



# **Predicting Visual Memorability:**

## A metric of the utility of information

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# Memorability

What could we do with such knowledge and technology?



or video

para

# **Predicting Memorability**

Human Memory	What is the capacity and fidelity	
	of human visual memory?	
Memory Game I	Is memorability consistency across different observers?	00% 01% 02% 05% 05% 05% 05% 05% 05% 05% 05
Memory Game II	How does memorability evolve over time?	
Computer Vision	Can computer vision methods predict memorability?	
Memory Game III, IV, V	Is memorability a general property of information?	

Jennifer

# Nature of human long term visual memory

#### What we know in 2008

Standing (1973) 10,000 images 83% Recognition

*... people can remember thousands of images* 

#### What we don't know in 2008...

*... what people are remembering for each item?* 



#### According to Standing

"Basically, my recollection is that we just separated the pictures into distinct thematic categories: e.g. cars, animals, single-person, 2people, plants, etc.) Only a few slides were selected which fell into each category, and they were visually distinct."



"Abstract Only

Sparse Details

Highly Detailed

# **Massive Memory Experiment I**

A stream of objects will be presented on the screen for ~ 3 second each.

Your primary task:

#### **Remember them ALL!**

afterwards you will be tested with ...

*Completely different objects...* 



*Different exemplars of the same kind of object...* 

Different states of the same object...





## Massive Memory I: Methods



Showed 14 observers 2500 categorically unique objects

- 1 at a time, 3 seconds each
- 800 ms blank between items

Study session lasted about 5.5 hours

Repeat Detection task to maintain focus

Followed by 300 2-alternative forced choice tests

## Examples of **Exemplar** Memory Tests



## Examples of **State** memory test



## **Recognition Memory Results**



## **Models of Object Recognition**

A massive memory for details lend credence to object recognition approaches that require brute force storage of *multiples* viewpoints and exemplars (and image alignment approaches)



## Human Memory: Summary

Massive Memory IVisual LTM can store a large<br/>number of items (Standing)with surprising fidelity



Massive Memory II

Maybe the categorical

distinctiveness of all items

was essential ?

If you see several sets of binoculars...



Will your memory representations be detailed enough ?





## Methods – The Study Stream

- **128** unique semantic categories of natural images
- **2912** natural images shown in the stream (3 seconds each, 800 msec ISI)

Number of exemplars per category: 4, 16, or 64 !



N= 24 observers

## Methods – The Study Stream

#### Online Task: Detect Exact Repeats

Repeats could be 2 to 1024 back in the stream Repeats could be from categories with 4, 16, or 64 exemplars 7% of images in the stream were repeats (192 / 2912)



## Methods – The Memory Test

#### Followed by 224 2-alternative forced choice tests



None of the tested categories were n-backed Test Pairs were always the same for all subjects Any effect of interference is due to the additional exemplars

### Objects & Scenes: Is it fair to compare?





We tried to span the categories with our exemplars and sampled the test item and foil uniformly

#### **Recognition Memory Comparison**



Konkle, Brady, et al. (2010), J. Exp. Psychology: General

Konkle, al. (2010), Psychological Science



#### Scene and object categories may be treated as entities at a similar level of abstraction in human long term memory

Recognition Memory Comparison









## Human Memory: Summary

Massive Memory I	Visual LTM can store a large number of items
<b>PNAS 2008</b>	with <u>surprising fidelity</u>



#### Massive Memory II & III

**JEP:G 2010** 

High memory for object and scene exemplars despite visual interference

Scene and object exemplars are on average equally well remembered in long term



Number of Exemplars (log scale)

Psych Science 2010 memory



Timothy Brady



Talia Konkle



#### George Alvarez

## **Recognition is Reconstruction from Memory**



## **Recognition is Re-collection & Re-construction from Memory**



# **Predicting Memorability**

Human Memory	High capacity and visual details fidelity		
	for exemplars of known categories/	concepts	
Memory Game I	Is memorability consistency across different observers?	100% - Group 1 - Group 2 - Chance - Other - Group 2 - Chance - Other - Group 2 - Chance - Other - Group 2 - Chance 	
Memory Game II	How does memorability evolve over time?		
<b>Computer Vision</b>	Can computer vision methods predict memorability?		
Memory Game III, IV, V	Is memorability a general property of information?	Jennifer	

Welcome to the

# **Visual Memory Game**

A stream of images will be presented on the screen for 1 second each.

