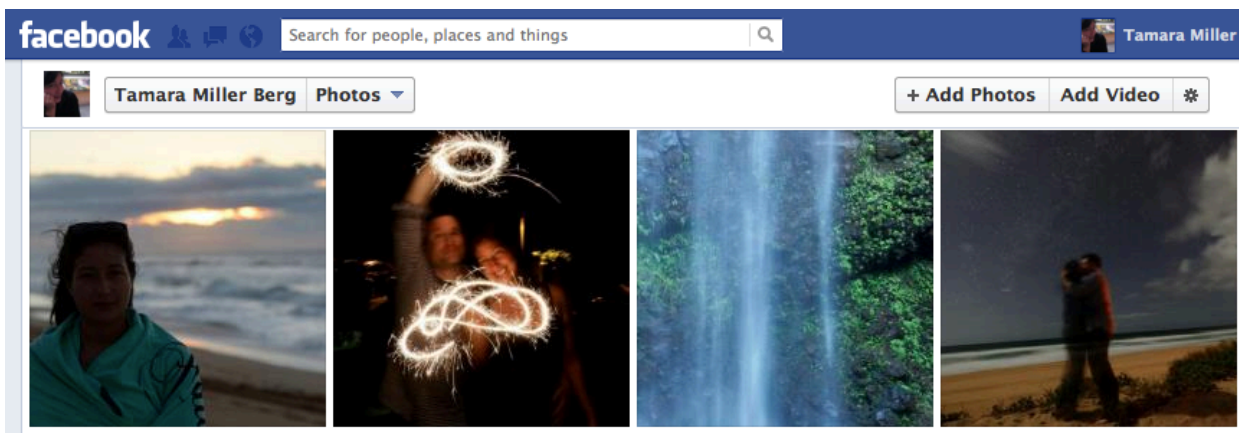


Computer Vision

Tamara Berg

Why computer vision?



100 billion – [Estimated](#) number of photos on Facebook, mid-2011.



40 million – Photos [uploaded](#) per day to Instagram.



6 billion – Photos [hosted](#) on Flickr (August 2011).

4.5 million – Number of [photos](#) uploaded to Flickr each day.

The goal of computer vision

- To perceive the story behind the picture



0	3	2	5	4	7	6	9	8
3	0	1	2	3	4	5	6	7
2	1	0	3	2	5	4	7	6
5	2	3	0	1	2	3	4	5
4	3	2	1	0	3	2	5	4
7	4	5	2	3	0	1	2	3
6	5	4	3	2	1	0	3	2
9	6	7	4	5	2	3	0	1
8	7	6	5	4	3	2	1	0

The goal of computer vision

- To perceive the story behind the picture
- What exactly does this mean?
 - Vision as a source of metric 3D information
 - Vision as a source of semantic information

Vision as measurement device

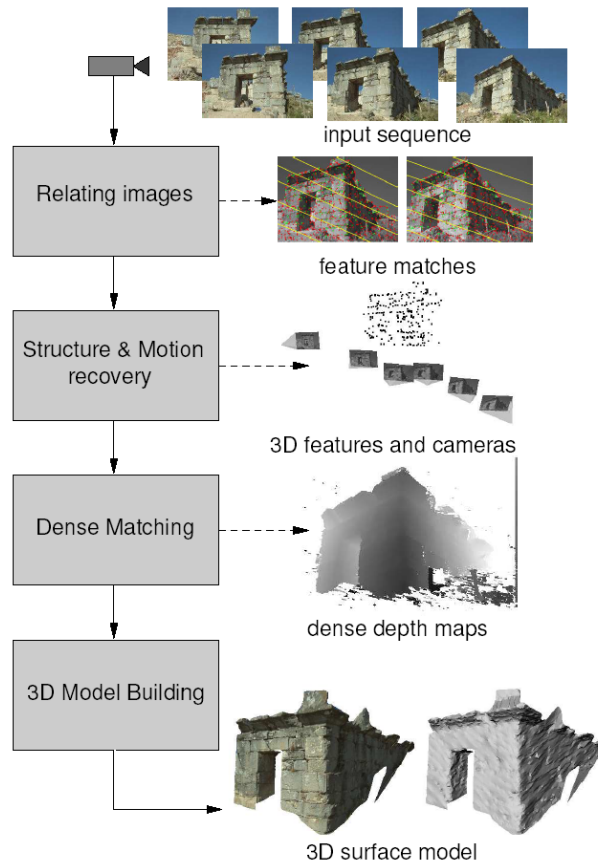
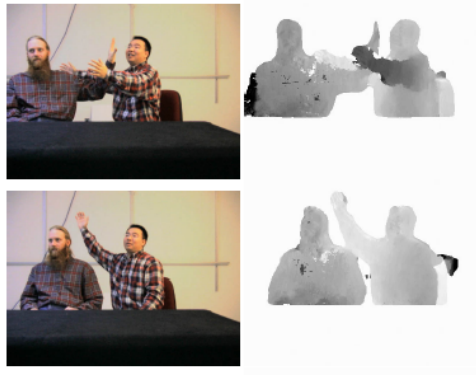


