

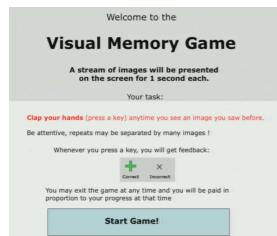
The memorability of visual images

Khosla, Raju, Torralba, Oliva (2015)

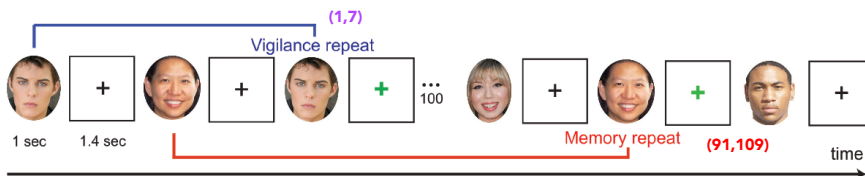
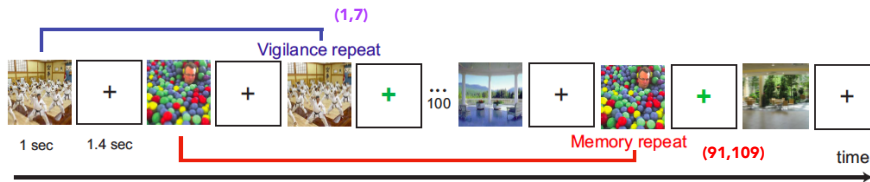


high memorability

low memorability



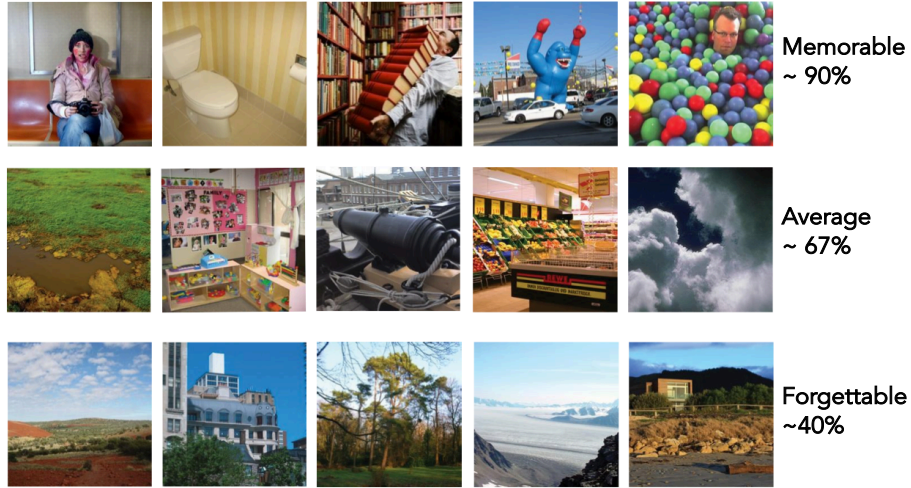
Visual memory experiments



- Continuous repeat detection task
- ~10,000 unique images sampled from 900 scene categories (Standing, 1973; Brady et al., 2008)
- ~10,000 unique face sampled from US demographic adult distribution (gender, race, age)
- ~10,000 unique words
- 2222 target images (memory repeats) whose repeats occurred ~ 91-109 after the first presentation

- Vigilance repeats every 1-7 images
- Each game level has 120 images
- ~ 80 scores per target images

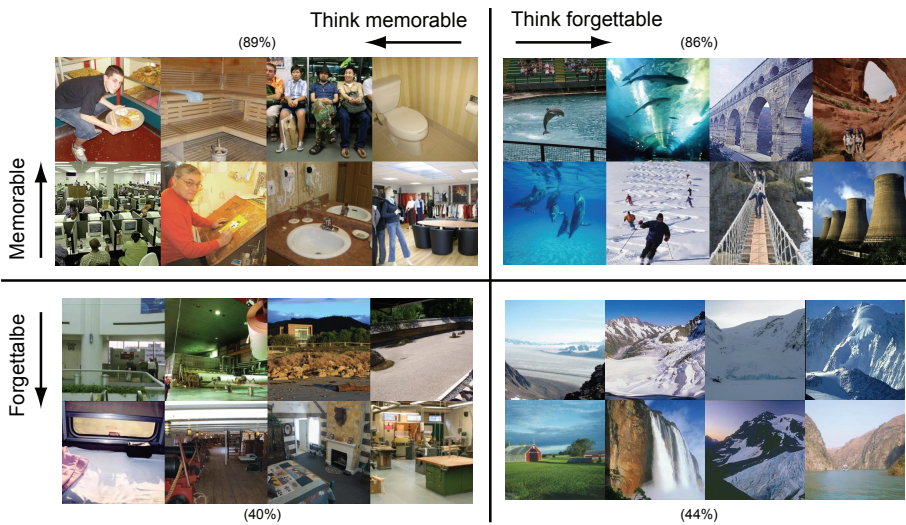
Large difference in image memorability & high consistency between observers' groups



