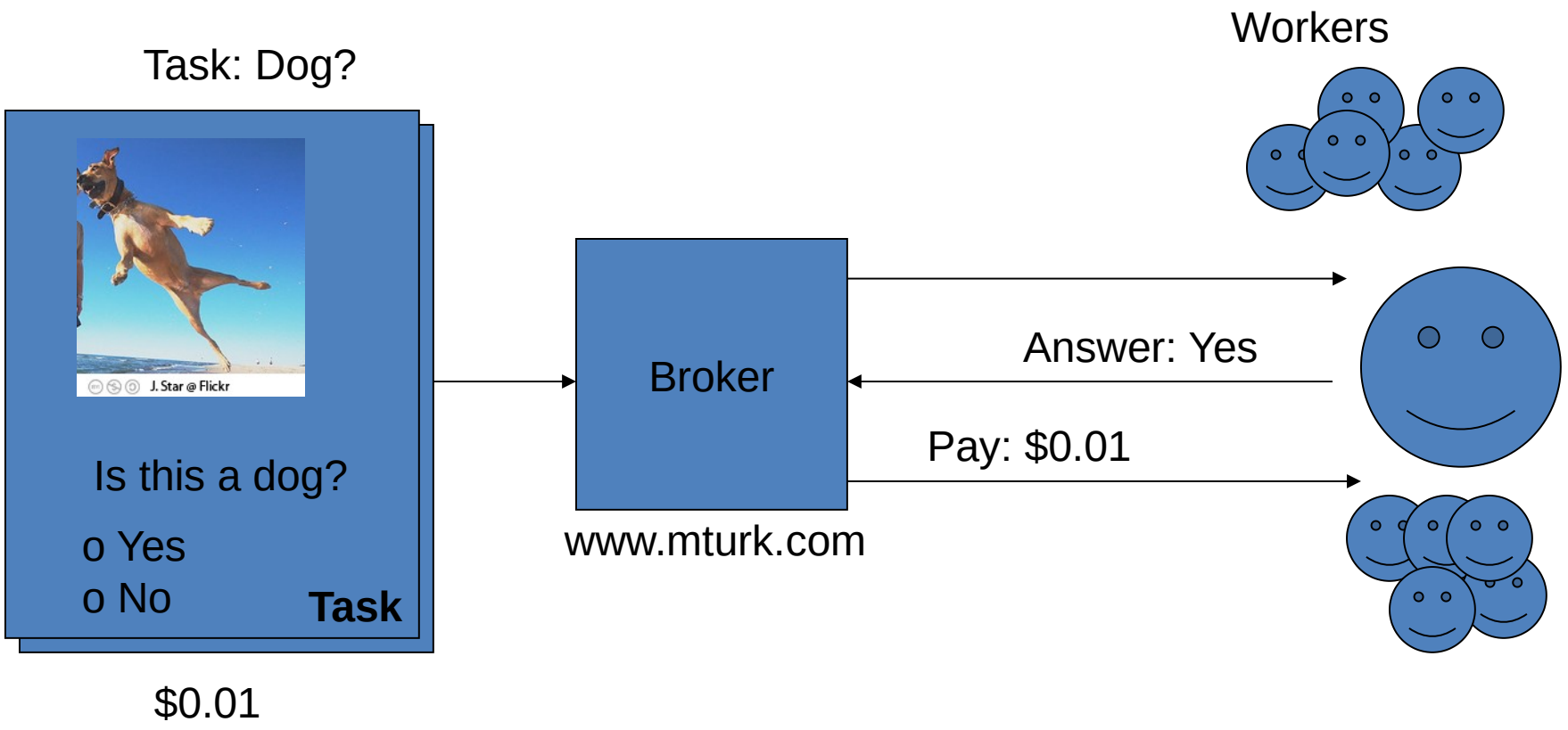
Artificial artificial intelligence.



Launched 2005.
Small tasks, small pay.
Used extensively in data collection.