Photo Tourism



Vision as a source of semantic information



Object categorization



sky

building

flag

banner

face

wall

street lamp

bus

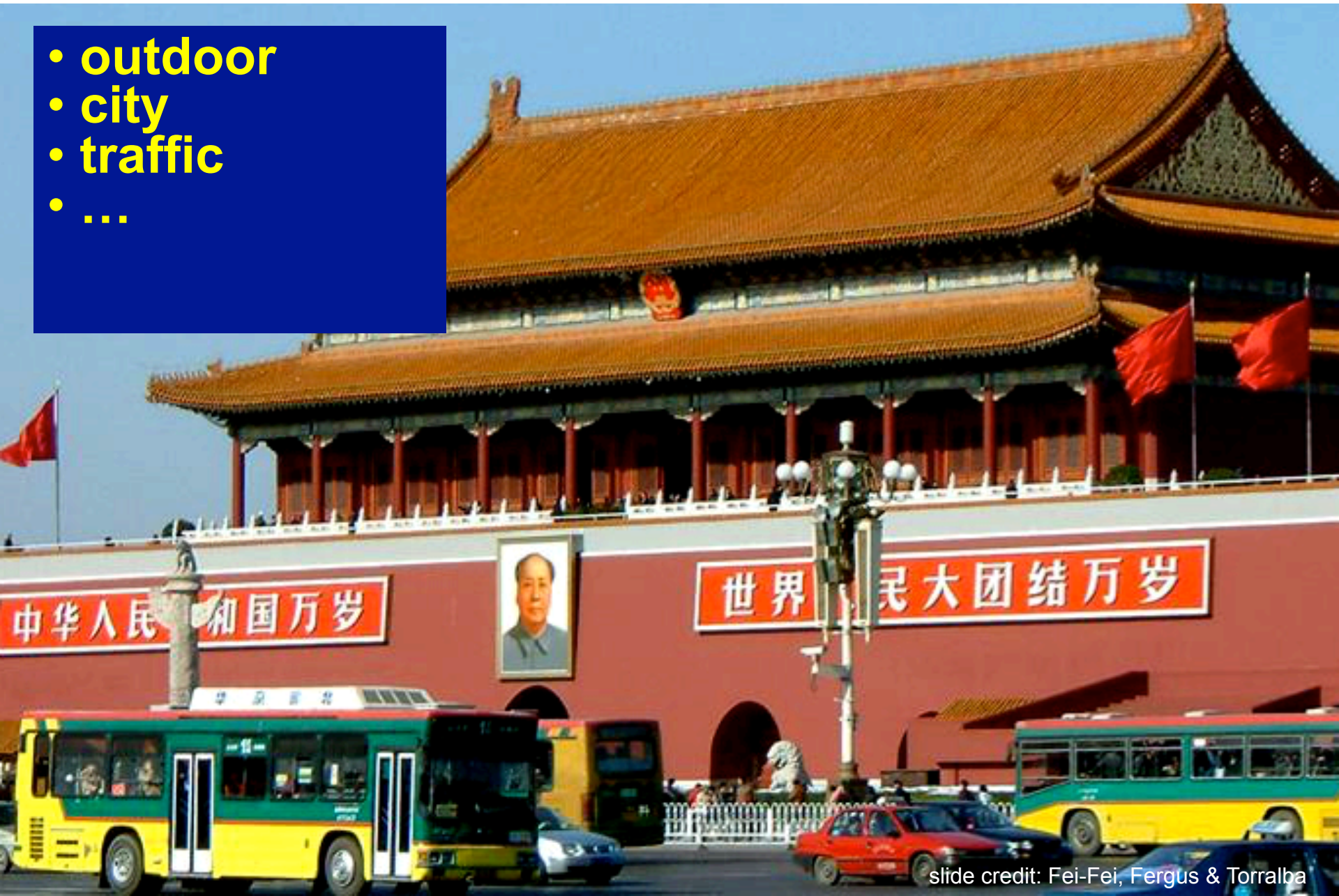
bus

cars

slide credit: Fei-Fei, Fergus & Torralba

Scene and context categorization

- outdoor
- city
- traffic
- ...



Why study computer vision?

- Vision is useful
- Vision is interesting
- Vision is difficult
 - Half of primate cerebral cortex is devoted to visual processing
 - Achieving human-level visual perception is probably “AI-complete”

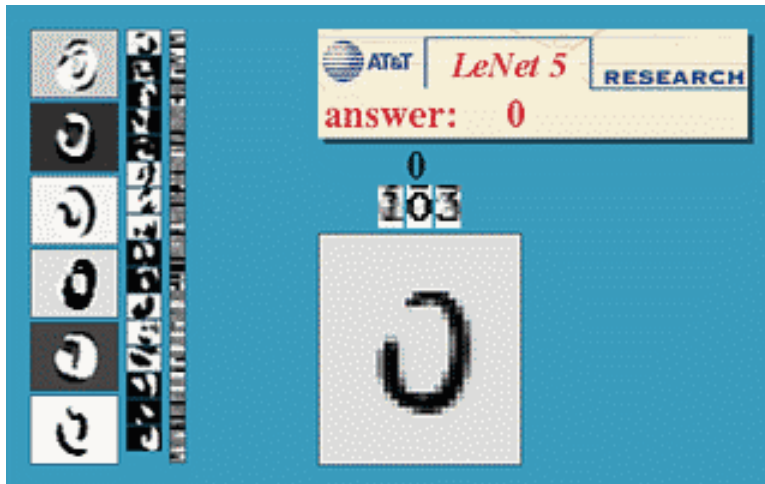
Progress to date

- The next slides show some examples of what current vision systems can do

Optical character recognition (OCR)

Technology to convert scanned docs to text

- If you have a scanner, it probably came with OCR software



Digit recognition, AT&T labs

<http://www.research.att.com/~yann/>



License plate readers

http://en.wikipedia.org/wiki/Automatic_number_plate_recognition

Also used for zipcode reading by the USPS

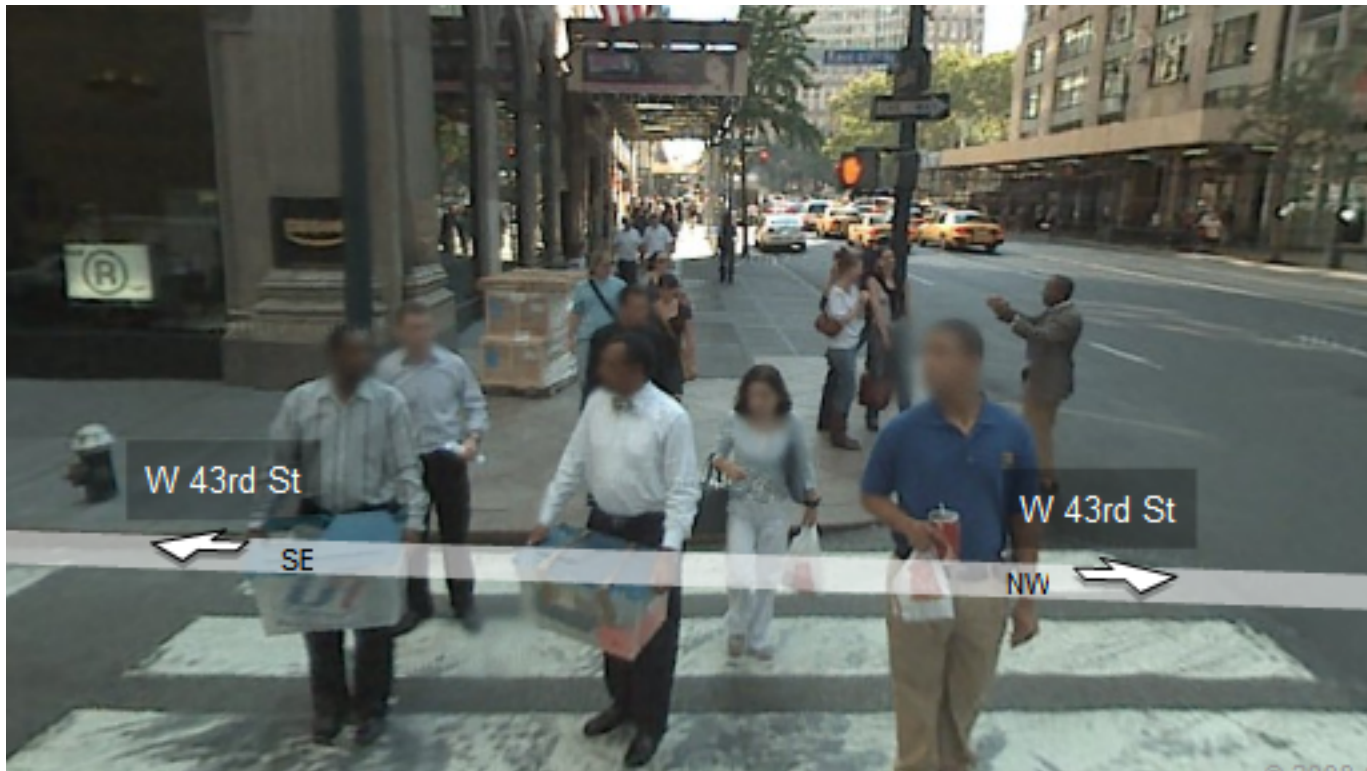
Source: S. Seitz

Face detection



- Many digital cameras now detect faces
 - Canon, Sony, Fuji, ...

