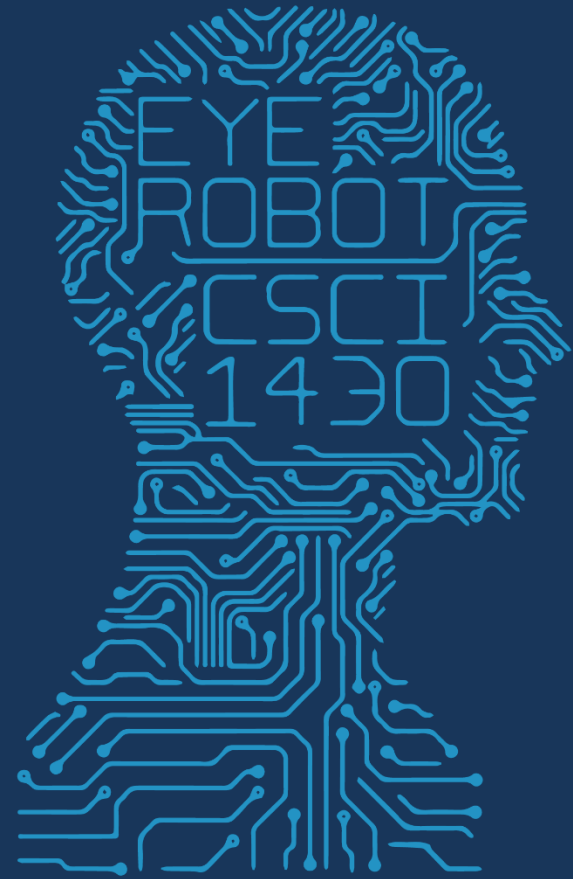




1950

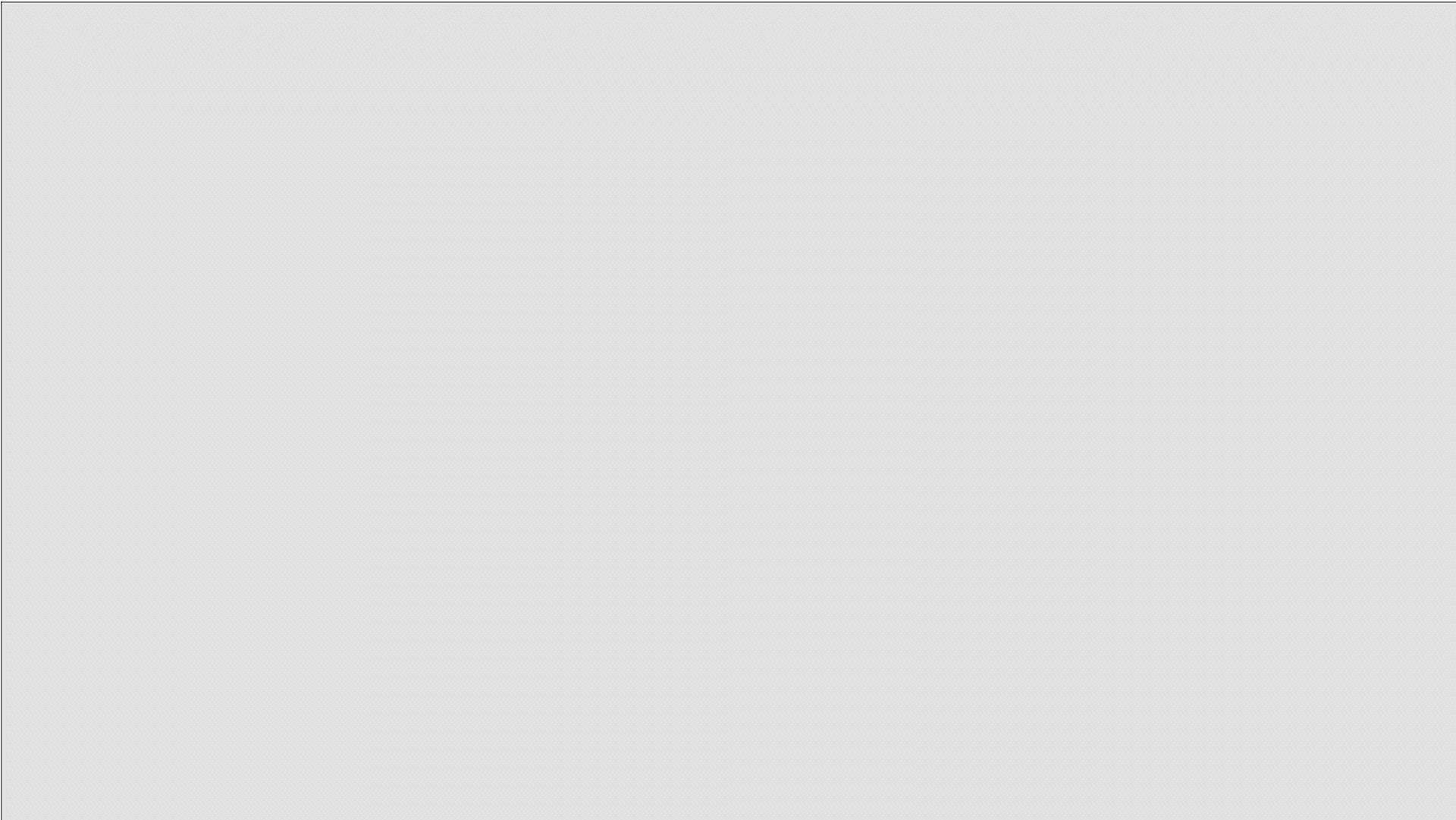
FUTURE VISION



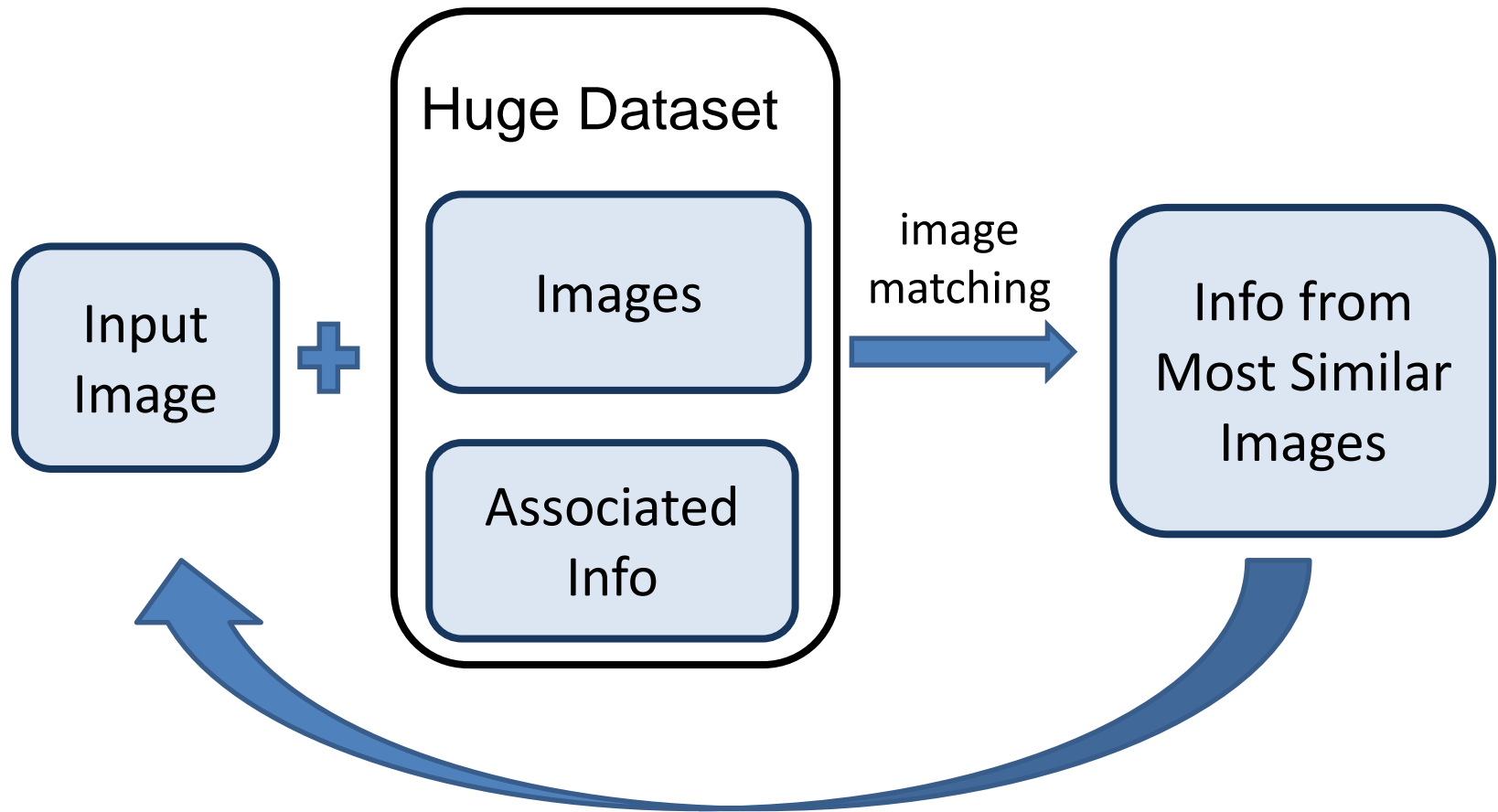
2017 MWF 1PM 368

COMPUTER VISION

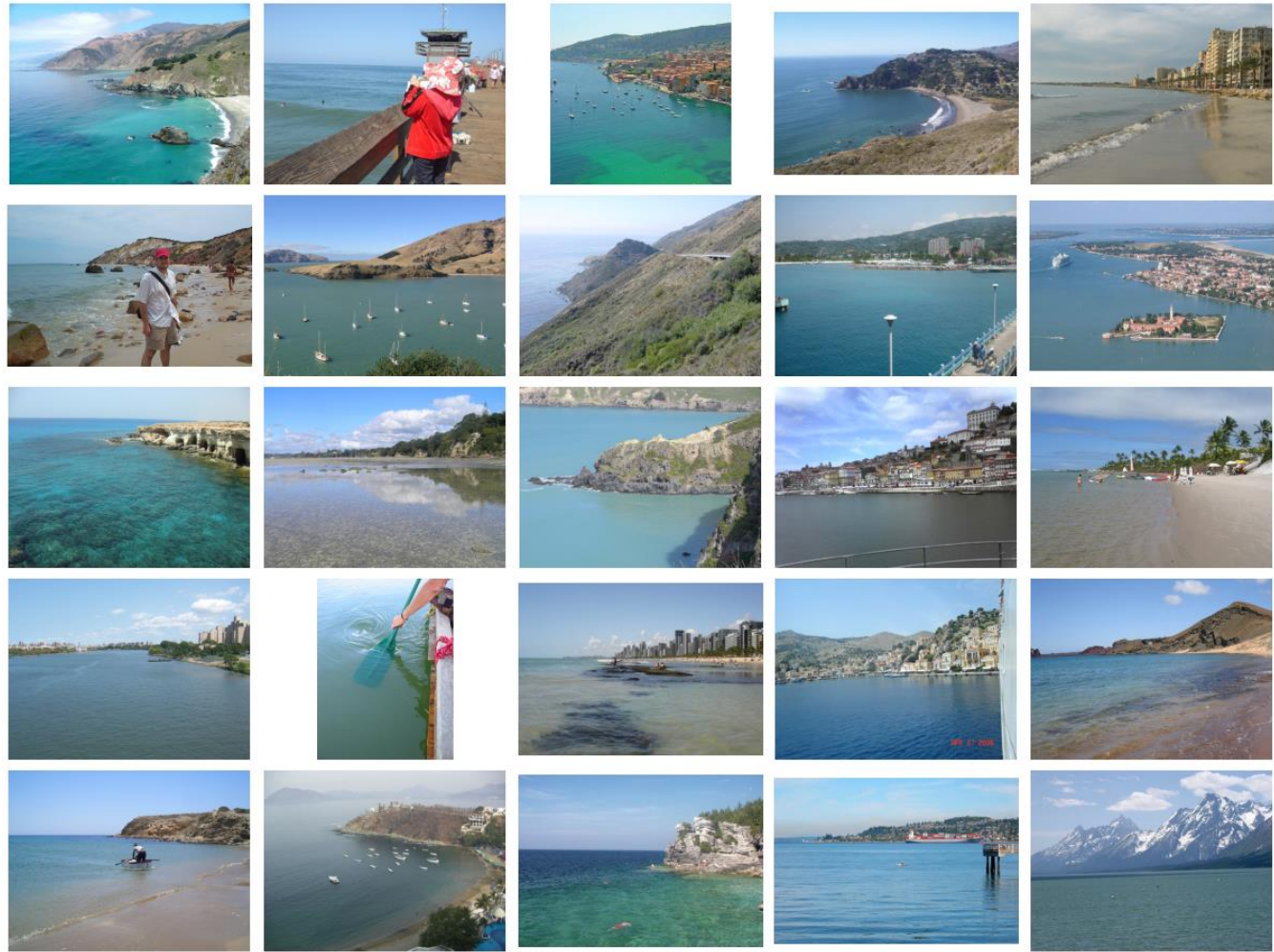
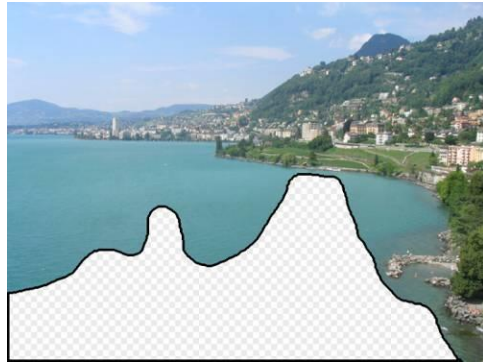