Image: Gizmodo

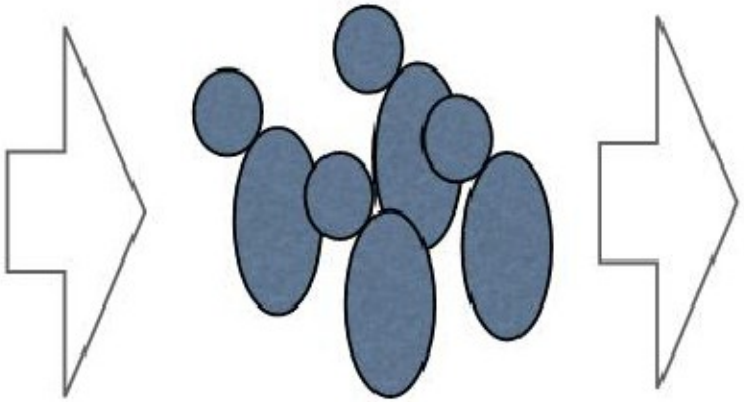
Amazon Mechanical Turk



Building datasets

6000 images from flickr.com

Annotators



amazon mechanical turk
Artificial Artificial Intelligence

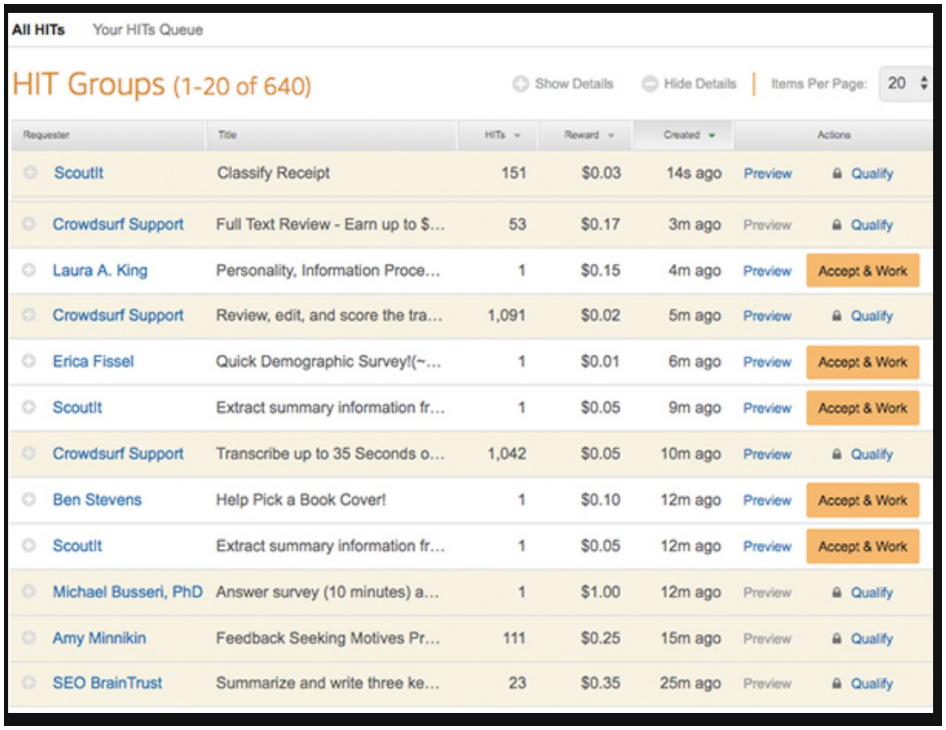
Is there an Indigo bunting in the image?

100s of training images

Slide credit: Welinder et al

Typical payments via Amazon Mechanical Turk

- To transcribe a receipt ($0.01)
- Summarize a block of text ($0.35)
- Take a behavioral economics survey ($1)