Face Detection for Privacy



Face Blurring for Google Streetview

Face Detection for Privacy



Face Blurring for Google Streetview

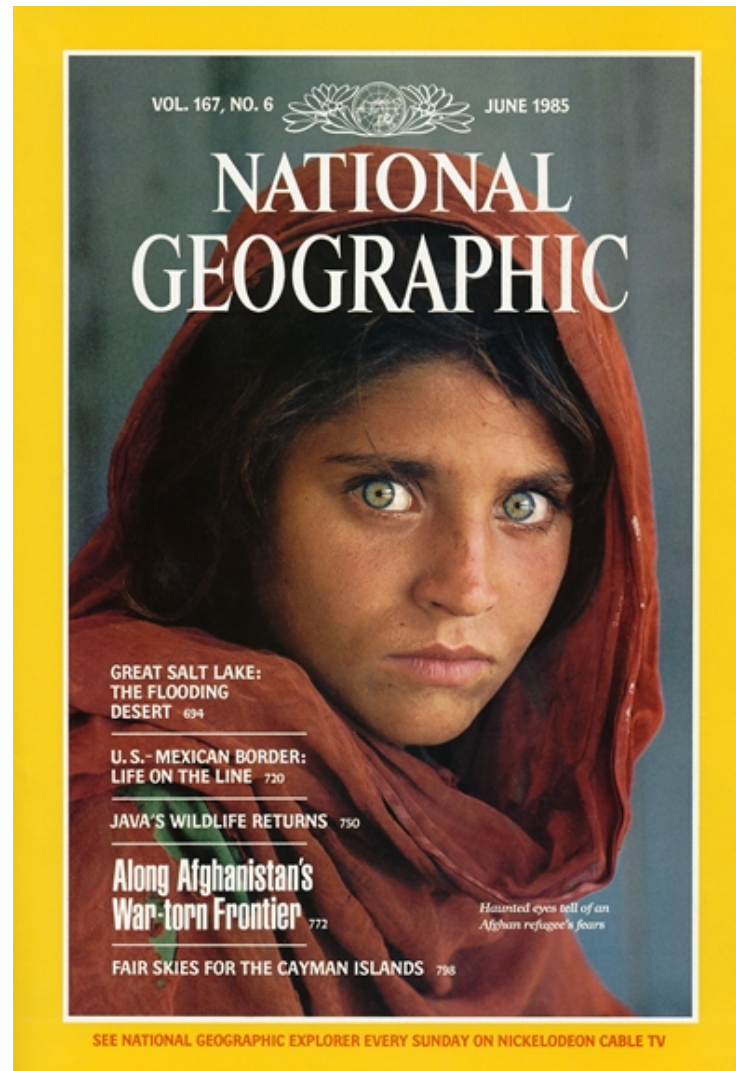
Object recognition (in supermarkets)



[LaneHawk by EvolutionRobotics](#)

“A smart camera is flush-mounted in the checkout lane, continuously watching for items. When an item is detected and recognized, the cashier verifies the quantity of items that were found under the basket, and continues to close the transaction. The item can remain under the basket, and with LaneHawk, you are assured to get paid for it...”

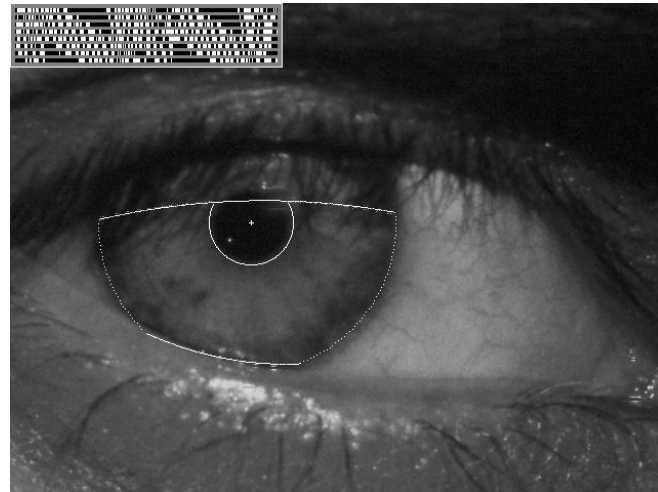
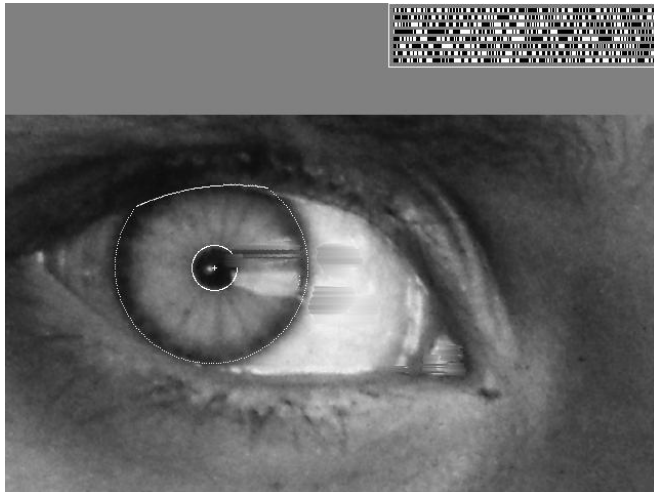
Who is she?



Vision-based biometrics



“How the Afghan Girl was Identified by Her Iris Patterns” Read the [story](#)

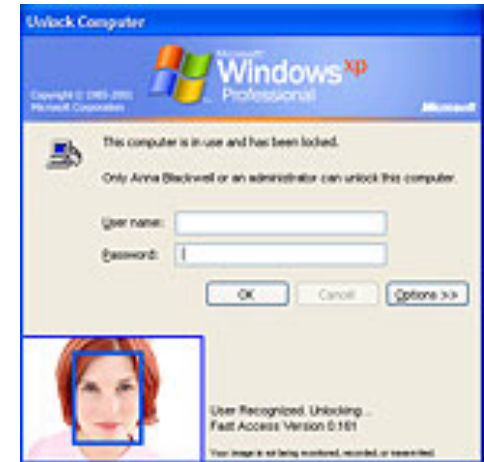
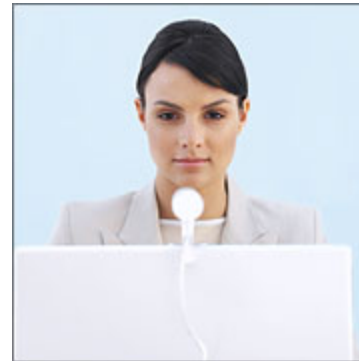


Source: S. Seitz

Login without a password...