# General Principal



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



... 200 total





Graph cut + Poisson blending

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/>



# 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



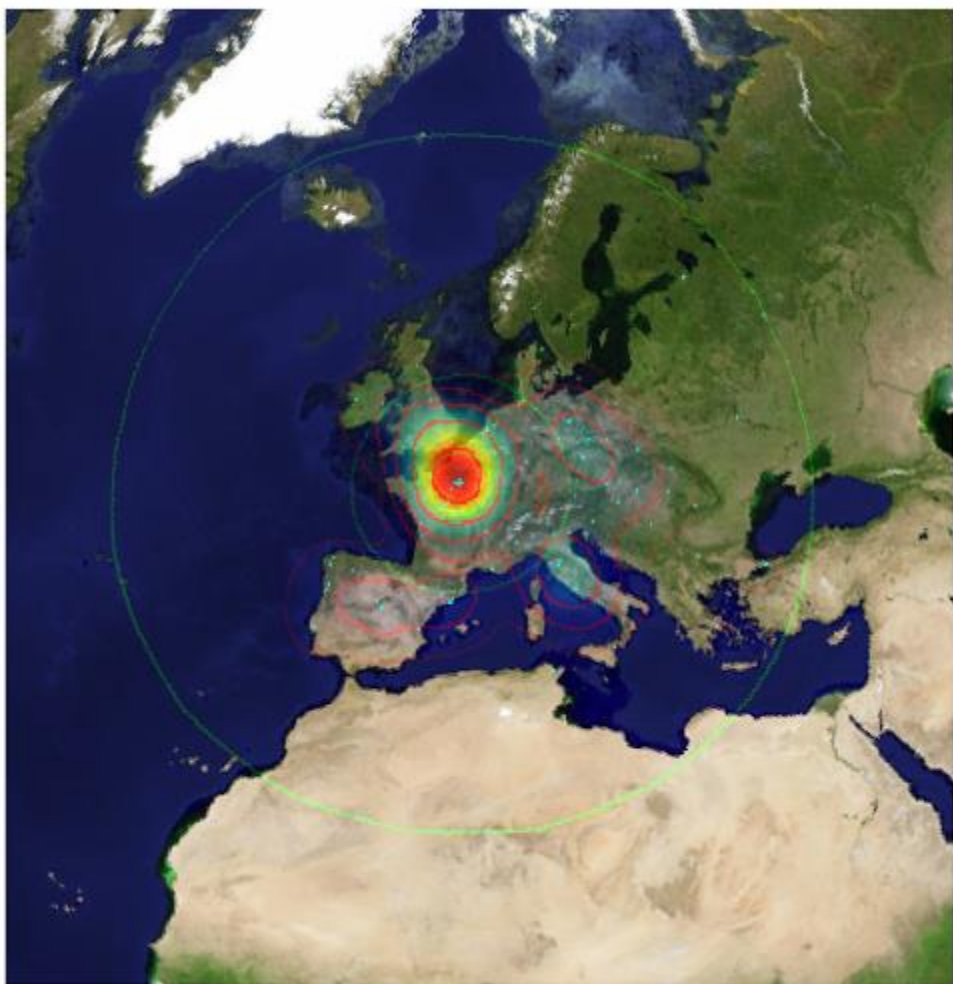
Poland



Paris



Paris





Im2gps



# Example Scene Matches



Madrid



england



France



Paris



Croatia



heidelberg



Macau



Malta



Cairo



Italy



Italy



Italy



Latvia



europe



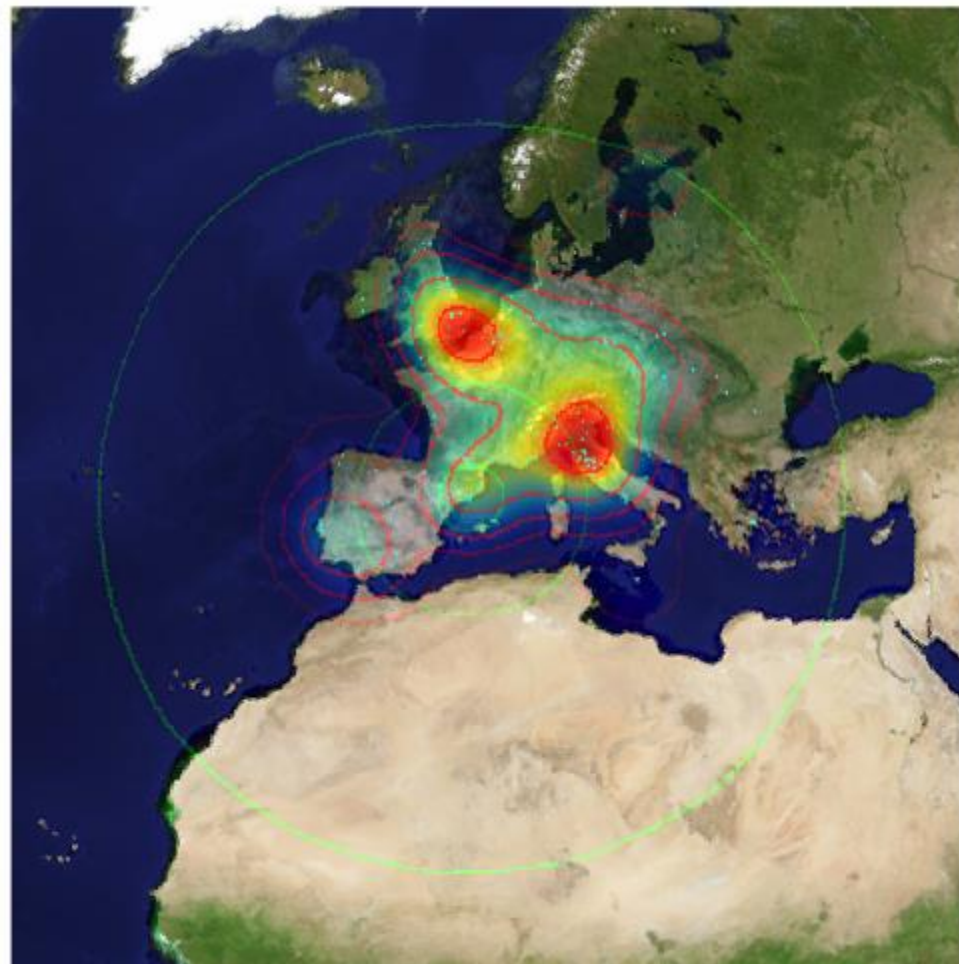
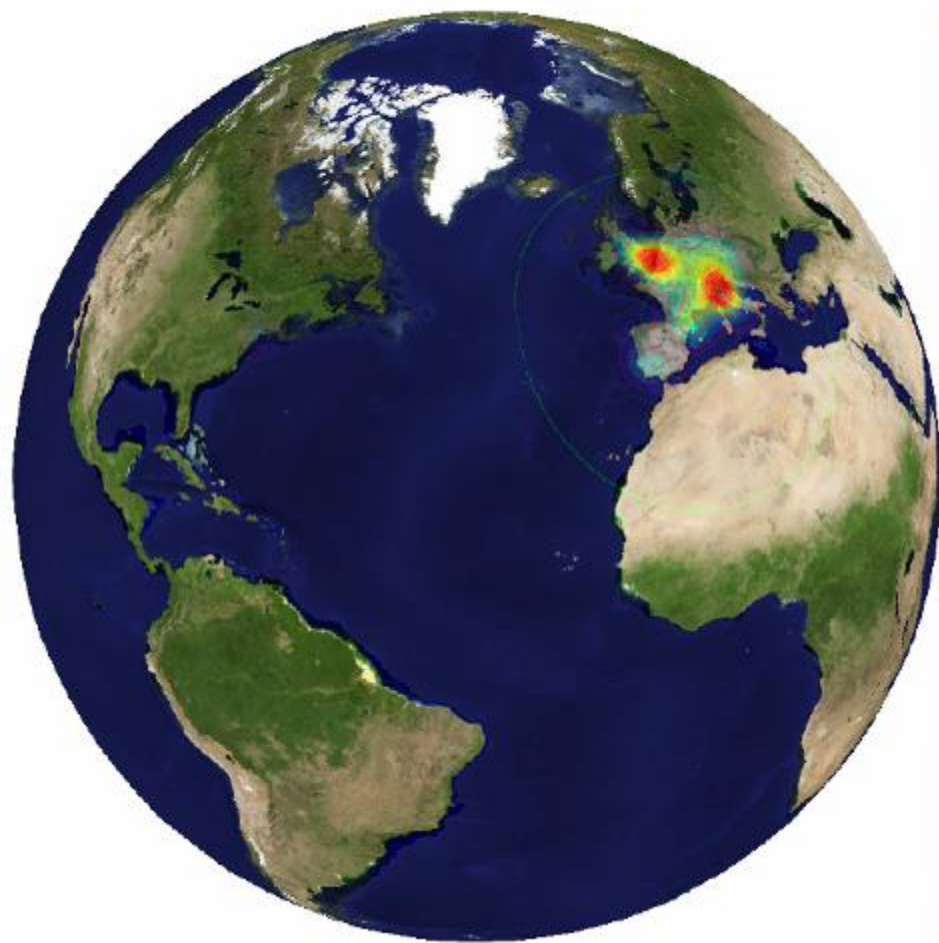
Barcelona