Your task:

Clap your hands (press a key) anytime you see an image you saw before.

Be attentive, repeats may be separated by many images !

Whenever you press a key, you will get feedback:



You may exit the game at any time and you will be paid in proportion to your progress at that time



#### Level 9 out of 30 complete!

#### Rest time remaining: 4:39

(game will automatically end if you do not press 'Start next level' before rest time is up)





Xiao et al (2010), CVPR; Ehinger et al (2011)



# **Visual Memory Game**



**Phillip Isola** 



- Continuous repeat detection task
- •~ 10,000 unique images sampled from 900 scene
- categories (Standing, 1973; Brady et al., 2008)
- **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
- N= 650 AMT workers
- ${\scriptstyle \bullet \sim}$  80 scores per target images

# Large difference in image memorability



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

2222 target images



 $\sim$  80 scores per image

## Subjective judgments <u>do not predict</u> image memorability



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

## Image memorability is distinct from image aesthetic



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

#### **Aesthetic judgments** Interestingness judgments



a) most aesthetic



a) most interesting



b) least aesthetic



b) least interesting

# **Predicting Memorability**

High capacity and visual details fidelity

for exemplars of known categories/concepts

Memory Game IHigh consistency across observers.Memorability is a singular attribute

**Human Memory** 



Memory Game II How does memorability evolve over time?



**Computer Vision** Can computer vision methods

predict memorability?





Jennifer

# Is memorability stable across time?



# When do memorability differences arise?

At stage of encoding: Some images (features) are encoded in less sufficient detail than others



## Intrinsic memorability

**Stable** characteristic of image across observer, randomized sequence, and time delay.

Sizeable differences between different images.

Memorability differences arise at the **perceptual encoding stage:** Some images (features) are encoded in less sufficient details than others <u>at the</u> <u>first glance</u>

→ May tell us about what visual information is deemed important by our recognition system !
## **Predicting Memorability**

High capacity and visual details fidelity

for exemplars of known categories/concepts

Memory Game IHigh consistency across observers.Memorability is a singular attribute

**Human Memory** 



Memory Game II	Memorability ranks are conserved
	across time

**Computer Vision** Can computer vision methods

predict memorability?







# Which feature types predict memorability?





## Which features types predict memorability?

## 1) Simple scalar stats?

brightness, number of objects, mean hue

"Aquarium"

## 2) Scene category?

e.g. Aquarium, broadleaf forest, art studio



## **3) Object content?**

number, size, and rough position of each object class

eye contact"

## "Funny, peaceful, **4)** Attributes?

actions, emotions, focus, subjective properties

#### Simple, scalar summary statistics do not correlate well with memorability





## Which features types predict memorability?

## 1) Simple scalar stats?

brightness, number of objects, mean hue

"Aquarium"

## 2) Scene category?

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## 3) Object content?

number, size, and rough position of each object class

"Funny, peaceful, eye contact"

## 4) Attributes?

actions, emotions, focus, subjective properties

## **Scene features**



Categories from Xiao et al. CVPR, 2010



## Which features types predict memorability?



## **Object features**



Segmentations from Choi et al. CVPR, 2010



## **Segmentation statistics**

**Object counts** "the image contains 4 object classes with 1 appearance each"

#### **Object** areas

"the image contains 1 object class that covers 40898 pixels, 1 object class that covers 21041 pixels, ..."

#### **Multiscale object areas**

"in the first quadrant, the image contains 1 object class that covers 12000 pixels, ..."

Sensitive to coarse position! (can tell difference between sky and close up face.)