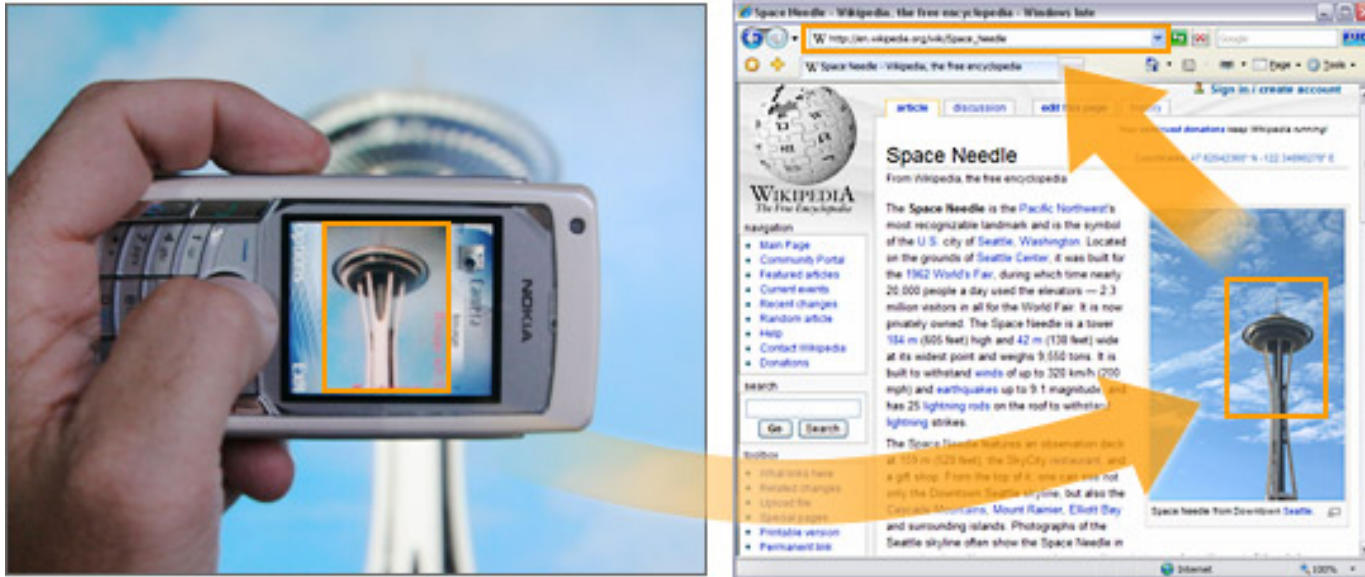


Fingerprint scanners on many new laptops, other devices



Face recognition systems now beginning to appear more widely
<http://www.sensiblevision.com/>

Object recognition (in mobile phones)



- This is becoming real:
 - **Lincoln** Microsoft Research
 - Point & Find
 - Google goggles

Sports



Sportvision first down line

Nice [explanation](http://www.howstuffworks.com) on www.howstuffworks.com

Smart cars

Slide content courtesy of Amnon Shashua

The screenshot displays the Mobileye website interface. At the top, there are navigation tabs for 'manufacturer products' and 'consumer products'. The main header reads 'Our Vision. Your Safety.' Below this, a top-down view of a car is shown with three camera fields of view highlighted in yellow: 'rear looking camera' at the back, 'forward looking camera' at the front, and 'side looking camera' on the side. The bottom section features three product highlights: 'EyeQ Vision on a Chip' with an image of the chip, 'Vision Applications' showing a pedestrian on a crosswalk, and 'AWS Advance Warning System' with a circular display showing a car icon and a distance of 0.8. On the right side, there is a 'News' section with two articles about Volvo's collision warning system and a 'read more' link. Below the news is an 'Events' section listing 'Mobileye at Equip Auto, Paris, France' and 'Mobileye at SEMA, Las Vegas, NV', also with a 'read more' link.

- [Mobileye](#)
 - Vision systems currently in high-end BMW, GM, Volvo models

Vision-based interaction (and games)



Nintendo Wii has camera-based IR tracking built in. See [Lee's work at CMU](#) on clever tricks on using it to create a [multi-touch display](#)!