Austria



# Voting Scheme



im2gps







Philippines



Houston



Thailand



Houston



Maldives



Philippines



NewZealand



Bermuda



Palau



Mexico2



Brazil



Mendoza



Brazil



Thailand



Arkansas

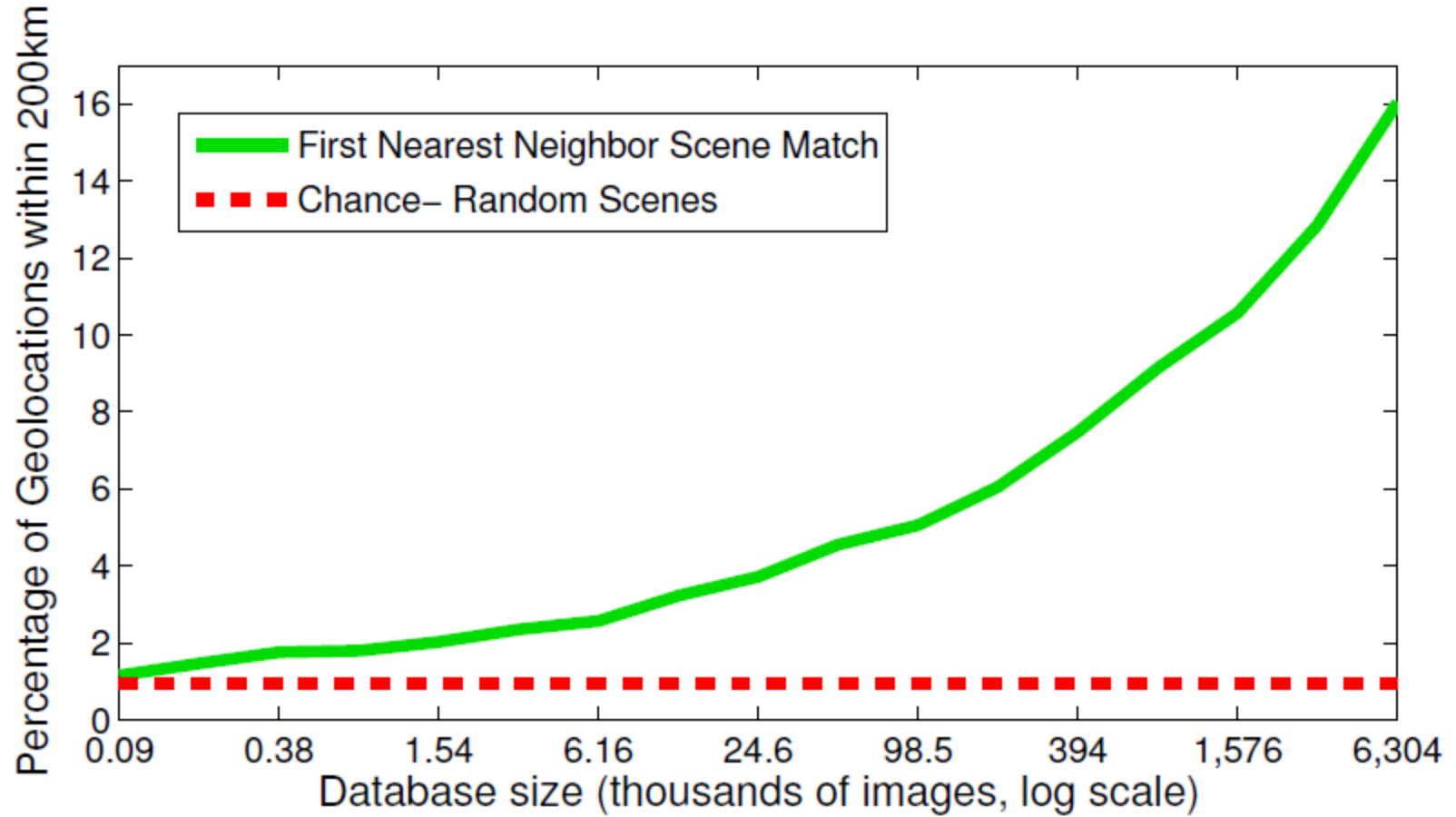


Hawaii





# Effect of Dataset Size



# Where is This?



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

# Where is This?



# Where are These?



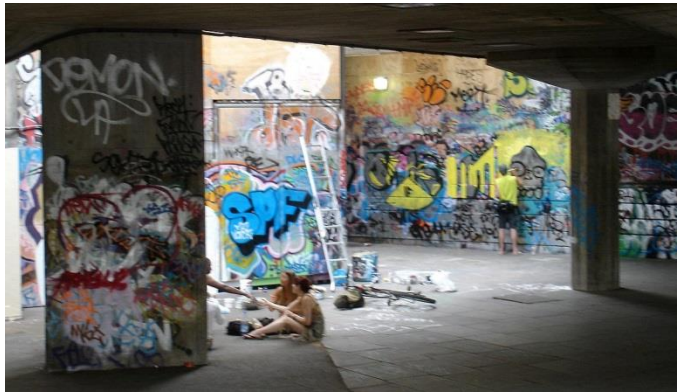
15:14,  
June 18<sup>th</sup>, 2006



16:31,  
June 18<sup>th</sup>, 2006



# Where are These?



15:14,  
June 18<sup>th</sup>, 2006



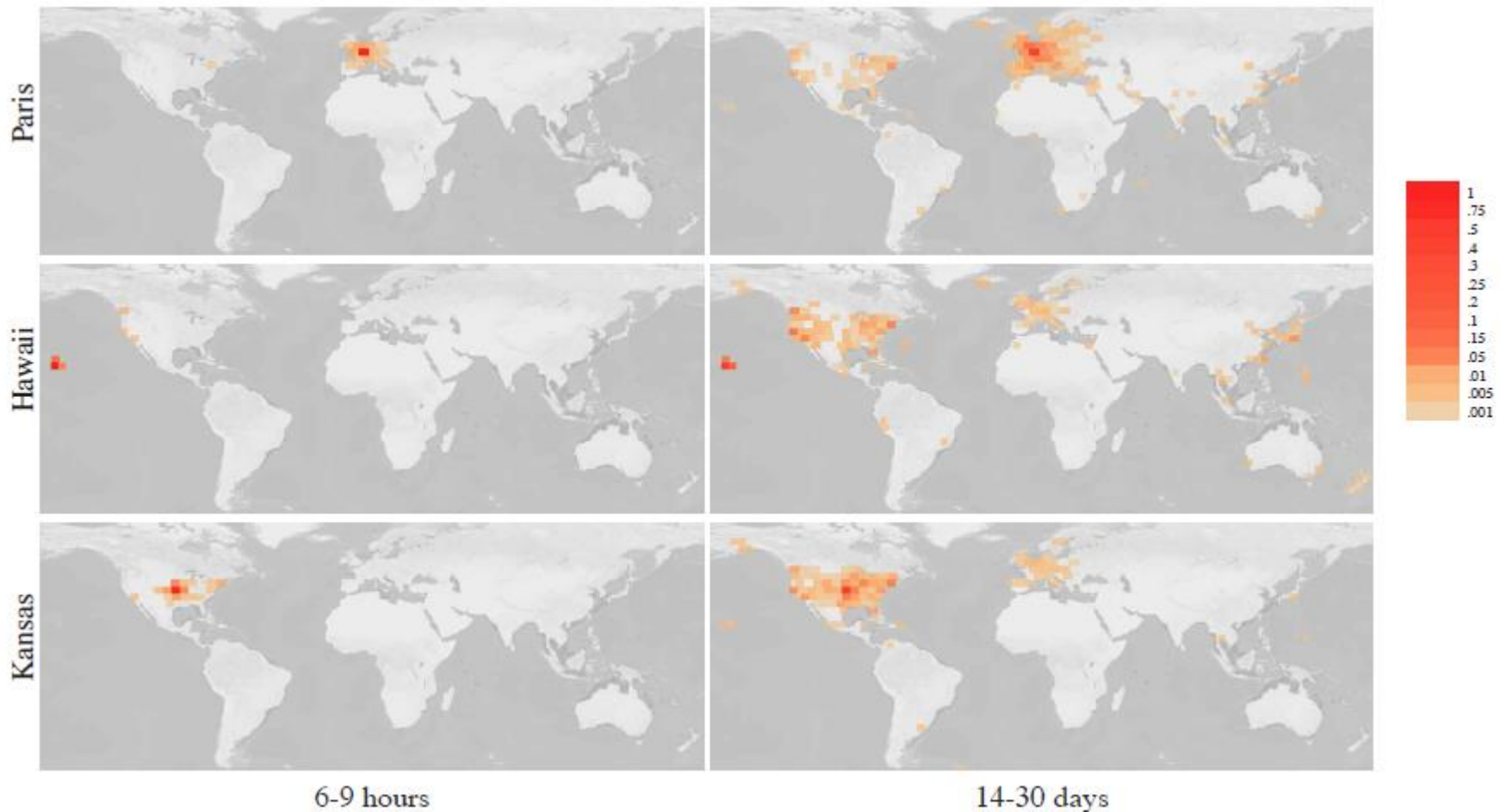
16:31,  
June 18<sup>th</sup>, 2006



17:24,  
June 19<sup>th</sup>, 2006

# Results

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



# Tiny Images



80 million tiny images: a large dataset for non-parametric object and scene recognition

Antonio Torralba, Rob Fergus and William T. Freeman. PAMI 2008.  
<http://groups.csail.mit.edu/vision/TinyImages/>

32x32



000001



000002



000003



000004



256x256



32x32



image\_001

image\_002

image\_003

image\_004

256x256



32x32

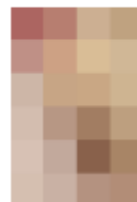
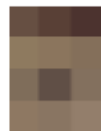


000001

0000

0000 - 000

0000 - 00



256x256



32x32

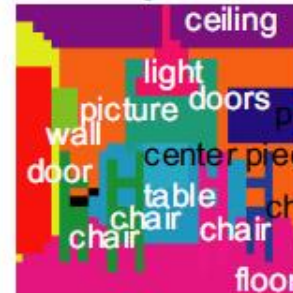
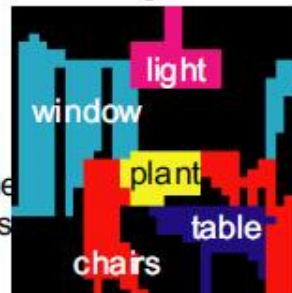
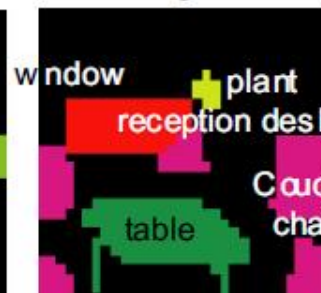
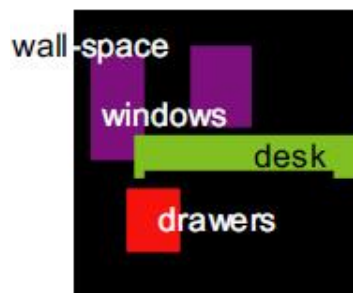