Mean HIT rate: 67.5% • SD: 13.5%
 Mean False alarm rate: 10.7% • SD: 7.6%

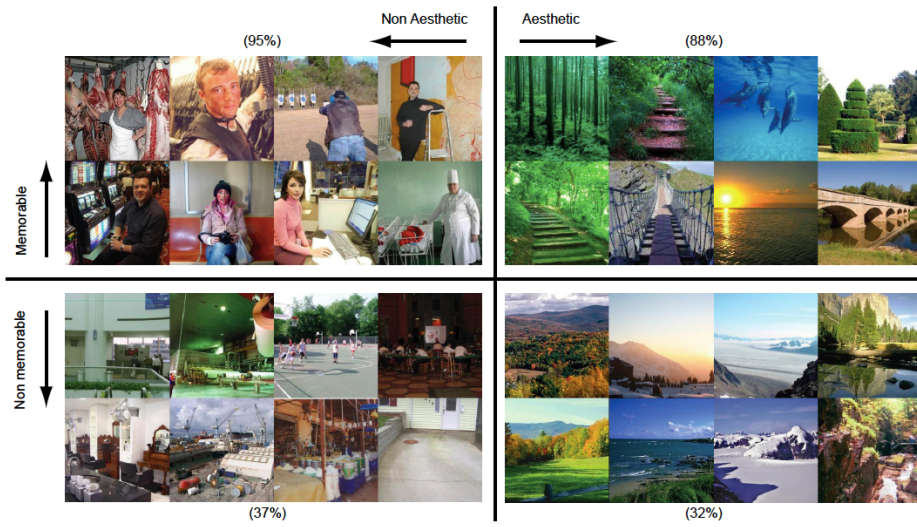
Isola et al (2011). *IEEE CVPR*

Subjective judgments do not predict image memorability



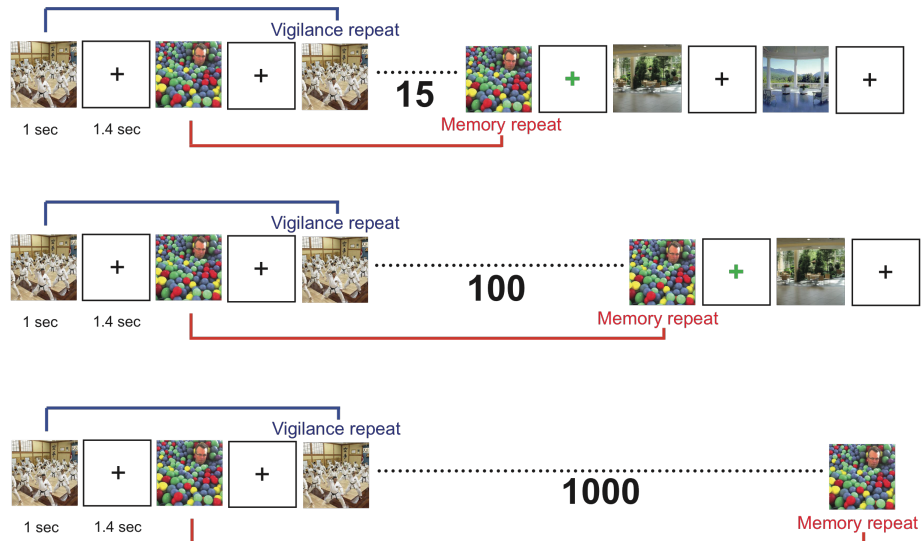
Isola et al (2011). *Neural Information Processing Systems (NIPS), PAMI (2014)*