ρ = 0.05

ρ = 0.05

ρ = 0.20



## **Object semantics**





## Which features types predict memorability?



## Attributes



Devi Parikh

#### Image rating Please rate the image on the properties listed on the right. Please provide a rating for ALL properties as accurately as possible. Spatial layout: Small / enclosed space 🔲 💿 💿 💿 🕞 Large / open space Perspective view 🖉 💿 💿 💿 💿 🖸 Flat view Empty space 🕒 💿 💿 💿 💿 🛗 Cluttered space Mirror symmetry (about central-vertical line) Aesthetic: Pleasant scene O O O O Unpleasant scene Unusual / strange scene 🔘 🔘 🔘 🔘 🔘 Routine / mundane scene Dull colors O O O O Bright colors Expert photography $\bigcirc \bigcirc \bigcirc \bigcirc \bigcirc \bigcirc$ Poor photography Content: Clear Sky O O O O Cloudy sky Blue sky O O O O Sunset sky Photograph of one main object $\bigcirc$ $\bigcirc$ $\bigcirc$ $\bigcirc$ $\bigcirc$ $\bigcirc$ Photograph of whole scene Zoomed into a scene or object O O O O Wide view Top down view of scene or object $\bigcirc \bigcirc \bigcirc \bigcirc \bigcirc$ $\bigcirc$ Side view



Phillip Isola

## ~ 100 Attributes



Devi Parikh



(a) *†*attractive



(b) ↑funny



(c) ↑makes-sad



(d) †qual. photo



(j) ↓peaceful



(f)  $\downarrow$ attractive



(g) ↓funny



(h)  $\downarrow$  makes-sad

(i)  $\downarrow$ qual. photo



(e) ↑peaceful

Isola, Parikh, Torralba, and Oliva, NIPS 2011

# What are the attributes of picture memorability?

- Focus: single subject/object, close up
- Setting: enclosed space, indoors
- **Subject**: people, faces, emotions, interactive and animate objects
- **Dynamics**: active, moving scenes
- **Other**: famous places, unusual scenes





## Which features types predict memorability?





**Phillip Isola** 

## **Can we estimate memorability?**



**Jianxiong Xiao** 



The result of the regression will be a function that will take as input the features of an image and will output an estimate of the image memorability. Trained on one half of images, one half of subjects, Tested on left out half of images, left out half of subjects, Non-linear kernels

## **Global image features**





## Human consistency $\rho = 0.75$

## Prediction by global features $\rho = 0.46$



a) Most memorable images (86%)



a) Predicted most memorable (87%)







- b) Predicted typical memorability (68%)



c) Predicted least memorable (52%)



b) Typical images (74%)



c) Least memorable images (34%)



### 0) Human guessing?

asking people how memorable an image is

= -0.02

Can we estimate image memorability?



Isola et al (2011). IEEE Proc. Computer Vision & Pattern Recognition (CVPR); (in revision), PAMI

## **Predicting Memorability**

High capacity and visual details fidelity

for exemplars of known categories/concepts

Memory Game IHigh consistency across observers.Memorability is a singular attribute

**Human Memory** 



Memory Game II	Memorability ranks are conserved
	across time

**Computer Vision** State of the art computer vision features can predict memorability

## **Memory Game** Is memorability a general property **III, IV, V** ... of information?





#### BUSINESS INSIDER Tech Finance Politics Strategy Life Entertainment All

#### What The Average Person Looks Like In Every Country

South African Mike Mike travels around the world taking pictures of faces and combining them in hi-tech composites. He calls the ongoing project The Faces Of Tomorrow.

You can compare all the women on the right.



#### http://www.businessinsider.com/faces-of-tomorrow-2011-2?op=1



Wilma Bainbridge

## **Memorability of Faces**



**Phillip Isola** 



<u>Novel dataset</u>: faces selection based on randomly generated first+last names following the distribution of the US census

Bainbridge, Isola, Oliva (in press). The intrinsic memorability of face images. Journal Experimental Psychology: General

## Face Memory Game



~10,000 unfamiliar faces, 2222 targets with ~ 80 memorability scores

## Database creation

cleaned nameslist2.txt - Notepad



File Edit Format View Help Martin Mendes Michael Ard Shawn Newhouse Vanessa Morey Marquerite Hake Joshua Baxter Brandi Layne Jack Gibson Gladys Aubin Edward Sperling Andrew Corriveãu Annie Arnett Lillie Curley Cheryl Griffin Ralph Jessen Judy Housley Della Lind Walter Qualls Myra Hauck Josephine Woo Clara Sandy Candace Jackson Matthew Bowie Marianne Glisson June Beech Daniel Ferreira Leonard Millet Maureen Rye Susie Callender Lucille Vang Sarah Marble John Farley Teresa Neeley Dale Bellamy Clarence Bowens Philip Mchugh Stanley Mcandrew Jason Esposito Harry Bewley Philip Rodgers Chris Speight Allen Hamby Dora Dacosta Lawrence South Jimmy Hamlett Dennis Winfrey Claudia Omara Alan Atwater Jessica Zander Glenda Pugliese Craig Schramm Joanne Madore Jesse Ellington Robyn Doran Doris Fender Stephanie Conklin Lois Frick Tonya Goebel