https://thehustle.co/making-money-on-amazon-mechanical-turk/

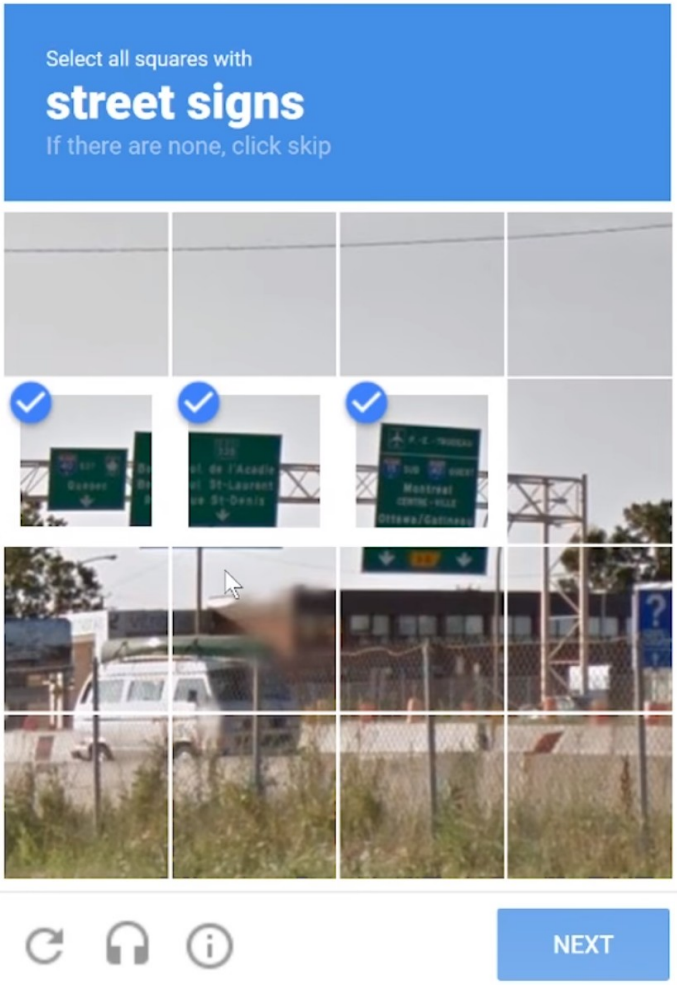
Vision (Segmentation): LabelMe

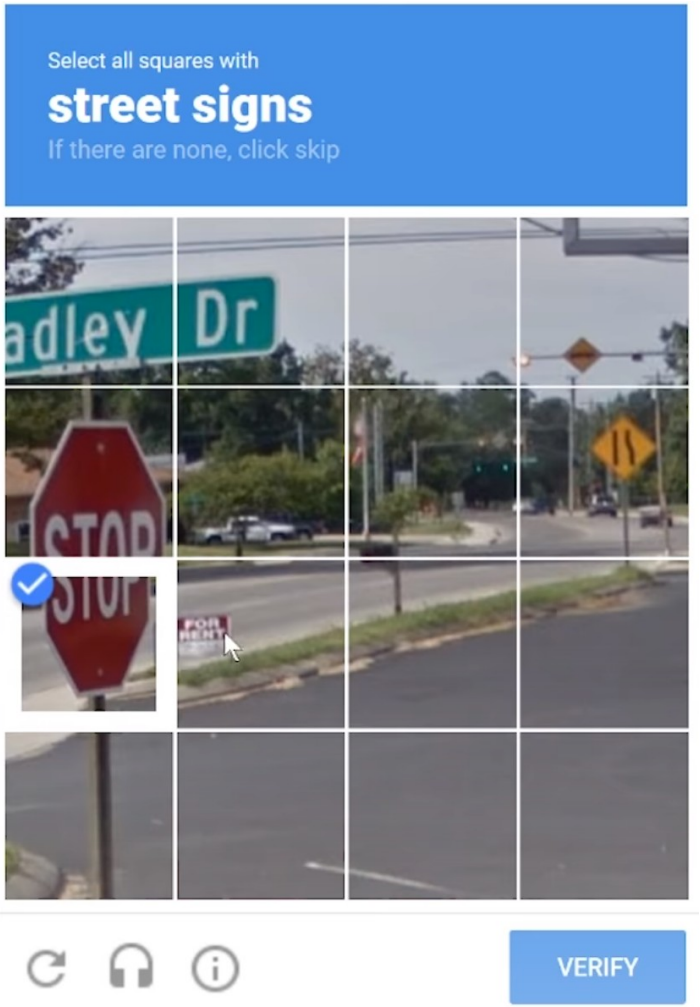
http://labelme.csail.mit.edu

"Open world" database annotated by the community*

Notes on Image Annotation, Barriuso and Torralba 2012. http://arxiv.org/abs/1210.3448

“Security checks”





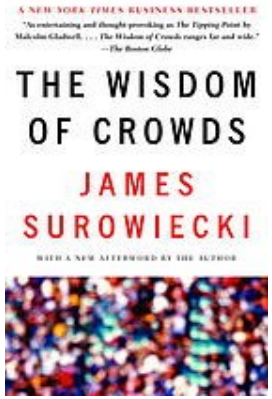
Issues

- Quality?
  - How good is it?
  - How to be sure?
- Price?
  - Trade off between throughput and cost
  - Higher pay can attract scammers

Ensuring Annotation Quality

- Consensus in multiple annotations "Wisdom of the Crowds"