Image memorability is distinct from image aesthetic



Isola et al (2011). *Neural Information Processing Systems (NIPS)*

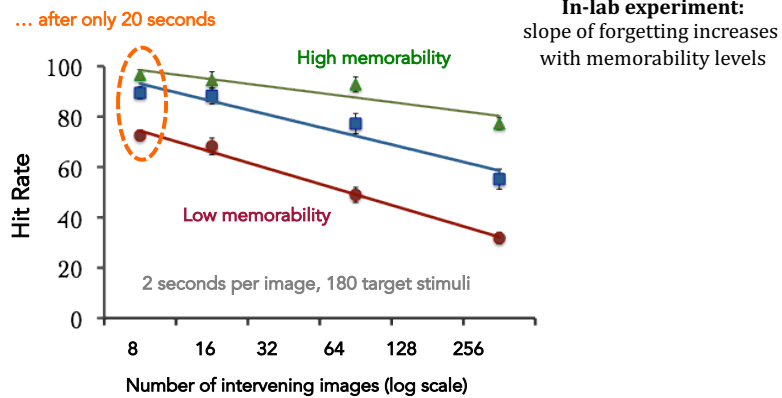
Is memorability stable across time? **Yes**



Isola et al (2014). *IEEE PAMI (Pattern Analysis and Machine Intelligence)*

When do memorability differences arise?

At stage of encoding: data suggest that some images (features) are encoded in less sufficient detail than others



What about faces?

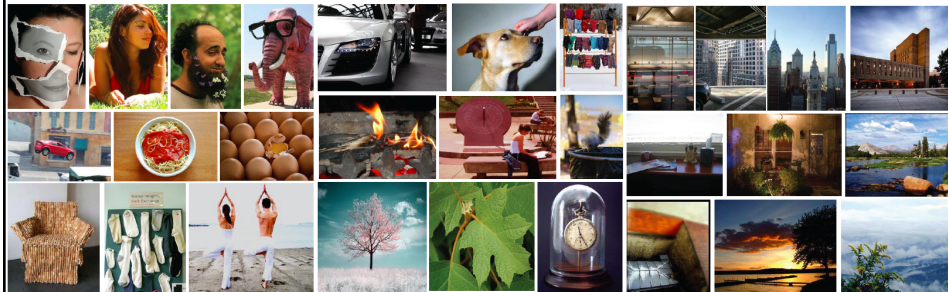
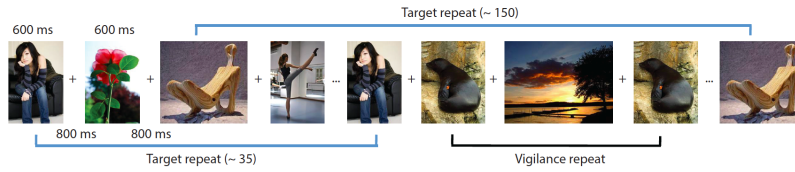


large differences in face memorability, high consistency between observers' groups

Bainbridge, Isola, Oliva, (2013). J. Exp. Psychology: General.