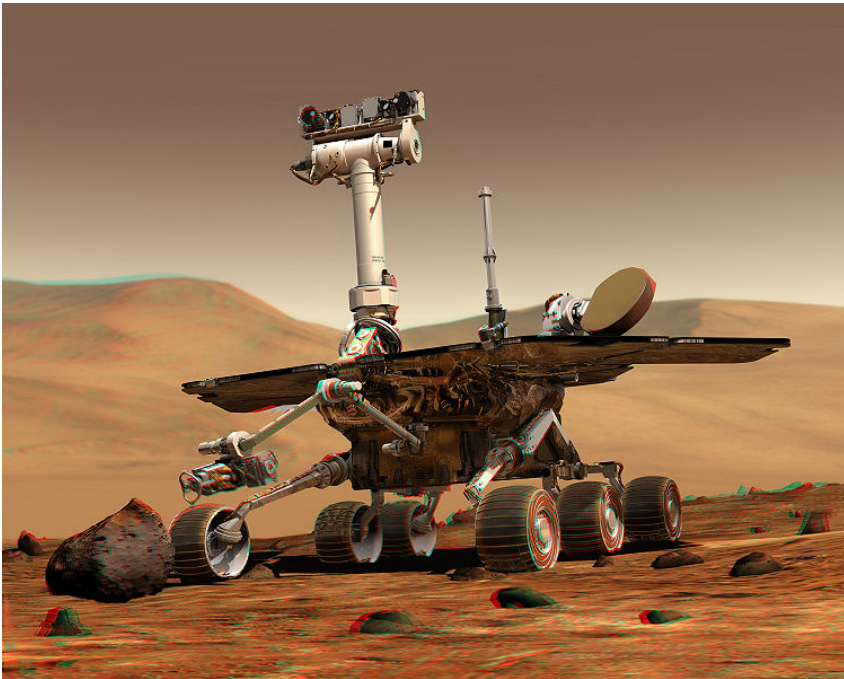


Kinect – projector+camera for depth

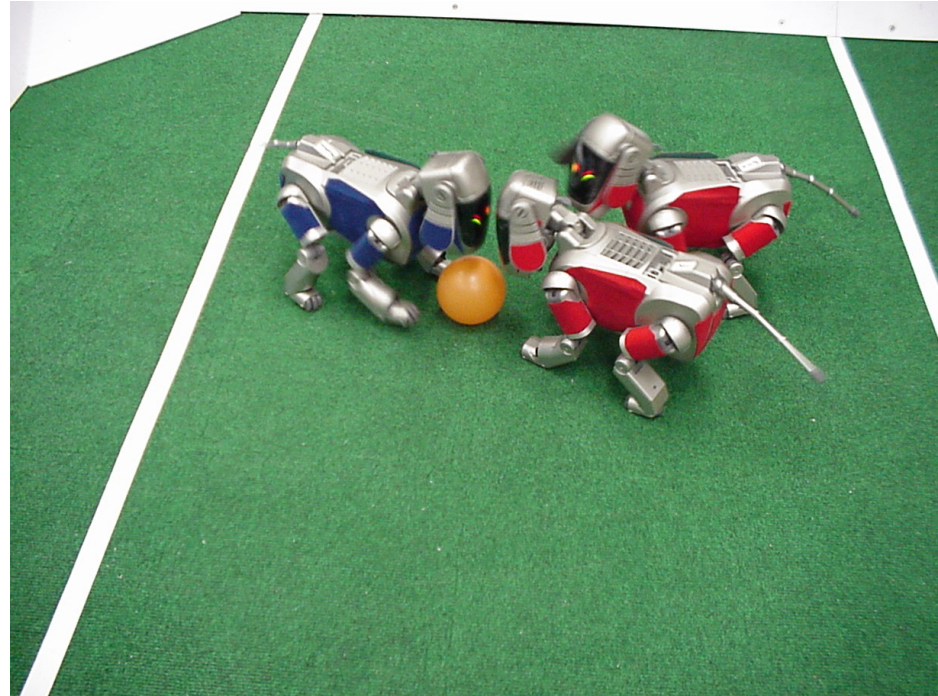


Assistive technologies

Robotics

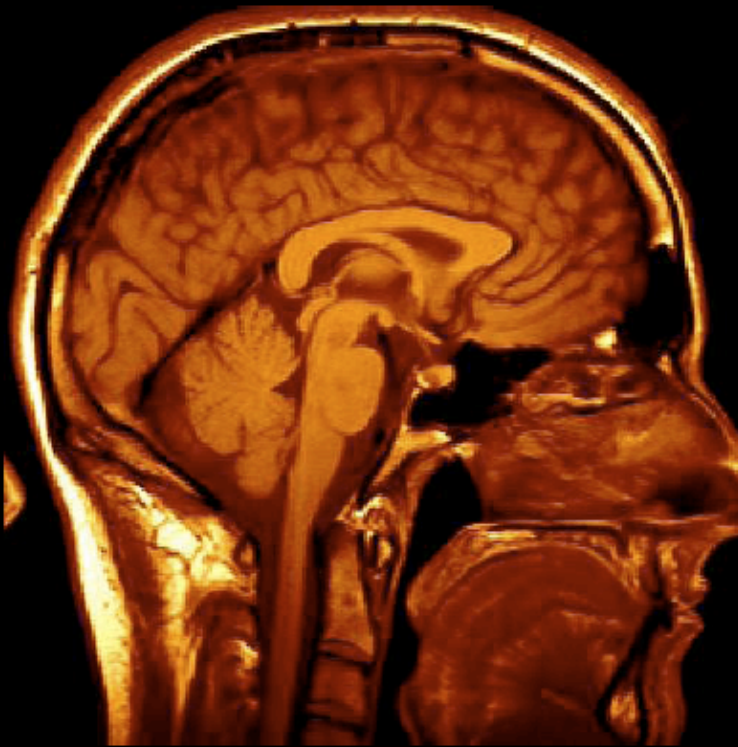


NASA's Mars Spirit Rover
http://en.wikipedia.org/wiki/Spirit_rover



<http://www.robotcup.org/>

Medical imaging



3D imaging
MRI, CT



Image guided surgery
Grimson et al., MIT

What I work on...

Two Example Projects

Moving recognition outputs toward human-like predictions

Extracting socio-identity information from pictures

Descriptive Text



“It was an arresting face, pointed of chin, square of jaw. Her eyes were pale green without a touch of hazel, starred with bristly black lashes and slightly tilted at the ends. Above them, her thick black brows slanted upward, cutting a startling oblique line in her magnolia-white skin—that skin so prized by Southern women and so carefully guarded with bonnets, veils and mittens against hot Georgia suns”

Scarlett O'Hara described in *Gone with the Wind*.

More Nuance than Traditional Recognition...



→ person



→ shoe



→ car

Human centric recognition outputs



car

Human centric recognition outputs



pink car

Human centric recognition outputs



→ car on road

Human centric recognition outputs



Little pink smart car
parked on the side
of a road in a
London shopping
district.

Telling the “*story of an image*”

generating image descriptions, a first attempt...

Baby Talk: Understanding and Generating Simple Image Descriptions

Girish Kulkarni, Visruth Premraj, Sagnik Dhar, Siming Li, Yejin Choi,
Alexander C Berg, Tamara L Berg (CVPR 2011)





“This picture shows one person,



“This picture shows one person, one grass,



“This picture shows one person, one grass, one chair,



“This picture shows one person, one grass, one chair, and one potted plant.



“This picture shows one person, one grass, one chair, and one potted plant. The person is near the green grass,



“This picture shows one person, one grass, one chair, and one potted plant. The person is near the green grass, and in the chair.



“This picture shows one person, one grass, one chair, and one potted plant. The person is near the green grass, and in the chair. The green grass is by the chair,



“This picture shows one person, one grass, one chair, and one potted plant. The person is near the green grass, and in the chair. The green grass is by the chair, and near the potted plant.”



“This picture shows one person, one grass, one chair, and one potted plant. The person is near the green grass, and in the chair. The green grass is by the chair, and near the potted plant.”

Methodology

- Vision – find and identify objects
- Text -- statistics from parsing lots of descriptive text
- Model predicts best image labeling given vision and text based estimates
- Generation algorithms to compose natural language

Some good results



This is a picture of one sky, one road and one sheep. The gray sky is over the gray road. The gray sheep is by the gray road.



Here we see one road, one sky and one bicycle. The road is near the blue sky, and near the colorful bicycle. The colorful bicycle is within the blue sky.



This is a picture of two dogs. The first dog is near the second furry dog.

Some bad results

Missed detections:



Here we see one potted plant.

False detections:



There are one road and one cat. The furry road is in the furry cat.

Incorrect attributes:



This is a photograph of two sheep and one grass. The first black sheep is by the green grass, and by the second black sheep. The second black sheep is by the green grass.



This is a picture of one dog.



This is a picture of one tree, one road and one person. The rusty tree is under the red road. The colorful person is near the rusty tree, and under the red road.



This is a photograph of two horses and one grass. The first feathered horse is within the green grass, and by the second feathered horse. The second feathered horse is within the green grass.