  Not enough on its own, but widely used



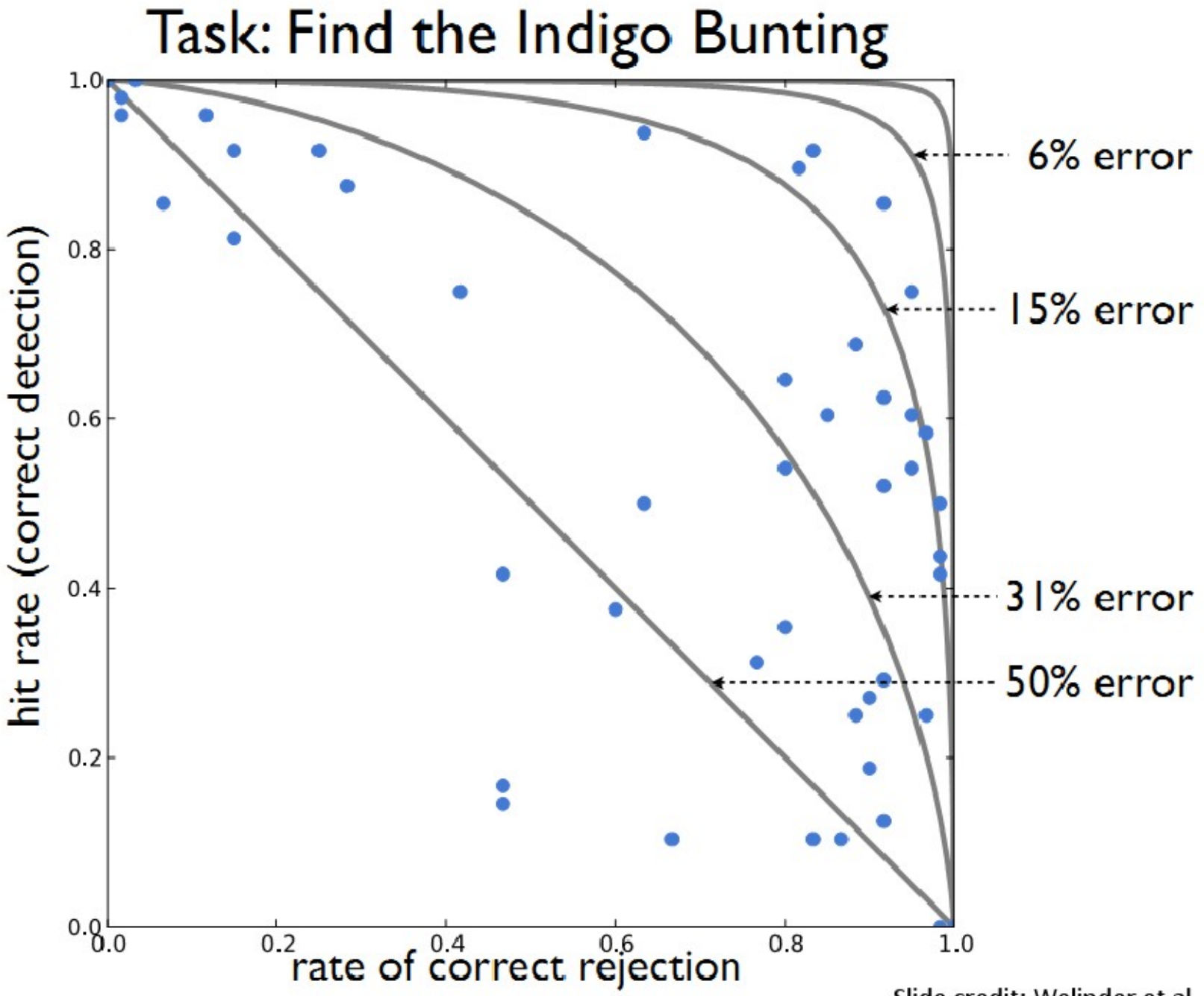
- Gold Standard / Sentinel
  - Special case: qualification exam

  Widely used & important. Find good annotators; keep them honest.