Large scale visual memorability

60,000 photographs with memorability scores



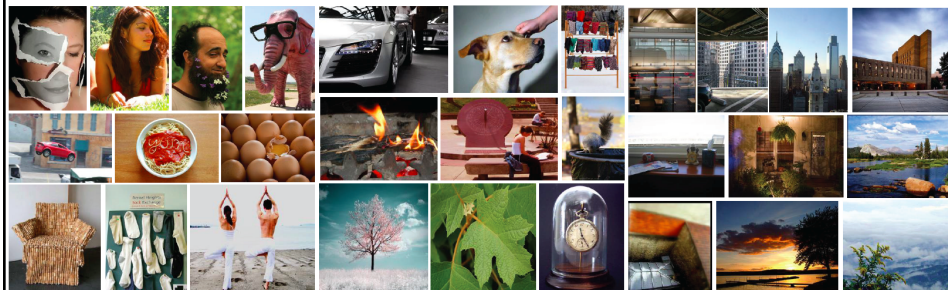
most memorable

<http://memorability.csail.mit.edu/>

less memorable

Most memorable

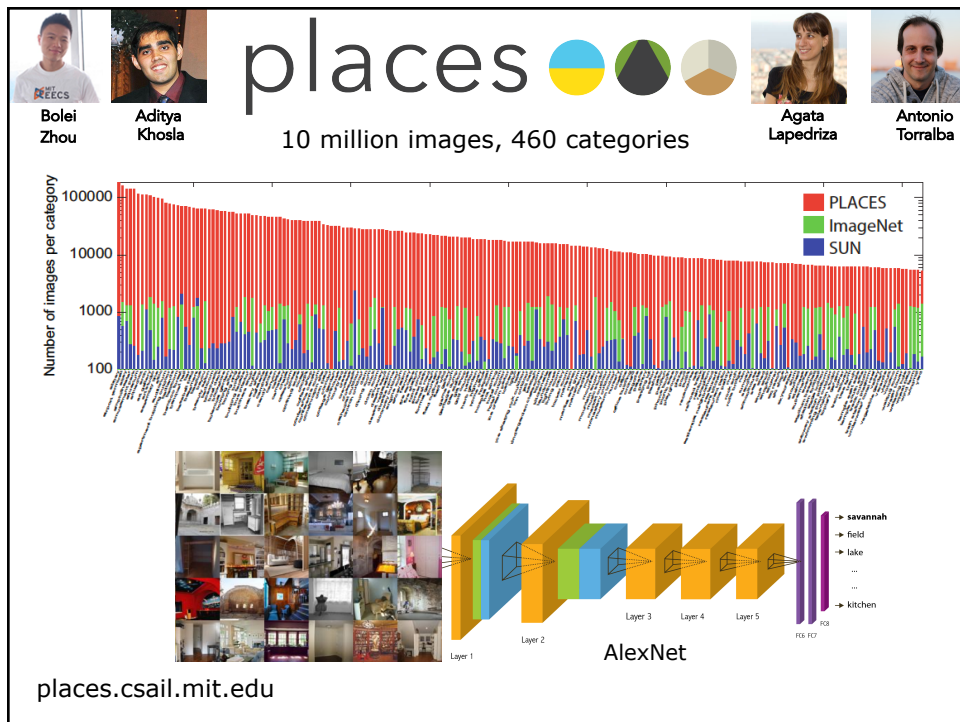
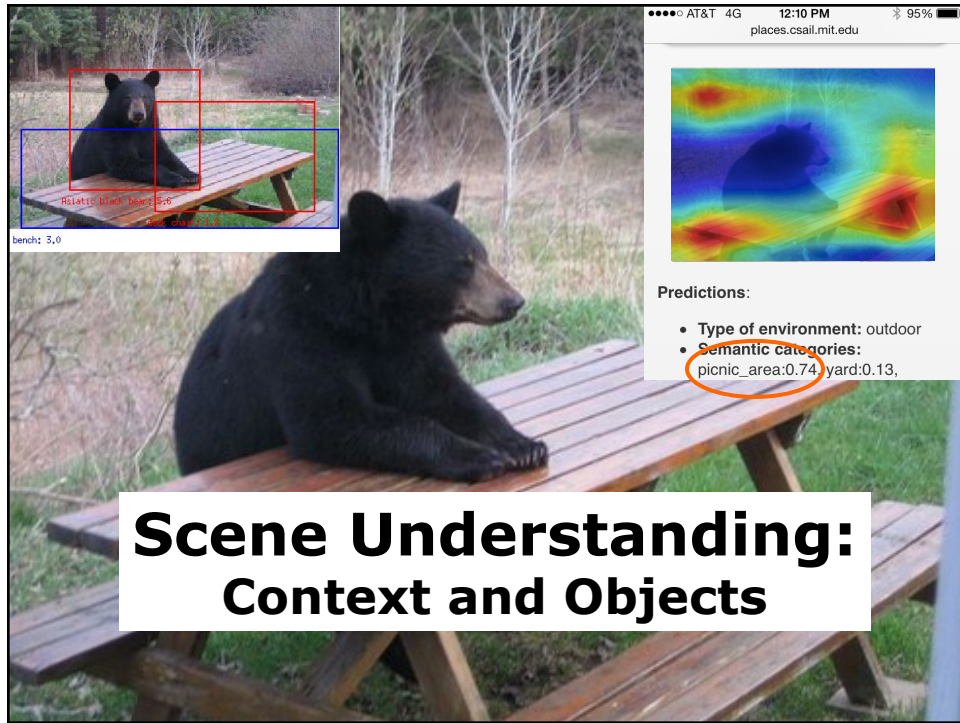
Least memorable



- Focus
- Enclosed Setting
- Dynamics
- Unusual

- No single focus
- Distant view
- Static
- Common

You need to recognize to remember!