## High human consistency for both correct detection and errors (false positive)



• HR: M = 51.6%, SD = 12.6, FAR: M = 14.4%, SD = 8.7

• Average 81.7 workers per target image

Bainbridge, Isola, Oliva (in press). The intrinsic memorability of face images. Journal Experimental Psychology: General

#### Rate attributes about the person in the image

Based on your own opinions, please rate this person on the following attributes on a scale of 1 = NOT AT ALL, and 9 = EXTREMELY.

{Note-- By making judgements about these images, you are participating in a study being performed by the cognitive scientists in the MIT Department of Brain and Cognitive Science. If you have questions about this research, please contact Dr. Oliva at oliva@mit.edu. Your participation in this research is voluntary. You may decline further participation, at any time, without adverse consequences. Your anonymity is assured; the researchers who have requested your participation will not receive any personal information about you.}



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Race	O White	Black	CEast Asia	South Asian	Hispanic	O Middle Eastern	Other

---

Please answer all questions before submitting the HIT. Thank you!

Submit HIT

### Which attributes make a face memorable?

True memories (high HIT, low FA):

Irresponsible Unhappy Unintelligent **Familiarity** (high HIT, high FA):

Kind Trustworthy Atypical



Bainbridge, Isola, Oliva (in press). The intrinsic memorability of face images. Journal Experimental Psychology: General

## **Can we manipulate memorability?**







## Modifying face memorability



Antonio Torralba MIT Aditya Khosla MIT



#### Goal

 Modify faces to be more/less memorable while keeping identity, and other attributes intact

#### Problem

 Features such as HOG/SIFT significantly outperform AAM based features for memorability prediction

## Testing Memory of Memorable & Forgettable face photographs



Two complementary Face memory experiments with 400 faces of different identities, with either a memorable or forgettable version of each identity (fillers are faces with random modification)

### **Modifying Face Memorability: Results**













 $\uparrow 0.20$ 

 $\uparrow 0.41$ 



 $\downarrow 0.11$ 



 $\downarrow 0.32$ 





















### **Memorability of Visualizations**





Zoya Bylinskii MIT

#### Memorable



#### Forgettable

Hanspeter Pfister Harvard Michelle Borkin Harvard



Consistency for HIT:  $\rho$  = 0.83; False Alarms:  $\rho$  = 0.78

Borkin, Vo, Bylinskii, Isola, Sunkavalli, Oliva & Pfister (in press). What makes a visualization memorable? IEEE Transactions on Visualization and Computer Graphics.



#### **Zoya Bylinskii** MIT

## **Fine-grained memorability**

*Only exemplars of the same category* 

#### Memorable

#### Forgettable



Each class has > 400 exemplars in a Visual Memory Game. Very high human consistency for HIT and False Alarms for instances of the same class

## Memorability

- Memorability is an intrinsic feature of the stimulus, reproducible across a diverse population and for diverse types of (visual) information
- Memorability is a new task for computer vision and can be used as a metric for quantifying/sorting information and present users with meaningful memorable (or forgettable) information
- Memorability provides a **tool** to investigate the cognitive and neural basis of **human memory**, and augment memory capacity
- <u>As a common factor across disciplines</u>, *memorability* may become a fairly general **quantification of the utility** of visual information.

## Datasets

#### Massive memory website cvcl.mit.edu/MM

Home | Papers | Stimuli | Demos



MIT | BCS | CVCL | Alvarez | Brady | Konkle | Oliva

#### SUN: Scene Understanding

http://groups.csail.mit.edu/vision/SUN/



#### **Scene Memorability Dataset**

http://web.mit.edu/phillipi/Public/ WhatMakesAnImageMemorable/

http://web.mit.edu/phillipi/ UnderstandingMemorability/



#### **10k US Adult Face dataset**

(available december 2013)