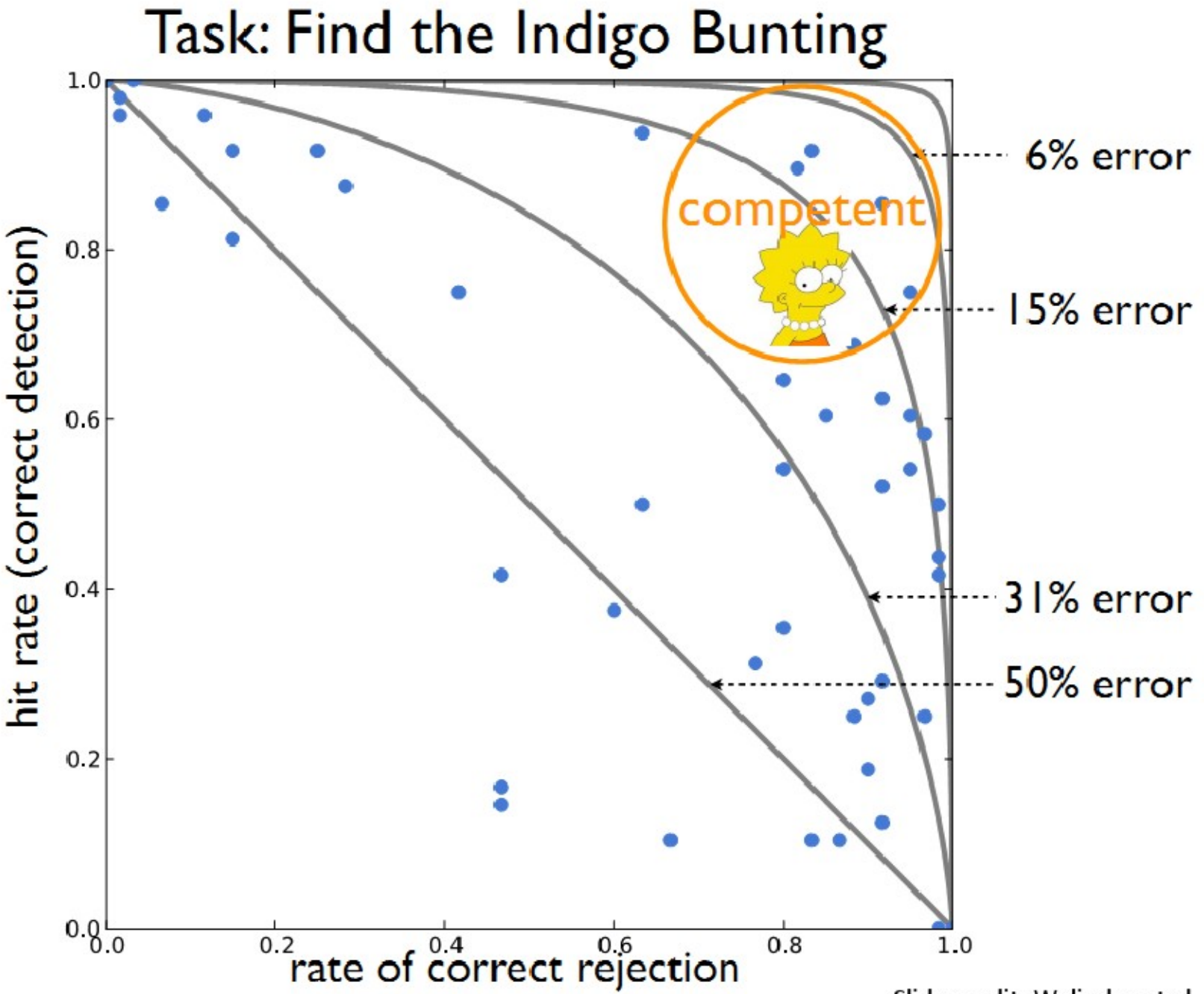
- Grading Tasks
  - A second tier of workers who grade others