Web demo: places.csail.mit.edu



Predictions:

- **Type of environment:** indoor
- **Semantic categories:** restaurant:0.27, coffee_shop:0.23, cafeteria:0.21, food_court:0.12, restaurant_patio:0.09



Predictions:

- **Type of environment:** outdoor
- **Semantic categories:** parking_lot:0.46, driveway:0.44



Predictions:

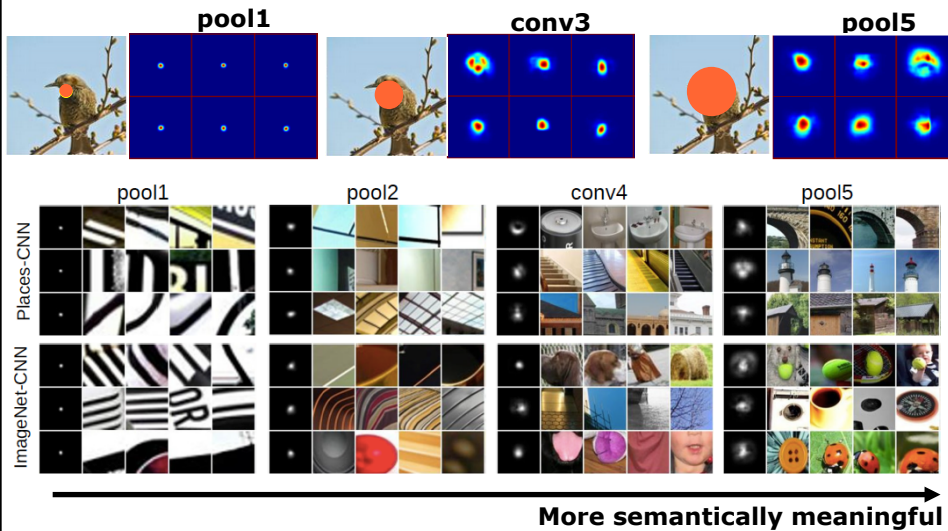
- **Type of environment:** indoor
- **Semantic categories:** conference_room:0.29, dining_room:0.27, banquet_hall:0.08, classroom:0.06



Predictions:

- **Type of environment:** outdoor
- **Semantic categories:** patio:0.38, restaurant_patio:0.35, restaurant:0.06

“Receptive fields” of CNN units



Zhou, Khosla, Lapedriza, Oliva, Torralba (2015), ICLR

Object detectors emerge inside the CNN

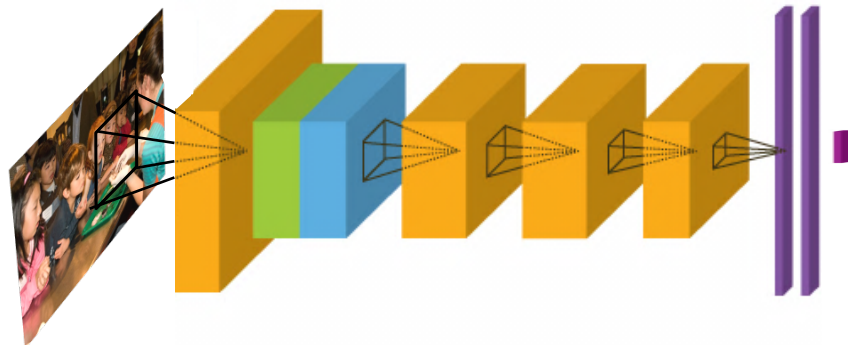
Buildings	Indoor objects	Furniture	Outdoor objects
56) building 	182) food 	18) billiard table 	87) car
120) arcade 	46) painting 	155) bookcase 	61) road
8) bridge 	106) screen 	116) bed 	96) swimming pool
123) building 	53) staircase 	38) cabinet 	28) water tower
119) building 	107) wardrobe 	85) chair 	6) windmill
9) lighthouse 	People	Lighting	Nature
Scenes	3) person 	55) ceiling lamp 	195) grass
145) cementery 	49) person 	174) ceiling lamp 	89) iceberg
127) street 	138) person 	223) ceiling lamp 	140) mountain
218) pitch 	100) person 	13) desk lamp 	159) sand

MemNet

CNN for Predicting Image Memorability

IMAGENET places

input



output

HybridNet from Zhou et al, NIPS 2014 (places.csail.mit.edu)