office

waiting area

dining room

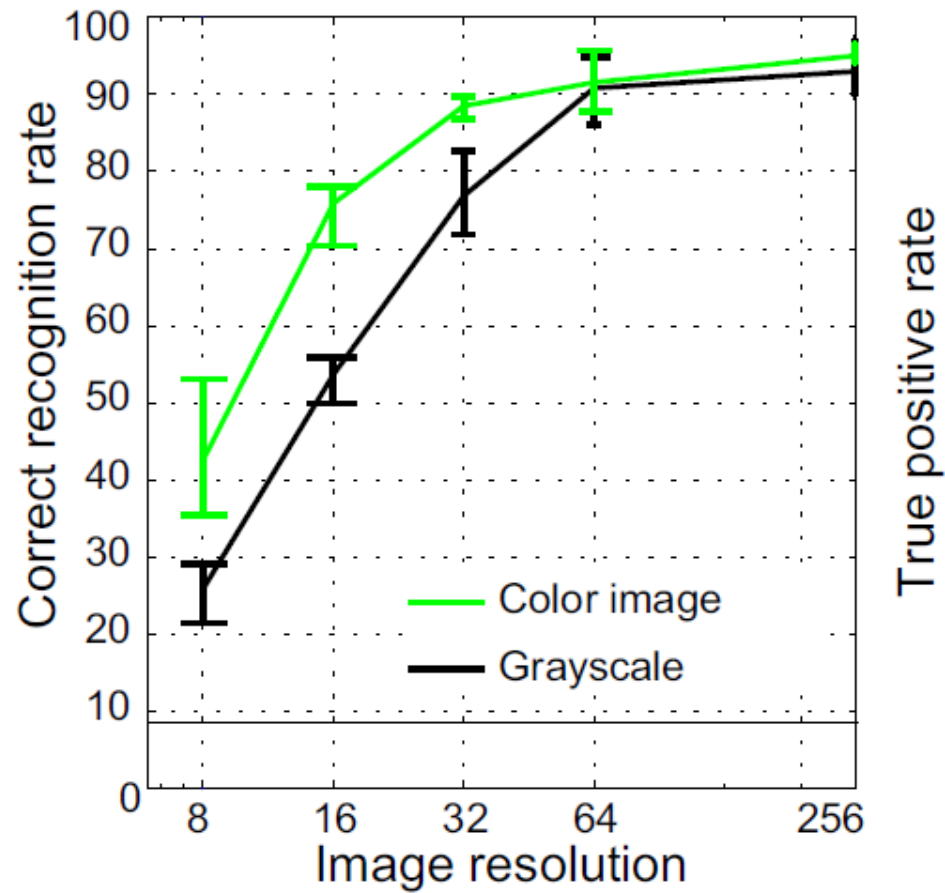
dining room



## c) Segmentation of 32x32 images

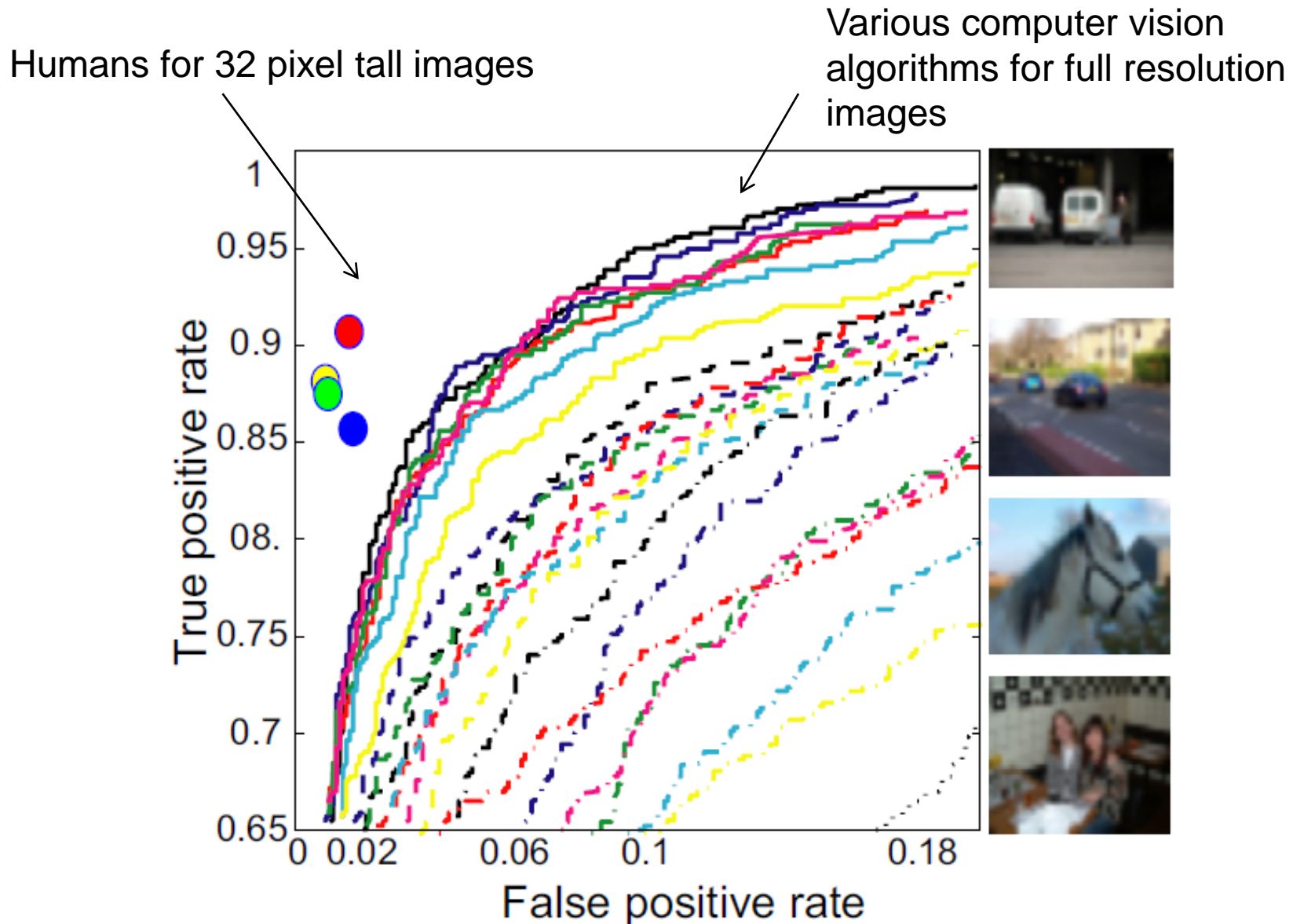


# Human Scene Recognition





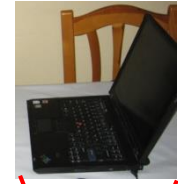
# Humans vs. Computers: Car-Image Classification



# Powers of 10

Number of images on my hard drive:

$10^6$



Number of images seen during my first 10 years:

(3 images/second \* 60 \* 60 \* 16 \* 365 \* 10 = 630,720,000)

$10^8$



Number of images seen by all humanity:

106,456,367,669 humans<sup>1</sup> \* 60 years \* 3 images/second \* 60 \* 60 \* 16 \* 365 =

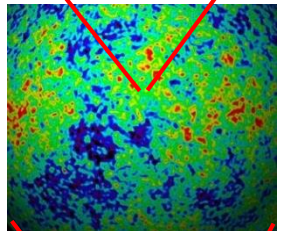
1 from <http://www.prb.org/Articles/2002/HowManyPeopleHaveEverLivedonEarth.aspx>

$10^{20}$



Number of photons in the universe:

$10^{88}$



Number of all 32x32 images:

$256^{32 \times 32 \times 3} \sim 10^{7373}$

$10^{7373}$



# Understanding scenes encompasses all kinds of knowledge





# But not all scenes are so original



# Lots Of Images

Target



7,900





# Lots Of Images

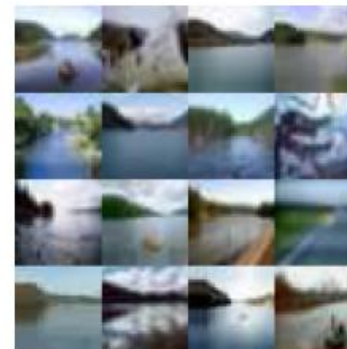
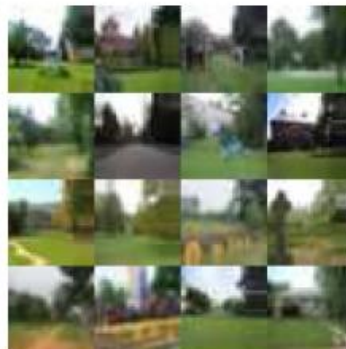
Target



7,900



790,000



# Lots Of Images

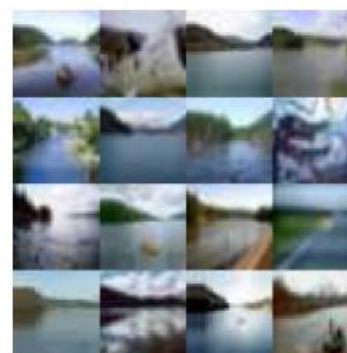
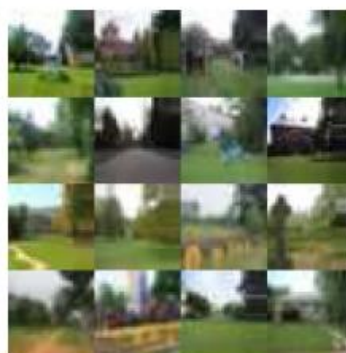
Target



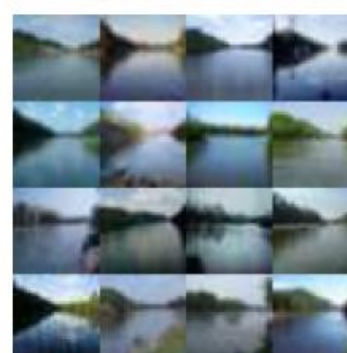
7,900



790,000



79,000,000





# 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

# Short cuts to AI

- With billions of images on the web, it's often possible to find a close nearest neighbor.
- In such cases, we can shortcut hard problems by “looking up” the answer, stealing the labels from our nearest neighbor.



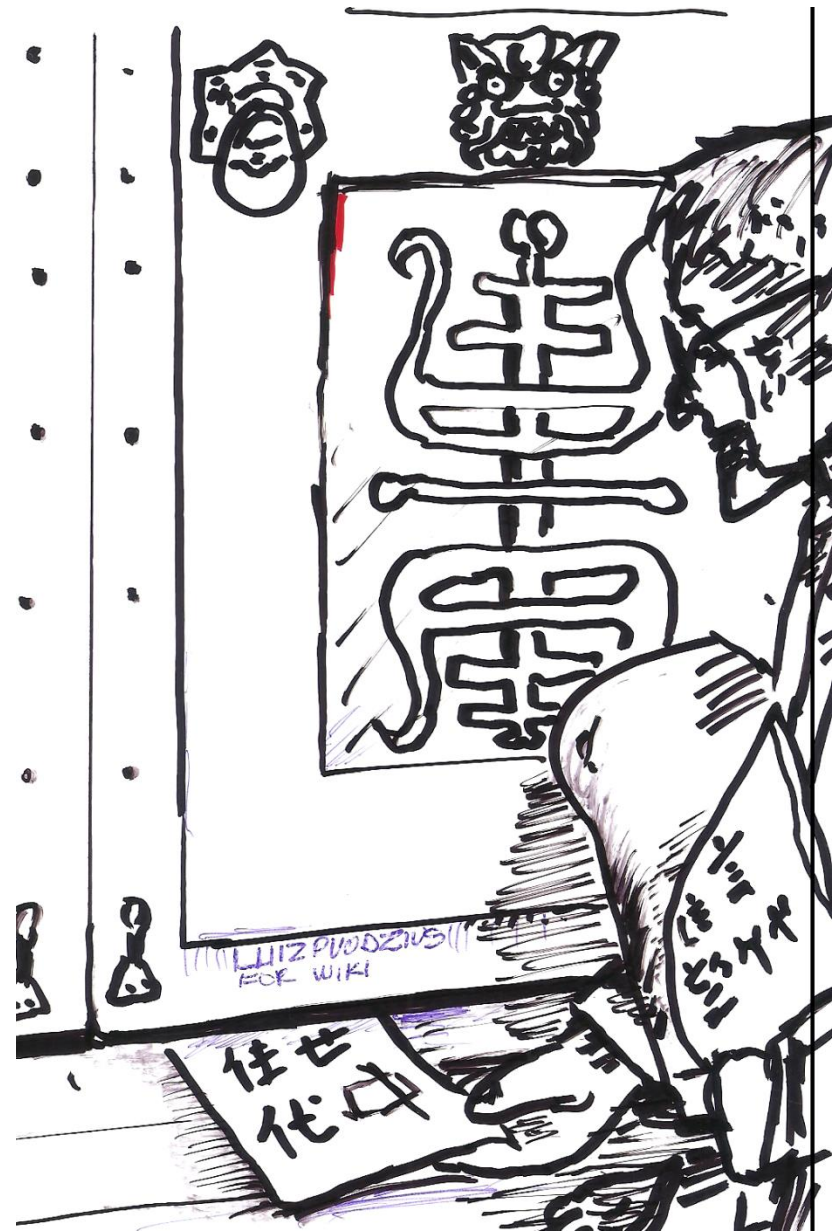
# So what is intelligence?

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

Strong AI: The simulation of a 'mind' is a 'mind'.