Our Generation Algorithm vs Humans



“This picture shows one person, one grass, one chair, and one potted plant. The person is near the green grass, and in the chair. The green grass is by the chair, and near the potted plant.”



- H1:* A Lemonaide stand is manned by a blonde child with a cookie.
- H2:* A small child at a lemonade and cookie stand on a city corner.
- H3:* Young child behind lemonade stand eating a cookie.

Sounds unnatural!

Caption guessing game



a) monkey playing in the tree canopy,
Monte Verde in the rain forest

b) capuchin monkey in front of my window

c) monkey spotted in Apenheul
Netherlands under the tree

d) a white-faced or capuchin in the
tree in the garden

e) the monkey sitting in a tree, posing
for his picture

Caption

guessing game



a) monkey playing in the tree canopy,
Monte Verde in the rain forest

b) capuchin monkey in front of my window

c) monkey spotted in Apenheul
Netherlands under the tree

d) a white-faced or capuchin in the
tree in the garden

e) the monkey sitting in a tree, posing
for his picture

Data Driven Generation

“Im2Text: Describing Images Using
1 Million Captioned Photographs”

Vicente Ordonez, Girish Kulkarni, Tamara L. Berg

NIPS 2011

“Collective Generation of Natural Image
Descriptions”

Polina Kuznetsova, Vicente Ordonez,

Alexander C. Berg, Tamara L. Berg and Yejin Choi

ACL 2012



Through the smoke



Duna Portrait #5



Mirror and gold

Data exists, but buried in junk!



the cat lounging in the sink

Captions in the Wild

<http://tamaraberg.com/sbucaptions>



The Egyptian cat statue by the floor clock and perpetual motion machine in the pantheon



Little girl and her dog in northern Thailand. They both seemed interested in what we were doing



Interior design of modern white and brown living room furniture against white wall with a lamp hanging.



Man sits in a rusted car buried in the sand on Waitarere beach



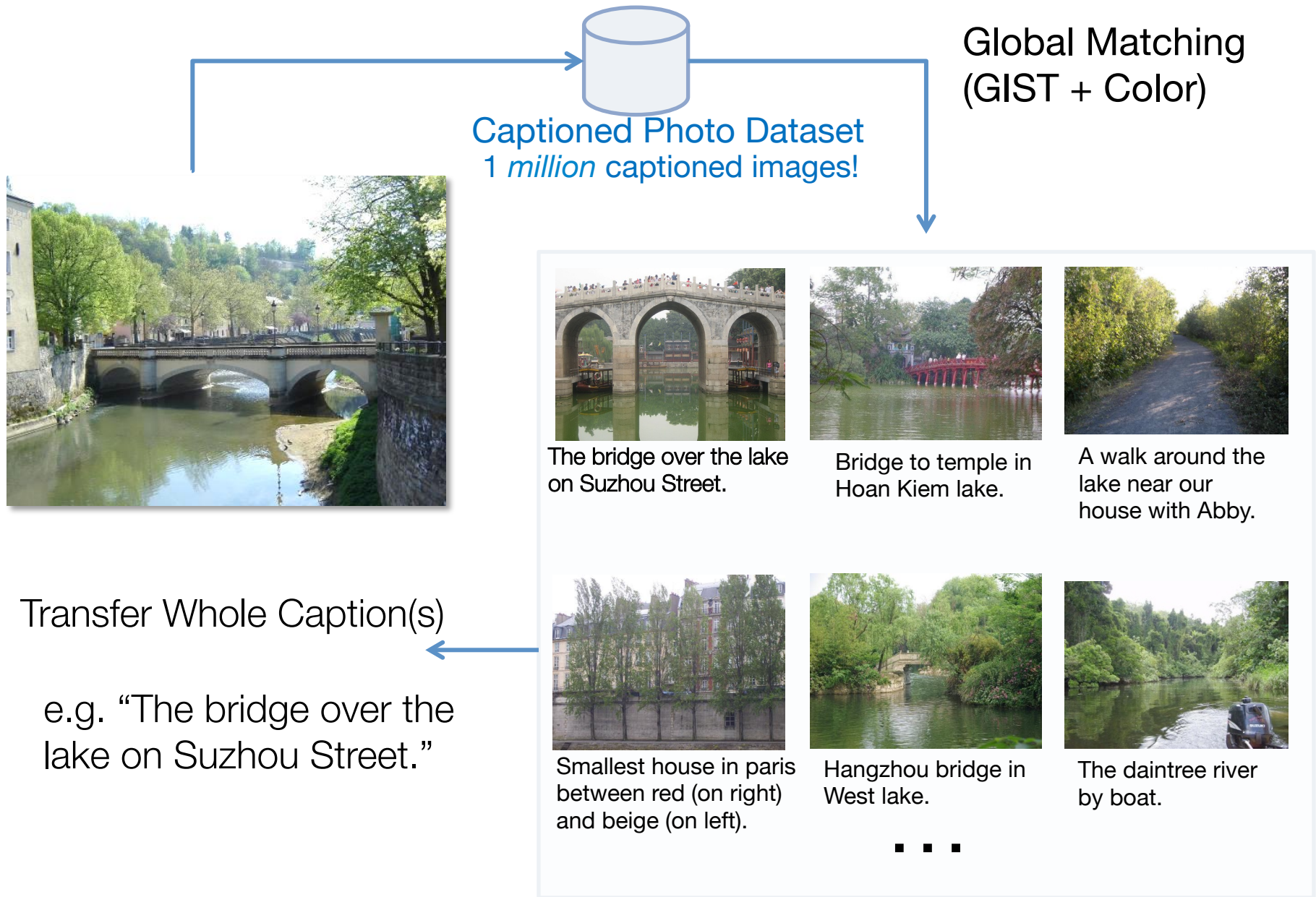
Our dog Zoe in her bed



Emma in her hat looking super cute

Harness the Web

Ordonez et al, NIPS 2011



Transfer pieces of Captions



Object appearance



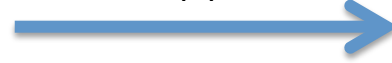
NP: the dirty sheep

Object pose



VP: meandered along a
desolate road

Scene appearance



PP: in the highlands of Scotland

Region
appearance &
relationship



PP: through frozen grass



Example Composed Description:

the dirty sheep meandered
along a desolate road in the
highlands of Scotland
through frozen grass

Two Example Projects

Moving recognition outputs toward human-like predictions

Extracting socio-identity information from pictures

Clothing & Identity...