  Not widely used

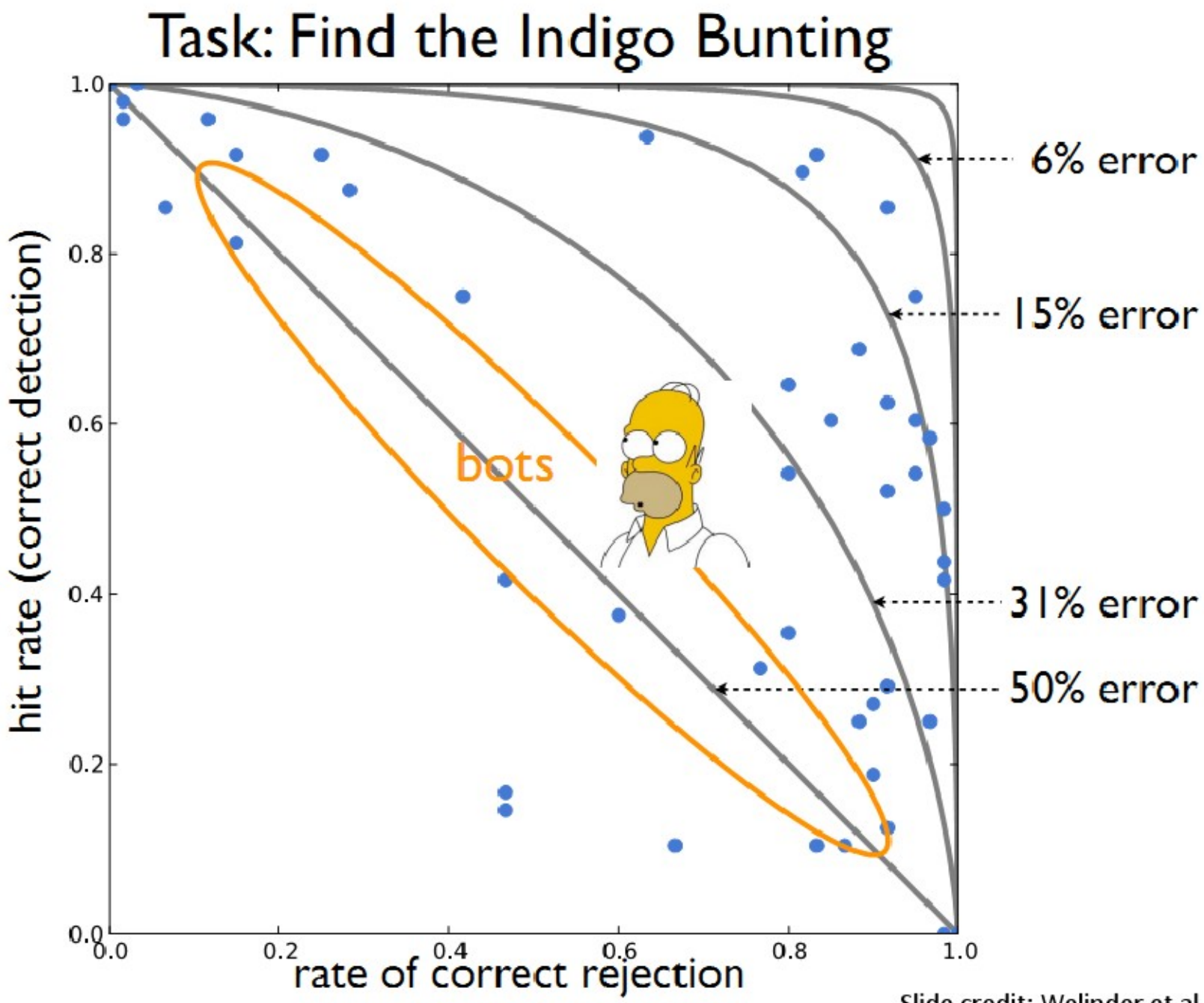
Slide credit: Welinder et al



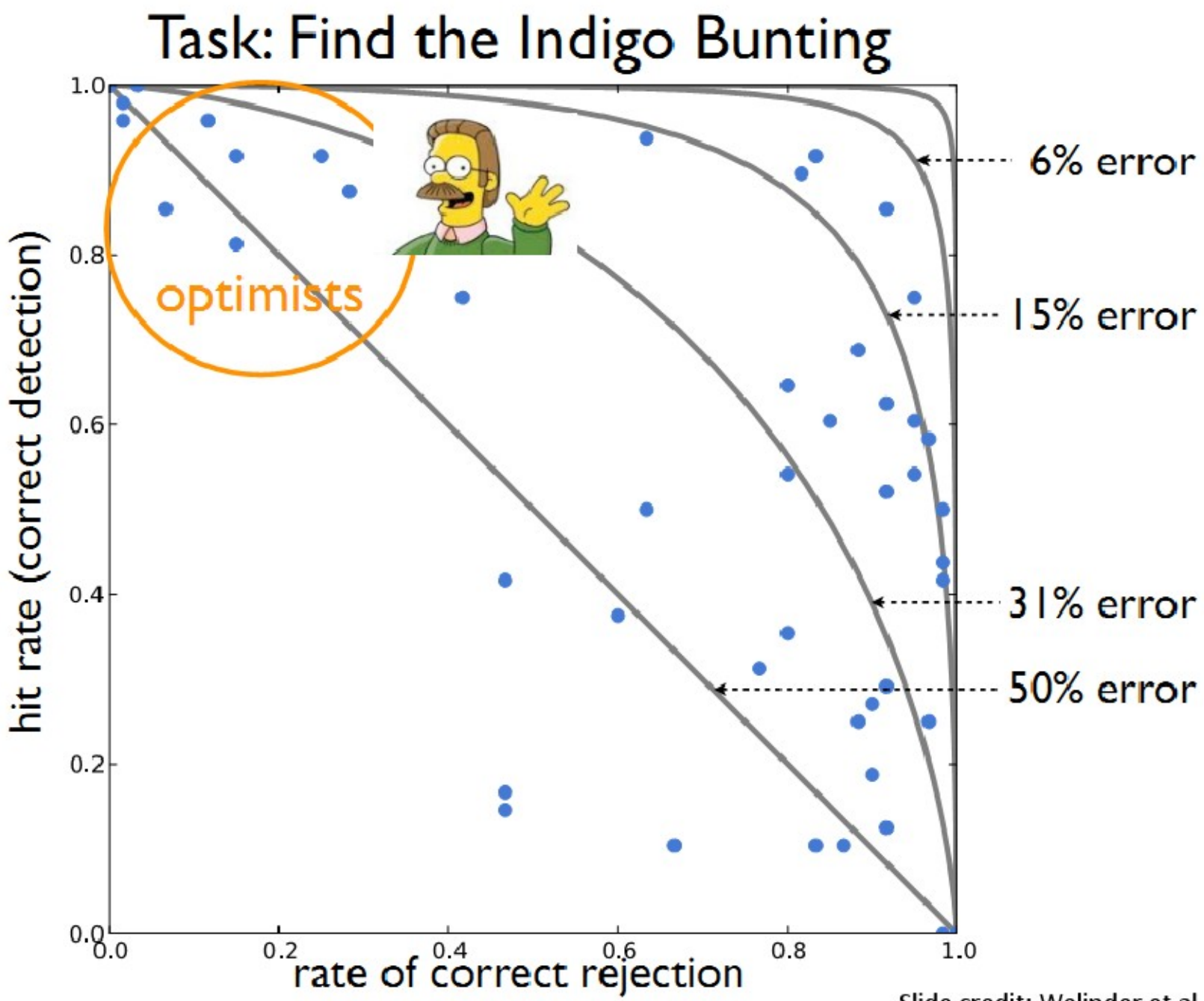