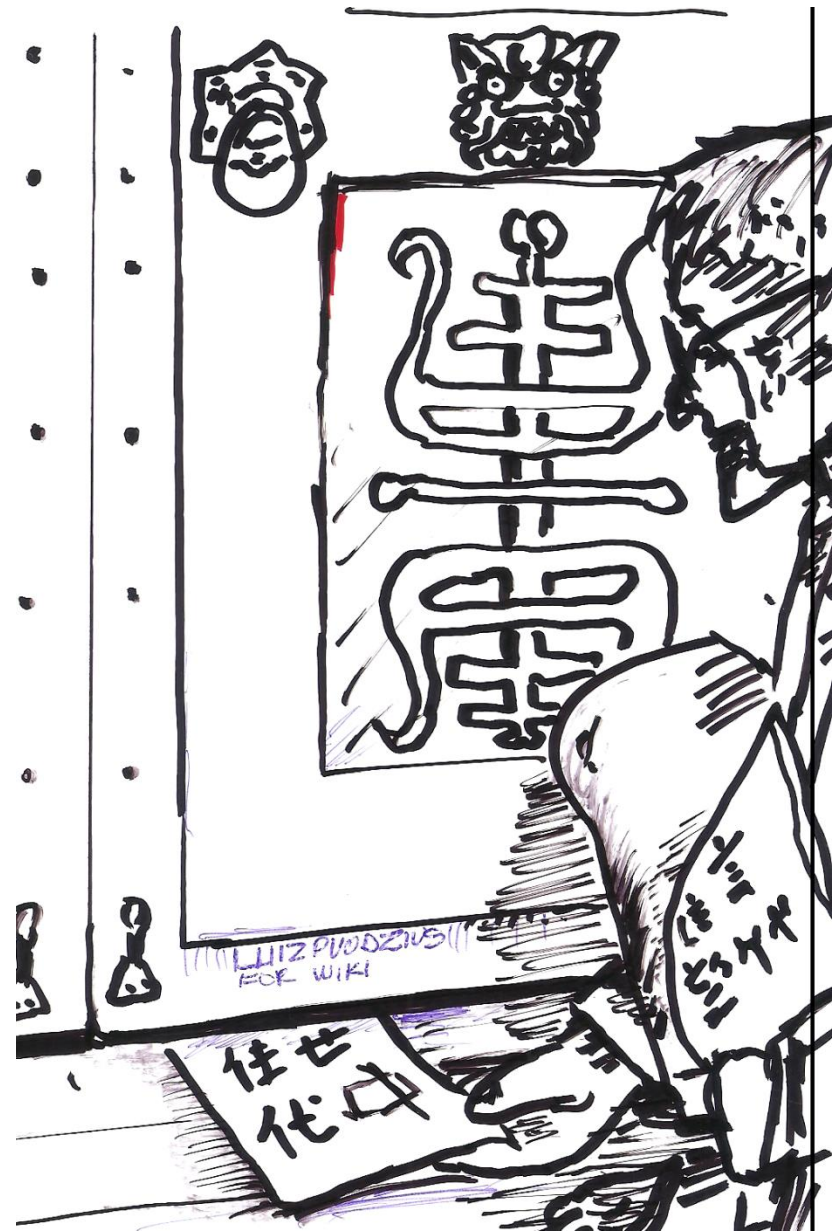
# Chinese Room, John Searle (1980)



# 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](http://BIGQUESTIONSONLINE.COM) | BY DON HOWARD



You and 156 others

30 Comments 20 Shares



Like



Comment

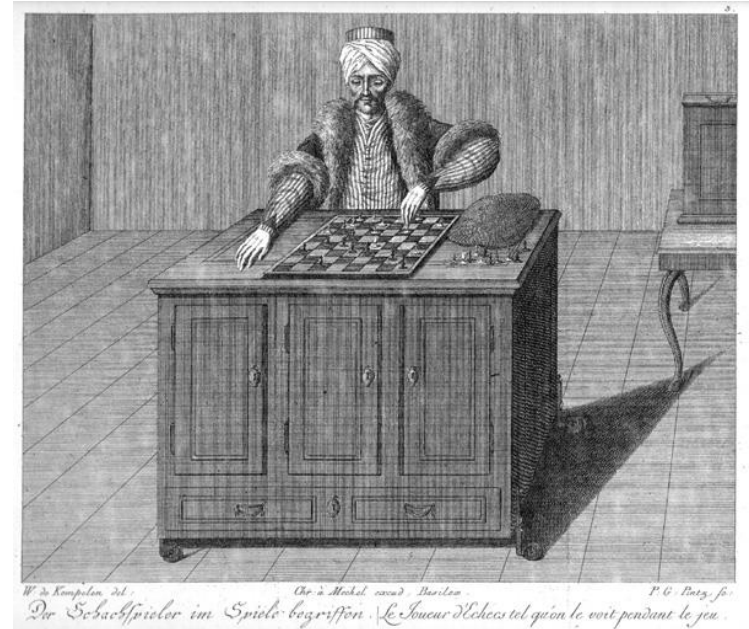


Share



# Mechanical Turk

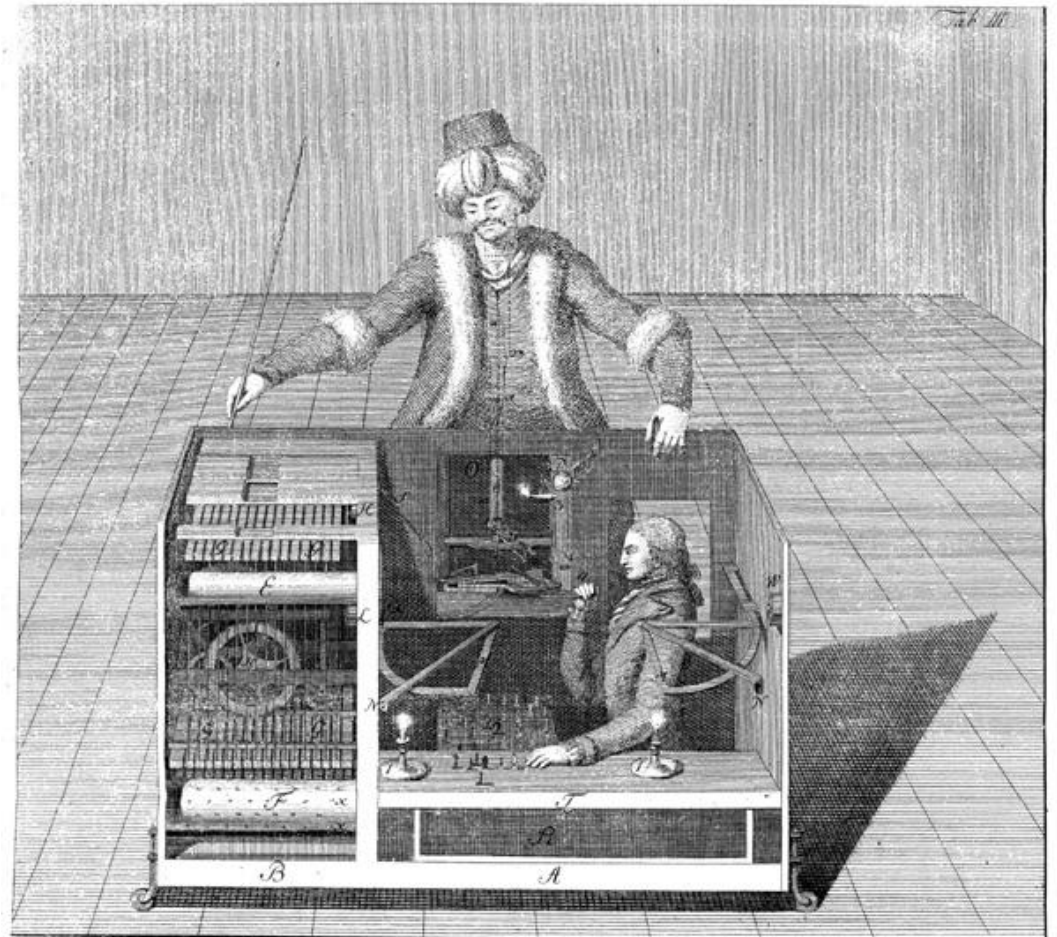
- von Kempelen, 1770.
- Robotic chess player.
- Clockwork routines.
- Magnetic induction (not vision)
- Toured the world; played Napoleon Bonaparte and Benjamin Franklin.





# Mechanical Turk

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



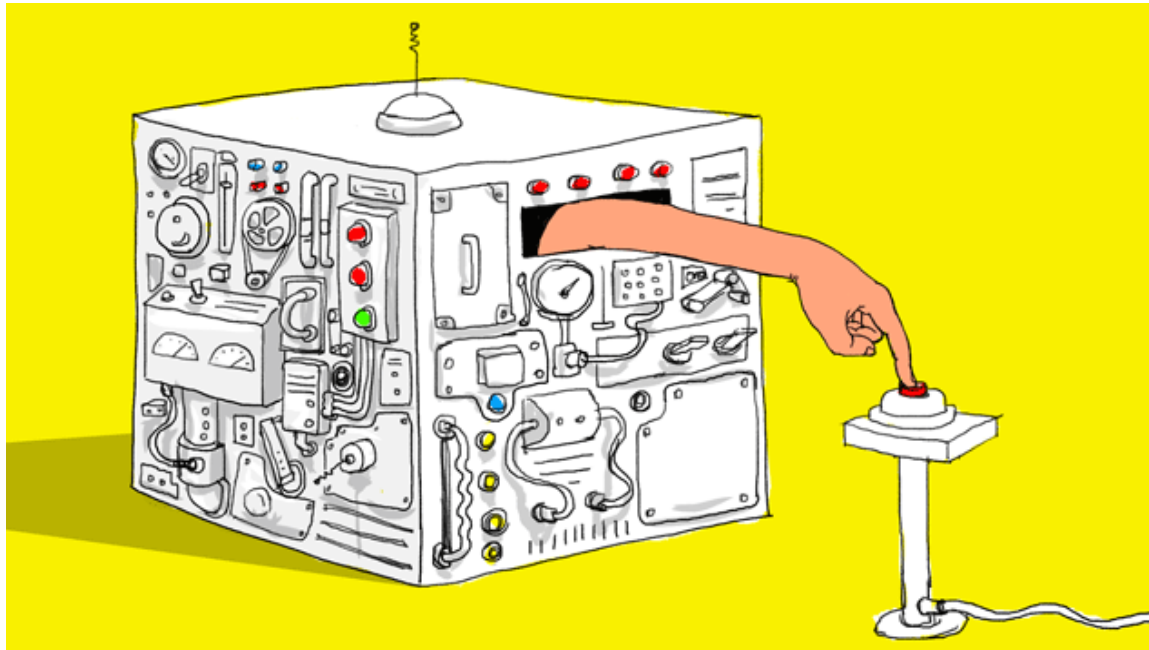
# Amazon Mechanical Turk

*Artificial artificial intelligence.*

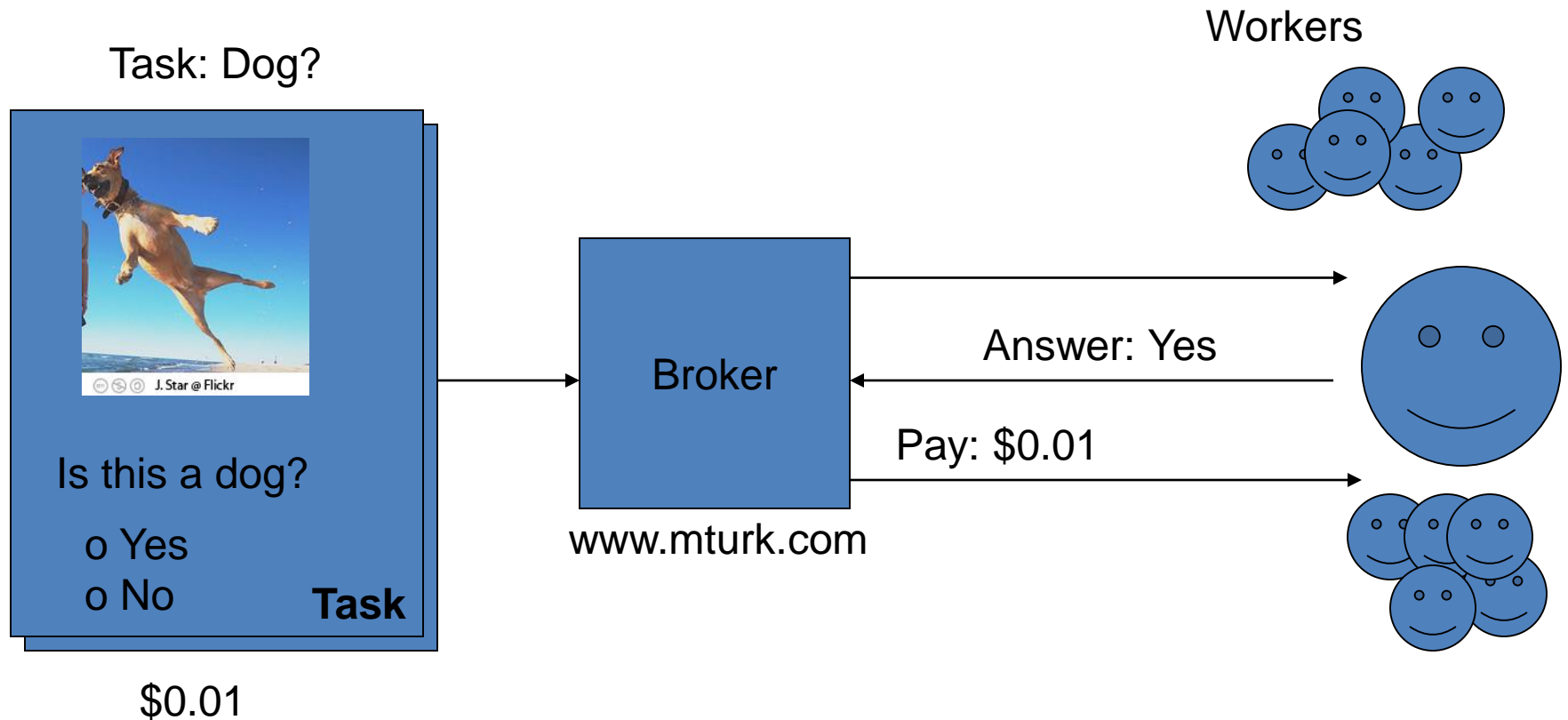
Launched 2005.