Wealth



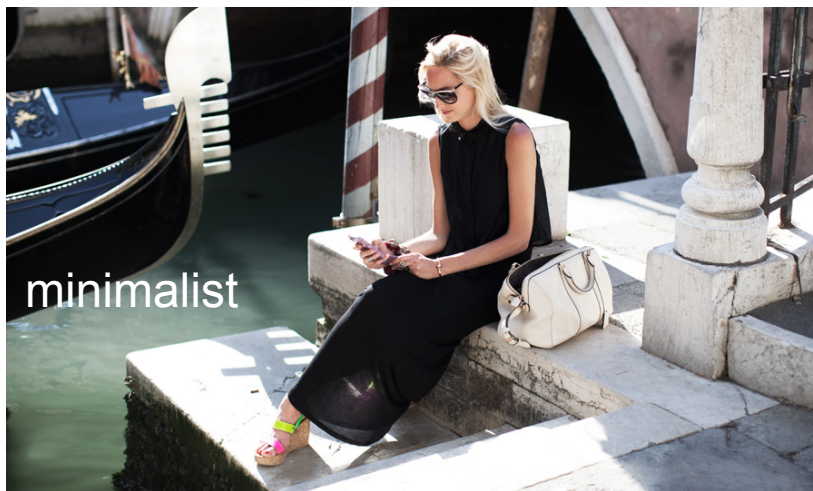


Occupation





Social Tribe



Clothing Recognition

“Parsing Clothing in Fashion Photographs”

Kota Yamaguchi, Hadi Kiapour, Luis E Ortiz Tamara L. Berg,
CVPR 2012.



null
 boots
 pants
 top
 hair
 skin

□ ■ ■ ■ ■ ■

“Paper Doll Parsing: Retrieving Similar Styles to Parse Clothing”

Kota Yamaguchi, Hadi Kiapour, Tamara L. Berg,
ICCV 2013.



null
 coat
 sweater
 jeans
 hat
 socks
 wedges
 hair
 skin

□ ■ ■ ■ ■ ■ ■ ■ ■

Locally ambiguous



Large Variation in appearance



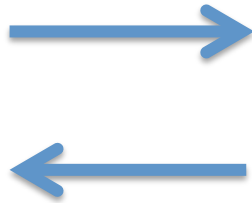
shirts

Layering



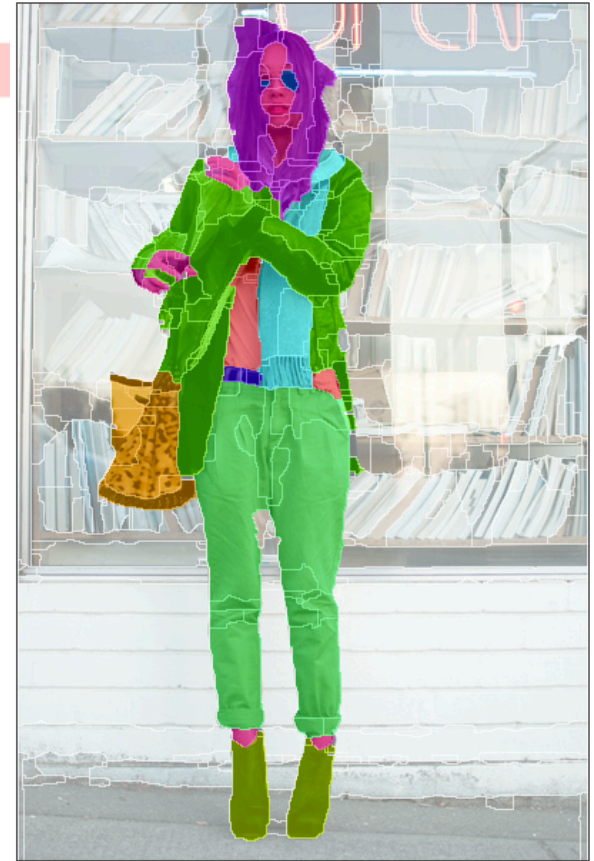
Key Intuition: Pose and Clothing are Related

POSE ESTIMATION

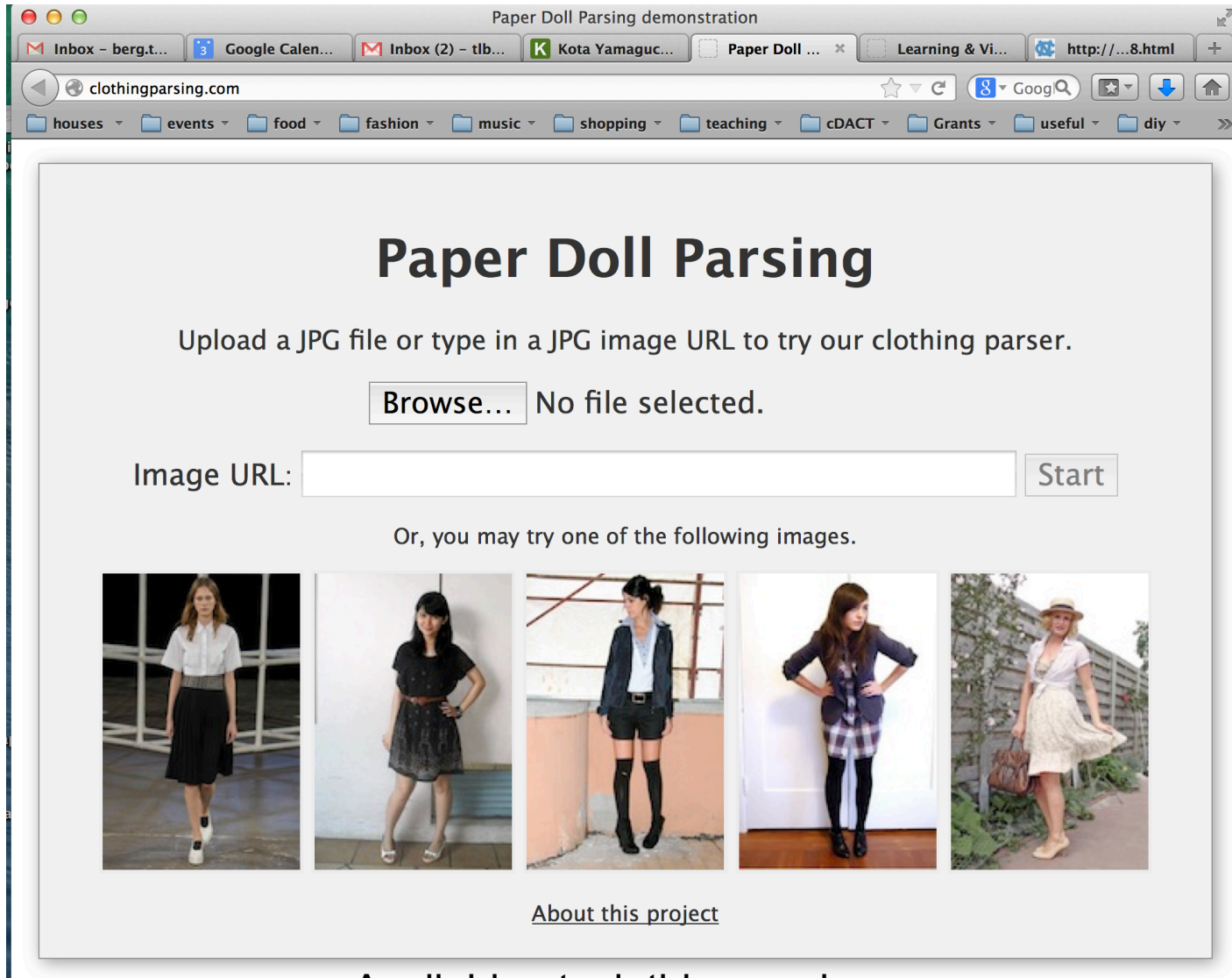


CLOTHING RECOGNITION

- bag
- belt
- boots
- hair
- jacket
- pants
- scarf
- skin
- sunglasses
- t-shirt