Slide credit: Welinder et al



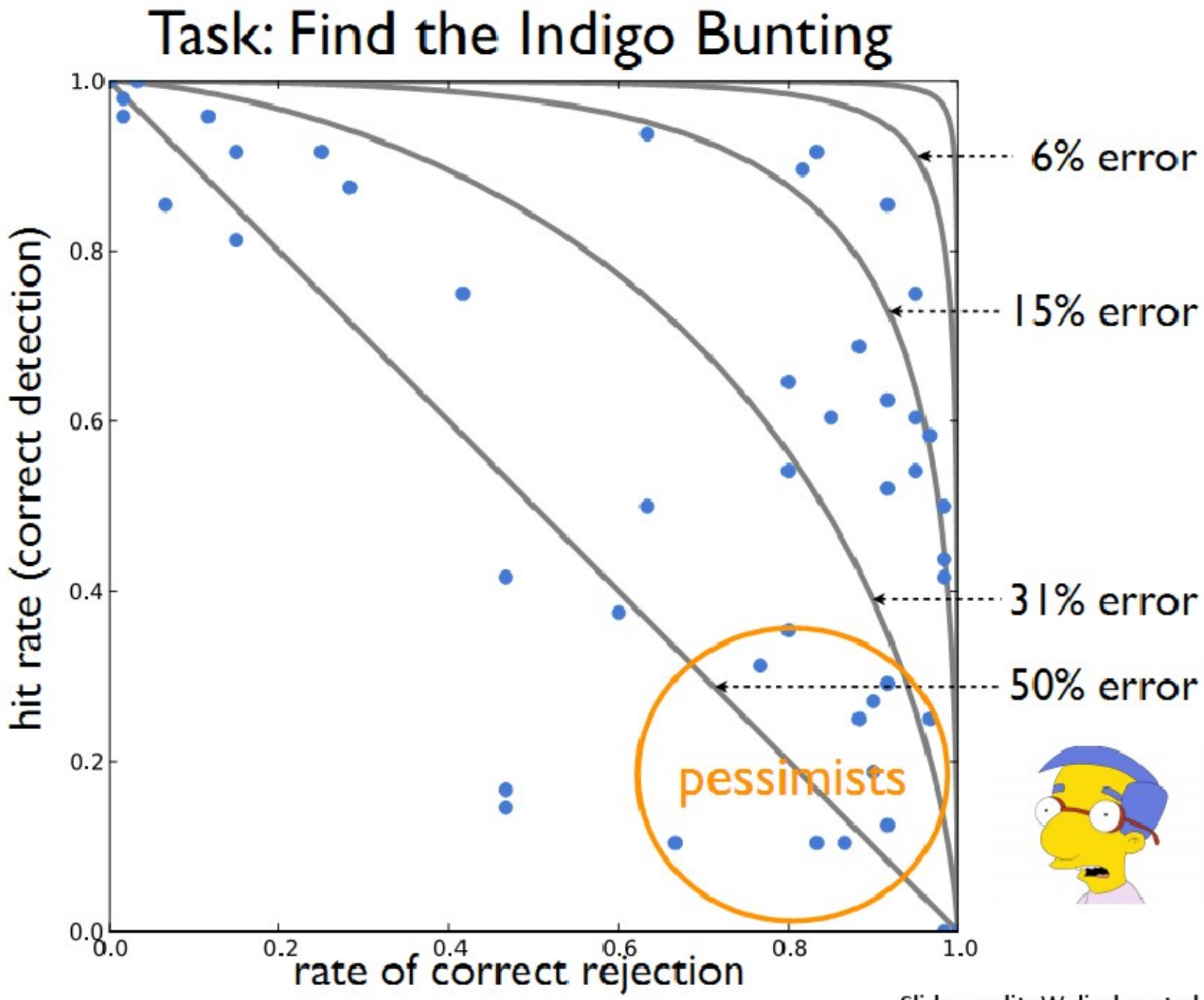
Slide credit: Welinder et al



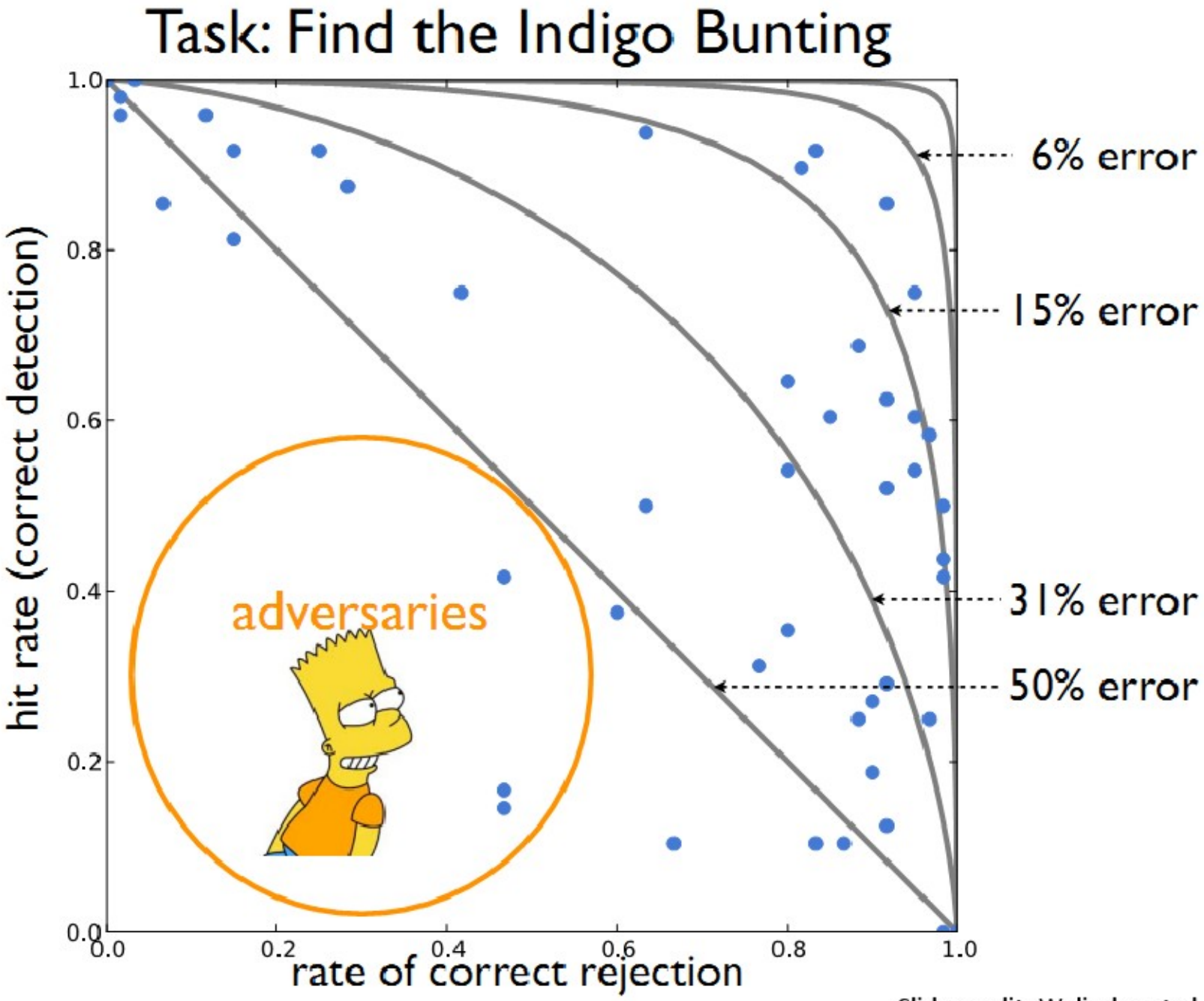
Slide credit: Welinder et al



Slide credit: Welinder et al



Slide credit: Welinder et al



Slide credit: Welinder et al