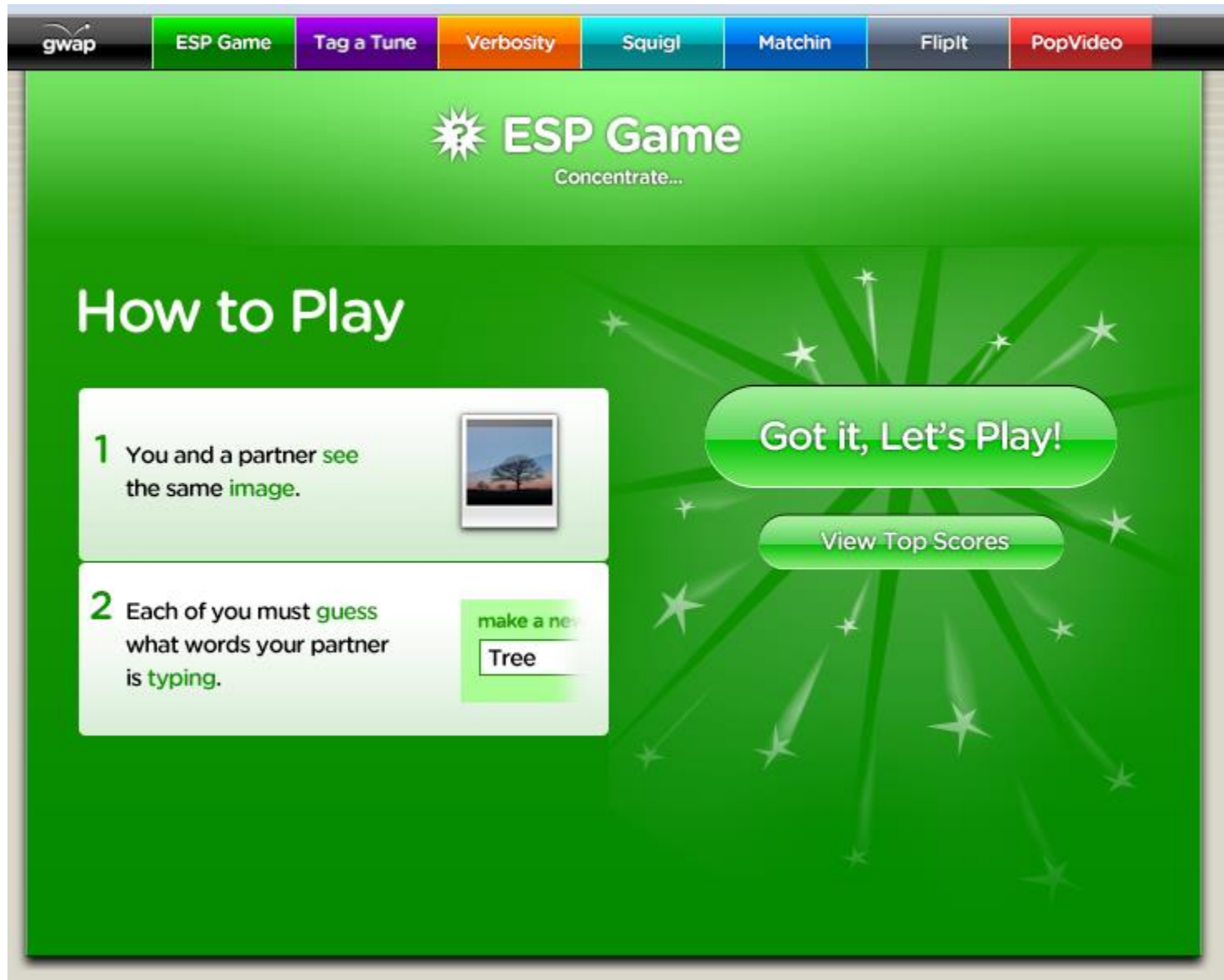
Small tasks, small pay.

Used extensively in data collection.



# Amazon Mechanical Turk





Luis von Ahn and Laura Dabbish. [Labeling Images with a Computer Game](#).  
ACM Conf. on Human Factors in Computing Systems, CHI 2004



score

0



ESP Game

Concentrate...

time

2:56

What do you see?

taboo words

student



Play Anonymously

guesses

+ submit

→ pass

# 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>

# Utility data annotation via Amazon Mechanical Turk



$$\times 100\,000 = \$5000$$

Alexander Sorokin

David Forsyth

CVPR Workshops 2008

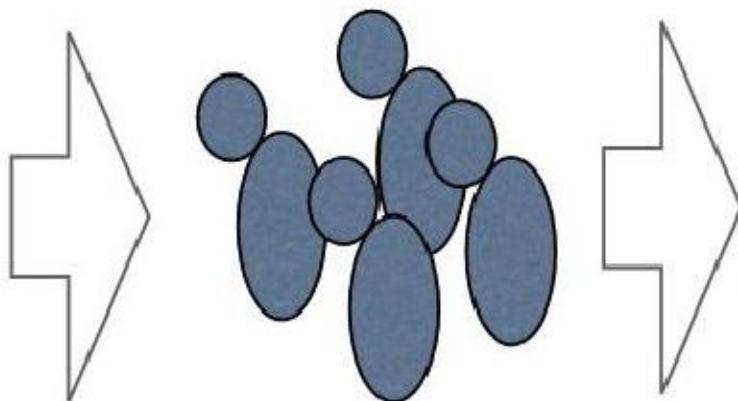
Slides by Alexander Sorokin

6000 images  
from flickr.com



# Building datasets

Annotators



amazon **mechanical turk**  
beta Artificial Intelligence

Is there an Indigo bunting in the image?

100s of  
training images

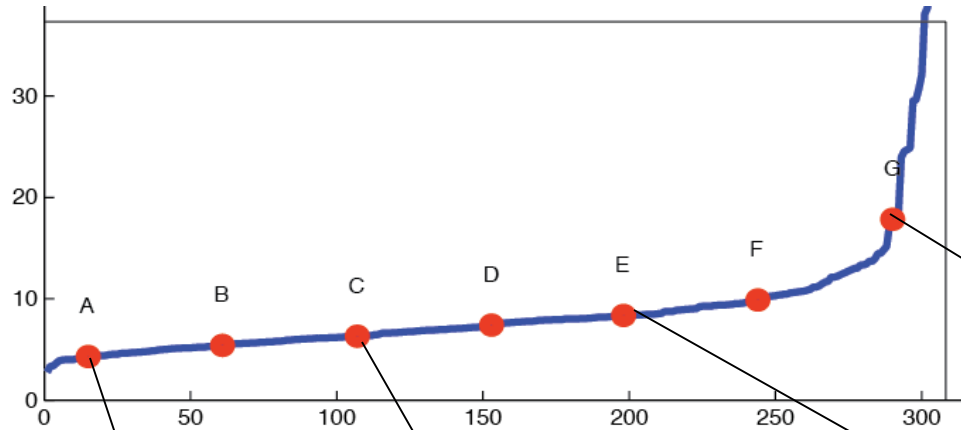




# Issues

- Quality?
  - How good is it?
  - How to be sure?
- Price?
  - Trade off between throughput and cost
    - *NOT* as much of a trade off with quality
  - Higher pay can actually attract scammers

# Annotation quality



Agree within 5-10 pixels  
on 500x500 screen

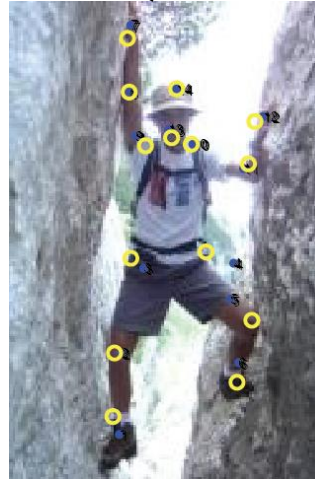
There are bad ones.



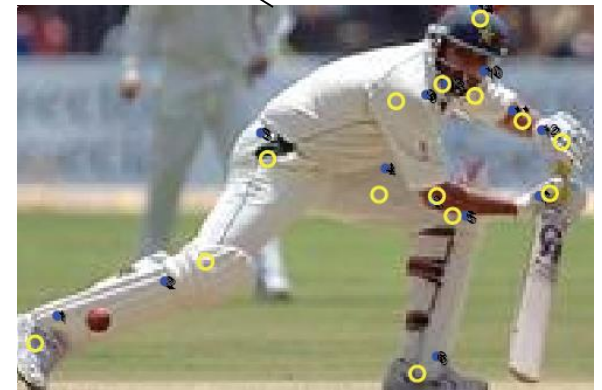
A



C



E

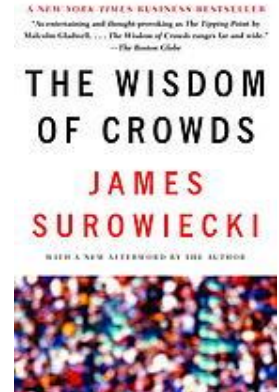


G

# Ensuring Annotation Quality

- Consensus / Multiple Annotation / “Wisdom of the Crowds”

Not enough on its own, but widely used



- Gold Standard / Sentinel

— Special case: qualification exam

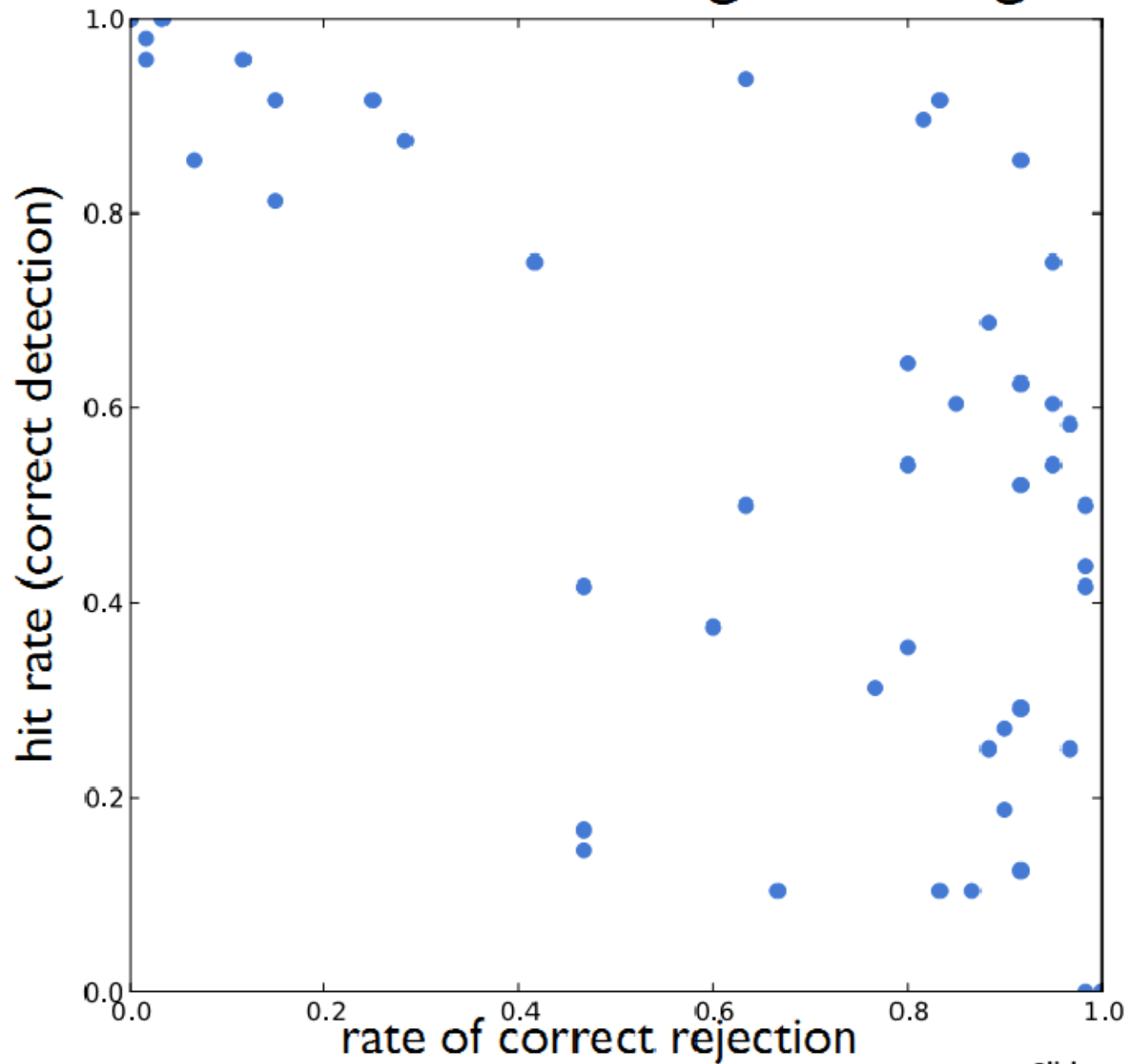
Widely used and most important. Find good annotators and keep them honest.