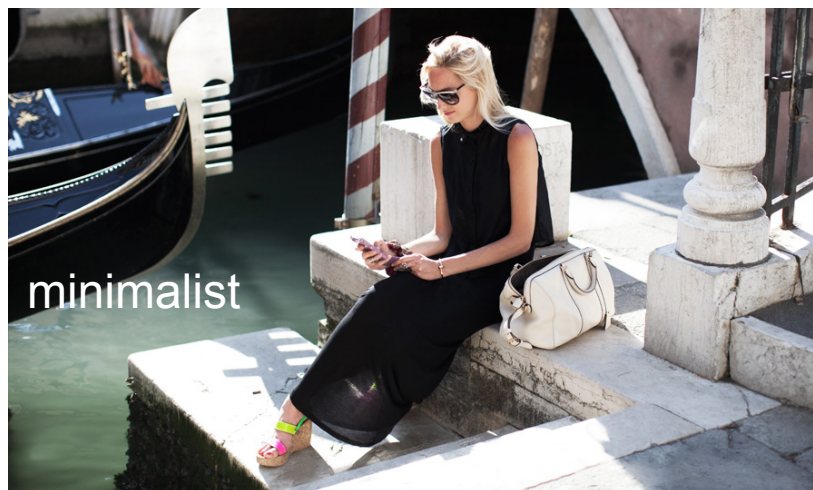


Recognizing Clothing - Demo





Social Tribe



Collecting Labels

- How?



How hipster is he?



1



2



3



4



5

Collecting Labels

- How?



How handsome is he?

People have different internal scales for rating.

Asking about individual images can produce unstable results.

Collecting style ratings

HIPSTER WARS

PLAY

RANKINGS

UPLOAD

LOGIN

ABOUT

FEEDBACK

Hipster

Goth

Preppy

Pinup

Bohemian

7

g+1

Hipsterwars
game!

Who's more **Hipster**?
(click on one)



Tie!

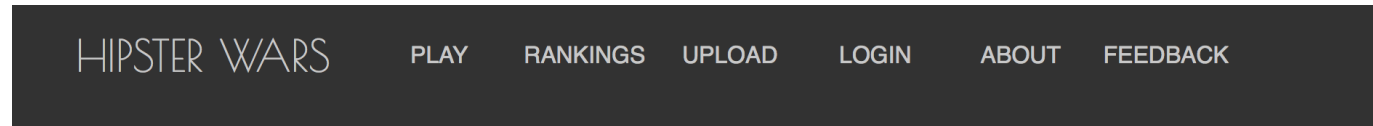


12499 clicks collected

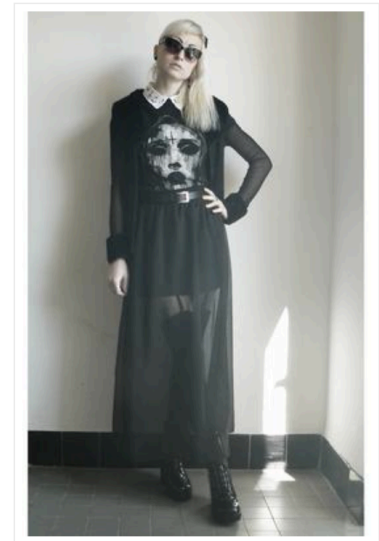
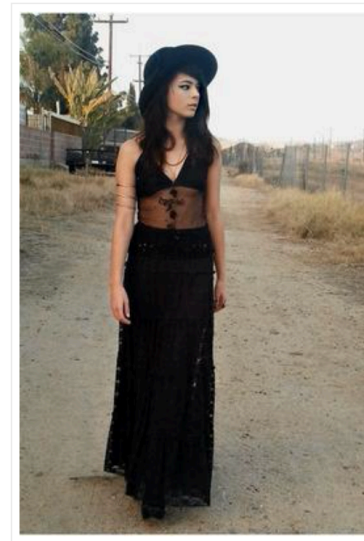
Goal: 10,000

Available at:
hipsterwars.com

Collecting style ratings



Who's more **Goth**?
(click on one)



Range of styles:

hipster, goth,
preppy, pinup,
bohemian

Available at:
hipsterwars.com

2987 clicks collected

Goal: 10,000



Like

Share

0

g+1

Hipster

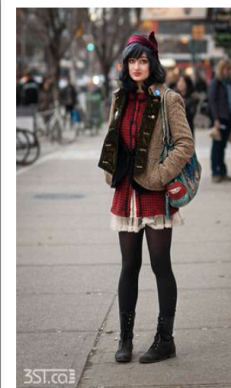
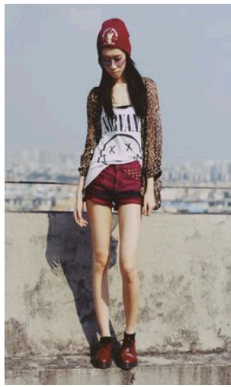
Goth

Preppy

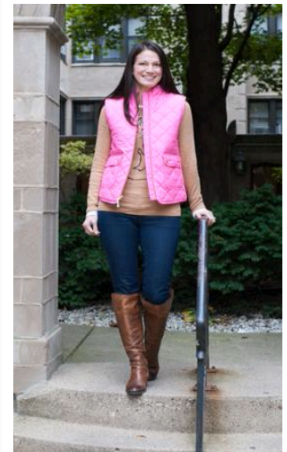
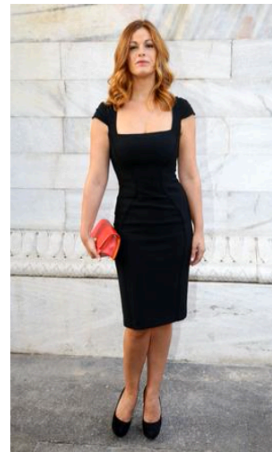
Pinup

Bohemian

Winning Hipsters!

Most
hipster

... Least hipster



How hipster are you?

Pinup



Goth



Hipster



Bohemian



Preppy



Most (Predicted)

Least (Predicted)



Thank you!

Vicente Ordonez, Kota Yamaguchi, Hadi
Kiapour, Xufeng Han, Polina Kuznetsova, Siming
Li, Girish Kulkarni, Visruth Premraj, Sagnik Dhar

Alex Berg, Yejin Choi, Luis Ortiz