- Grading Tasks

— A second tier of workers who grade others

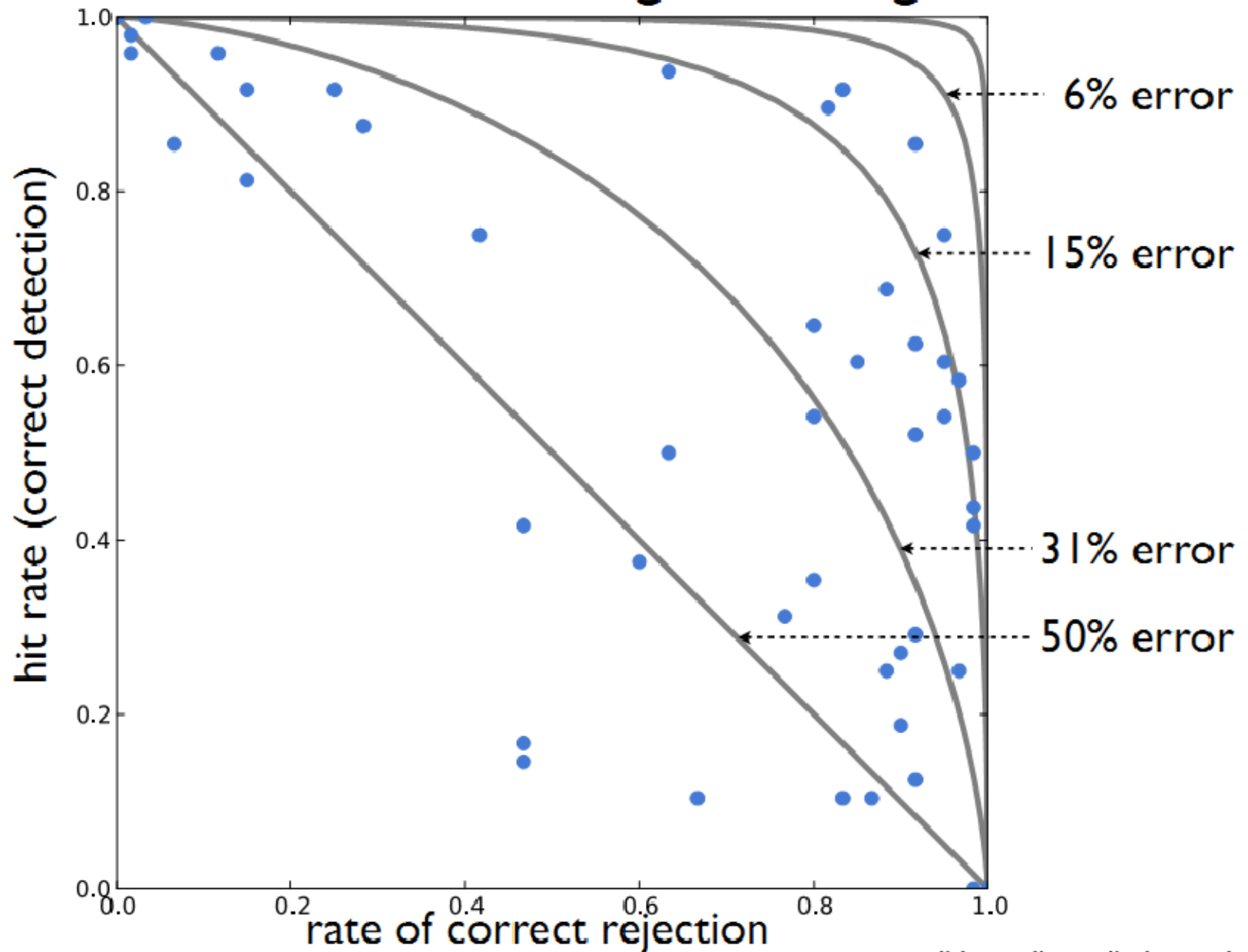
Not widely used

# Task: Find the Indigo Bunting

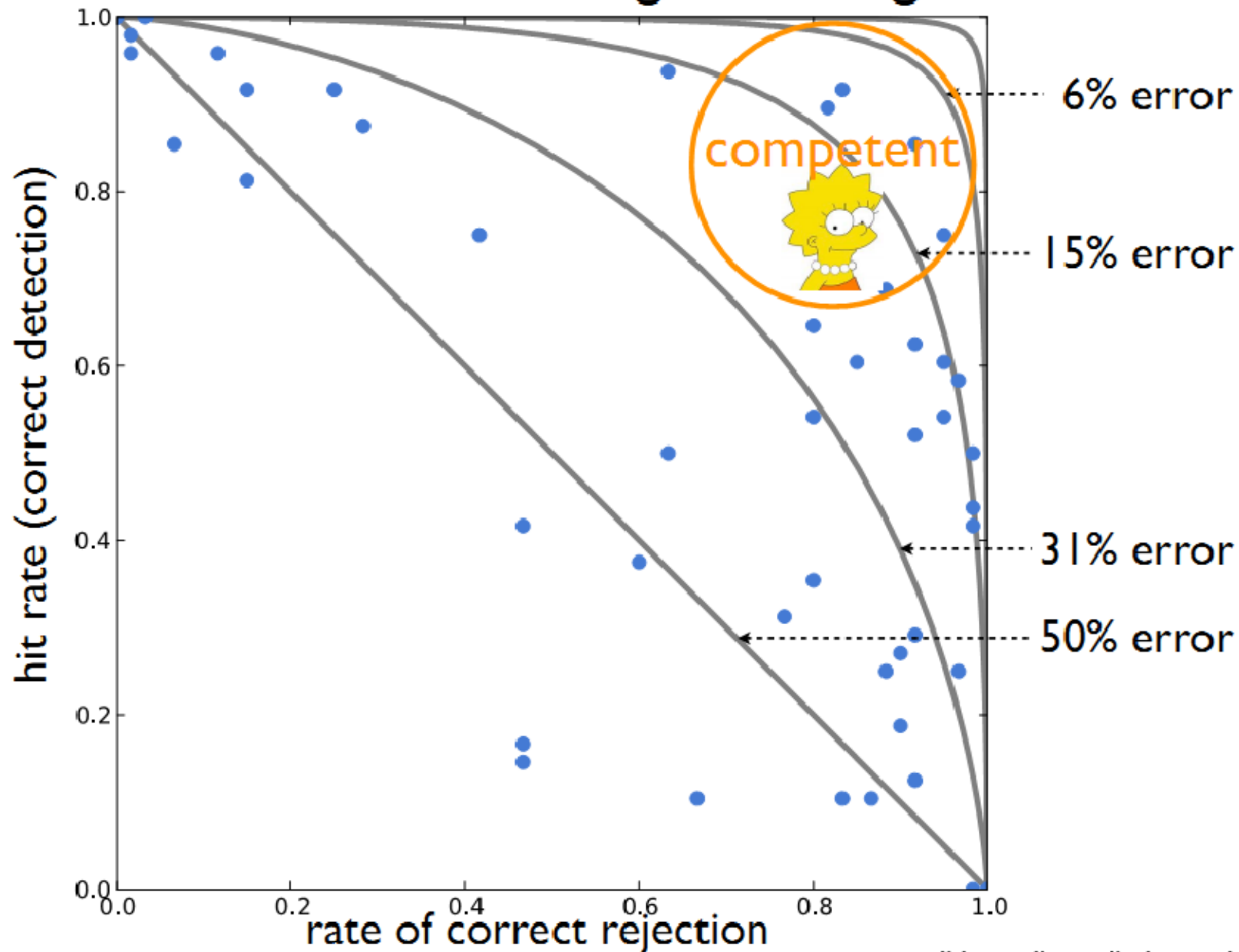




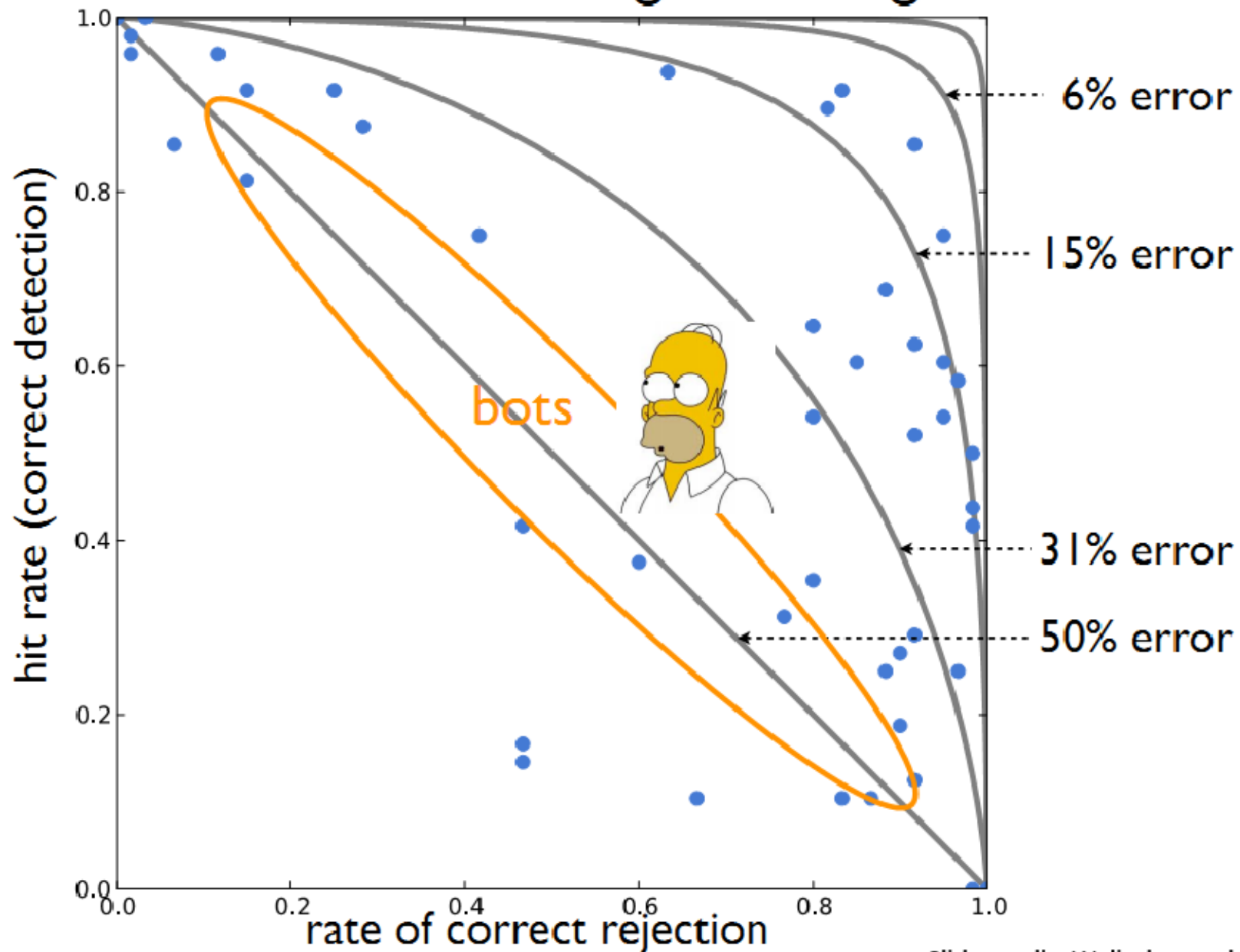
# Task: Find the Indigo Bunting



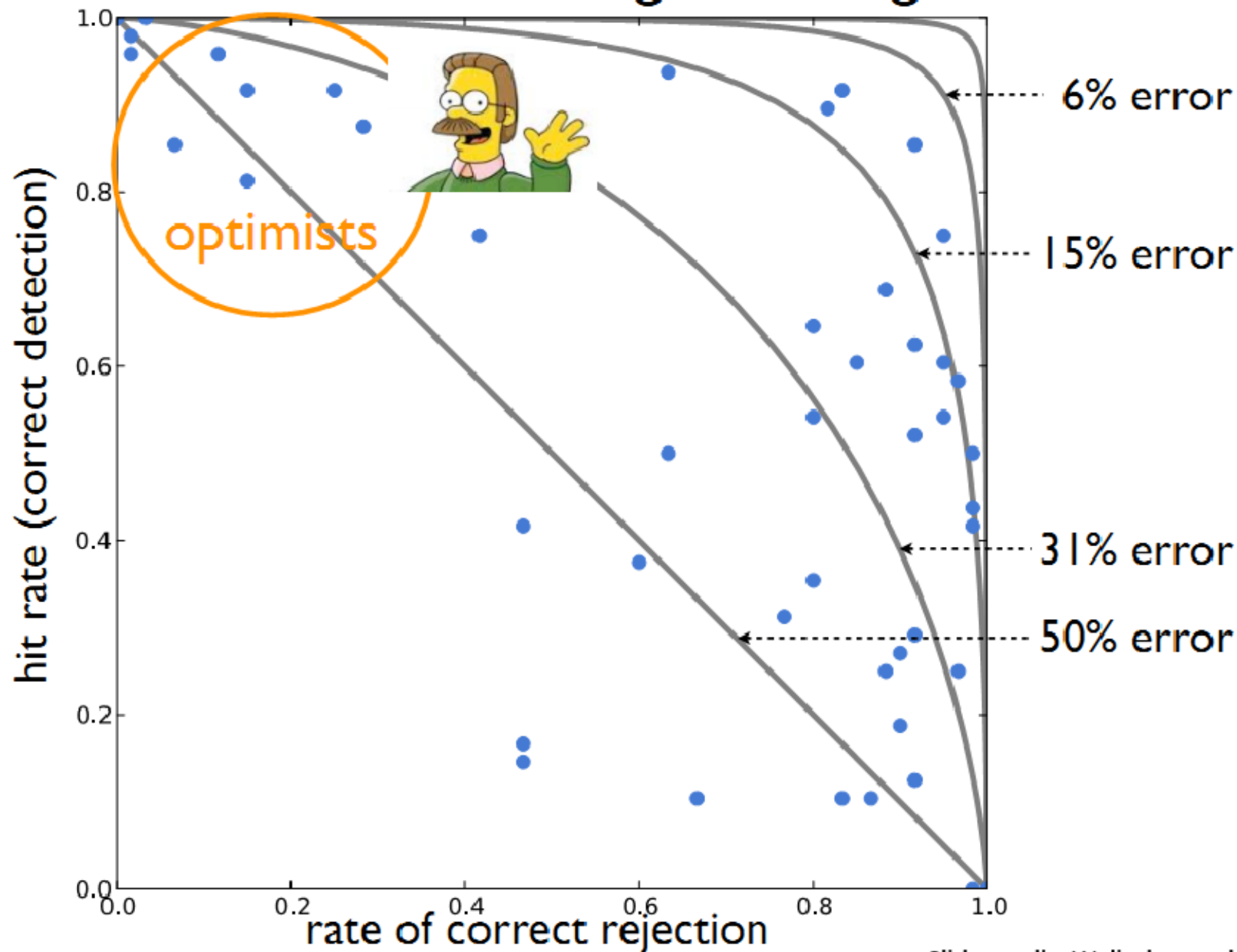
# Task: Find the Indigo Bunting



# Task: Find the Indigo Bunting

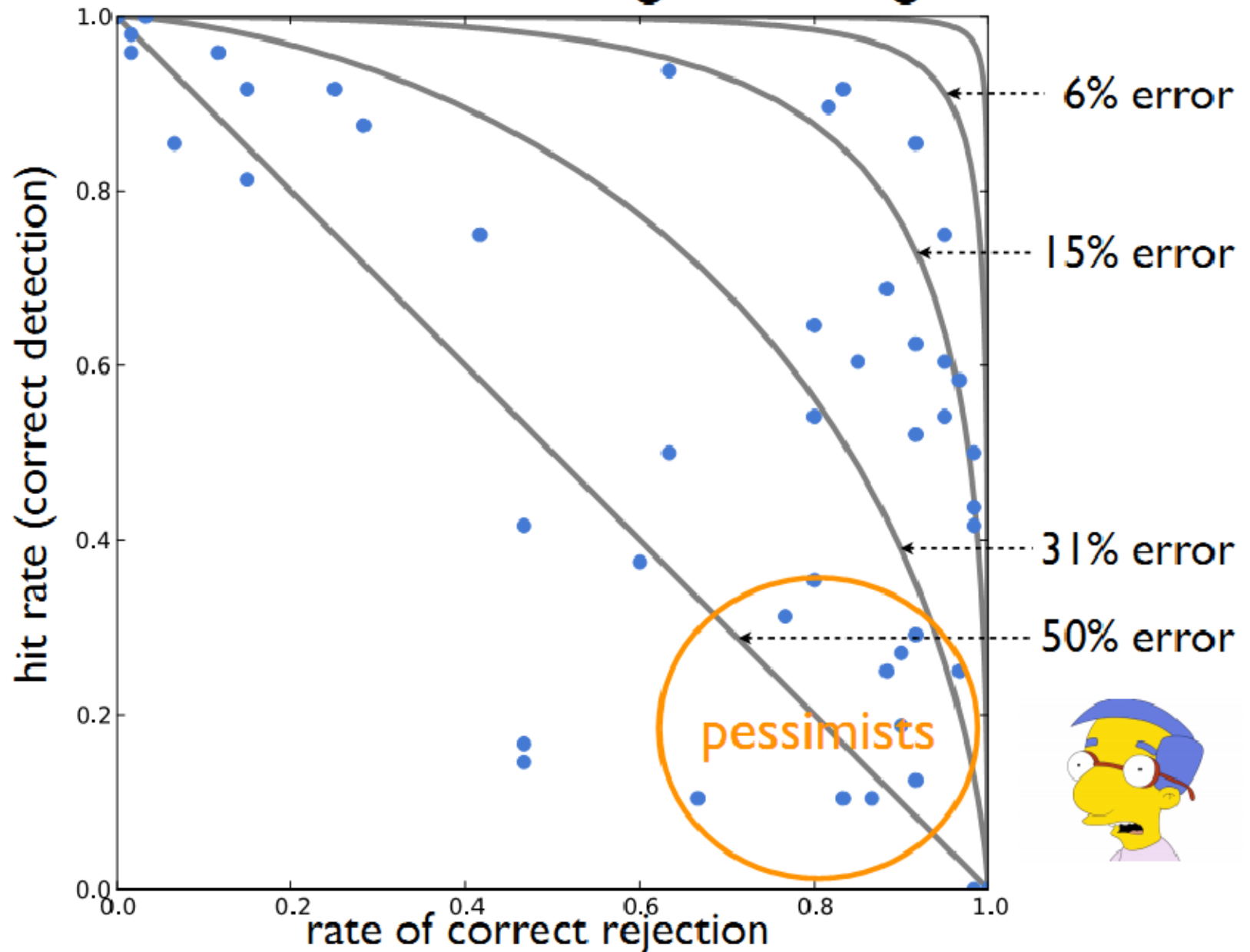


# Task: Find the Indigo Bunting

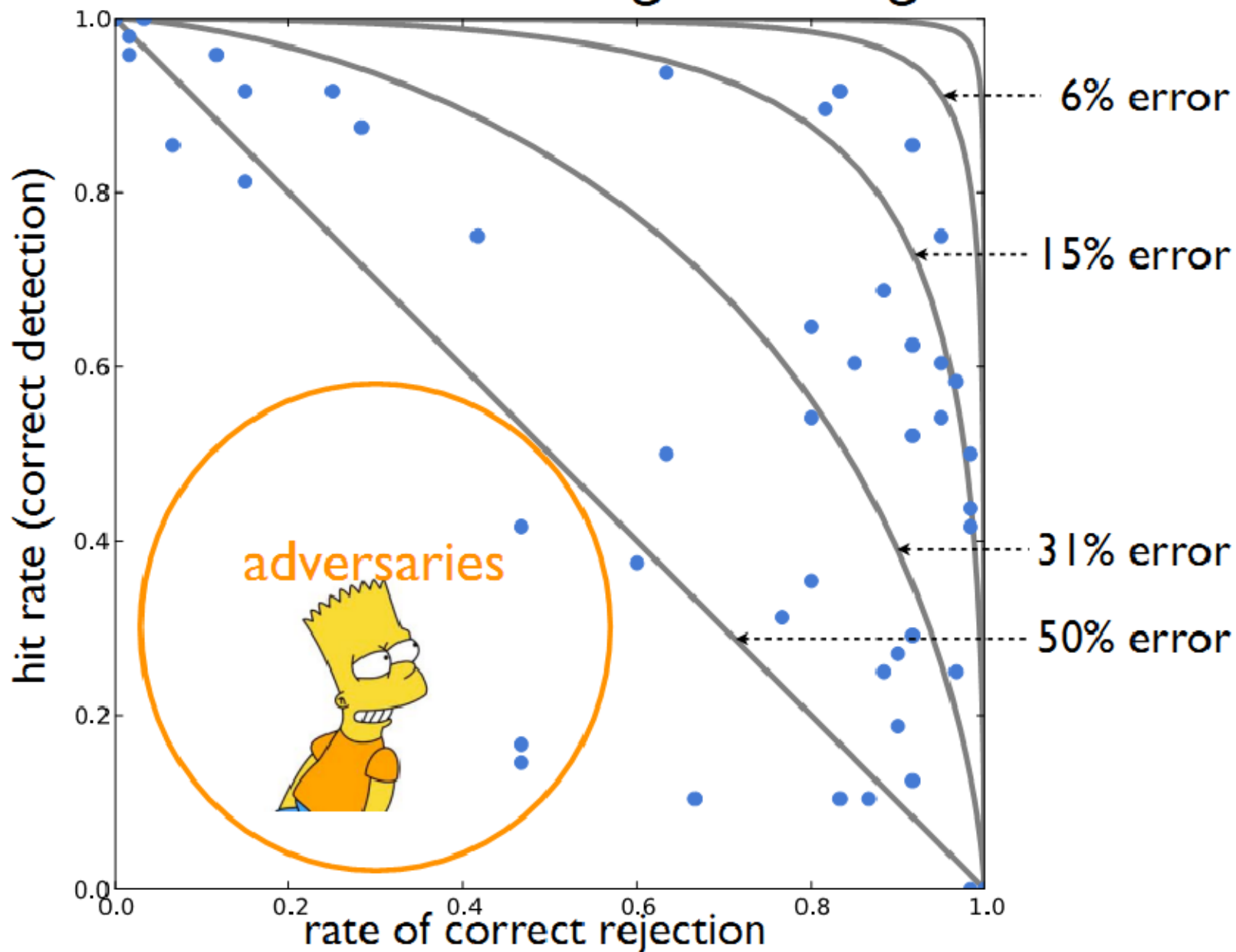




# Task: Find the Indigo Bunting



# Task: Find the Indigo Bunting



## Search

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Everyone's Uploads

indigo bunting

SEARCH

[Full Text](#) | [Tags Only](#)  
[Advanced Search](#)

Sort: **Relevant** [Recent](#) [Interesting](#)

View: **Small** [Medium](#) [Detail](#)



From Steve...



From dwaynejava



From OwmenSA



From Steve...



From Jim Adams...



From Jim Adams...



From owleblood



From Dave&...



From Captain...



From tomelizab...



From jeffcrafter



From dwaynejava



From hart\_curt



From dwaynejava



From Bird Man...



From KirkH1



From Dave 2x



From Dave 2x



From Dave 2x



From KirkH1



From Dave&...



From Buzzle82



From tomelizab...



From iceberg\_c...



From tanagertgirl



From Dan and...



From dmarshman



From Bird Man...



From Birds&...



From Dave 2x



From Christian...



From Dan and...



From MomOnTheR...



From MoGov



From kenh571



From DansPhotoArt